PREDICTING THE CALIFORNIA BEARING RATIO (CBR) OF CHEMICALLY STABILIZED EXPANSIVE SOIL USING SOFT COMPUTING TECHNIQUES (CASE STUDY OF THE ARTIFICIAL NEURAL NETWORK MODEL)

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ABSTRACT

The usefulness of an Artificial Neural Network model in calculating the California Bering ratio (CBR) of an expansive clay soil stabilized with chemical additives is investigated in this study. The geotechnical features of an expanding clay soil mixed with lime, rice husk ash, and saw dust ash at various percentages were determined by experiments. The Liquid limit, Plasticity index, Optimum moisture content, Maximum dry density, percent Lime, percent Rice husk ash and percent Saw dust ash were used as input variables in a multilayer perception (MLP) neural network model, with the corresponding CBR value at 0, 7, and 28 days as the output. The results indicated a high predicted accuracy of 97.32, 97.38, and 96.13 percent for CBR predictions of 0, 7, and 28 days respectively, with a very low root mean square error value. The study showed that computer-generated models are able to strongly estimate the CBR for sustainable road construction.

KEY WORDS: Artificial Neural Network, Expansive Soil, Chemical stabilization, California Bearing Ratio, Additive

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1. INTRODUCTION

The California bearing ratio (CBR) is a common index test for determining the stiffness module and shear strength of a sub grade. CBR is an indirect measure that compares the strength of sub grade material to the strength of ordinary crushed rock, which is expressed in percentages. CBR tests are performed on natural or compacted soils in water- soaked or non-soaked situations, and the results are compared to the curves of standard tests to determine the sub grade soil strength. For geotechnical engineering and earth structures such as earth dams, bridge abutments, fills behind retaining walls and highway embarkments in road construction. (Aytekin, 2000). CBR testing, on the other hand, is costly, time-consuming and exhausting. It's difficult to get a good sense of the wet CBR of sub grade materials along the entire length of the road. As a result, taking a large number of samples is not feasible. In many cases, little soil investigation data is gathered due to restricted budgets and poor planning circumstances in impoverished nations such as Nigeria, and results are frequently inaccurate due to sample disruption and poor laboratory settings. It is preferable to anticipate the CBR value of sub grade soil using simply determinable factors to avoid these scenarios. As a result, developing predictive models might be beneficial. Since the turn of the century, the use of computer algorithms to properly analyze massive volumes of data, discover patterns and then use these patterns to make predictions has yielded astounding results. The Artificial Neural Network is one of these algorithms. These algorithms had been widely and repeatedly used in a variety of fields. However, due to the limited knowledge of digital technology in Information Technology (IT) in Nigeria, its usage in the Nigeria construction industry has been almost non-existent

2. LITERATURE REVIEW

Different types of soils are used in civil engineering projects; however, some soils are suitable for building in their natural state, while others, such as problematic soils, require treatment. These soils must be dug and refilled, or their properties must be altered, before they can sustain the applied loads by the upper structures. Problematic soils include expansive soils, for example. Expansive soils exhibit significant volume changes (swelling and shrinking) as a result of changes in moisture content. Adsorbed water causes expansive soil to swell, posing major dangers to civil engineering projects, especially light structures like houses, highways, and pavements. These constructions usually suffer substantial damage from settlements as a result of uneven soil movement, resulting in greater maintenance costs.

High plasticity, excessive heave, and great swell-shrink potential distinguish expansive soils, which are made composed of clay, shale, or marl. The black cotton soil (BCS) is a well-known expansive soil with a high-volume change propensity that occurs largely in geologic settings with lacustrine and basaltic origins, such as the Lake Chad Basin and India (Ackroyd and Hussain, 2006). According to Ackroyd and Husain (2006), the Black Cotton Soil's expansive nature is due to the presence of the montmorillonite group, which dominates the clay fraction. The engineering qualities of expansive soil given on site are frequently less than ideal for civil engineering projects. (Nalbantoglu, 2006). Geotechnical engineers usually prefer to change the parameters of expansive soils in situ through stabilization rather than excavating and replacing them totally due to cost considerations. One of the many different soil stabilization procedures utilized is chemical stabilization (Buhler and Cerato, 2007; Hussey et al., 2010).

The California bearing ratio (CBR) is defined as the ratio of resistance to the sinking of a penetration piston into the soil at a velocity of 1.27 mm/min (0.05 in./min) to the resistance shown by a standard crushed rock sample at the same penetration depth. CBR resistance is defined as the ratio of the applied stress (unit-strength), according to a specific energy compressed soil in a predetermined moisture content on the speed control to sunk penetration piston to reach the required depth, and the applied standard tension, in the experiment by using the crushed rock listed in Table 1 for the piston to reach the same depth (Aytekin, 2000). The bearing ratio test in California can be done in the lab or in the field. ASTM D 1883-99 (2003) describes the laboratory CBR test, while ASTM D 4429-93 describes the field CBR test (2003). In the laboratory, the CBR test is typically performed on compacted soil samples, while in the field the CBR test would be performed at ground surface, or on a level surface excavated in a test pit, trench, or bulldozer cut (Day, 2001).

$$CBR = \frac{\text{Applied stress in Experiment (or Load)}}{\text{Standard stress (or Load)}} \quad (1)$$

Tests are conducted on natural or compacted soils in wet or dry circumstances, and the findings are compared to established test curves to determine the sub grade soil's strength. For geotechnical engineering and earth constructions such as earth dams, highway embankments, bridge abutments, and the fills behind retaining walls, the CBR test findings are critical. There have been attempts to construct CBR prediction models, based on the fact that the CBR of soils is influenced in various ways by the soil index properties. The majority of the earlier models, on the other hand, were simply statistical correlations between CBR and categorization data and/or soil index features. CBR has been linked to soil grain dispersion and plasticity in several studies. For cohesive soils, Black (2002) found a link between CBR and plasticity index (PI). Agarwal and Ghanekar (2000) attempted to build a relationship between CBR and either the liquid limit (LL), the plastic limit (PL), or the plasticity index (PI) (PI). They were unable to uncover any substantial association between these variables, however.

