PREDICTION OF CALIFORNIA BEARING RATIO OF STABILIZED SOIL USING ARTIFICIAL NEURAL NETWORK

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ABSTRACT

The laboratory test process for finding of California bearing ratio (CBR) of soils is not only expensive but also time consuming. Hence accurate prediction of CBR plays an important role as it is used in pavement design. The thickness of pavement depends on the values of CBR of soils. The strength of soil or CBR can be improved using lime and rice husk ash (RHA) when they are mixed with proper ratio. RHA is very cheap and available in Bangladesh. Lime is also available in our local market. In this study, the prediction of CBR of stabilized soil was performed by ANN which is a computational tool of MATLAB based on the properties of biological neural system. To observe CBR values, lime was added to soil as 0, 3, 4, and 5 % while RHA as 0, 8, 12 and 16% of the weights of the soil samples. Then CBR values were observed at 0, 7 and 28 days of curing period (CP). The maximum CBR value found as 17.20 at a combination of 12% of RHA and 4% of lime at 28 days of curing period. ASTM D1883 -07 standard was used to get observed CBR values which is used as target variable in ANN. RHA (%), lime (%), curing period (days), optimum moisture content (%) and maximum dry density (kN/m^3) were taken as input variable in the ANN programme. Best ANN model has been selected with 12 neurons in hidden layer with mean absolute error (MAE) value 0.164 and regression (R^2) value 0.985.

Keywords: *Artificial neural network, California bearing ratio, stabilized soil, lime, rice husk ash*

INTRODUCTION

The strength of a soil to be used as a sub-grade in pavement is assessed from its CBR value. If the CBR value of soil is low, the thickness of pavement will be high, which will result in high cost of construction and vice-versa (Sabat, 2013). There are different techniques of improving the CBR value of soil, one being stabilization. Soil stabilization may be defined as any process by which a soil material is improved and made more stable resulting in improved bearing capacity, increase in soil strength, and durability under adverse moisture and stress conditions (Joel and Agbede, 2011). Soil stabilization aims at improving soil strength and increasing resistance to softening by water through bonding the soil particles together, water proofing the particles or combination of the two (Sherwood, 1993). RHA is the woody sheath surrounding the kernel or grain and consists of two interlocking halves. The rice grain must be removed from the husk after harvesting either by hand threshing or milling. Thus husk is the by-product of the process of obtaining grain (Hossain et al., 2011). Typical chemical composition of RHA found in Bangladesh is given in Table1 where it can be seen that the predominant component of RHA is silica. This silica enters the rice plant through its roots in a soluble form, probably as a silicate or monosilicate acid and then moves to the outer surface of the plant where it's become concentrated by evaporation and polymerization to form a cellulose-silica membrane (Kumar et al., 2012). Materials containing reactive silica are known as pozzolans and are commonly used in soil improvement. Also lime has binding characteristics. Lime stabilization may refer to pozzolanic reaction in which pozzolana materials reacts with lime in presence of water to produce cementations compounds (Sherwood, 1993 Euro soil stab 2002). As the soil-lime reaction is time dependent (Bell, 1996; Rajasekaran and Rao, 2000; Dash and Hussain, 2012) it is expected that strength of soil can be increased with the curing period.

Rice husk is one of the most widely available agricultural wastes in many rice producing countries around the world. Globally, approximately 600 million tons of rice paddy is produced each year. On average 20% of the rice paddy is husk, giving an annual total production of 120 million tones of RHA (Kumar et al., 2012). In Bangladesh there are a large number of rice mills which produce RHA as a result huge amount of waste. Disposal of waste can be reduced using RHA as a soil stabilizer.

2. METHODOLOGY

The study works were completed in a sequential manner to reach the expected goals of the study. The total works were done in such a manner so that it can be adjusted with programming simulation. In the first phase, soil and additive materials used in this study were characterized and in the second phase the maximum dry density and optimum moisture contents were determined. Again the mixing, compaction and CBR were tested in the laboratory consisted of third steps; in the forth step experimental CBR value is predicted by ANN models. Also the experimental method, curing period and construction of models were conducted as well. According to Das, B.M., 2009, the optimum moisture content and maximum dry density of soil sample were determined by standard proctor test and the testing standard is ASTM D698.

2.1 Materials

The materials used in the experiment are soil, RHA and lime.

2.1.1 Soil

The soil used in the experimental program is a non-expansive clayey silt soil, obtained from a site situated in Khulna. The geotechnical properties of the soil are: Gravel size- 0 %, Sand size 7%, Silt size- 71 %, Clay size- 22 %, Specific Gravity -2.80, Liquid limit- 34%, Plastic limit- 20 %, Plasticity index- 14 %, MDD- 17.74 (kN/m^3), OMC- 14.7 % and Soaked CBR-4.30 %.

2.1.2 Rice Husk Ash

Rice husk ash was collected from local rice mills. Typical chemical composition of RHA found in Bangladesh is given in Table 1.

