Prediction of California Bearing Ratio (CBR) from Index Properties of Fine-Grained Soil

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ABSTRACT: The California Bearing Ratio (CBR) value is an important variable in pavement design since it determines the strength of the subgrade soils. However, it should be noted that the CBR test is arduous and time-consuming. As a result, this work attempts to establish relationships between CBR and several soil index parameters such as liquid limit (LL), plastic limit (PL), optimum moisture content (OMC), and maximum dry density (MDD). Regression analysis and neural networks were used to develop three prediction models for correlating soaked CBR values with LL, PL, OMC, and MDD for soil samples taken from different locations in Guwahati, Assam, India. Because Assam is prone to flooding, and some rural roads are inundated for two to three days under water, a soaked CBR is considered. According to the results, ANN can more accurately predict soaked CBR values.

KEYWORDS: California bearing ratio, Artificial neural network, Multiple regression, Optimum moisture content, Maximum dry density.

1. INTRODUCTION

Most of the road systems in India have flexible pavements. There are different methods of designing a flexible pavement. The California Bearing Ratio (CBR) is an important design parameter for flexible pavements. It is an empirically determined process required to access the subgrade strength of roads and pavements. The CBR test can be conducted directly in the laboratory according to IS-2720: Part 16 1987 on soil samples derived from the site. A remoulded specimen is prepared from a representative sample and compacted at predetermined OMC in order to conduct the CBR test on subgrade soil. The prepared specimen is immersed in water for four days before being tested for penetration. A week or so is required to determine the soaked CBR value of a soil sample, which might create significant delays in a large project. The determination of soaked CBR value is not only tedious but also expensive due to the requirement of very costly equipment. It is very arduous to acquire a decent idea about the soaked CBR of subgrade materials over the entire length of the road. As a result, because of lack of finances and time, only a few laboratory studies on soaked CBR are undertaken when planning various construction projects. Due to this, in many circumstances, the soil investigation data obtained is insufficient. To address this issue, a significant number of specimens must be collected for testing. The liquid limit (LL), plastic limit (PL), type of soil, optimum moisture content (OMC), maximum dry density (MDD) and other factors can all influence the CBR value of a soil.

The main objective of this study is to develop three prediction models using multiple linear regression (MLR), multiple non-linear regression (MNLR) and artificial neural network (ANN) for correlating soaked CBR with LL, PL, OMC and MDD and to compare the results with the previously developed models to determine the best fit prediction model.

Prior to the development of the prediction models, a thorough literature review was conducted. Agarwal and Ghanekar (1970) established a prediction model based on 48 case studies to predict the value of CBR from LL, PL/PI. However, their investigation did not succeed to develop any strong relation between the parameters. In fact, a much better correlation was observed when they incorporated LL and OMC. Based on compaction parameters, a CBR correlation for cohesive soils was developed by Roy et al. (2009). For soaked CBR of alluvial soils, Patel and Desai (2010) provided a relationship between OMC, MDD, and PI. Datta and Chattopadhyay (2011) found that especially in case of CI (intermediate plasticity clay) soils, the values predicted from correlation as proposed by Patel and Desai comply with the tested values. But the predicted model failed to produce any correlation for other types of soils. Venkatasubramanian and Dhinakaran (2011) proposed two prediction models for predicting the values of CBR using ANN and MLR and based on the values of correlation coefficient, R^2 and root mean square error (RMSE), they concluded that MLR's predicted outcomes had a higher degree of accuracy. Yildirim and Gunaydin (2011) estimated the CBR value from sieve analysis, Atterberg limits, OMC and MDD using ANN and MLR. Strong correlations (R^2 = 0.80 – 0.95) between the various soil parameters are implied by Regression analysis and artificial neural network estimation. Varghese et al. (2013) also used ANN and MLR for predicting the CBR value of fine-grained soil from LL, PL, OMC and MDD and found that ANN gives better correlation compared to MLR. For the prediction of soaked CBR value for fine-grained subgrade soils, a regression-based model in terms of grain size analysis, LL, PL, MDD and OMC was developed by Ramasubbarao and Siva Sankar (2013). The statistical metrics suggested that the model created by Regression Analysis for connecting soaked CBR value with MDD performed better. Talukdar (2014) correlated soaked CBR value with MDD, OMC, LL, PL and PI of fine-grained soil and concluded that CBR value decreases with the increase in the PI and OMC but increases with the increase in the MDD. Korde and Yadav (2015) used regression analysis to correlate CBR value with LL, PL, and PI. They found that the CBR value decreases with increase in PI and LL. The effect of moisture content (MC), PI, and MDD on the CBR values of fine-grained soil was inspected by Nguyen and Mohajerani (2015). For the samples tested at OMC, wet side of OMC, and soaked conditions, they identified a strong connection between CBR with MC, PI, and MDD. Bassey et al. (2017) investigated the relationship between CBR and other geotechnical parameters of soil in relation to study location. Soil samples were taken from three areas in Nigeria's Akwa Ibom state: Ibiono, Oron, and Onna. The non-linear regression analysis demonstrated a significant relationship between CBR and (PI, OMC) for Ibiono, CBR and (OMC, MDD) for Onna, and CBR and (LL, PI, OMC) for Oron specimen, according to the statistical parameters. Rani and Nagaraj (2017) used simple linear regression and multiple linear regression to develop correlations between CBR and soil index properties. The relationship holds good if the anticipated CBR is within the scope of 0.2 to 3.5%. Using genetic expression programming (GEP), ANN, and the Krigging method, Alam et al. (2020) correlated CBR with specific gravity, uniformity coefficient, curvature coefficient, liquid limit, plastic limit, plasticity index, OMC and MDD. The findings revealed that all three approaches can predict the CBR value, but the Krigging approach can predict the CBR value with near-exact precision from the index properties. It has been observed from the literature review that most of the researches have been done to determine the unsoaked CBR value from the various index properties. Hence, there is a need to develop a prediction model to predict the soaked CBR value so as to tackle the problem of severe flood in Guwahati region.