The Artificial Neural Network is a frequent machine learning application (ANN). Machine learning is a kind of artificial intelligence (AI) that allows computers to learn and develop without being explicitly programmed. The construction of computer programs that can access data and learn on their own is what machine learning is all about. The Artificial Neural Network (ANN) is a massively parallel distributed processor made up of simple processing units with a natural predisposition for storing and distributing experience data. (Haykin,2009). It is appropriate for non-linear concerns such as judgment, experience, and surrounding circumstances since it can generalize the result by learning from the associations between input and output provided by training data. The three layers that make up an ANN are the input layer with input neurons, hidden layer(s) with hidden neurons, and output layer(s) with output neurons (Bayram et al, 2015). It is appropriate for non-linear concerns such as judgment, experience, and surrounding circumstances since it can generalize the result by learning from the associations between input and output provided by training data. The traditional construction of an ANN consists of a number of processing elements (PEs), also known as nodes, organized in layers: an input layer, an output layer, and one or more hidden layers. ANNs can be single layer or multilayer, depending on their structure. A single-layer ANN takes inputs from outside the network and outputs to the outside network; otherwise, it is a multilayer ANN. The concept of architecture is what enables an ANN to approximate any reasonable function. The weights can be changed, and the act of doing so is referred to as training. Learning is the terminology for the training effect. Learning can be done by assigning weights based on a set of training data or by updating the weights automatically depending on some criterion. ANNs are being used by many researchers in a variety of applications, including robotics (Sharkawy et al, 2018; Ito et al, 2006), speech recognition (Passricha and Aggarwai, 2018; Palaz et al, 2015), human face recognition, medical applications (Fukuoka, 2002; Moreno-Escobar et al, 2007), and manufacturing (Sharkawy et al, 2018).

The goal of this study was to predict the California Bearing ratio of a chemically stabilized expansive soil using soft computing techniques with focus on the performance of the Artificial Neural Network Model. The geotechnical parameters of expansive clay soil mixed with three selected chemical stabilizer additives were investigated in this study. The Liquid limit (LL) in %, Plasticity index (PI) in %, Optimum moisture content (OMC) in %, Maximum dry density (MDD) in g/cm^3, %Lime(L), %Rice husk ash(RHA) and %Saw dust ash(SDA) were the geotechnical input variables while the corresponding California bearing ratio (CBR) value at 0, 7 and 21 days were the output.. The performance of the derived models were then measured using the root mean square error (RMSE) and the coefficient of determination (R)

3. MATERIALS AND METHOD

3.1 Materials

3.1.1 Black cotton soil

The expansive soil at Numan, Adamawa State, Nigeria, that would be stabilized is black cotton soil. On the Nigerian geographical map, Numan is located at latitude 9°29'10"N and longitude 12°02'36"E. The sample would be collected using the hand carved sampling method, which is a disturbed sampling method. It would be gathered at a depth of 0.4 to 1.0 meters. After that, the sample would be placed in airtight bags and transported to a geotechnical laboratory, where it would be pulverized using a hammer**.**

3.1.2 Lime

One of the chemical additions that will be employed in this research is lime. Calcium oxide (CaO), sometimes known as fast lime or burnt lime, is the type of lime used. At solid temperature, it is white, caustic, alkaline, and crystalline (Ikeagwuani et al, 2016). It is quite affordable, and it is made by driving out carbon dioxide by heating limestone, coral, sea shells, or chalk, which are mostly $CaCO_3$. It has a melting point of 2600 degrees Celsius.

3.1.3 Rice Husk Ash

Rice husk is abundant in rice-growing countries such as India, China, Indonesia, Thailand, and, more recently, Nigeria. Rice husk is mostly utilized as a fuel in industries for process energy and power generation in boilers. Rice husk ash is a byproduct of the rice husk burning process that has a high percentage of amorphous silica and is used in a variety of applications. Rice husk was supplied from a local rice mill and burned in a basket rice husk burner using a tube. Powdered ash was collected and sieved via a 600 IS sieve. The fraction of ash that went through a 600 IS sieve would be studied.

3.1.4 Saw Dust Ash

A saw mill in a timber shed near Akure provided saw dust. It would be scooped out with a shovel from a stack of sawdust that had been created quickly and cleanly, with no signs of tree bark in considerable numbers. The sawdust would then be thrown in the furnace and burned at a temperature of around 800°C until it was all transformed to ash. The Sawdust would be allowed to cool slowly in the Furnace after being burned into ash. This is done to prevent moisture from entering the system before it is removed. Butt et al., 2016. The resulting Sawdust ash would then be sieved using a 75um British test sieve and stored in airtight polythene bags until needed.

3.2 Experimental Procedure

The British Standard for soil testing was used for all of the experimental procedures. The black cotton soil would be subjected to an index properties test to assess the soil's intrinsic physical attributes in order to classify it using the AASHTO classification system. The percentage by weight of particles, gravel, and sand in the soil, specific gravity, Plastic and Liquid limit, Maximum dry density and optimal moisture content, color, and differential free swell test are some of the other data derived from this index test.

X-ray fluorescence analysis will be used to determine the chemical characteristics of the chemical stabilizing agents, which include lime, rice husk ash, and saw dust ash. Because ash lacks a binder, the lime in the stabilized soil mix serves as both a stabilizing and binding agent.

3.3 The Stabilized Soil Experimental Set-up

Test was performed on samples of black cotton soil, Lime, rice husk ash and saw dust ash mixture (BC-LRHASDA) with lime(L) varied at a percentage of 0, 2,4,6,8,10,12, rice husk ash (RHA) varied at a percentage of 0,5,7.5,10,12.5 with sawdust ash (SDA) varied at a percentage of 0,4,8,12,16. All varied by weight of the black cotton soil. The tests include Atterberg limit test (Liquid limit, Plastic limit, Plasticity index), Compaction tests (Maximum dry density and optimum moisture content), California Bearing ratio test (%CBR at 0, 7 and 28 days).

A total of 175 stabilized soil samples was prepared and experimental tests performed on them. The experimental information database gathered would then be used in developing the ANN model for CBR prediction at 0, 7 and 21 days of curing.

