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Implementation of Artificial Neural Network for Forecasting California Bearing Ratio of Treated Cement-Laterite Soil Improved with Bamboo Leaf Ash

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ABSTRACT

Finding the California Bearing Ratio (CBR) of soil stabilised by an environmentally friendly binder composite is one of the most important steps in designing an appropriate mix. By utilising an artificial neural network (ANN) to forecast soil parameters and additions of Portland cement and Bamboo Leaf Ash (BLA), this study aims to estimate the California Bearing Ratio (CBR) of treated cement-lateritic soils. The precise and accurate findings are obtained by selecting six factors as input variables. Maximum Dry Density (MDD) (kg/m^3), Plasticity Index (PI) (%), Liquid Limit (LL) (%), Cement (%), Bamboo Leaf Ash (BLA) (%), and OMC (%) were the six input variables. In contrast, the output variables were CBR soaked (%) and CBR unsoaked (%). 1288 samples from a database were used in the investigation. Training is done using a multilayer perceptron-backpropagation algorithm. The network topology is acquired after the fixing of several hidden neurones. With a 99.5% accuracy rate, the model can predict CBR results.

1. INTRODUCTION

The stability and durability of the soil dictate how much weight well-compacted and treated soils can bear when used as foundation materials. A typical crushed rock sample's impedance is compared to the resistance that arises from lowering a penetration piston into the soil at a rate of 1.27 mm/min (0.05 in/min) using the California Bearing Ratio (CBR), according to Yildrim and Gunaydin [1]. For the speed control to lower the penetration piston to the required depth, CBR resistance is essentially defined as the ratio of the applied stress to the energy-compressed soil at the specified moisture content. The CBR test can be performed in the field and lab. ASTM-D 1883-99 and ASTM-D 4429-93 [2, 3] explain the CBR test in the field and the laboratory, respectively. Laboratory samples of compacted soil are frequently used for CBR testing. The CBR test is conducted in a field trial on a ground level excavated from a test pit [4]. Both soaked (in water) and unsoaked (without water) CBR testing is conducted on natural or compacted soils. The subgrade soil strength is assessed by comparing the test results with the curves from the standard tests [5, 6]. In order to increase a local clay's California Bearing Ratio (CBR), Karimiazar et al. [7] investigated the use of nano-silica and nano-alumina. Nano additives (0.1%), cement (2%-8%), and cement with nano-additive (3% cement + 0.1%-1.5%). The cured and compacted sample was also tested for unsoaked CBR after seven days drying. CBR (soaked) (%). The maximum improvement in the soaked CBR of untreated clay amended by 1% nano-alumina and 1% nano-silica are: 27% and 49%, respectively. Ice37: Furthermore, the incorporation of 3% cement increased the CBR values by an average value of about approximately 28%, while that increase was full-fledged by using nano-silica and cement, which augmented up to a magnitudeofaround196 and 164 times respectively for soaked conditions. It is also observed that the cement-based reactive powder with nano-additives was prepared using about 6% to 7% of the traditional CBR requirement to produce a similarly soaked CBR. The results revealed that the clay combined with 1% nano-silica and WBA (3 wt%) showed superior CBR value over other samples tested. In contrast, the soil admixed by NWA@1 percentage and WBA indicates a maximum reduction in free swell potential. As a result of the interaction between nano-additive and sepiolite, homonymous material was formed with less porosity while revealing Calcium Silicate Hydrate (CSH) or/and calcium aluminate hydrate (CAH) product inside the fabric [8-10]. The CBR test is essential in geotechnical engineering and earth structures like road pavements and dam embankments [11]. It typically requires 4 days to establish soaked CBR in the case of a laboratory test, which is a motivation for any soil specimen. It has been published that the CBR test is time-consuming, tedious, and boring to conduct in the laboratory [12, 13], so appropriate models are also needed from this perspective. Studies indicate that CBR can be estimated based on laboratory assessments of the type and content quantities [14, 15]. This scenario has led to a new field in the construction industry: dependable predictions. Due to valuable contribution, using artificial neural networks (ANNs) is becoming more common in geotechnical engineering [16-18].

1.1 Artificial neural networks in civil engineering

Artificial neural networks (ANNs) have demonstrated high precision in practice and have been widely used in modelling a wide range of engineering problems related to nonlinearity in recent years [19]. Methods We employ artificial neural networks (ANNs) and regression analysis (RA). The authors developed simple and robust CBR models using conventional material properties such as gradient, Atterberg limits, and compressive strength. The Highway and Airport Engineering Laboratory at Mansoura University prepared quality assurance reports, which comprised a database of 207 CBR values. The CBR values ranged between 26% and 98%. The data were equally divided into training and testing (used for model validation) at a ratio of 80:20 and tested in parallel with the experimental samples from 11 laboratories. The model developed by RA and ANNs, in which the CBR values were related to the maximum dry density and D60. Regarding the coefficient of determination (R^2), both approaches created a CBR model with excellent prediction accuracy, and the recommended model's validation was adequate. Timani and Rain [20] state that layers of different materials with changing thicknesses make up the flexible pavement. CBR, elastic modulus, moisture condition, and unit weight are the basic subgrade properties used in pavement component design. CBR characterisation is important for any activity requiring flexible pavement. Numerous researchers have suggested ANN techniques as a superior alternative to CBR since they are less time-consuming and laborious than CBR [21-24].

Artificial neural networks (ANN) have emerged as a true model and tool for various applications, including prediction, identification, classification, and pattern recognition. Due to its increased relevance and utility, this machine learning (ML) model has become a viable substitute for statistical models and regular regression [25]. ANNs are mathematical models of human cognition or neural ecology that have been made simpler. The primary differentiating factor of ANN is the unique structure of its information processing system. An artificial neural network (ANN) comprises several neurones, strongly coupled processing units collaborating to solve certain problems. Neurones that share comparable properties are arranged in layers inside an ANN [26]. Neural networks are commonly classified into single, bilayer, and multilayer categories according to the number of layers they are composed. The direction and flow of information processing can also be used to categorise ANNs. Compared to statistical approaches, artificial neural networks (ANNs) are becoming more and more dependable due to their unique capacity to understand complicated systems when the input and output are known via either in situ or field research [27].