Table 1: Chemical composition of RHA (Sultana et al., 2014)

Constituent	Fe_2O_3	SiO_2	Al_2O_3	CaO	MgO	K_2O
% Composition	2.97	74.20	2.42	2.55	2.17	3.95

2.1.3 Lime

Lime used in the experimental program was commercially available quick lime which was purchased from the local market of Khulna.

2.2 Problems Formulation

Different samples/mixes of soil-lime–RHA were prepared by adding lime and RHA to soil. Lime was added to mixes as 0, 3, 4 & 5% and RHA as 0, 4, 8 & 16% by dry weight of soil. Standard Proctor compaction tests were conducted on these samples to obtain OMC and MDD. CBR tests were conducted at 0, 7 and 28 days of curing. To conduct the CBR tests the samples were compacted at OMC, soaked in water for 96 hours under a surcharge weight of 5kg. To study the effect of curing, the samples were cured for 7 and 28 days also and then soaked in water and CBR tests were conducted on these samples. CBR tests were conducted on different samples according to the procedure given in ASTM D1883 -07 standard. Characteristics of CBR test result of stabilized soil is shown in Table 2, and Table 3.

Table 2: Characteristics of CBR test result of soil stabilized with lime and RHA

Variable Name	Simbology	Unit	Range	
Lime	---	%	0	5
Rice husk ash	RHA	%	0	16
Curing period	CP	Days	0	28
Optimum moisture content	OMC	%	14.70	21.9
Maximum dry density	MDD	kN/m^3	14.50	17.48
California bearing ratio	CBR	%	4.30	17.20

Table 3: CBR test result of soil stabilized with lime and RHA

Lime (%)	RHA (%)	OMC (%)	MDD (kN/m^3)	CBR		
				0 day curing	7 days curing	28 days curing
0	0	14.7	17.48	4.30	5.30	10.43
0	8	17.4	16.66	5.22	7.10	11.00
0	12	18.6	15.97	6.23	8.12	15.00
0	16	19.5	15.48	5.94	8.00	13.48
3	0	15.3	17.18	4.78	6.23	11.52
3	8	18.3	16.27	5.72	7.90	12.80
3	12	19.2	15.58	6.81	9.42	16.52
3	16	20.6	15.09	6.45	8.55	14.71
4	0	16.9	16.93	5.30	6.96	12.61
4	8	19.2	15.88	6.10	8.62	15.00
4	12	20.5	15.24	7.30	10.50	17.20
4	16	21.4	14.80	7.03	9.78	16.01
5	0	17.8	16.46	5.00	6.52	12.10
5	8	20.1	15.44	6.01	8.04	14.00
5	12	21.3	14.85	6.90	10.00	16.74
5	16	21.9	14.50	6.52	9.64	15.51

3. RESULTS AND DISCUSSION

Figure 1 shows the variation of MDD with different percentage of RHA and lime. With increase in percentage of addition of lime and RHA; MDD of soil goes on decreasing.

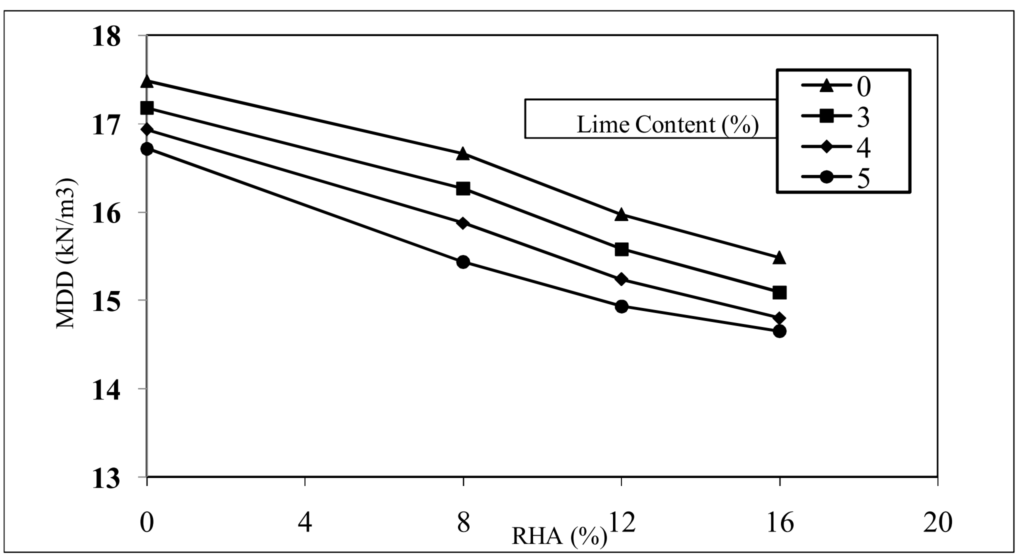

Figure 1: Variation of MDD with RHA and lime

Figure 2 shows the variation of OMC with different percentage of RHA and lime. With increase in percentage of lime and RHA; OMC of soil goes on increasing.