3.4 ANN Methodology

For the development of the ANN Model, the experimental 175 datasets gathered was divide into two group. The first group contain 126 (70%) of the dataset which was used as the training data to train the ANN Model. The second group would contain 26 (15%) of the dataset which was used to validate and 26(15%) to test the accuracy of the developed ANN models. Based on the algorithm used for the training of the ANN Model, the Levenberg Marquardt (LMNN) models was used.

The input variables for the ANN Model formulation were LL (percent), PI (percent), OMC (percent), and MDD (g/cm3), as well as percent Lime(L), percent Rice husk ash(RHA), and percent Saw dust ash (SDA) (SDA). CBR at 0,7 and 28 days after cure are the output variables. ANN models were created to predict wet CBR at 0 days, 7 days, and 28 days. Multilayer Perception networks are the type of ANN architecture that was used. Multilayer perception networks are a type of artificial neural network (ANN) that has a feed forward design and is capable of approximating nearly any continuous function to an indefinite degree of precision. One input layer, one or more hidden layers, and one output layer make up the Multilayer Perception (MLP). The number of neurons in the hidden layer and a variety of multilayer networks with different transfer functions were tried to forecast the California bearing ratio value in order to build the best suited ANN architecture (CBR). The number of iterations (epoch), learning rate, error objective, and number of hidden layers are all viable training parameters that can be tweaked until a good ANN training convergence is achieved. Also, while the training is steady, an adaptive learning rate would be utilized to keep the learning step size as large as possible (Hagan et al., 1996). Figure 1 depicts a schematic diagram of the MLP ANN architecture.

The ANN toolbox of MATLAB computer-aided Software was used to perform the necessary computation for the ANN development**.**

3.5 Data Normalization

Data scaling is an important step in network training. Normalizing the inputs to the range is recommended because it greatly improves learning speed. These values are in the sigmoid transfer function zone where the output is the most sensitive to changes in the input values. Only the supplied data would be standardized for better outcomes. A linear normalizing function was utilized for the input parameters as follows; (Rafiq et al., 2001):

$$X_n = -1.0 + 2.0\ {X_i - X_{i,min}}\Big/{X_{i,max} - X_{i,min}} \tag{2}$$

where X_n is normalized value of input $X_{i;}$ and $X_{i,min}$ and $X_{i,max}$ denote the minimum and maximum values of X_i, respectively. For the output parameters a nonlinear normalization function was used.

3.6 Performance Evaluations

In order to evaluate the performance of the proposed ANN models, coefficient of determination (R^2), mean squared error (MSE), and mean absolute error (MAE) would be used as the criteria between the actual and predicted values. R^2, MSE, and MAE are given in the form of formulas as follows:

$$R = 1 - \sum_{i=1}^{n}(h_i - t_i)^2 \Big/ \sum_{i=1}^{n}(h_i - \bar{h}_i)^2 \quad (3)$$

$$\text{RMSE} = \sqrt{\sum_{i=1}^{n}(h_i - t_i)^2 \Big/ n} \quad (4)$$

Where h_i and t_i are, respectively, the actual output and the calculated output value for the ith output, $\bar{h}_i$ is the average of the actual outputs, and n is the number of sample.

4. RESULT AND DISCUSSION

4.1 Material Index Properties Result

Table 2 showed the physical properties test result conducted on the expansive clay soil. The test result showed a very high presence of moisture content (71.66%), liquid limit (73.59%) and Plasticity index (41.25%). This shows high swelling potential of the soil (PI > 35%) which are characteristics of an expansive clay soil. The soil is classified as Silty Clay (Gs = 2.632 with 90.76% fines) with tendency of having an expansive behavior with its PI > 35.5%.

4.2 Materials Chemical Composition

Table 3 showed the result of the chemical analysis and XRD tests performed on the black cotton soil, lime, rice husk ash and the saw dust ash.

4.3 CBR ANN Predictions Result

4.3.1 0days CBR Result

4.3.1.1 ANN Architecture

Figure 2 showed the multilayer perceptron (MLP)ANN architecture for the 0days CBR predictions. The input variables were eight (8), the number of hidden neurons used were twenty-two (22) and the number of epochs passed through by the model was twenty. The epoch and the number of hidden neurons determines the performance of the neural network. Different parameters of these two values were tried and the performance monitored until the optimal performance was reached and the values recorded. The data were splitted into training, test and validation data with 123 data used for validation corresponding to 70% of the data while 26 data were used for validation and another 26data used for testing both corresponding to 15% of the volume of data for both testing and validation. These values were randomly selected throughout the whole process to prevent bias in our modelling result.

4.3.1.2 Error Histograms

Figure 3 showed the error histograms for the 0days CBR result. The error histogram showed how closer to zero or far away from zero the difference between the predicted CBR and the actual CBR for the 0days predictions are. The closer to zero the histograms are, the more accurate the result will be. From the chart, a large proportion of the differences between the predicted and actuals fall within the yellow zero line, especially most of the training datasets. This shows little differences between the predicted and actual values.

4.3.1.3 ANN Regression Results

Figure 4 showed the residuals and Root Mean Square Error (RMSE) result for the regression line of fit for training, validation, testing and all parameters of the dataset. It also showed the accuracy level of the regression with the given R score. The values above the regression line of fit for all phases (training, testing, validation and all) represented the values that were predicted correctly while the values below the line of fit represented the values that were not predicted correctly. The distance of each values from the line of fit is a measure of how accurate or inaccurate each values were.

For the training phase, almost all values were encompassed by the line of fit, this was accompanied by the high degree of accuracy of 99.522%. For the validation phase, a large proportion of the values were within the line of fit while some were far apart below the line of fit, with a high degree of accuracy of 92.18%. The test has a degree of accuracy of 91.09% while for all the values put together, the accuracy of the regression model line was estimated at 97.315%. This showed high capabilities of the developed ANN model in estimating the CBR values of the stabilized expansive clay soil given the inputs variables into the ANN developed . The RMSE value of 8.888×10^{-16} showed a very low error value, almost negligible. This is also a demonstration of the MLP ANN model in being able to strongly estimate the California bearing ratio value of the stabilized expansive clay soil.