Adaptivity, nonlinearity, homogeneity, and fault tolerance are the main benefits of the ANN over alternative modelling software. Understanding the underlying relationship between variables is unnecessary for ANNs because they are data-driven systems. These parametric nonlinear models can most remarkably approximate any continuous relationship between input and output [28, 29]. Consequently, MLR and ANN are employed in the study of Harini and Naagesh [30] to compute the CBR of fine-grained soils. Fine-grained soils CBR. Soil metrics associated with CBR include some of the easiest to acquire, as they are based on basic engineering tests such as optimum moisture content and maximum dry density (OMC-MDD), liquid limit, plastic limit (LL-PL), PI (%/attritions). A series of forty different soil data sets is used in the study. It was also found that the ANN model displayed better performance than MLR in predicting CBR from soil factors. The proposed ANN model was effectively tested on real-life laboratory data, providing a strong correlation of 0.94. This study focuses on deploying an ANN to forecast the CBR of treated cement laterite soil stabilised with Bamboo Leaf Ash. However, the prediction analysis in this study is done in the context of reinforced eco-friendly soil stabilisers using an artificial neural network, and the prediction is performed in both the soaked and unsoaked CBR.

2. METHODS

Determining the particle size distribution, specific gravity, and Atterberg limits were among the initial analyses performed on the soil samples. Tests were also conducted on the natural soil samples for compaction and California Bearing Ratio (CBR).

These techniques were applied to each soil sample's unstabilised and stabilised stages, A and B. The following procedure was employed:

i. The treated soil samples were then treated with cement at 0, 2, 4, 6, 8, 10, and 12%, then individually mixed with Bamboo Leaf Ash at various ratios of 2, 4, 6, 8, 10, 12, 14, and 16% by the weight of dry soil.
ii. These samples were subjected to the California Bearing Ratio, compaction, and Atterberg limits.
iii. All tests were done by the study [31] and BS 1377 [32] for natural soil samples.

The liquid limit, plasticity index, maximum dry density, optimum moisture content, percentages of cement, and Bamboo Leaf Ash were among the test results obtained in the laboratory that were used as inputs to construct an artificial neural network (ANN) model for predicting the soaked and unsoaked CBR values of stabilised soils.

2.1 The design procedure for the artificial neural network

Six (6) major stages comprised designing and implementing the Artificial Neural Network (ANN) for this research project. These stages include data acquisition, feature selection and data normalisation, ANN architecture optimisation, ANN algorithm optimisation, ANN initialisation and training, testing, validation, and deployment. Feed-forward neural network backpropagation using Levenberg-Marquardt is a classical gradient-based optimisation method that is used to solve nonlinear least squares problems. It also has a fast convergence speed the moment the initial value is given correctly. A MATLAB training ANN model was utilised to compute the data and select the optimal model. The degree of correlation between the target of the soft computing models and their final outputs was measured using the Coefficient of Correlation (R) and the Mean Square Error (MSE). Cement (%), Bamboo Leaf Ash (BLA) (%), Liquid Limit (LL) (%), Plasticity Index (PI) (%), Maximum Dry Density (MDD) (Kg/m^3), and OMC (%) were the six input variables. In comparison, the two output variables were CBR Unsoaked (%) and CBR Soaked (%). The experimental findings gathered one thousand two hundred eighty-eight sets of soil data; 70% were used for training, 15% for testing, and 15% for data validation.

2.2 Data division

The randomised data produced training, testing, and validation datasets. Training data was utilised to identify possibly predictive connections. It is a set of samples that are used to fit the weights, or parameters, of the classifier so that it can learn. The strength and usefulness of a predictive relationship were assessed using a test dataset, a collection of examples explicitly created to assess the efficacy (generalisation) of a fully specified classifier. In addition to the training and testing sets, a validation set was necessary to avoid overfitting, especially if any classification parameters had to be changed. Training, testing, and validation datasets were created using the randomised data. Training data was used to find potentially predictive relationships. It is a collection of examples that are used to fit the classifier's weights or parameters so that it can be trained.

Test dataset: a set of instances created specifically for testing a completely specified classifier's ability to generalise; it was used for assessing the usefulness and strength of the predictive link. Besides the training and testing sets, the overfitting issue also called for a validation set, especially when any of the parameter settings for classification were to be varied.

2.3 Data stabilisation

The data stabilisation process was finished to rule out input weight bias. This enables the network to assign equal importance to various input values, irrespective of their magnitude. Furthermore, input stabilisation reduces the search interplanetary to a unitary hypercube by drastically band-restricting inputs to a border between 0 and 1. This speeds up computation and training. This makes Bayesian estimate and weight decay much easier. The process of obtaining the corresponding normalised value (P_i) for every network input P_i is demonstrated by Eq. (1).

$$\overline{P_i} = P^t{}_{min} + \left(\frac{P_i - P_{min}}{P_{max} - P_{min}}\right)(P^t{}_{max} - P^t{}_{min}) \tag{1}$$

P^t_{max} is the maximum value, and P^t_{min} is the target's minimum value. At the same time, P_i is the actual input data, and P_{max} and P_{min} are the maximum and minimum input values, respectively.

2.4 Performance indices of the study statistical

This is for accuracy and precision. It uses the root mean square error (RMSE) and coefficient of determination (R^2). This information on short-term efficiency is a starting point for comparing actual and expected values. The assessment is more accurate than the RMSE. The coefficient of determination, or R square, measures the variation that the model interprets or the reduction in variance that occurs when using a model. When R^2 is near to 1, which ranges from 0 to 1, the model has strong predictive ability. The overall prediction accuracy can be assessed by utilising these performance criteria. The mean absolute error displays the average divergence of the projected values from the corresponding observed values, or MAE, which offers insight into the long-term performance of models. The model's long-term prediction is better with a lower MAE.

2.5 The training algorithm of the ANN and network performance criteria

The algorithm employed was Levenberg-Marquardt (LM). The Levenberg-Marquardt (LM) procedure is a second-order technique that trains a network by continuously changing its weights and biases through an optimisation technique. This method, essentially a trust region version of the Gauss-Newton method, is fast, efficient, and often the best choice for supervised training. The Levenberg-Marquardt approach attempts to iteratively reduce an error function E(w) by varying the weight and bias values of the different layers of the network, as shown in Eq. (2). This is carried out until a stop benchmark or a predefined allowed minimum rate is reached.

$$E(\boldsymbol{w}) = \frac{1}{2}\sum_{p=1}^{P}\sum_{m=1}^{M} e_{pm}^2 \tag{2}$$

Therefore, P denotes the count of patterns from the input-output training pair, M indicates the number of outputs, and N is the number of weight elements in total. The synopsis of the algorithm, which is the artificial neural network is contained in Table 1. One of the objectives of assessing the work of a soft computing network is to find out how close the output as computed by the network is to the output that would have been generated from a physical process. In this study, Eqs. (3)-(5) show the application of root mean square error (RMSE) and coefficient of correlation (R).

$$CMD = \sqrt{1 - \frac{\sum_{i=1}^{N}(y - \hat{y})^2}{\sum_{i=1}^{N}(y)^2}} \tag{3}$$

$$VAF = \left[1 - \frac{var(y - \hat{y})}{var(y)}\right] \times 100 \tag{4}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y - \hat{y})^2} \tag{5}$$

where, y is the desired value, $\hat{y}$ Is the network's output, and var. stands for the corresponding operand's mathematical probabilities

Table 1. The ANN algorithm employed for the study

Algorithm	Network Weight Adaptation	Description
Levenberg-Marquardt (LM) Algorithm	$\Delta w = (J^T J + \mu I)^{-1} J^T e$	The Jacobian matrix J and the network error vector e are calculated during the weight update.