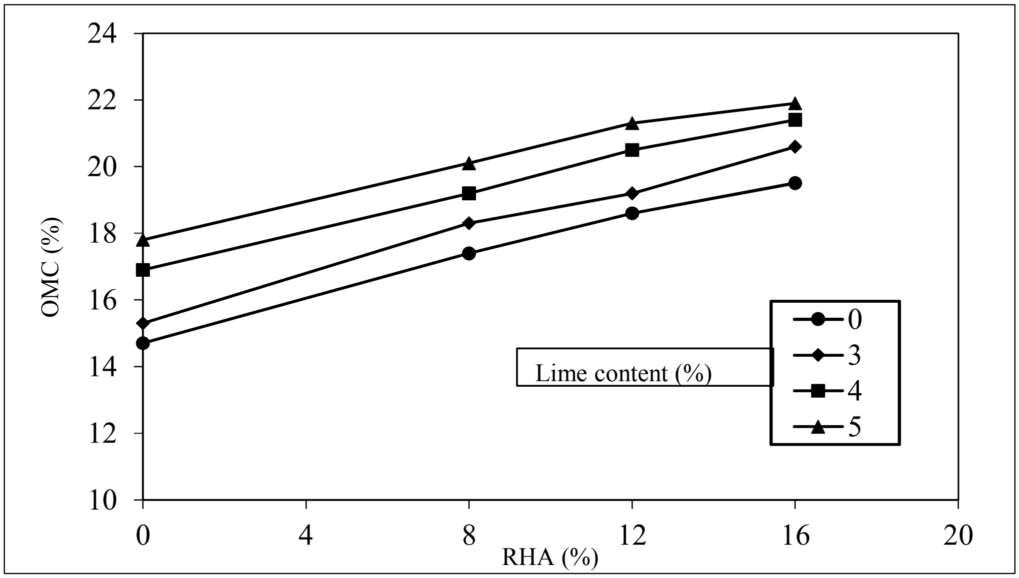

Figure 2: Variation of OMC with RHA and lime

Figures 3, 4 and 5 show the variation of CBR with different percentage of RHA and lime at 0,7 and 28 days of curing respectively.

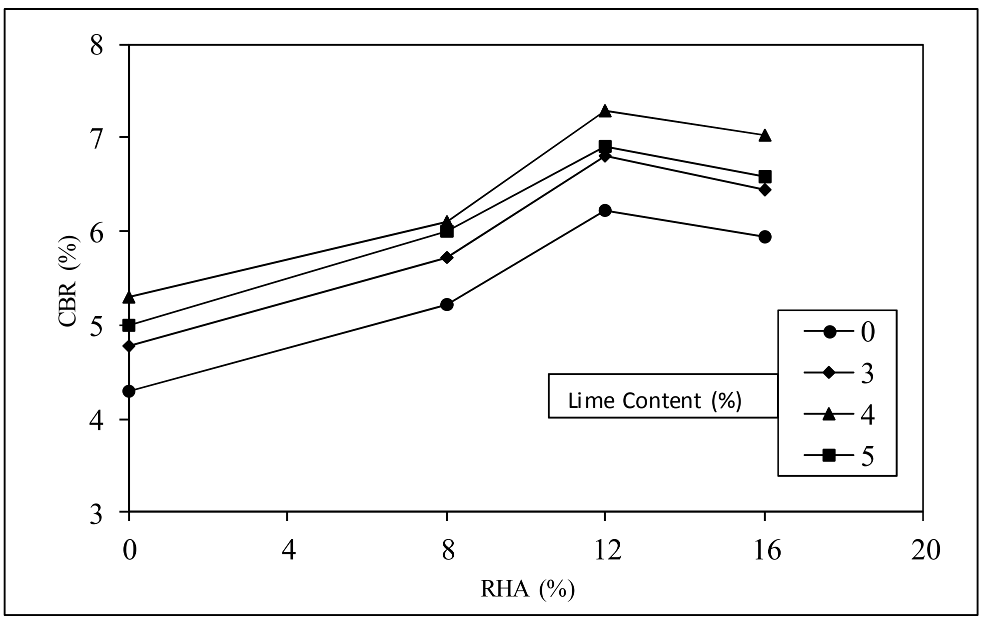

Figure 3: Variation of CBR (0 day curing) with RHA and lime

Figure 3 shows that the maximum CBR value occurs at 12% of RHA and 4% of Lime at 0 day curing.