4.3.2 7days CBR Result

4.3.2.1 ANN Architecture

Figure 5 showed the multilayer perceptron (MLP)ANN architecture for the 7days CBR predictions. The input variables were eight (8), the number of hidden neurons used were twenty-two (22) and the number of epochs passed through by the model was twelve (12). The epoch and the number of hidden neurons determines the performance of the neural network. Different parameters of these two values were tried and the performance monitored until the optimal performance was reached and the values recorded. The data were splitted into training, test and validation data with 123 data used for validation corresponding to 70% of the data while 26 data were used for validation and another 26data used for testing both corresponding to 15% of the volume of data for both testing and validation. These values were randomly selected throughout the whole process to prevent bias in our modelling result.

4.3.2.2 Error Histograms

Figure 6 showed the error histograms for the 7days CBR result. The error histogram showed how closer to zero or far away from zero the difference between the predicted CBR and the actual CBR for the 0days predictions are. The closer to zero the histograms are, the more accurate the result will be. From the chart, a significant proportion of the differences between the predicted and actuals fall within the yellow zero line, especially most of the training datasets. This shows little differences between the predicted and actual values.

4.3.2.3 ANN Regression Results

Figure 7 showed the residuals result and Root Mean Square Error (RMSE) result for the regression line of fit for training, validation, testing and all parameters of the dataset. It also showed the accuracy level of the regression with the given R score. The values above the regression line of fit for all phases (training, testing, validation and all) represented the values that were predicted correctly while the values below the line of fit represented the values that were not predicted correctly. The distance of each values from the line of fit is a measure of how accurate or inaccurate each values were.

For the training phase, almost all values were encompassed by the line of fit, this was accompanied by the high degree of accuracy of 98.73%. For the validation phase, a large proportion of the values were within the line of fit with only 8 values out of the 26 randomly selected values within the inaccurate part of the regression line. This is accompanied with a high degree of accuracy of 95.77%. The test has a degree of accuracy of 94.72% while for all the values put together, the accuracy of the regression model line was estimated at 97.384%. This showed high capabilities of the developed ANN model in estimating the CBR values of the stabilized expansive clay soil given the inputs variables into the ANN developed model. The RMSE value of 9.566×10^{-15} showed a very low error value, almost negligible. This is also a demonstration of the MLP ANN model in being able to strongly estimate the California bearing ratio value of the stabilized expansive clay soil.

4.3.3 28 days CBR Result

4.4.3.1 ANN Architecture

Figure 8 showed the multilayer perception (MLP)ANN architecture for the 28 days CBR predictions. The input variables were eight (8), the number of hidden neurons used were twenty-four (24) and the number of epochs passed through by the model was nineteen (19). The epoch and the number of hidden neurons determines the performance of the neural network. Different parameters of these two values were tried and the performance monitored until the optimal performance was reached and the values recorded. The data were spitted into training, test and validation data with 123 data used for validation corresponding to 70% of the data while 26 data were used for validation and another 26 data used for testing both corresponding to 15% of the volume of data for both testing and validation. These values were randomly selected throughout the whole process to prevent bias in our modelling result.

4.3.3.2 Error Histograms

Figure 9 showed the error histograms for the 28days CBR result. The error histogram showed how closer to zero or far away from zero the difference between the predicted CBR and the actual CBR for the 0days predictions are. The closer to zero the histograms are, the more accurate the result will be. From the chart, a large volume of the differences between the predicted and actuals fall within the yellow zero line, especially most of the training datasets. This shows little differences between the predicted and actual values.

4.3.3.3 ANN Regression Results

Figure 10 showed the residuals result for the regression line of fit for training, validation, testing and all parameters of the dataset. It also showed the accuracy level of the regression with the given R score. The values above the regression line of fit for all phases (training, testing, validation and all) represented the values that were predicted correctly while the values below the line of fit represented the values that were not predicted correctly. The distance of each values from the line of fit is a measure of how accurate or inaccurate each values were.

For the training phase, all values were encompassed by the line of fit, this was accompanied by the high degree of accuracy of 99.86%. For the validation phase, a large proportion of the values were within the line of fit with only 8 values out of the 26 randomly selected values within the inaccurate part of the regression line. This is accompanied with a high degree of accuracy of 93.97%. The test has a degree of accuracy of 82.71% while for all the values put together, the accuracy of the regression model line was estimated at 96.13%. This showed high capabilities of the developed ANN model in estimating the CBR values of the stabilized expansive clay soil given the inputs variables into the ANN developed model.

Figure 11 showed the RMSE value of the predictive model. The RMSE value of 9.566×10^{-15} showed a very low error value, almost negligible. This is also a demonstration of the MLP ANN model in being able to strongly estimate the California bearing ratio value of the stabilized expansive clay soil.

5. CONCLUSIONS

- The optimal MLP ANN architecture with the maximum effective predictive performance was the architecture with twenty-two (22) hidden neurons and twenty(20) epochs for 0days CBR predictions
- For the zero days CBR predictions, the model had 99.522% degree of accuracy at the training phase, the validation phase, had a high degree of accuracy of 92.18%., the Test phase has a degree of accuracy of 91.09% while for all the values put together, the accuracy of the regression model line was estimated at 97.315%. The Root Mean Square Error (RMSE) value for the 0days CBR predictions was 8.888×10^{-16} which is a very low error value, almost negligible
- The optimal MLP ANN architecture with the maximum effective predictive performance was the architecture with twenty-two (22) hidden neurons and twelve (12) epochs for 7days CBR predictions

- For the 7 days CBR predictions, the model had 98.73% degree of accuracy at the training phase, the validation phase, had a high degree of accuracy of 95.77%., the Test phase has a degree of accuracy of 94.72% while for all the values put together, the accuracy of the regression model line was estimated at 97.38%..The Root Mean Square Error (RMSE) value for the 7days CBR predictions was 9.566×10^{-15} which is a very low error value, almost negligible.
- The optimal MLP ANN architecture with the maximum effective predictive performance was the architecture with twenty-four (24) hidden neurons and nineteen (19) epochs for 21days CBR predictions
- For the 28 days CBR predictions, the model had 99.86% degree of accuracy at the training phase, the validation phase had a high degree of accuracy of 93.97%., the Test phase has a degree of accuracy of 82.71% while for all the values put together, the accuracy of the regression model line was estimated at 96.13%.The Root Mean Square Error (RMSE) value for the 28 days CBR predictions was 9.566×10^{-16} which is a very low error value, almost negligible
- These results are a strong demonstration of the MLP ANN model in being able to strongly estimate the California bearing ratio value of the stabilized expansive clay soil.

