

# Soft Computing Technique for Prediction of CBR from Index Properties of Subgrade Soil

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**ABSTRACT:** The objective of this work is to develop soft computing technique for prediction of CBR of subgrade soil from its index properties. Soft Computing Techniques have been recognized as attractive alternatives to the standard, well established “hard computing” paradigms. In the present work two techniques namely: Artificial Neural Networks(ANN) and Multiple Linear Regression(MLR) were considered and conducted. Soil samples were collected from the subgrade layer of two road projects at different chainages in Mysore district and required tests were conducted on the collected soil samples. Data obtained from the experimental result were used in the soft computing technique for both training and testing of artificial neural network and regression models. Four ANN and MLR models were developed with the different combination of inputs in order to know their importance in the prediction of CBR. From the results obtained, it was observed that all ANN models performs better than MLR models. In particular ANN model with all input parameters shows better results than other ANN models.

**KEYWORDS:** Artificial Neural Network, Multiple Linear Regression, CBR, NNM1, NNM2, NNM3, NNM4, MDD, OMC, LL, PL, PI, Gravel, Sand and Silt & Clay

## I. INTRODUCTION

California Bearing Ratio (CBR) used to assess the stiffness modulus and shear strength of subgrade. The flexible pavement design in India was standardized in 1970 by IRC, which gives design curves from which the thickness of different pavement layers can be found for a given traffic load and CBR value of subgrade soil. As the CBR value of subgrade soil increases the thickness of pavement decreases. In other words, the design of flexible pavement is very much dependent on the CBR value of subgrade. CBR value can be measured directly in the laboratory, but it takes at least 4 days to measure the CBR value for each soil sample. Hence it is not really possible to find CBR value for large number of soil samples within a stipulated time. This would result in serious delay in the progress of the project which leads to escalation of project cost. Hence for proper design, time and cost point of view it is very much essential to correlate CBR of soils with easily determinable parameters.

Index properties of soil are used to characterize soils and determine their basic properties such as moisture content, specific gravity, particle size distribution, consistency and moisture-density relationship. Index property like particle size distribution which gives the percentage of various sizes of particles in a dry soil sample affects the CBR in such a way that as the percentage of gravel increases CBR value also increases since bearing capacity of granular soil will be more, but as the percentage of silt & clay increases CBR value decreases since it may easily undergo settlement and bearing capacity of soil will be lesser compare to granular soil. Liquid limit of cohesive soil will be more because in cohesive soil percentage of silt & clay will be more which increases the surface area available for binding moisture, meanwhile it decreases the CBR value, and it is vice versa in case of granular soils. Hence in general we can say that liquid limit as well as plastic limit of soil inversely affects its CBR value. Dry density is one of the main index property which affects CBR value directly, i.e. as dry density increases CBR value also increases. Dry density is a measure of degree of compaction, at maximum compaction bearing capacity of soil will be more, which increases CBR value as well as dry density. Increase in moisture content will increase dry density to maximum and it tends to decrease as water content increases, hence water content at which maximum dry density occurs is termed as optimum moisture content which will be used to measure CBR of soil.

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An ANN is a computational model made up of number of artificial neurons inspired by biological neuron. A neuron is an information-processing unit which is fundamental to the operation of a neural network. These basically consist of inputs, which are multiplied by synaptic weights and then computed by a mathematical function which determines the activation of the neuron is called Activation function which limits the amplitude of output of the neuron. The model of a neuron also includes an externally applied bias (threshold) that has the effect of lowering or increasing the net input of the activation function. A neural network has ability to learn from its environment through an iterative process of adjustments applied to its weights and thresholds.

The MLR is used to explain the relationship between one continuous dependent variable from two or more independent variables. In this work MLR was used to determine the statistical relationship between a response (CBR) and the explanatory variables (Index properties).

## II. RELATED WORK

Many researchers have given correlations of CBR with index properties of soil. However the validity and applicability of such correlation need to be established for their acceptances in general practice. Various attempts have been made to predict the CBR of sub grade soil using their index properties, which take less time and are easier to perform as compared to the standard procedure of CBR testing.

- A method is proposed for correlating CBR values with the liquid limit, plastic limit, plasticity index, OMC, Maximum dry density, UCC values of various soils taken from in and around three different districts in Tamil Nadu namely Thanjavur, Tiruchirapalli and Pudukkottai districts using ANN by Venkatasubramanian C and Dhinakaran G(2012).
- T.Datta and B.C.Chottopadhyay (2011) presented the paper to check the applicability and limitations of available methods by comparing predicted and tested values of CBR of various soils. Large number of test data for simple soil properties were used to validate the efficacy of some of the available correlation for CBR.

## III. EXPERIMENTAL WORK

The experiments were conducted on the 15 soil samples collected from subgrade layer of a road projects i.e. "Upgrading two Lane Outer Ring Road (Orr) to six Lane along with service road from Mysore - Bangalore road to Mysore - Nanjangud road". The frequency of soil sample collection was done as per MORTH specification for quality control of subgrade. As per the data required for the present work laboratory tests such as Grain size analysis, Atterberg limits, Standard proctor and CBR test were conducted in accordance with IS 2720:1985.

The data obtained from the tests results were collected and used for training and testing of regression and neural network models. The index properties of soil: i) Maximum Dry Density(MDD), ii) Optimum Moisture Content(OMC), iii) PL, iv) LL, v) PI, vi) Gravel, vii) Sand and viii) Clay were used as input data parameters and the respective CBR value of soil used as target data for training as well as testing.