2. MATERIALS AND METHODS

This study has been performed by collecting 45 soil samples from various places in Guwahati, Assam, India. The physical parameters of these soil samples are assessed using different laboratory tests as per the standard Indian Codes. The grain size distribution, liquid limit, and plastic limit tests, as well as the IS (Indian Standard) light compaction test to assess OMC and MDD and the soaked CBR test, are all performed in the laboratory.

The liquid limit and plastic limit tests are carried out on oven dried soil samples passing through 425 micron IS Sieve (fractions smaller than 425 micron) according to the guidelines given in IS-2720: Part 5 1985. The former is done by using the Casagrande apparatus while the latter is done by roll and thread method. The grain size distribution has been carried out by wet sieve analysis on oven dried samples as per IS-2720: Part 4 1985. The main purpose is to figure out what quantities of sand and finer material are present. Finally, using the Indian Standard Plasticity Chart given in IS-1498 1970, the samples are categorized and given a group symbol. The compaction parameters are established by executing the IS light compaction test according to IS-2720: Part 7 1980. The IS light compaction test, which has a compactive energy of 60450 kgf m/m^3, is the Indian equivalent of the Standard Proctor test (Shukla, 2015). The CBR test is performed as per the guidelines given in IS-2720: Part 16. The worst conditions in the field are tried to be recreated when the CBR test is accomplished in soaked conditions. The soil sample is soaked in water for 4 days before being tested to achieve this condition. The CBR value is obtained after the penetration test is successfully conducted.

3. RESULTS AND DISCUSSION

The various tests mentioned in the previous section have been conducted as per the required guidelines. The summary of the various tests results along with the soil types is described in Table 1.

Table 1 Physical characteristics and classification of the samples under investigation

Sl. No.	Latitude and Longitude	Fines	Sands	Gravel	Liquid Limit	Plastic Limit	OMC	MDD	Plasticity Index	Soaked CBR (CBRs)	Classification
		%	%	%	%	%	%	g/cc	%	%	Group Symbol
1	26°7′17″ N 91°49′15″ E	76.35	23.65	0.00	54	26.6	13.5	1.86	27.4	5.75	CH
2	26°7′15″ N 91°49′00″ E	77.42	22.58	0.00	54.2	25.5	13.8	1.86	28.7	5.67	CH
3	26°7′13″ N 91°48′42″ E	71.24	28.76	0.00	56.2	25.2	13.7	1.84	31	5.84	CH
4	26°7′12″ N 91°48′00″ E	73.20	26.80	0.00	54.8	27.4	13.7	1.85	27.4	5.51	CH
5	26°7′00″ N 91°47′25″ E	71.26	28.74	0.00	58.7	28	13.6	1.87	30.7	5.1	CH
6	26°6′55″ N 91°45′45″ E	75.63	24.37	0.00	56	27	14.6	1.84	29	5.07	CH
7	26°6′42″ N 91°44′59″ E	78.62	21.38	0.00	57.8	28.7	14.8	1.84	29.1	5.29	CH
8	26°11′49″ N 91°45′56″ E	79.56	20.44	0.00	44	24.1	11.3	1.9	19.9	7.55	CI
9	26°11′51″ N 91°45′46″ E	84.25	15.75	0.00	41	21.6	11.2	1.92	19.4	8.2	CI
10	26°11′52″ N 91°45′37″ E	64.58	35.42	0.00	48	22.9	12.6	1.92	25.1	7.31	CI
11	26°11′52″ N 91°45′29″ E	74.12	25.88	0.00	43.4	23.4	12	1.89	20	7.35	CI
12	26°11′53″ N 91°45′22″ E	68.65	31.35	0.00	48	22.1	12	1.87	25.9	7.08	CI
13	26°11′54″ N 91°45′11″ E	71.25	28.75	0.00	40.4	24.2	12.2	1.87	16.2	7.03	CI
14	26°11′55″ N 91°45′01″ E	65.23	34.77	0.00	45	23	13.2	1.87	22	6.4	CI
15	26°11′55″ N 91°44′59″ E	68.52	31.48	0.00	44	21.2	13.3	1.87	22.8	6.52	CI
16	26°11′55″ N 91°46′11″ E	75.32	24.68	0.00	48	26	12.9	1.85	22	6.1	CI
17	26°11′55″ N 91°46′21″ E	74.83	25.17	0.00	49	24	12.4	1.86	25	6.55	CI
18	26°11′55″ N 91°46′44″ E	81.25	18.75	0.00	38.5	20.9	13.5	1.76	17.6	6.25	CI
19	26°11′55″ N 91°47′00″ E	74.59	25.41	0.00	48	22.3	14.2	1.78	25.7	6.11	CI
20	26°11′55″ N 91°47′37″ E	77.45	22.55	0.00	37.8	20.6	12.4	1.87	17.2	7.53	CI
21	26°11′55″ N 91°47′57″ E	74.56	25.44	0.00	48	26.8	13.7	1.83	21.2	5.59	CI