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Table 1: Standard stresses according to the amount of penetration in the test by using crushed rock (Bowles, 1970).

Penetration (mm)	Standard Stress (kgf/cm^2)	Standard load (kgf)
2.54	70.4	1362.6
5.08	105.6	2034.9
7.62	133.7	2587.7
10.16	161.9	3133.5
12.70	183.0	3541.9

Table 2 Physical Characterization of the Clay sample

Physical Properties	Test Result
Natural moisture content	71.66%
Specific gravity(Gs)	2.87
Liquid Limits(LL)	73.59%
Plastic Limits (PL)	32.34%
Shrinkage limits(SL)	13.74%
Plasticity Index(PI)	41.25
Maximum Dry Density	$1.32 g/cm^3$
Optimum Moisture Content	34%
Grain size distribution: • Coarse Particles • Fine Particles • Clay • Silt	 9.36% 90.74 80.76 10.00

Table 3: Chemical elements of research materials

Chemical elements	Clay (%)	Rice Husk Ash(RHA)	Hydrated Lime (%)	Saw Dust ash (%)
Silica(SiO_2)	51.39	89.08	0.00	62.87
Alumina(Al_2O_3)	17.21	1.75	0.13	9.87
Iron(Fe_2O_3)	9.33	0.78	0.08	4.45
Calcium(CaO)	3.66	1.29	59.03	10.35
Magnesium oxide (MgO)	1.17	0.64	0.25	4.21
Sodium(Na_2O)	1.72	0.85	0.05	0.035
Potassium(K_2O)	0.39	1.38	0.03	1.71
Manganese oxide (MnO)	0.25	0.14	0.004	0.00
Titanium(TiO_2)	0.98	0.00	0.00	0.00
P_2O_5	0.17	0.61	0.00	0.00
H_20	4.23	1.33	0.04	0.00
Loss on Ignition(LOI)	9.48	2.05	40.33	5.85

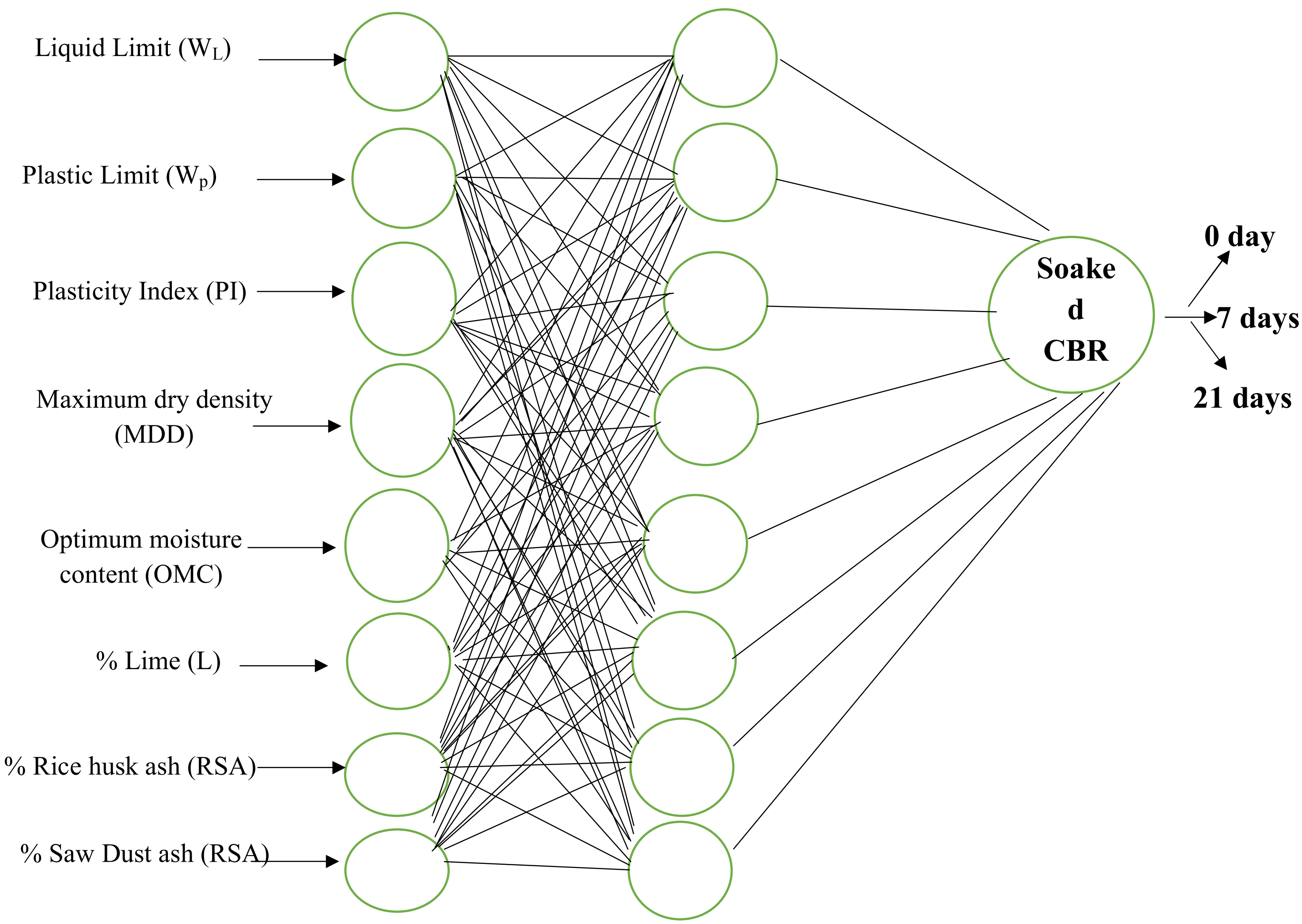


Figure 1: The ANN architecture for CBR Predictions.