3. RESULTS AND DISCUSSIONS

Table 2 lists the specifics of the ANN model's components.

The six input variables were cement (%), Bamboo Leaf Ash (BLA) (%), liquid limit (LL) (%), plasticity index (PI) (%), maximum dry density (MDD) (Kg/m^3), and optimum moisture content (OMC) (%). In comparison, the two output variables were CBR Unsoaked (%) and CBR Soaked (%). The model consisted of one hidden layer with ten layers of neurones. Figures 1 to 14 show values of soaked and unsoaked CBR with varying proportions of cement and BLA as predicted by the model and observed in the laboratory. These values indicate the ANN models' accuracy and high precision [33].

Table 2. The ANN model details of components used

Inputs number	6
Outputs number	2
Hidden layer neurons	10
Output layer neurons	2
Epochs	21

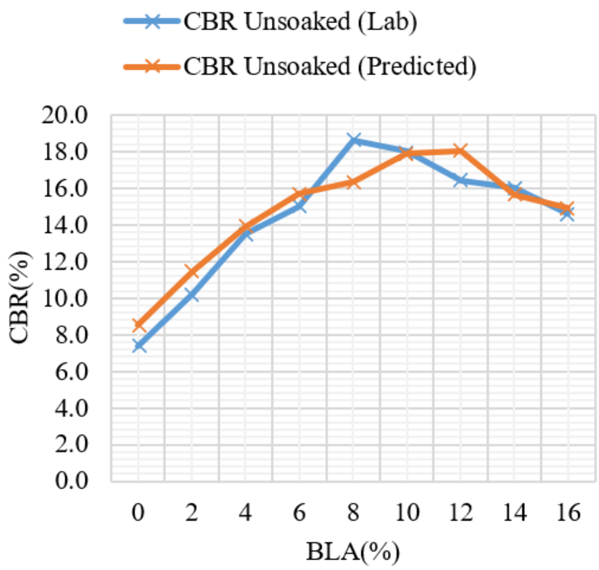

Figure 1. Evaluation of the expected unsoaked CBR values with the observed (lab) values of A-7-5 + BLA + 0% cement

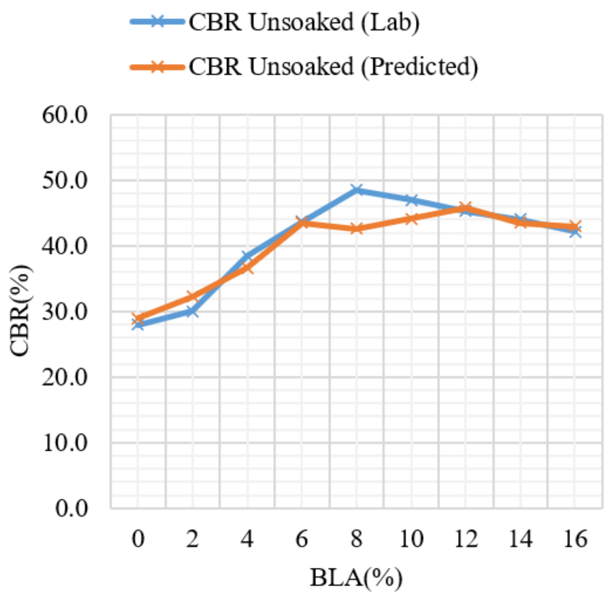

Figure 2. Evaluation of the expected unsoaked CBR values with the observed (lab) values of A-7-5 + BLA + 2% cement

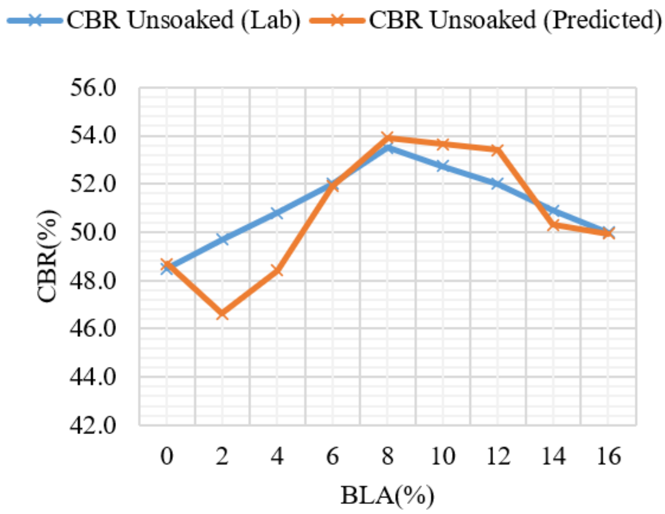

Figure 3. Evaluation of the expected unsoaked CBR values with the observed (lab) values of A-7-5 + BLA + 4% cement

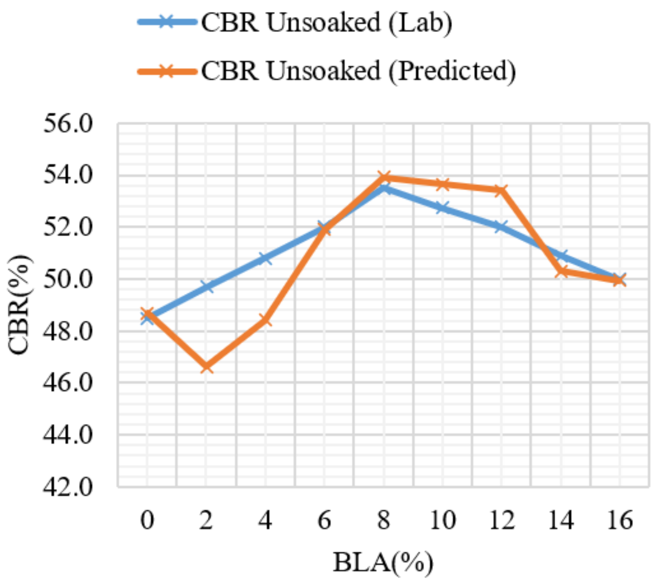

Figure 4. Evaluation of the expected unsoaked CBR values with the observed (lab) values of A-7-5 + BLA + 6% cement