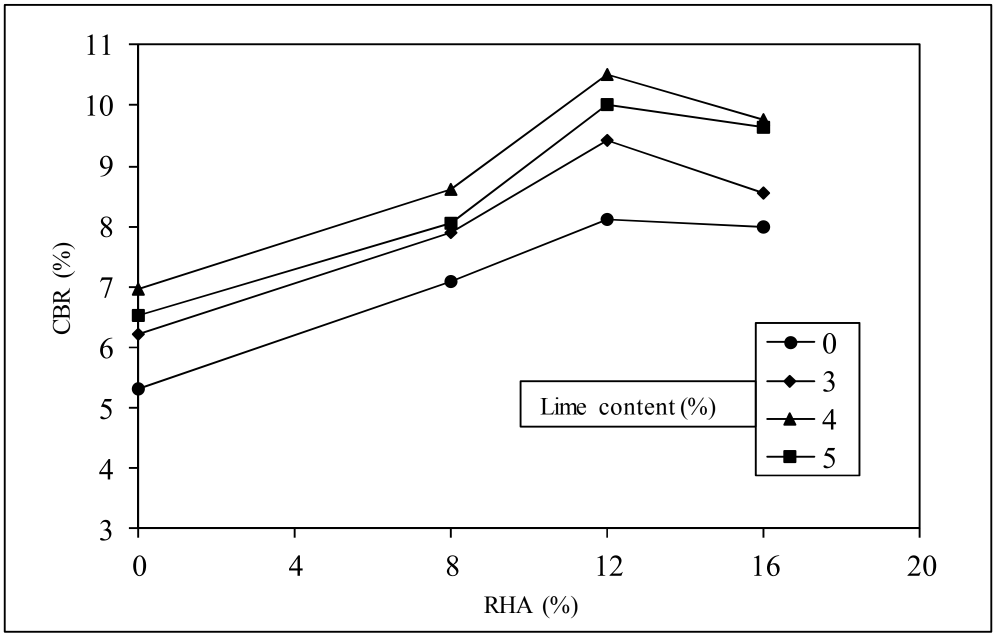

Figure 4: Variation of CBR (7 days curing) with RHA and lime

Figure 4 shows that the maximum CBR value occurs at 12% of RHA and 4% of Lime at 7 days curing.

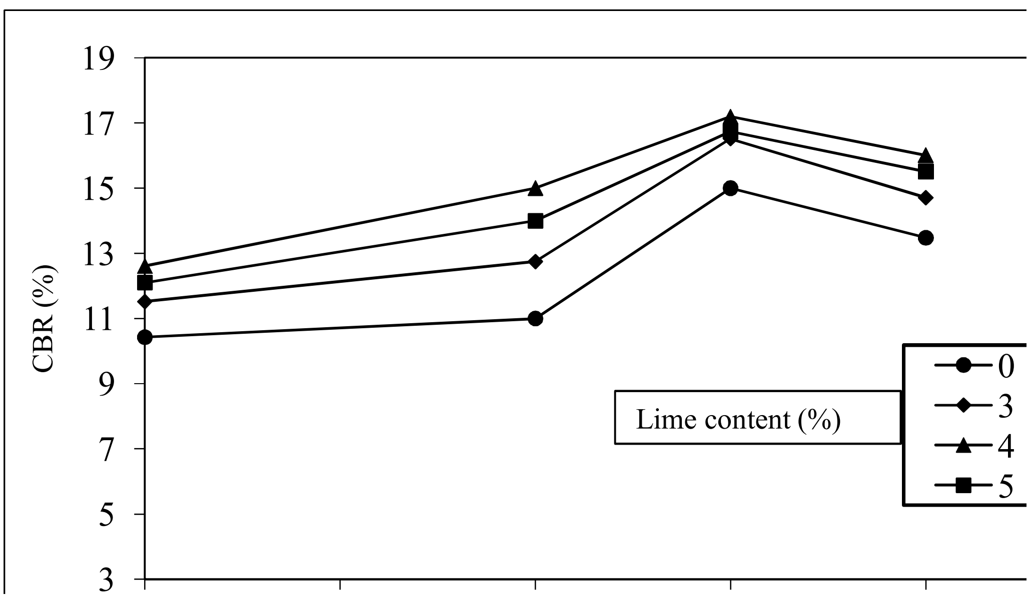

Figure 5: Variation of CBR (28 days curing) with RHA and lime

Figure 5 shows that the maximum CBR value occurs at 12% of RHA and 4% of Lime at 28 days curing.

From these figures it is observed that the CBR of soil goes on increasing, up to 4% addition of lime, further addition of lime decreases the CBR. The CBR increases up to 12% addition of RHA and more addition of RHA results in lowering of CBR values. Increase in curing period further increases the CBR values irrespective of the percentage of RHA and lime. The CBR increases to a value of 17.20% , when the percentage of lime is 4%, RHA is 12% and curing period is 28 days. There is almost 4 times increase in CBR value at this proportion and at this curing period.

3.1 Fundamentals of Neural Network Modeling

Artificial neural network (ANN) model is a mathematical structure with the ability to represent the complex nonlinear and dynamic processes that relate inputs and outputs of any system. On the premise of modeling system convergence, the neural network weights can be changed through continuous self-training by inputting new training data, leading to dynamic model adjustment (Song et al., 2011).