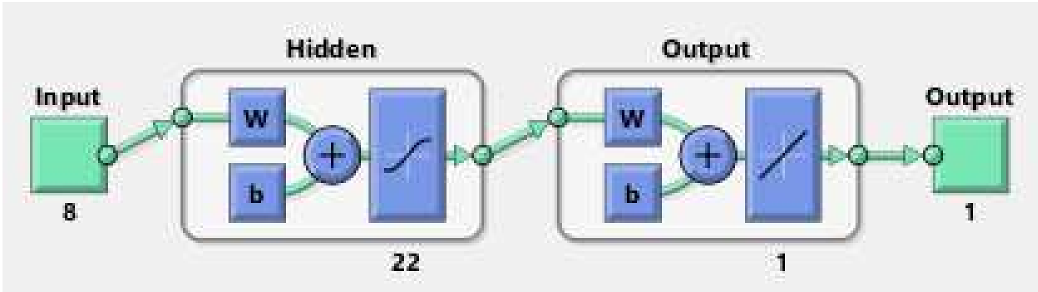


Figure 2: 0 days CBR ANN architecture

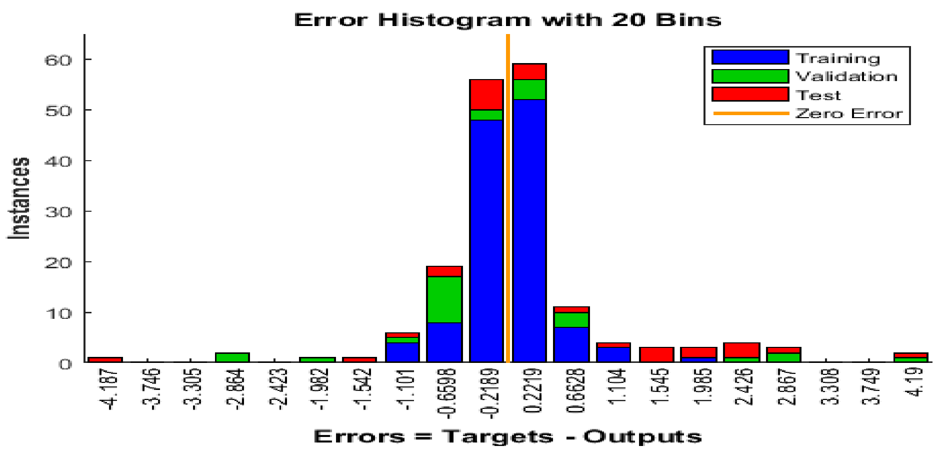


Figure 3: 0 day CBR Error Histograms

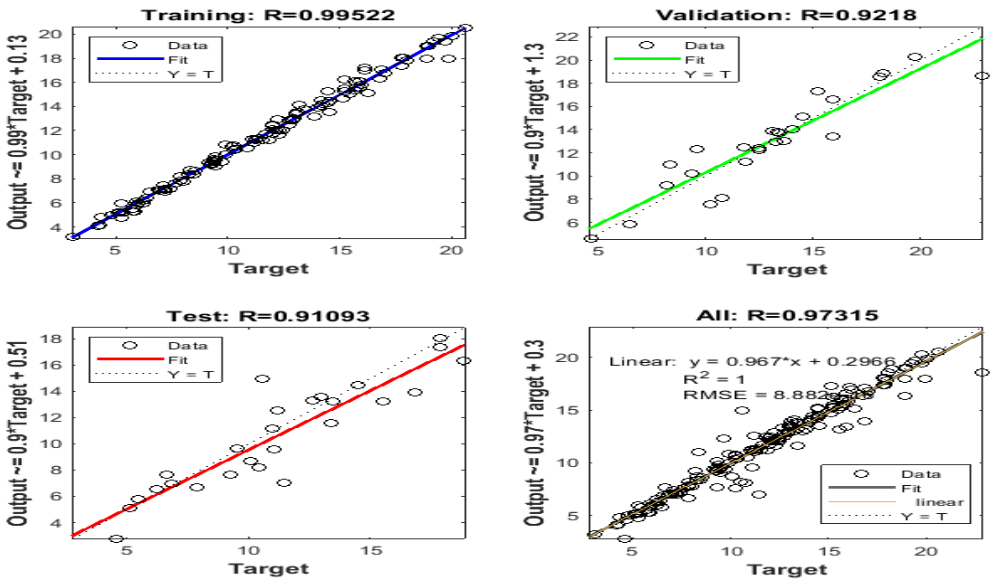


Figure 4: 0 day CBR Error Regression Residuals Plot

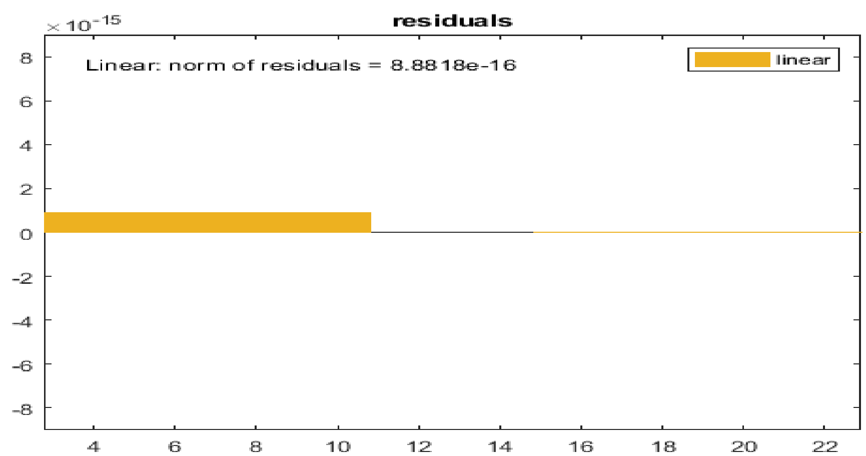
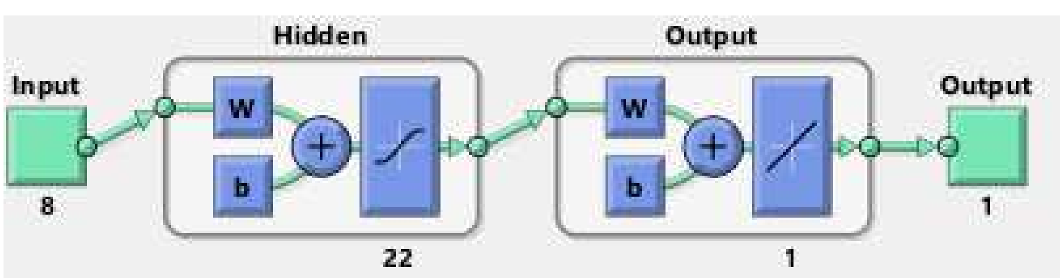