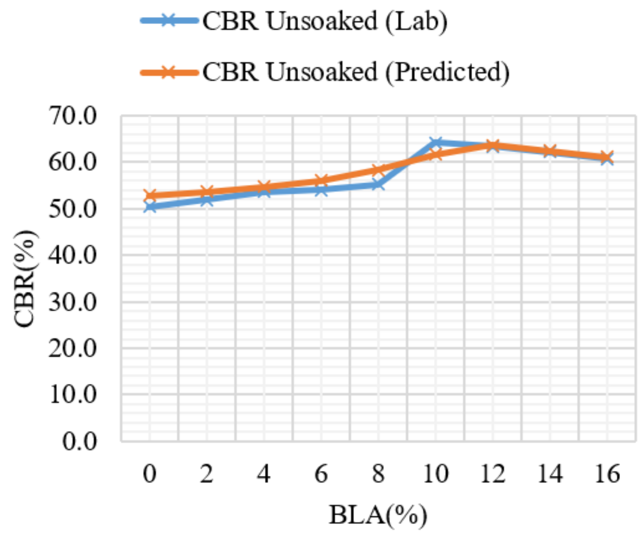

Figure 5. Evaluation of the expected unsoaked CBR values with the observed (lab) values of A-7-5 + BLA + 8% cement

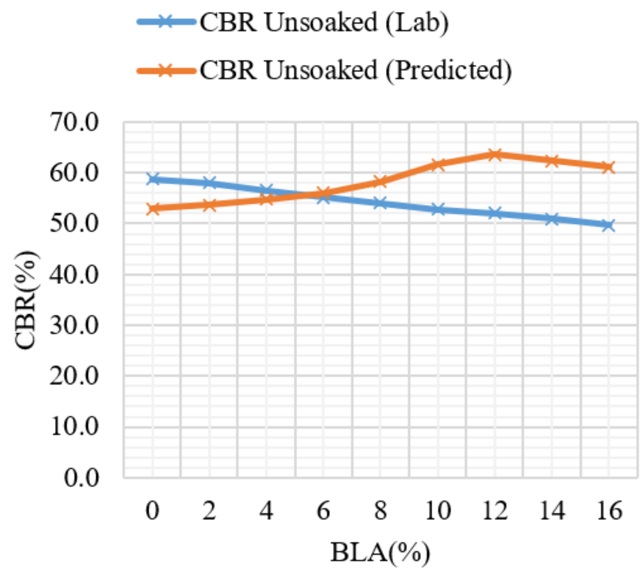

Figure 6. Evaluation of the expected unsoaked CBR values with the observed (lab) values of A-7-5 + BLA + 10% cement

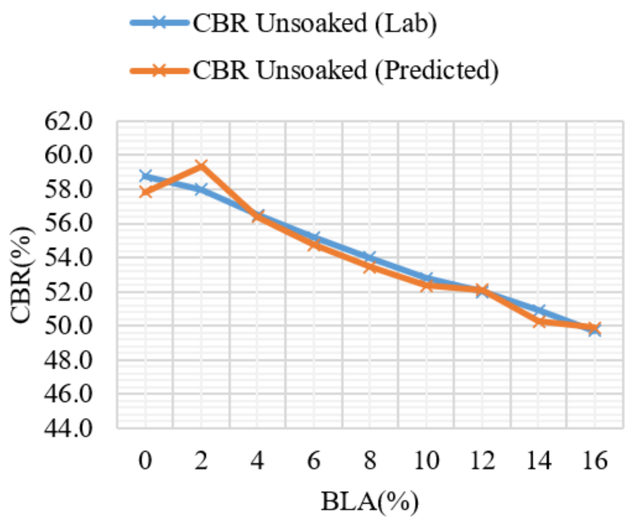

Figure 7. Evaluation of the expected unsoaked CBR values with the observed (lab) values of A-7-5 + BLA + 12% cement

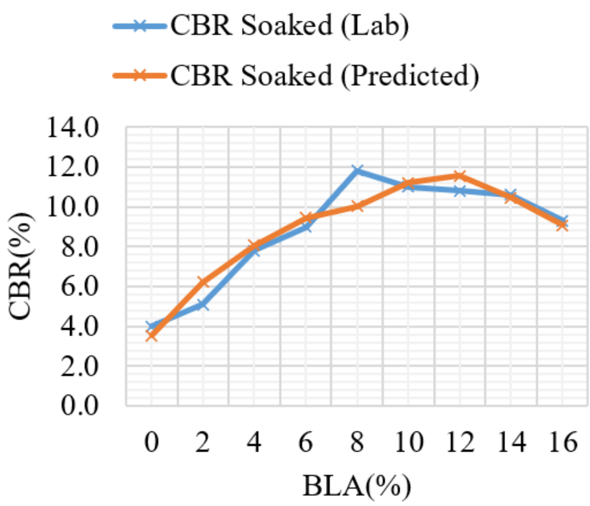

Figure 8. Evaluation of the expected soaked CBR values with the observed (lab) values of A-7-5 + BLA + 0% cement

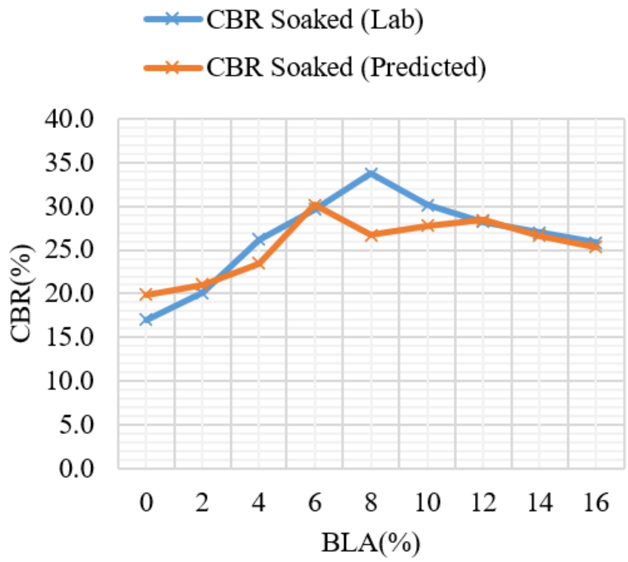

Figure 9. Evaluation of the expected soaked CBR values with the observed (lab) values of A-7-5 + BLA + 2% cement