Neural networks are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems. As in nature, the connections between elements largely determine the network function. Typically, neural networks are adjusted, or trained, so that a particular input leads to a specific target output. There, the network is adjusted, based on a comparison of the output and the target, until the network output matches the target. Typically, many such input/target pairs are needed to train a network. Neural networks have been trained to perform complex functions in various fields, including pattern recognition, identification, classification, speech, vision, and control systems. Neural networks can also be trained to solve problems that are difficult for conventional computers or human beings. The toolbox emphasizes the use of neural network in engineering, financial, and other practical applications.

Feed Forward Network

A single-layer network of *S* Log-sigmoid transfer function neurons having *R* inputs is shown in Figure 6. Feed forward networks often have one or more hidden layers of sigmoid neurons followed by an output layer of linear neurons. Multiple layers of neurons with nonlinear transfer functions allow the network to learn nonlinear and linear relationships between input and output vectors. The linear output layer lets the network produce values outside the range -1 to +1. On the other hand, if the outputs of a network is needed to constrain (such as between 0 and 1), then the output layer should use a sigmoid transfer function (such as Log-sigmoid transfer function). For multiple-layer networks the number of layers determines the superscript on the weight matrices provided in Figure 7. The appropriate notation is used in the two-layer hyperbolic tangent sigmoid transfer function/Linear transfer function network shown next. This network can be used as a general function approximator. It can approximate any function with a finite number of discontinuities arbitrarily well, given sufficient neurons in the hidden layer.

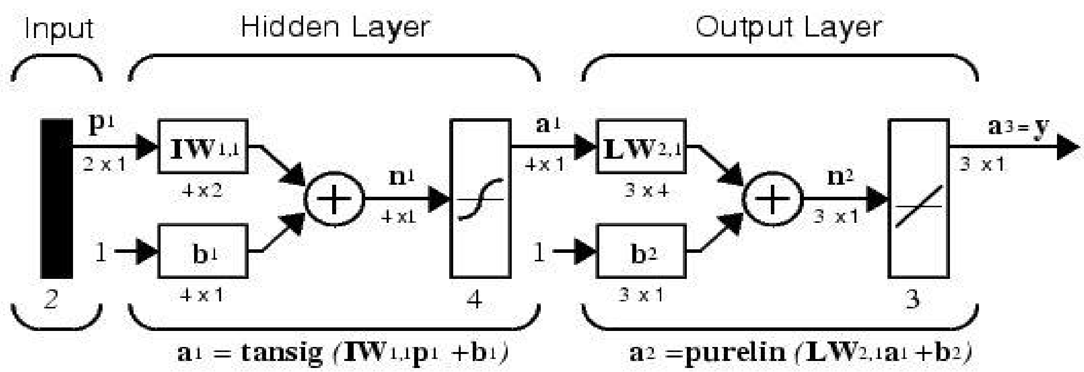

Figure 6: Single-layer feed forward network

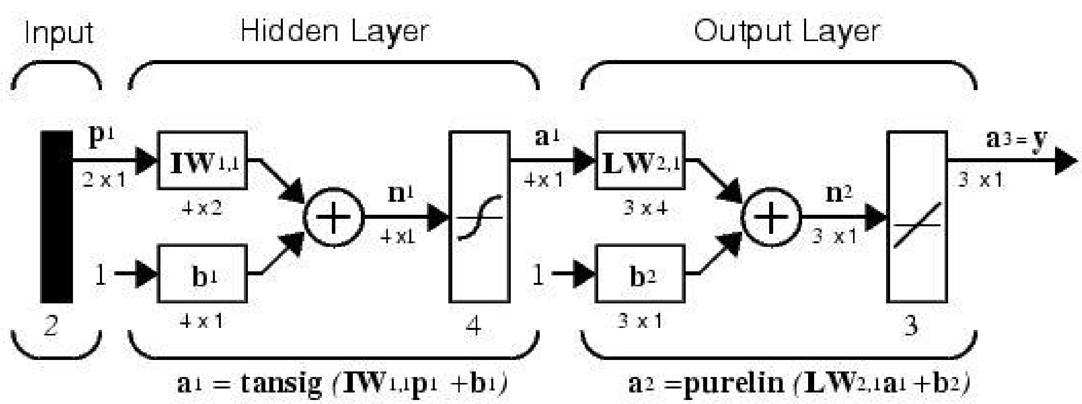

Figure 7: Multy-layer feed forward network

3.1.2 Development of ANN Model and Analysis of Results

Artificial Neural Network (ANN) model have been developed to predict the CBR values of lime and RHA stabilized soil. The models have been developed by taking, RHA (%), lime (%), curing period (days), OMC (%) and MDD (kN/m^3) as input variables and CBR (%) as output variable. Total 48 samples were prepared which generated 48 data sets .Out of 48 data sets, 34 data sets are used for training the model (ANN Model) and 7 data sets for testing and rest 7 data sets for validation of the model. Feed forward neural network, with back propagation training algorithm, is used to develop the model. The numbers of inputs taken as five, number of hidden layer taken as one and numbers of neurons in the hidden layer are three to fifteen. The activation function for input layer, hidden layer and output layer is hyperbolic tangent sigmoid. The neural networks tool box of MATLAB is used for necessary computations required for development of the model. Figure 8 shows architecture of the neural network model for prediction of CBR of lime and RHA stabilized soil. Table 4 shows the statistical parameters of data set considered for development of the ANN model.