Table 1 (continued)

Sl. No.	Latitude and Longitude	Fines	Sands	Gravel	Liquid Limit	Plastic Limit	OMC	MDD	Plasticity Index	Soaked CBR (CBRs)	Classification
		%	%	%	%	%	%	g/cc	%	%	Group Symbol
22	26°11′55″ N 91°48′01″ E	66.35	33.65	0.00	49.6	27.7	12.7	1.85	21.9	6.08	CI-CH
23	26°8′33″ N 91°38′36″ E	74.68	25.32	0.00	31.4	16.2	10	1.94	15.2	10.79	CL
24	26°8′33″ N 91°38′27″ E	74.58	25.42	0.00	30.2	20.1	10.5	1.94	10.1	10.29	CL
25	26°8′32″ N 91°38′13″ E	70.25	29.75	0.00	27	15.2	10	1.92	11.8	11.17	CL
26	26°8′32″ N 91°38′00″ E	72.56	27.44	0.00	28.7	20	10.3	1.92	8.7	10.33	CL
27	26°8′30″ N 91°37′44″ E	77.25	22.75	0.00	30	18.7	11	1.96	11.3	10.14	CL
28	26°8′30″ N 91°37′13″ E	70.00	30.00	0.00	24.6	13.3	10.1	1.97	11.3	11.83	CL
29	26°8′27″ N 91°37′13″ E	75.46	24.54	0.00	31.2	18.4	11.3	1.89	12.8	9.03	CL
30	26°8′05″ N 91°37′09″ E	74.58	25.42	0.00	26	11.9	10.3	1.97	14.1	11.77	CL
31	26°7′50″ N 91°37′02″ E	74.56	25.44	0.00	32.2	18.3	13.2	1.92	13.9	8.39	CL
32	26°7′33″ N 91°37′02″ E	67.58	32.42	0.00	34.8	17.8	11.4	1.92	17	9.09	CL-CI
33	26°7′26″ N 91°37′02″ E	75.82	24.18	0.00	34.4	22.7	12.8	1.93	11.7	8.21	CL-CI
34	26°39′10″ N 92°47′33″ E	76.58	23.42	0.00	62.12	37.3	13.9	1.84	24.82	4.88	MH
35	26°37′30″ N 92°49′55″ E	79.58	20.42	0.00	68.54	40.2	14.5	1.82	28.34	4.37	MH
36	26°37′00″ N 92°50′12″ E	69.22	30.78	0.00	52.4	32.2	14	1.85	20.2	5.27	MH
37	26°36′30″ N 92°51′32″ E	74.10	25.90	0.00	60.9	32.7	14.3	1.82	28.2	4.71	MH
38	26°35′55″ N 92°51′52″ E	66.85	33.15	0.00	52	31	14.3	1.86	21	5.31	MH
39	26°34′33″ N 92°52′02″ E	65.48	34.52	0.00	52.5	29.8	13.7	1.89	22.7	5.93	MH
40	26°34′02″ N 92°52′27″ E	72.33	27.67	0.00	56	32	14.3	1.87	24	5.99	MH
41	26°32′57″ N 92°53′37″ E	71.02	28.98	0.00	65	34	15.5	1.78	31	4.02	MH
42	26°32′47″ N 92°54′01″ E	76.31	23.69	0.00	59	31	15.2	1.76	28	4.03	MH
43	26°32′07″ N 92°54′39″ E	57.32	42.68	0.00	58	33	15.7	1.82	25	4.38	MH
44	26°31′47″ N 92°55′00″ E	71.22	28.78	0.00	49	32	14.2	1.84	17	5.71	MI
45	26°31′08″ N 92°55′35″ E	78.65	21.35	0.00	50.4	28.6	12.3	1.86	21.8	6.37	MI-MH