Figure 5: 7 days CBR ANN architecture



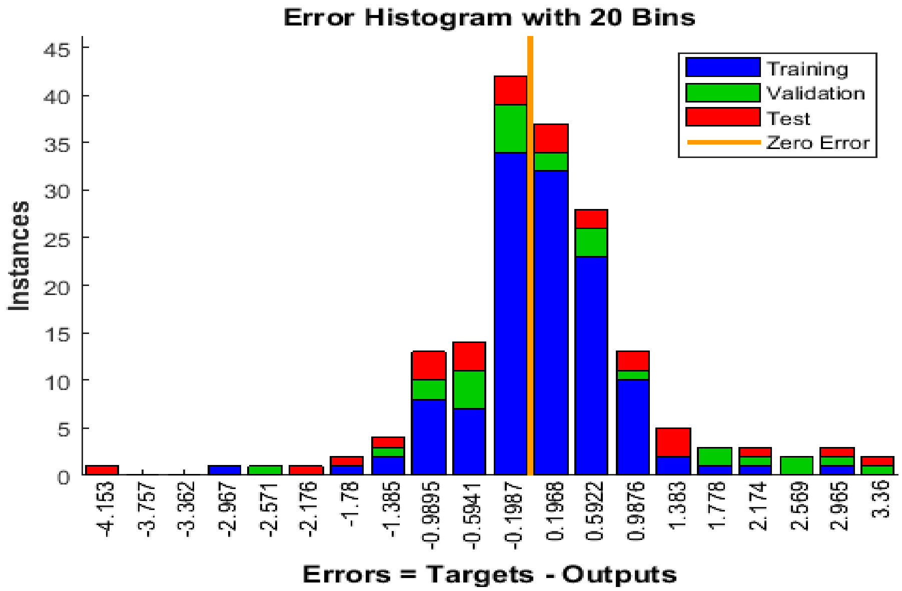


Figure 6: 7 days CBR Error Histograms

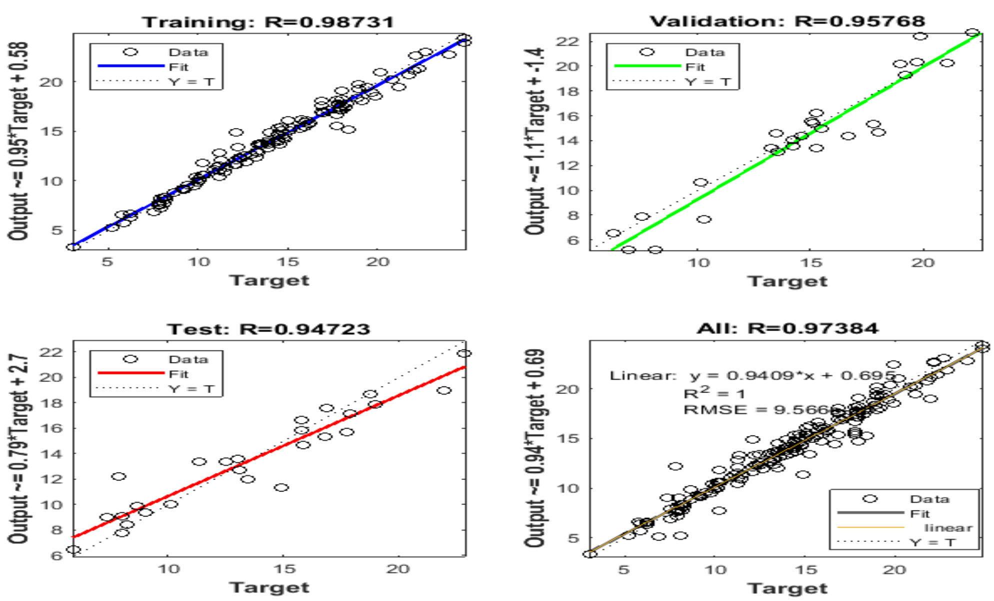
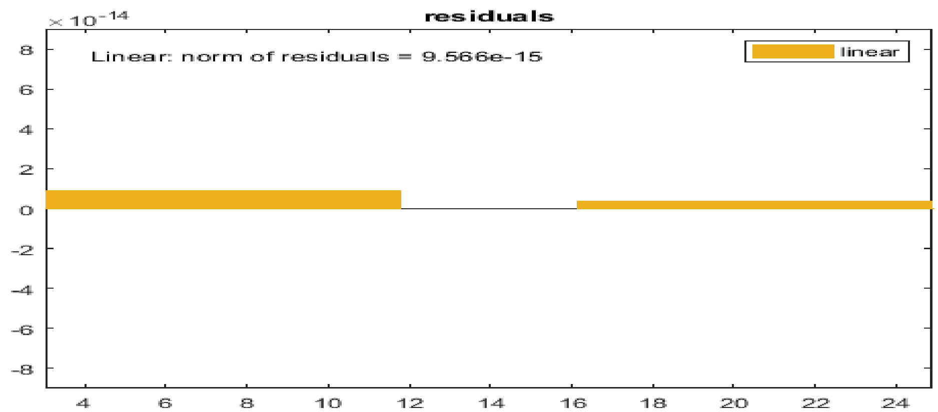