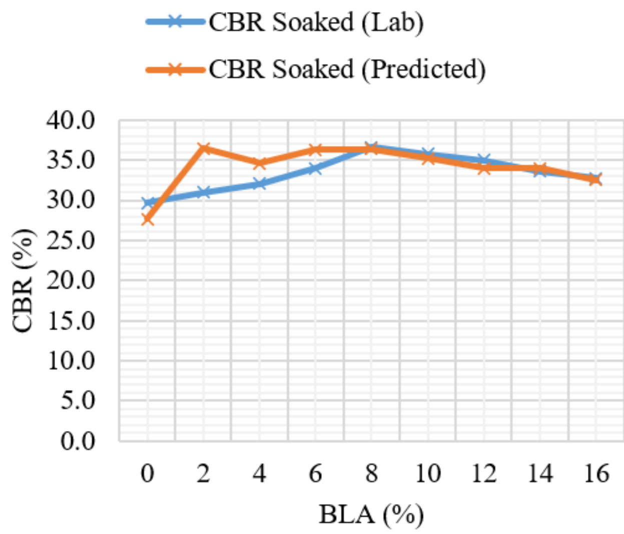

Figure 10. Evaluation of the expected soaked CBR values with the observed (lab) values of A-7-5 + BLA + 4% cement

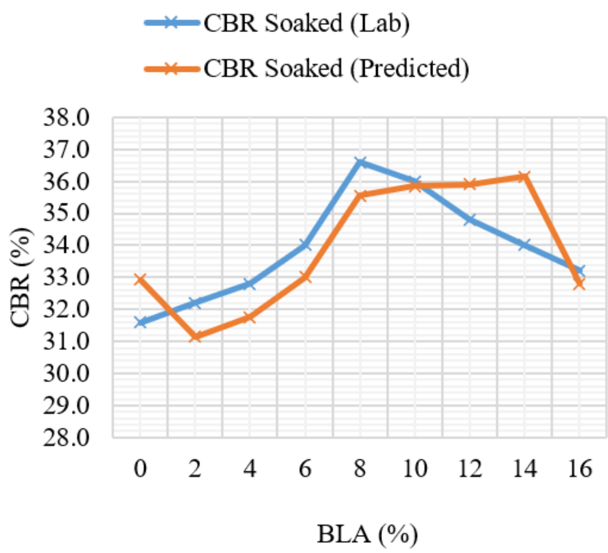

Figure 11. Evaluation of the expected soaked CBR values with the observed (lab) values of A-7-5 + BLA + 6% cement

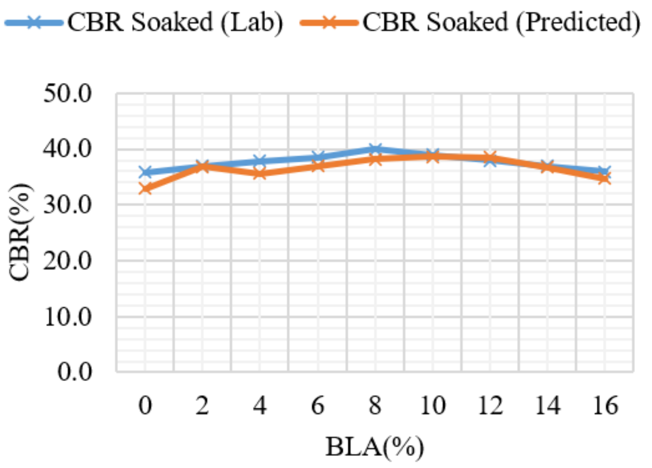

Figure 12. Evaluation of the expected soaked CBR values with the observed (lab) values of A-7-5 + BLA + 8% cement

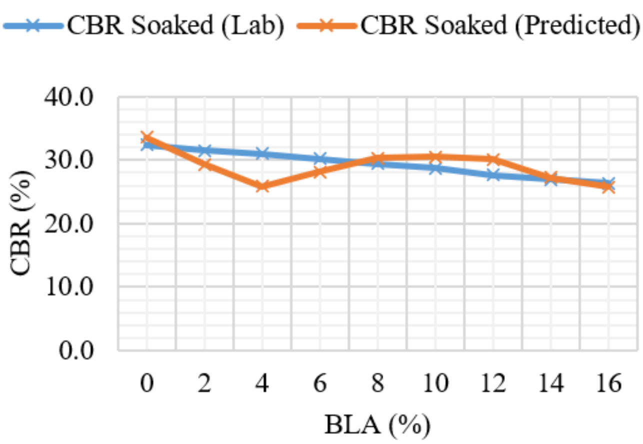

Figure 13. Evaluation of the expected soaked CBR values with the observed (lab) values of A-7-5 + BLA + 10% cement

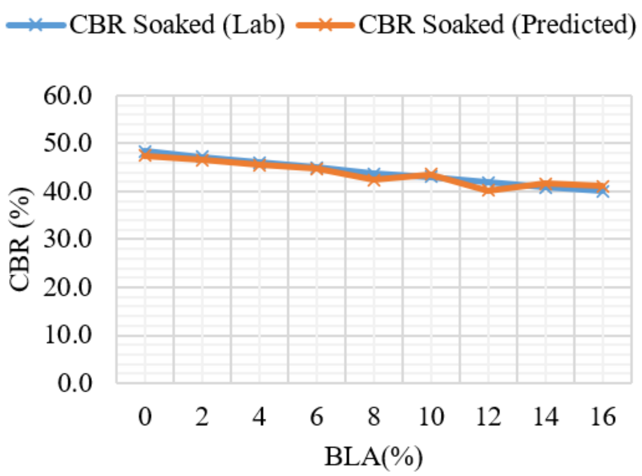

Figure 14. Evaluation of the expected soaked CBR values with the observed (lab) values of A-7-5 + BLA +12%

3.1 The ANN results for Bamboo Leaf Ash at A-7-5 soil for the regression analysis

The regression diagram for the training dataset's projected (output) and observed California Bearing Ratio (CBR) during the ANN model's training phase is displayed in Figure 15. The predicted and target values for the testing dataset during the ANN model's testing phase are displayed in Figure 16. The goal (observed) and anticipated (output) values for dataset validation during the ANN model's validation stage are displayed in Figure 17. At training, testing, and validation, as well as throughout all phases of prediction analysis, the neural network's performance was demonstrated by its coefficient of correlation (R), which was 0.9981, 0.99553, 0.98608, and 0.99485, respectively. These findings are consistent with Tesfaye and Potdar's work [33]. The authors employed ANN to predict the CBR of treated soil. In order to measure CBR values, a mixture of eggshell and waste glass was added to the soil in amounts ranging from 4% to 12% of the weight of the soil samples.