3.1 Correlation of LL and PL with soaked CBR

The correlation of LL and PL with soaked CBR can be studied by plotting LL and PL as independent variable and soaked CBR as dependent variable as shown in Figures 1(a) and 1(b). From the figure, it has been found that soaked CBR value varies logarithmically with LL and third order polynomial function with PL. It has been found that the relation of LL with soaked CBR exhibits a better correlation compared to PL. However, it is found that soaked CBR value decreases with increase in both LL and PL. According to Smith (1986), if a proposed model has a R value ≥ 0.8, the measured and projected values have a strong relationship. As the correlation coefficient, R (*square root of* R^2) in the earlier case exhibits a higher value (R = 0.95) than the latter one (R = 0.91), there exists a strong correlation between LL and soaked CBR. The linear equations derived from the current study's data points are as follows:

$$CBR_s = -7.54\, ln\,(LL) + 35.316\; (\boldsymbol{R^2 = 0.90}) \tag{1}$$

$$CBR_s = 0.0003(PL)^3 - 0.0113(PL)^2 - 0.2527(PL) + 16.053\; (\boldsymbol{R^2 = 0.83}) \tag{2}$$

3.2 Correlation of OMC and MDD with soaked CBR

In this case also, the soaked CBR values are treated as dependent variables while the OMC and MDD values are taken as independent variables. The graphs showing the relationship between OMC, MDD and soaked CBR are plotted in Figures 2(a) and 2(b). It has been found that the soaked CBR value varies logarithmically with OMC and third order polynomial function with MDD. The relation of OMC with soaked CBR exhibits a better correlation compared to MDD. However, as soaked CBR value increases, there is an increase in MDD and decrease in OMC. It has been found that the correlation coefficient, R in the earlier case exhibits a higher value (R = 0.95) than the latter one (R = 0.92) and hence exists a strong correlation between OMC and soaked CBR value. The linear equations derived from the current study's data points are as follows:

$$CBR_s = -16.08\, ln\,(OMC) + 48.002\ (\boldsymbol{R^2 = 0.90}) \tag{3}$$

$$CBR_s = -1594.2(MDD)^3 + 9068.1(MDD)^2 - 17142(MDD) + 10778\ (\boldsymbol{R^2 = 0.85}) \tag{4}$$

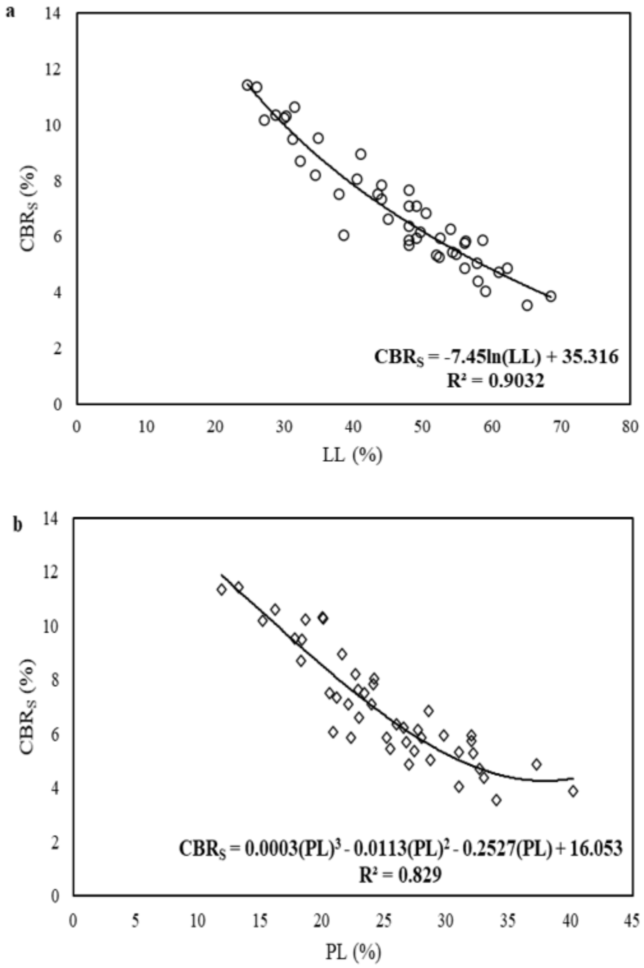

Figure 1 (a) Relation of soaked CBR with LL and (b) Relation of soaked CBR with PL

3.3 Multiple Linear Regression (MLR) Model in terms of LL, PL, OMC and MDD

In the multiple linear regression analysis, the dependent variable was the soaked CBR value, whereas the independent variable was the remaining soil properties. The regression analysis has been conducted using XLSTAT 2014. Soaked CBR value can be expressed as:

$$CBR_s = f(LL, PL, OMC\ and\ MDD) \tag{5}$$

The summary output of the regression model has been shown in Table 2 and the correlation matrix is shown in Table 3.