Table 4: Univariate statistical analysis of parameters considered for development of the ANN model.

Parameter	Mean	Median	Standard deviation	Variance	Kurtosis	Asymmetry
LIME	3.00	3.50	2.16	4.67	1.50	-1.19
RHA	9.00	10.00	6.83	46.67	0.34	-0.75
CP	11.67	7.00	14.57	244.00	---	1.29
OMC	18.92	19.20	2.07	4.27	-0.51	-0.52
MDD	15.86	15.73	0.88	0.77	-1.00	0.29
CBR	9.39	8.08	3.77	14.22	-0.82	0.67

The univariate analysis showed that LIME, RHA and OMC showed a slight negative bias with a distribution near to normal (Table 4). CP, MDD and CBR were positively skewed. LIME and RHA present a leptokurtic distribution and OMC, MDD and CBR present a platykurtic distribution. Among the variables with less variability: LIME, OMC, MDD, CBR and the opposite is true for CP and RHA.

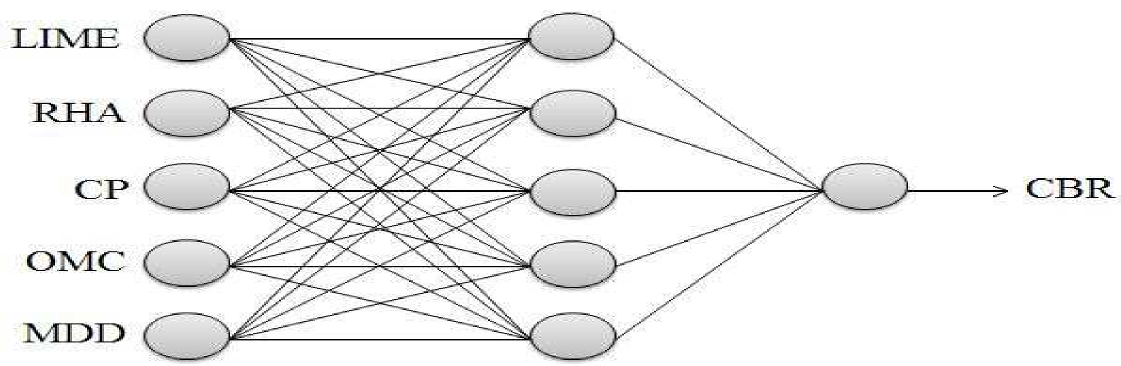

Figure 8: Architecture of the ANN model for prediction of CBR

3.1.3 Model Evaluation

ANN models were evaluated based on the mean absolute error (MAE) and regression(R). Table 5 shows that values of R for training and validation come out to be satisfactorily. To achieve the best ANN structure for prediction of CBR, various structures of feed forward ANN with different number of neurons in hidden layer was investigated. Finally, with consideration on MAE and R appropriate model was selected. The results of training, testing & validation of ANN models are given in Table 5. According to Table 5, the best results were obtained from (5-12-1) structures. Figure 9 shows best neural network structure.

Table 5: Results of training, testing validation of ANN

ANN Model Structure	MAE	Regression, R			
		Training	Validation	Test	All
5.3.1	0.5617	0.9751	0.9893	0.9837	0.9804
5.4.1	0.4633	0.988	0.9725	0.9420	0.9820
5.5.1	0.3945	0.9995	0.9695	0.9533	0.9851
5.6.1	0.4389	0.9921	0.9906	0.9478	0.9846
5.7.1	0.3238	0.9941	0.9918	0.9909	0.9932
5.8.1	0.2708	0.9993	0.9649	0.9850	0.9913
5.9.1	0.3089	0.9971	0.954	0.9701	0.9901
5.10.1	0.2984	0.9985	0.9953	0.9753	0.9911
5.11.1	0.2728	0.9992	0.9846	0.9265	0.9914
5.12.1	0.1644	0.9948	0.9890	0.9889	0.9926
5.13.1	0.2133	0.9999	0.9646	0.9877	0.9915
5.14.1	0.2807	0.9995	0.9820	0.9655	0.9903
5.15.1	0.2121	0.9993	0.9875	0.8268	0.9901