Figure 7: 7 days CBR Error Regression Residuals Plot



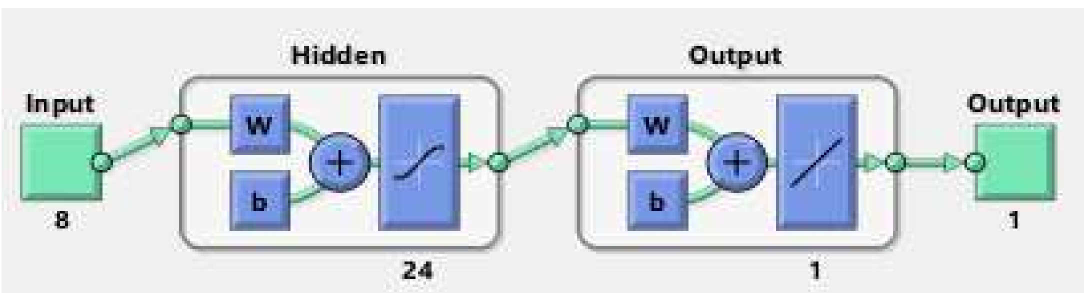


Figure 8: 28 days CBR ANN architecture

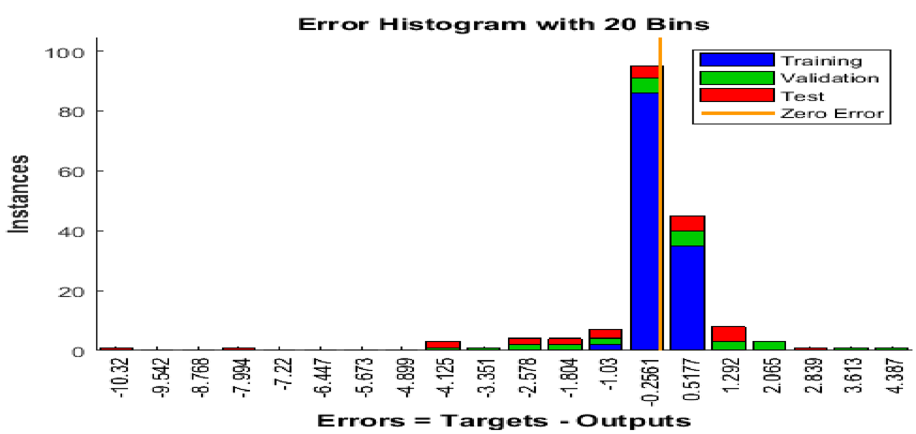


Figure 9: 28 days CBR Error Histograms

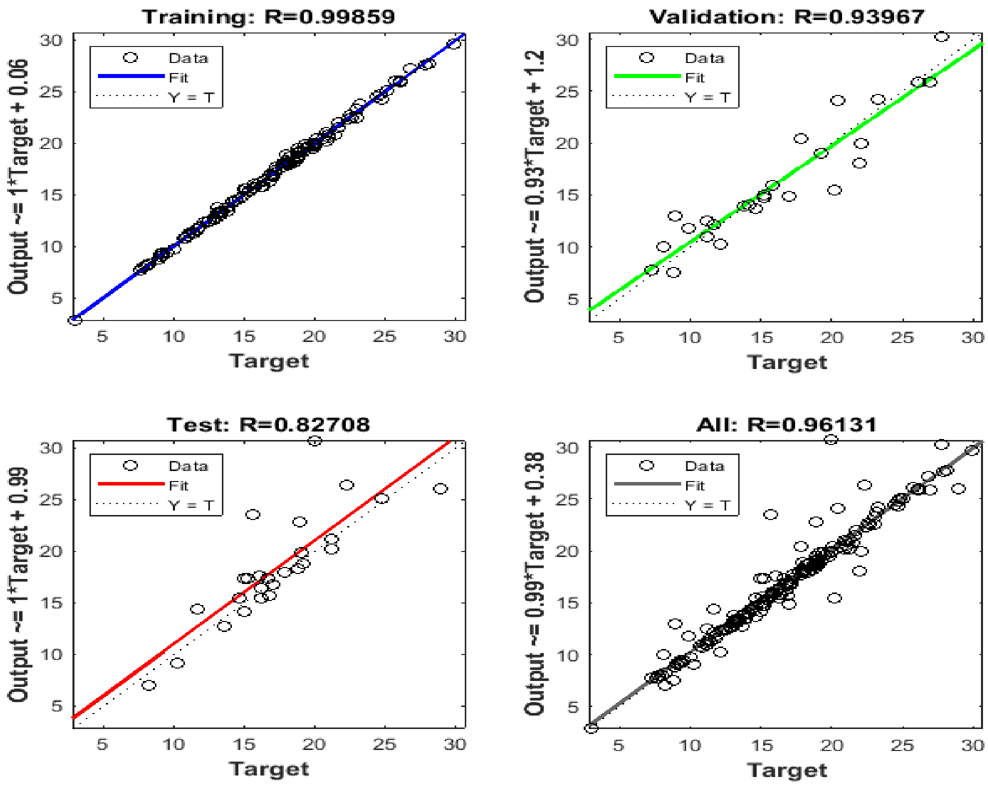


Figure 10: 28 days CBR Error Regression Residuals Plot

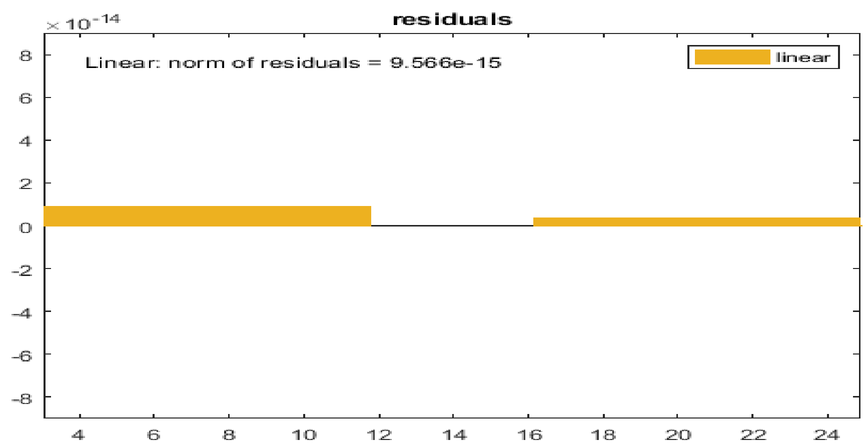


Figure 11: 28 days CBR Error Root Mean Square error (RMSE) value