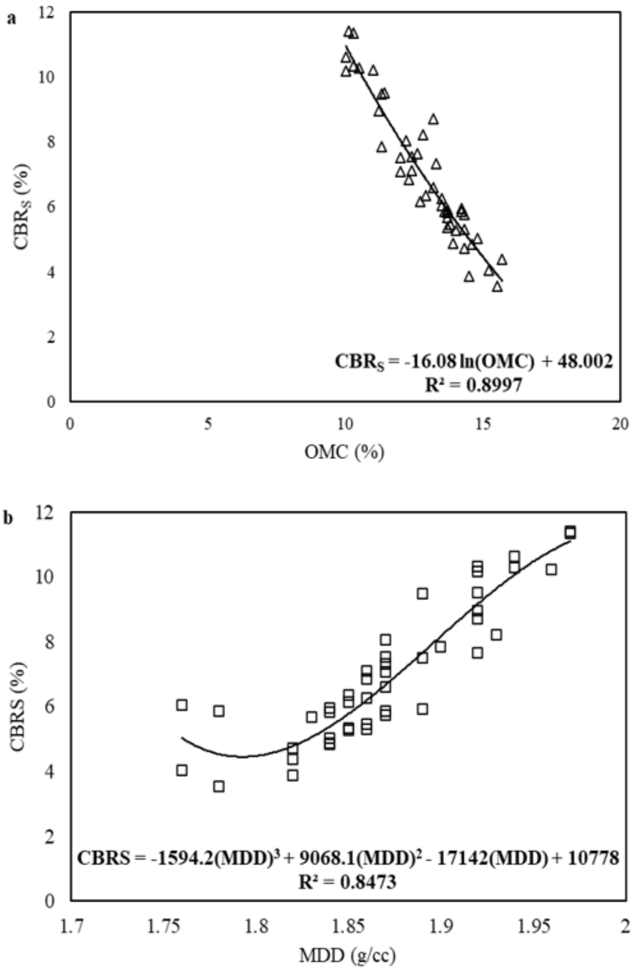

Figure 2 (a) Relation of soaked CBR with OMC and (b) Relation of soaked CBR with MDD

Table 2 Summary output of MLR Model in terms of LL, PL, OMC and MDD

Linear Regression Statistics				
Soil Propertie-s	**Coefficie-nts**	**Standa-rdised error**	**P-value**	**t Stat**
Intercept	-0.1367	5.2019	0.9792	-0.0263
LL	-0.0782	0.0170	< 0.0001	-4.5923
PL	-0.0282	0.0271	0.3035	-1.0424
OMC	-0.4408	0.1020	< 0.0001	-4.3216
MDD	9.1269	2.3528	0.0004	3.8791

Table 3 Correlation matrix of the Regression Model

Variab-les	LL	PL	OMC	MDD	CBRS
LL	**1.000**	0.911	0.861	-0.746	-0.939
PL	0.911	**1.000**	0.812	-0.678	-0.879
OMC	0.861	0.812	**1.000**	-0.816	-0.933
MDD	-0.746	-0.678	-0.816	**1.000**	0.855
CBRS	-0.939	-0.879	-0.933	0.855	**1.000**

From Table 2, the correlation coefficient has been found to be 0.97, which is very close to unity, hence bearing a very strong relationship between the various input parameters. Hence, the above model may be proposed for estimating soaked CBR value. The equation for the soaked CBR prediction using MLR is given below:

$$CBR_s = -0.137 - 0.078(LL) - 0.028(PL) - 0.441(OMC) + 9.127(MDD)\ (\boldsymbol{R^2 = 0.958}) \tag{6}$$

3.4 Multiple Non-Linear Regression (MNLR) Model in terms of LL, PL, OMC and MDD

Here also, the soaked CBR value is used as the dependent variable, and the remaining soil parameters as independent variables. The regression analysis has been conducted using XLSTAT 2014. The summary output of the regression model is shown in Table 4.

Table 4 Summary output of MNLR Model in terms of LL, PL, OMC and MDD

Nonlinear Regression Statistics		
Soil Parameter	**Coefficients**	**Standardised error**
pr1	65.7634	52.1005
pr2	-0.1467	0.0542
pr3	-0.1707	0.0732
pr4	-2.1679	0.5130
pr5	-46.5596	57.5461
pr6	0.0009	0.0006
pr7	0.0023	0.0013
pr8	0.0692	0.0200
pr9	14.8554	15.5479

From Table 4, it has been inferred that the R value approaches to unity and hence bearing a strong correlation between the various input parameters. The equation for the soaked CBR prediction using MNLR is given below:

$$CBR_s = 65.763 - 0.147(LL) - 0.171(PL) - 2.168(OMC) - 46.559(MDD) - 0.001(LL)^2 + 0.002(PL)^2 + 0.069(OMC)^2 + 14.855(MDD)^2 \; (\boldsymbol{R^2 = 0.985}) \tag{7}$$