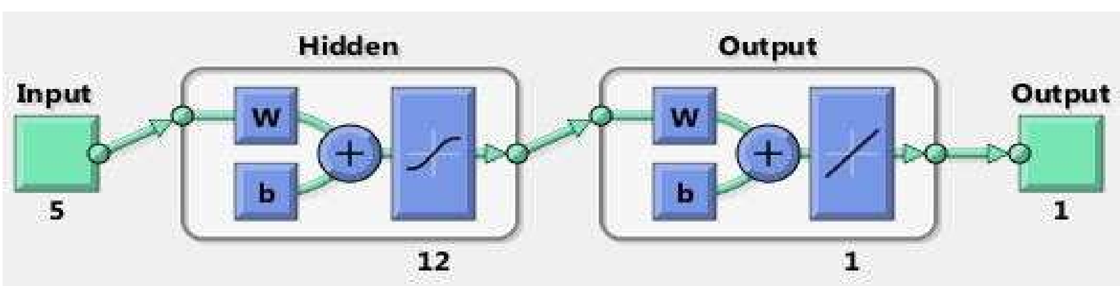

Figure 9: Best Neural Network Structure (5-12-1)

The best values of MAE in neural network have been achieved equal as 0.1644 and regression values for training, validation, test, and all have been achieved as 0.9948, 0.9890, 0.9889 and 0.9926 respectively. Figure 10 shows best performance plot of model at 5-12-1 structure. Regression analysis plot of training, validation, test, and all shown in Figures 11. All the figures are generated by MATLAB 2013a. Figure 12 shows a graph plotted between observed and predicted CBR values of the soil stabilized with RHA and lime. From the graph it has been found that a very good correlation exists between observed values and predicted values having R (Coefficient of correlation) value as 0.9926. According to Smith (1986) if $R \geq 0.8$, strong correlation exists between two sets of variables. As the R-value is 0.9926, hence the model is an efficient model for prediction of CBR values.

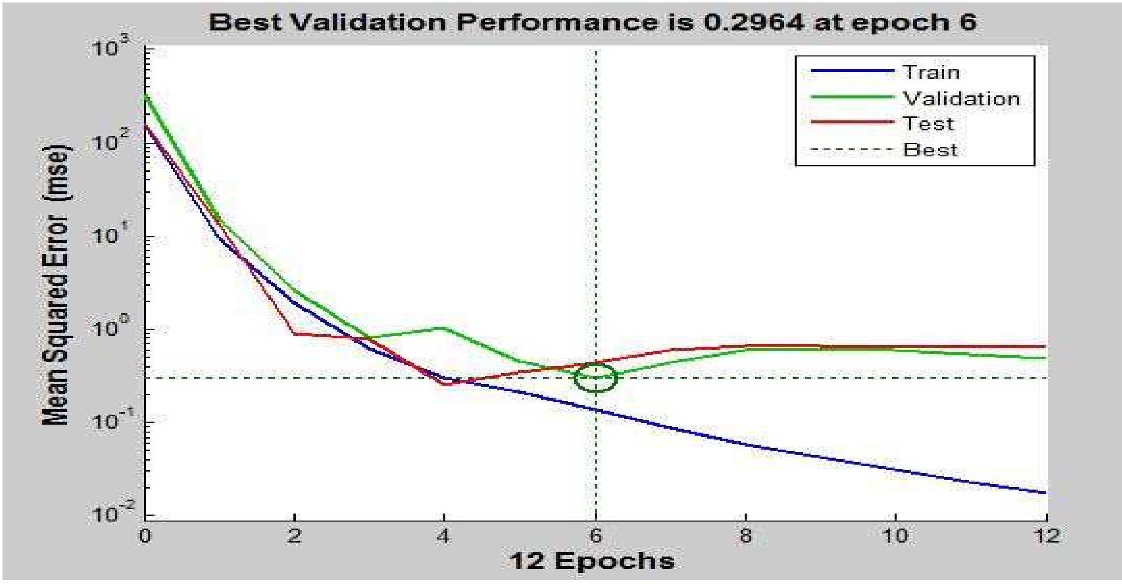

Figure 10: Performance Plot of Best Neural Network for prediction of CBR (5-12-1)