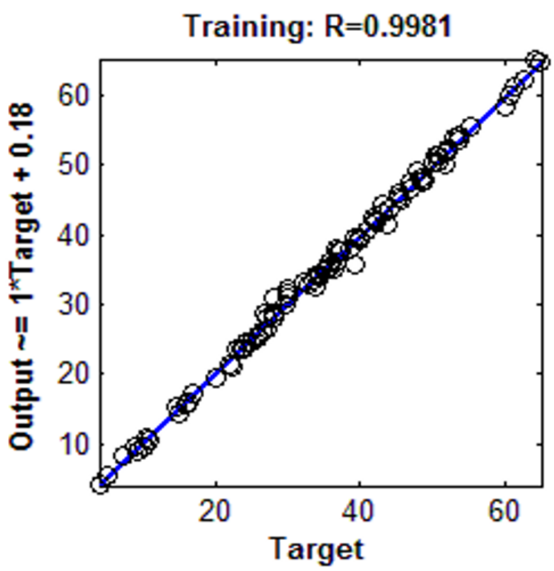

Figure 15. The regression analysis illustrating the predicted (output) and target (observed) values for ANNs training dataset at their learning phase in models of Bamboo Leaf Ash + A-7-5 soil mixes with cement

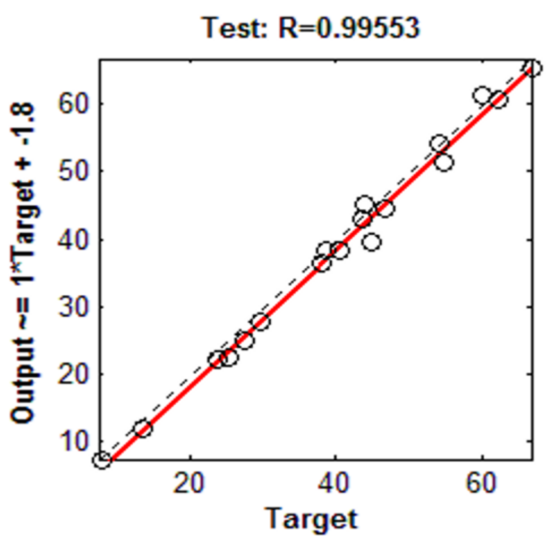

Figure 16. Regression plot of means for testing dataset (Bamboo Leaf Ash and A-7-5 soil with cement) The output versus observed values at the time of testing process is shown in a regression manner

Table 3. The experimental results

Stabilizing Cement-Treated Soil Sample A-7-5 with Bamboo								
Cement (%)	**BLA**	**LL**	**PL**	**PI**	**MDD**	**OMC**	**CBR (Unsoaked)**	**CBR (Soaked)**
0	0	62.8	34.1	28.7	1452	15.2	7.4	4.0
0	2	60.4	33.0	27.4	1440	15.8	10.2	5.1
0	4	59.1	32.6	26.5	1430	16.3	13.5	7.8
0	6	58.0	32.0	26.0	1422	16.9	15.0	9.0
0	8	56.8	31.7	25.1	1410	18.1	18.6	11.8
0	10	55.8	31.0	24.6	1402	19.1	18.0	11.0
0	12	53.8	30.6	23.2	1390	19.8	16.4	10.8
0	14	51.9	30.2	21.7	1375	20.7	16.0	10.6
0	16	50.4	30.2	20.2	1364	21.9	14.6	9.3
2	0	58.2	30.2	28.0	1464	16.0	28.0	17.0
2	2	57.1	30.1	27.0	1455	16.5	30.0	20.1
2	4	56.2	29.7	26.5	1445	17.0	38.4	26.2
2	6	55.4	29.3	26.1	1434	18.3	43.7	29.6
2	8	54.8	28.8	26.0	1425	19.8	48.5	33.7
2	10	52.7	28.8	23.9	1430	20.9	47.0	30.1
2	12	50.8	28.0	22.8	1440	22.2	45.3	28.2
2	14	49.2	27.8	21.4	1447	23.5	44.0	27.0
2	16	48.5	27.5	21.0	1454	24.8	42.2	25.8
4	0	54.5	29.7	24.8	1480	16.5	48.5	29.7
4	2	54.0	29.7	24.3	1470	17.0	49.7	31.0
4	4	53.2	29.5	23.7	1460	18.4	50.8	32.1
4	6	51.9	28.9	23.0	1455	19.2	52.0	34.0
4	8	51.2	28.4	22.8	1447	20.5	53.5	36.6
4	12	48.7	27.7	21.0	1465	22.0	52.0	35.0
4	14	46.2	25.7	20.5	1480	22.8	50.9	33.6
4	16	45.0	25.0	20.0	1495	24.3	50.0	32.8
6	0	52.8	32.0	20.8	1493	20.6	58.4	31.6
6	2	52.0	32.0	20.0	1480	21.2	60.0	32.2
6	4	51.2	31.8	19.4	1472	21.7	62.5	32.8
6	6	50.8	31.8	19.0	1466	22.4	64.1	34.0
6	8	50.0	31.2	18.8	1460	23.0	66.7	36.6
6	10	49.5	31.0	18.5	1468	23.5	64.8	36.0
6	12	49.0	30.7	18.3	1474	25.2	62.0	34.8
6	14	48.2	30.4	17.8	1460	25.8	61.4	34.0
6	16	47.7	30.3	17.4	1496	26.3	59.9	33.2
8	0	51.2	30.8	20.4	1520	20.8	50.4	35.8
8	2	50.7	30.5	20.2	1502	21.4	51.8	37.0
8	4	50.0	30.3	19.7	1494	21.9	53.6	37.8
8	6	49.2	29.7	19.5	1481	22.7	54.0	38.5
8	8	48.7	29.2	19.5	1470	23.8	55.2	40.0
8	10	48.2	28.8	19.4	1476	24.2	64.1	39.0
8	12	46.0	28.7	18.1	1487	25.7	63.4	38.0
8	14	46.0	28.5	17.5	1502	26.6	62.2	36.9
8	16	45.5	28.5	17.0	1525	27.5	60.7	36.0
10	0	47.5	29.3	18.2	1535	21.6	58.8	32.4
10	2	46.2	29.0	17.2	1528	22.4	58.0	31.5
10	4	45.5	28.7	16.8	1520	22.9	56.5	31.0
10	6	45.1	28.4	16.7	1513	23.6	55.2	30.2
10	8	44.0	28.0	16.0	1501	24.7	54.0	29.4
10	10	43.2	27.4	15.8	1510	25.3	52.8	28.7
10	12	42.5	27.0	15.5	1517	26.0	52.0	27.7
10	14	40.1	25.9	14.2	1527	27.1	50.9	27.0
10	16	39.3	25.6	13.7	1539	28.0	49.7	26.4
12	0	43.1	26.1	17.0	1542	23.0	52.2	48.4
12	2	42.3	25.4	16.9	1536	24.3	50.0	47.2
12	4	41.8	24.9	16.9	1528	25.3	48.7	46.0
12	6	40.4	24.4	16.0	1520	26.0	48.0	45.0
12	8	40.0	24.4	15.6	1515	27.1	46.8	43.7
12	10	38.9	23.5	15.4	1520	30.0	45.4	43.0
12	12	37.8	23.1	14.7	1527	31.1	44.6	41.9
12	14	36.0	22.0	14.0	1530	32.2	43.5	40.8
12	16	35.4	21.4	14.0	1538	33.0	42.7	40.0