3.5 Artificial Neural Network (ANN) Model in terms of LL, PL, OMC and MDD

The data is separated into three sets: training, testing, and validation set, to prevent the over-fitting of the trained model and to check the generalization capacity of the network after the training phase. A multi-layer feed-forward network is used and the training of the network is done by back propagation method. The training set is the biggest of them all, and it's used to find patterns in the data. The testing set is utilised to understand the trained network's generalisation capacity, and the validation set is utilised to do the final performance check. The model is developed by considering LL, PL, OMC and MDD as the input variable and only soaked CBR as output variable. For prediction of the soaked CBR value, four different network architectures with different neurons in the hidden layer are chosen. Mean square error (MSE) and mean absolute error (MAE) are used as standards of assessment of error made by the network. A neural network architecture usually consists of an input layer, one or more hidden layers and an output layer. A network architecture is shown in Figure 3 with 4 input-1 hidden layer with 10 neurons-1 output i.e. 4-10-1. Hidden layers allow a neural network's function to be split down into particular data manipulations. Each function in the hidden layer is tailored to deliver a certain result. The number of neurons in the hidden layers has a significant impact on the overall design of the neural network. Despite the fact that these neurons have no direct interaction with the outside world, they have a significant impact on the final product. Different combinations of network architectures are used as shown in Table 5 to check the accuracy of the network model and the regression plot for the various network architectures are shown in Figures 4(a), 4(b), 4(c) and 4(d) with predicted value as output in Y-axis and measured value as target in X-axis. After analysing the different network architectures, finally 4-10-1 network architecture having 10 number of neurons in the hidden layer has been selected, as this network is found to have the lowest values of MSE and MAE.

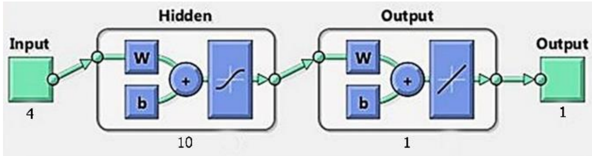

Figure 3 Neural Network architecture

Table 5 Summary output of ANN Model in terms of LL, PL, OMC and MDD

Network Architecture	R-value for training	R-value for testing	MSE	MAE
4-1-1	0.992	0.995	0.102	0.252
4-5-1	0.989	0.999	0.074	0.204
4-10-1	0.988	0.998	0.069	0.198
4-15-1	0.974	0.999	0.163	0.204

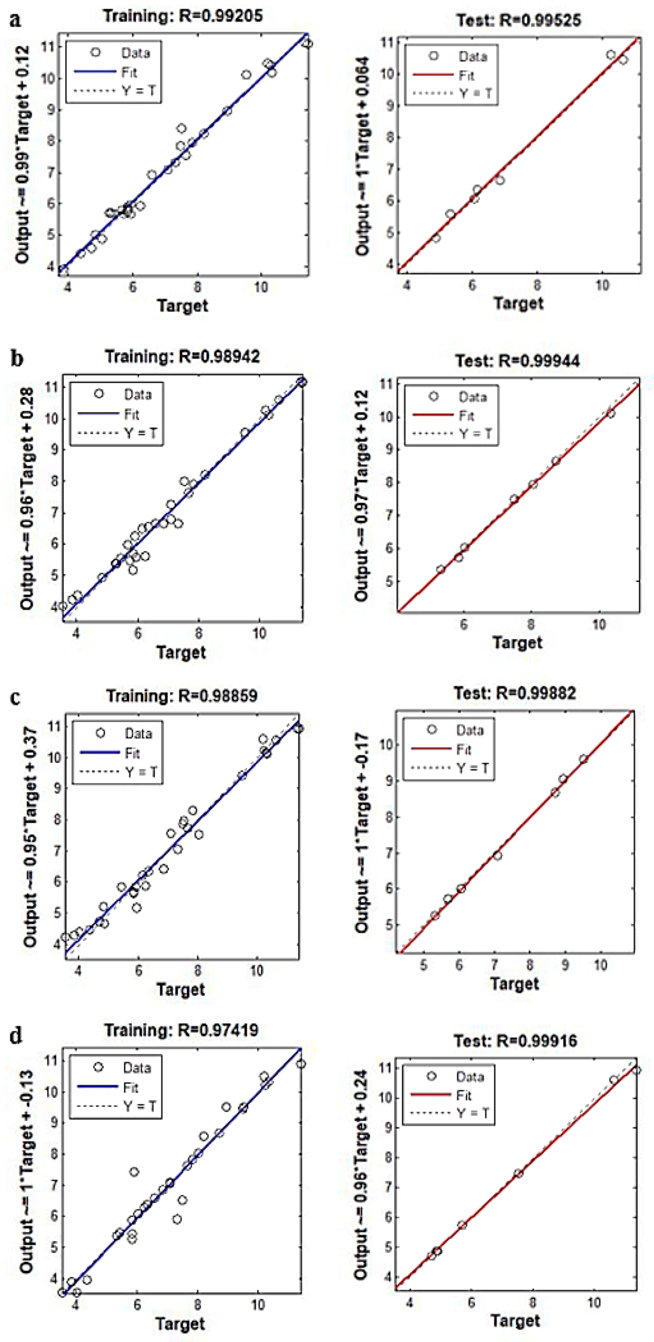

Figure 4 Regression plot for various network architectures: (a) Network 4-1-1, (b) Network 4-5-1, (c) Network 4-10-1, and (d) Network 4-15-1.