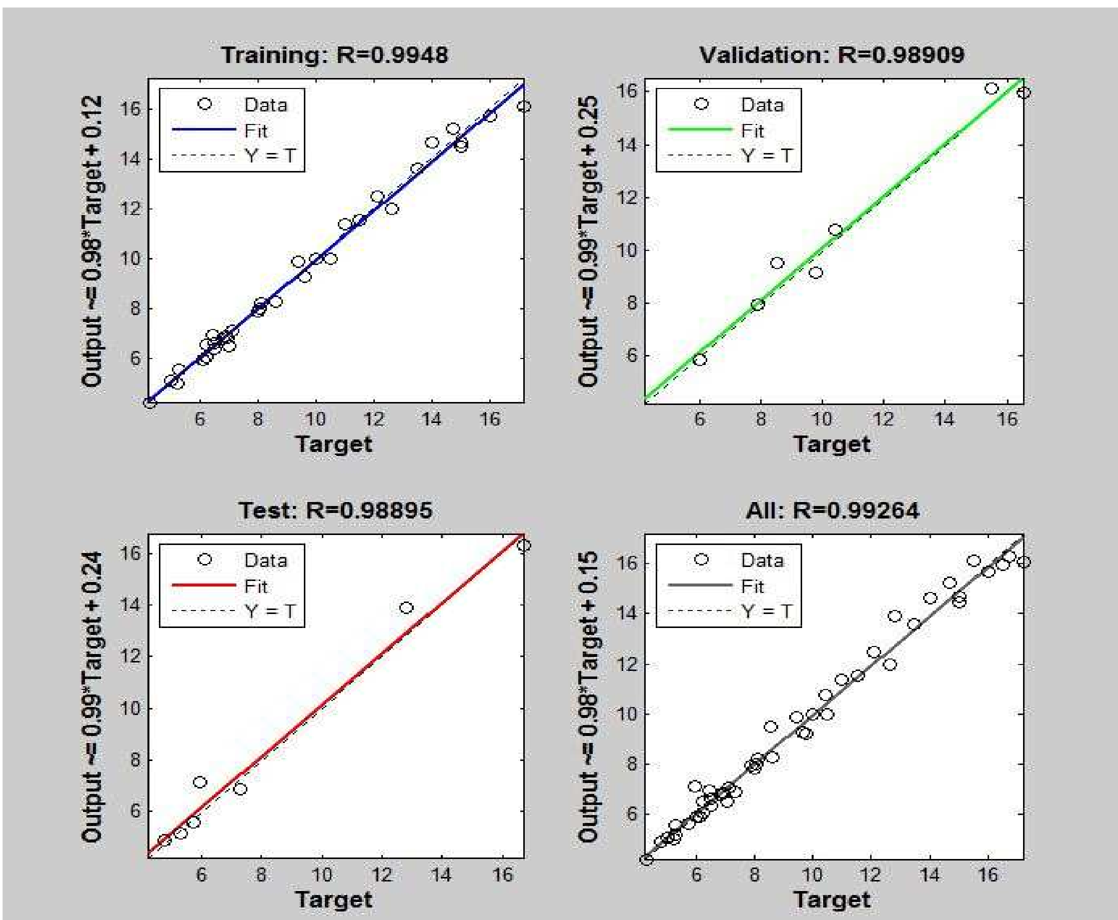

Figure 11: Regression between target vs. training, validation, test and all (5-12-1)

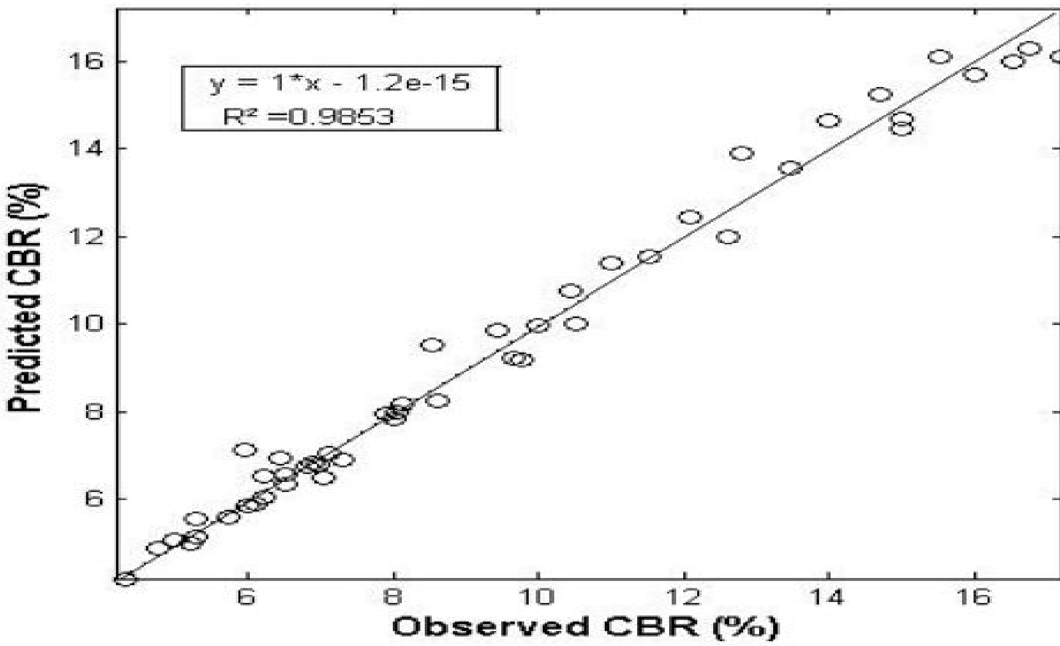

Figure 12: Predicted *vs*. Observed CBR

4. CONCLUSIONS

Exact prediction of CBR plays an important role in the pavement construction. Therefore, the goal of this research is offering a suitable model for predicting this quantity accurately. In this paper, the feed forward artificial neural network was used for the prediction of CBR of soil stabilized with lime and RHA. At the first, by using of ANN toolbox with the one hidden layer and changing the number of neurons of the layer, different models were created and tested. Finally on the basis MAE and R values, the structure with 12 neurons in the hidden layer was selected as the suitable model.

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