Table 4. The ANN predicted result

ANN Output		Error		Squared Error	
CBR (Unsoaked)	CBR (Soaked)	CBR (Unsoaked)	CBR (Soaked)	CBR (Unsoaked)	CBR (Soaked)
8.5136	3.5402	-1.1136	0.4598	1.2	0.2
11.4579	6.2225	-1.2579	-1.1225	1.6	1.3
13.9137	8.0561	-0.4137	-0.2561	0.2	0.1
15.6829	9.4387	-0.6829	-0.4387	0.5	0.2
16.3493	10.0232	2.2507	1.7768	5.1	3.2
17.8614	11.1965	0.1386	-0.1965	0.0	0.0
18.0266	11.5672	-1.6266	-0.7672	2.6	0.6
15.6237	10.4597	0.3763	0.1403	0.1	0.0
14.9169	9.0864	-0.3169	0.2136	0.1	0.0
28.9640	19.9128	-0.9640	-2.9128	0.9	8.5
32.2079	21.0183	-2.2079	-0.9183	4.9	0.8
36.6646	23.4778	1.7354	2.7222	3.0	7.4
43.4830	30.1596	0.2170	-0.5596	0.0	0.3
42.6140	26.7282	5.8860	6.9718	34.6	48.6
44.1362	27.7602	2.8638	2.3398	8.2	5.5
45.8342	28.4218	-0.5342	-0.2218	0.3	0.0
43.5215	26.6273	0.4785	0.3727	0.2	0.1
42.9766	25.3363	-0.7766	0.4637	0.6	0.2
48.6866	27.6706	-0.1866	2.0294	0.0	4.1
46.6299	36.4334	3.0701	-5.4334	9.4	29.5
48.4158	34.6267	2.3842	-2.5267	5.7	6.4
51.8963	36.2784	0.1037	-2.2784	0.0	5.2
53.9124	36.4257	-0.4124	0.1743	0.2	0.0
53.4027	33.9738	-1.4027	1.0262	2.0	1.1
50.3026	33.9598	0.5974	-0.3598	0.4	0.1
49.9392	32.5558	0.0608	0.2442	0.0	0.1
57.7512	32.9263	0.6488	-1.3263	0.4	1.8
61.0779	31.1476	-1.0779	1.0524	1.2	1.1
63.4067	31.7576	-0.9067	1.0424	0.8	1.1
65.5990	33.0109	-1.4990	0.9891	2.2	1.0
64.6210	35.5431	2.0790	1.0569	4.3	1.1
64.6223	35.8506	0.1777	0.1494	0.0	0.0
63.5090	35.9106	-1.5090	-1.1106	2.3	1.2
62.2477	36.1437	-0.8477	-2.1437	0.7	4.6
59.0926	32.7914	0.8074	0.4086	0.7	0.2
52.8609	32.9031	-2.4609	2.8969	6.1	8.4
53.6551	36.8603	-1.8551	0.1397	3.4	0.0
54.7308	35.5949	-1.1308	2.2051	1.3	4.9
56.0608	36.9850	-2.0608	1.5150	4.2	2.3
58.2707	38.1287	-3.0707	1.8713	9.4	3.5
61.5976	38.6441	2.5024	0.3559	6.3	0.1
63.5832	38.5577	-0.1832	-0.5577	0.0	0.3
62.3854	36.7554	-0.1854	0.1446	0.0	0.0
61.0425	34.6588	-0.3425	1.3412	0.1	1.8
57.8307	33.6311	0.9693	-1.2311	0.9	1.5
59.3619	29.3560	-1.3619	2.1440	1.9	4.6
56.3837	25.9035	0.1163	5.0965	0.0	26.0
54.7657	28.1685	0.4343	2.0315	0.2	4.1
53.4447	30.3384	0.5553	-0.9384	0.3	0.9
52.3655	30.5309	0.4345	-1.8309	0.2	3.4
52.1074	30.0916	-0.1074	-2.3916	0.0	5.7
50.2648	27.2933	0.6352	-0.2933	0.4	0.1
49.9102	25.7429	-0.2102	0.6571	0.0	0.4
53.0250	47.5188	-0.8250	0.8812	0.7	0.8
49.6671	46.5039	0.3329	0.6961	0.1	0.5
47.8092	45.4910	0.8908	0.5090	0.8	0.3
47.2864	44.6576	0.7136	0.3424	0.5	0.1
46.9443	42.4138	-0.1443	1.2862	0.0	1.7
46.5554	43.6012	-1.1554	-0.6012	1.3	0.4
45.2645	40.2422	-0.6645	1.6578	0.4	2.7
42.9694	41.6075	0.5306	-0.8075	0.3	0.7
40.8450	41.0484	1.8550	-1.0484	3.4	1.1
				137.0	**211.8**
			RMSE	**1.4867**	**1.8484**
			VAF		

The experiment's result is displayed in Table 3, which is also utilised for the ANN prediction, as shown in Table 4. Laboratory-related tests were consequently carried out to obtain the best model. The highest CBR value was 5.8 at an addition of 8% eggshell waste glass powder. CBR was used in the model's development as an output layer variable. CBR was a function of optimum moisture content, maximum dry density, and the combined effects of liquid limit, plastic limit, and plastic index. An ANN model with 5, 6, and 1 neuron in the input, hidden, and output layers was the most successful model that could be developed. The correlation coefficient (R), mean square error (MSE), and mean absolute error (MAE). Root mean square error (RMSE) This research discussed the above and shed insight on the potential for stabilisation using Bamboo Leaf Ash in various proportions to produce an economically viable CBR, as it has been proven from the literature that bamboo is a good material for soil stabilisation [34].