3.6 Validation of the Models

In the validation step, the predicted models' performance is evaluated. The prediction models' efficiency and accuracy are tested here by considering another 15 samples collected from different locations of Guwahati that were not used during model preparation. The models' predictions are extremely close to the analytical results which are shown in Figures 5(a), 5(b), 5(c), 5(d), 5(e), 5(f) and 5(g). After analysing the various models, it has been found that soaked CBR value predicted using ANN has been found to have a better correlation with lowest value of MSE and MAE.

Although many researchers have carried out the similar approaches to predict the CBR value from different properties of soil, but very limited studies have been found to develop prediction models based on soaked CBR value. A comparison has been made to determine the best fit regression model for predicting the CBR_s from index soil properties for Guwahati region. From Figure 6, it has been found that the present regression model best fits the data and predicts very close to the target value.

It is critical for ANN to be able to learn and model non-linear and complicated relationships. ANN does not impose any limits on the input variables, unlike other prediction algorithms. Furthermore, many researches have shown that ANNs are better at modelling heteroskedasticity. Regression analysis, on the other hand, is prone to model overfitting. Hence, ANN can predict the soaked CBR value with higher degree of precision.

Table 6 Data base for soaked CBR for model validation

S. No.	Latitude and Longitude	Fines	Sands	Gravel	LL	PL	OMC	MDD	PI	CBR_S	Classification
		%	%	%	%	%	%	g/cc	%	%	Symbol
1	26°30′55″ N 92°56′15″ E	56.32	43.68	0.00	50.12	28.35	13.85	1.82	21.77	6.10	MI-MH
2	26°11′33″ N 91°46′12″ E	63.25	36.75	0.00	44.50	25.50	13.60	1.75	19.00	6.20	CI
3	26°30′33″ N 92°56′29″ E	58.25	41.75	0.00	46.85	28.35	13.30	1.76	18.50	6.30	MI
4	26°11′02″ N 91°46′34″ E	65.20	34.80	0.00	38.75	22.35	12.35	1.88	16.40	7.25	CI
5	26°10′57″ N 91°46′55″ E	68.22	31.78	0.00	45.00	26.00	13.50	1.87	19.00	6.12	CI
6	26°10′32″ N 91°47′02″ E	70.15	29.85	0.00	38.25	24.20	12.05	1.87	14.05	8.52	CI
7	26°30′55″ N 92°55′59″ E	57.25	42.75	0.00	39.75	25.85	11.25	1.85	13.90	8.12	MI
8	26°30′55″ N 92°56′03″ E	78.65	21.35	0.00	52.23	30.25	14.22	1.75	21.98	5.85	MH
9	26°10′11″ N 91°47′24″ E	75.75	24.25	0.00	45.00	23.00	13.40	1.87	22.00	7.23	CI
10	26°30′11″ N 92°56′35″ E	72.69	27.31	0.00	33.50	18.35	11.85	1.72	15.15	7.65	ML
11	26°30′11″ N 92°56′55″ E	78.32	21.68	0.00	35.20	20.00	11.20	1.75	15.20	7.95	MI-MH
12	26°10′02″ N 91°47′45″ E	87.65	12.35	0.00	40.65	24.65	13.05	1.85	16.00	7.95	CI
13	26°30′02″ N 92°57′12″ E	79.22	20.78	0.00	46.25	32.25	13.30	1.82	14.00	6.38	MI
14	26°30′02″ N 92°57′33″ E	94.22	5.78	0.00	55.00	34.85	13.50	1.82	20.15	5.89	MH
15	26°09′55″ N 91°47′59″ E	84.21	15.79	0.00	46.25	25.15	13.50	1.85	21.10	6.80	CI

4. CONCLUSIONS

For the design of flexible pavements, it is incumbent on part of the engineer to ascertain the California Bearing Ratio (CBR) of the soil subgrade. CBR value of soil may depend upon many factors like liquid limit (LL), plastic limit (PL), plasticity index (PI), optimum moisture content (OMC), maximum dry density (MDD), type of soil, permeability of soil, etc. The determination of soaked CBR value is not tedious but also expensive due to the requirement of very costly equipment. To resolve this problem and to have a preliminary assessment of the stability of soils, prediction models for these engineering properties are highly preferable. An extensive experimental study has been conducted on 45 naturally occurring fine-grained soils to investigate the variation pattern of soaked CBR value against the index properties of soil. Various statistical analysis has been done to determine the best fit model. The salient observations of this study can be summed up as follows:

1) The soaked CBR value varies logarithmically with LL and third order polynomial function with PL. It has been found that the relation of LL with soaked CBR exhibits a better correlation compared to PL. However, it is found that soaked CBR value decreases with increase in both LL and PL.
2) The soaked CBR value varies logarithmically with OMC and third order polynomial function with MDD. The relation of OMC with soaked CBR exhibits a better correlation compared to MDD. However, as soaked CBR value increases, there is an increase in MDD and decrease in OMC.
3) The MLR and MNLR models developed in terms LL, PL, OMC and MDD showed convincingly good prediction results.
4) The predicted values of soaked CBR obtained from ANN showed the best performance with the measured values having the highest correlation coefficient and lowest value of MSE and MAE.
5) The proposed neural network model can act as a good prediction model for predicting the value of soaked CBR which is a significant parameter required for the design of flexible pavements.

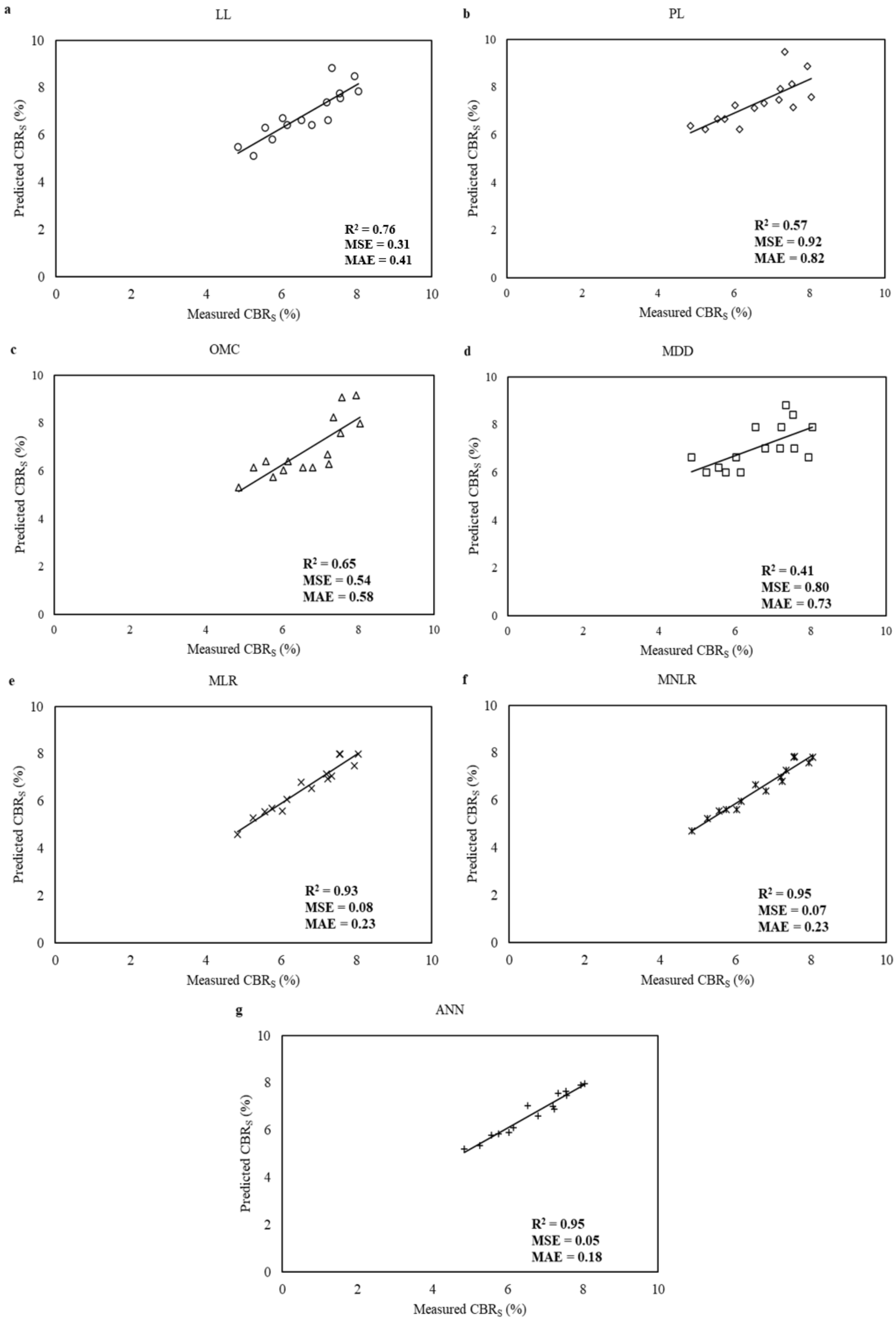

Figure 5 Comparison of measured values with predicted values for: (a) LL, (b) PL, (c) OMC, (d) MDD, (e) MLR, (f) MNLR, and (g) ANN

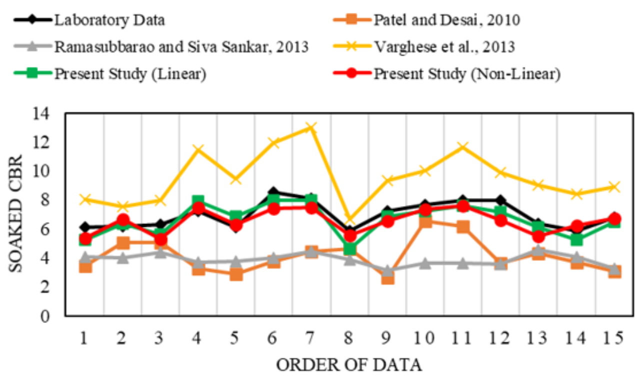

Figure 6 Comparison of soaked CBR with laboratory data and predicted data

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