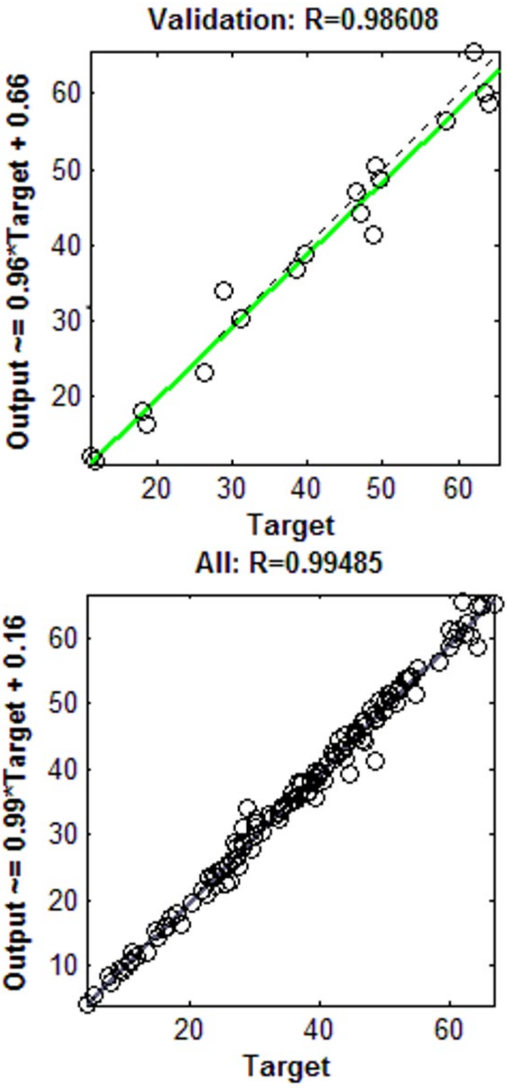

Figure 17. The regression plot shows the predicted (output) and target (observed) values for (a) the validation dataset and (b) all predicted values of the ANN model (Bamboo Leaf Ash and A-7-5 soil and cement)

Figure 18 shows the training outcomes. As additional training epochs are finished, the error generally falls as the network overfits the training data in the default setup. Still, it may begin to grow on the validation data set. The best performance from epoch 21 with the lowest validation error is chosen when training ends after six consecutive increases in a validation error. Figure 19 shows the ANN error plot for Bamboo Leaf Ash, A-7-5 soil, and cement to determine the prediction rate. It has been demonstrated that the compatibility of bamboo ash with treated cement-laterite soil may be accurately predicted using artificial neural networks (ANNs) [35-38].

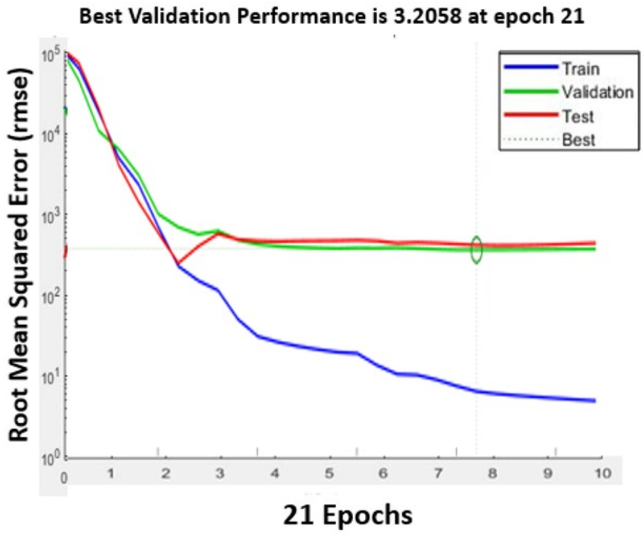

Figure 18. Training performance of the ANN training

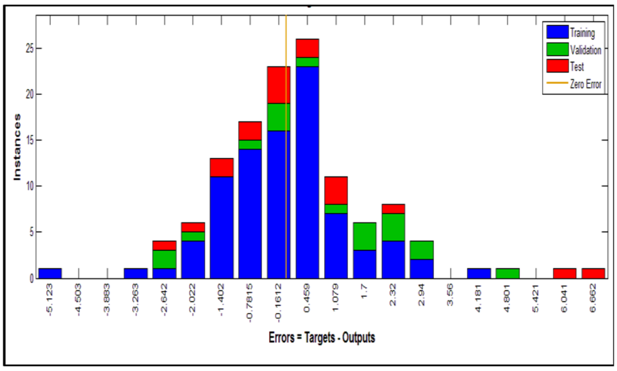

Figure 19. The ANN error plot for Bamboo Leaf Ash and A-7-5 soil and cement

4. CONCLUSION

The impact of adding Bamboo Leaf Ash on laterites treated with cement is examined in this work. It attempts to use an artificial neural network (ANN) to create a forecasting tool. A database of laboratory test results, specifically CBR, is comprised of ANN models. ANNs are trained using a feed-back propagation algorithm and displayed as a multilayer perception system using the following model input variables: The output is the California Bearing Ratio (CBR) in both soaked and unsoaked states. The inputs include cement (%), Bamboo Leaf Ash (%), rice husk ash (%), maximum dry density (MDD) (kg/m^3), liquid limit (%), optimum moisture content (%), and plasticity index (%). It has been determined that the best model, consisting of a single hidden layer with ten (10)hidden layer neurones, can predict the CBR results. When tested against unobserved data, the optimal ANN exhibits good accuracy with R of 0.99 and RMSE of 0.99. A significant limitation of this research is it involves using only an admixture of cement and Bamboo Leaf Ash in soil treatment. In summary, the model can be recommended as a trustworthy resource for estimating values of soaked and unsoaked CBR of laterites stabilised with Bamboo Leaf Ash (BLA) treated with cement.

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