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Table 1: Training Data set for both ANN & MLR

MDD (gm/cc)	OMC (%)	LL (%)	PL (%)	PI (%)	Gravel (%)	Sand (%)	Silt (%)	CBR (%)
1.86	8.98	34	23	11	14.7	55	30.3	13.27
1.97	8.5	27	18	9	13.8	55.6	30.6	14.7
1.92	8.1	31.4	21	10.4	5.8	62.8	31.4	12.7
2.045	9.2	33	21.8	11.2	14	59.3	26.7	14.9
2.11	7.64	25	13	12	15.8	55.1	29	16.8
2	8.4	30	19.2	10.8	14.3	54.9	30.8	13.93
2.02	8.04	28	16.7	11.3	12.5	61	26.5	16
1.99	8.4	29	19.15	9.85	11.7	57.6	30.7	15.68
2.19	6.98	26.5	14.8	11.7	19.5	56	24.5	17.7
2.23	6.74	24.8	16	8.8	19.5	59.2	21.3	18.74
2.12	7.96	28.6	17.8	10.8	21	51	28	17.86
2.2	7	25.6	18.3	7.3	22	54	24	19.04

The Table 1 shows laboratory test results obtained for 12 soil samples which were used for training of ANN and MLR models.

Table 2: Testing Data set for both ANN & MLR

MDD (gm/cc)	OMC (%)	LL (%)	PL (%)	PI (%)	Gravel (%)	Sand (%)	Silt (%)	CBR (%)
2.055	8	29.7	18.95	10.75	14.8	60.9	24.3	13.54
2.13	9	27.5	15.2	12.3	12.7	62	25.3	16.5
2.12	7.3	26	15.2	10.8	15.8	57	27.2	18.05

The Table 2 shows laboratory test results obtained for 3 soil samples which were used for testing of ANN and MLR models.

### IV. ANN MODELS FOR PREDICTION OF CBR

After much iteration with different combination of network properties, the network which gives the optimum results has been found. The network was created by considering following network properties using neural network tool in matlabas shown in Figure 1 below.

- Network type - feed-forward backprop
- Training Function - trainlm
- Performance Function - MSE
- Activation Function – tansig
- Number of hidden layers - 2

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- Number of neurons in hidden layer - 16
- Inputs – matrix p (MDD, OMC, PL, LL, PI, Gravel, Sand and Silt).
- Target – matrix t (CBR).

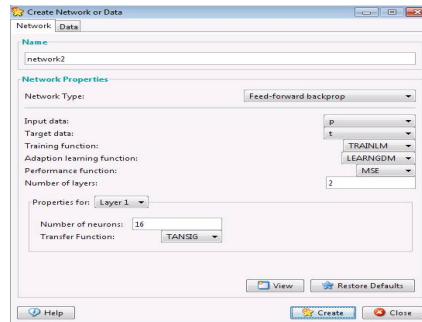


Figure 1

**Figure 1:** Creation of neural network using nntool in matlab.

The network was created by considering above network properties using nntool in matlab as shown in Figure 1.

In present work few ANN models has been created by considering different combination of input parameters, In order to know the input importance in estimating required output, While network properties for all models remains same as mentioned above.

**Neural Network Model1 (NNM1)** -Inputs:MDD, OMC, LL, PL, PI, Gravel, Sand and Silt & Clay.Target /output:CBR  
No inputs was removed in this model, it was trained and tested for eight inputs and one output.

**Neural Network Model2 (NNM2)** -Inputs:MDD, OMC, LL, PL, PI.Target /output:CBR

Here in this model, 3 inputs Gravel, Sand and Silt & Clay obtained from Grain size analysis test were removed. A model was trained and tested for five inputs and one output

**Neural Network Model3 (NNM3)** -Inputs:MDD, OMC, Gravel, Sand and Silt & Clay.Target /output:CBR

Here in this model, 3 inputs LL, PL and PI obtained from Atterberg Limit test were removed. A model was trained and tested for five inputs and one output

**Neural Network Model4 (NNM4)** -Inputs:LL, PL, PI, Gravel, Sand and Silt & Clay.Target /output:CBR

Here in this model, 2 inputs MDD and OMC obtained from Standard compaction test were removed. A model was trained and tested for six inputs and one output.

All these models were trained and tested to predict CBR value of subgrade soil from the index properties.

### Training and testing of ANN models

Once the network weights and biases have been initialized, the network is ready for training. The created network has been trained with input data matrix p and target t.

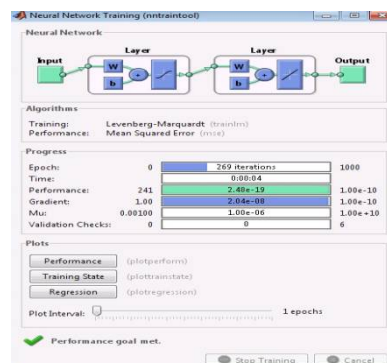


Figure 2

**Figure 2:** Training of neural network using ntraintool.

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The Figure 2 shows neural network training tool which has met the performance goal for the given input and target data. During training the weights and biases of the network are iteratively adjusted to minimize the network performance function. All ANN models were trained for performance  $R^2=1$ , which shows the predicted values were as same as actual values for training.

The trained network were tested with new input data to obtain predicted CBR values, the performance of the network is measured by MSE error calculated with respect to supplied targets. If the network output is not nearer to the target then the weights of connection were reinitialized and network trained again for new weights. Once again after successful training, the network was tested. The process continued until obtained predicted values were satisfactory. The performance of each model was measured by Mean Square Error (MSE), mean absolute error (MAE) and correlation coefficient (CC) values.

## V. MLR MODELS FOR PREDICTION OF CBR

The multiple regression coefficients were obtained by fitting training set data and model was evaluated by using equation below,

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \beta_8 X_8$$

Where,

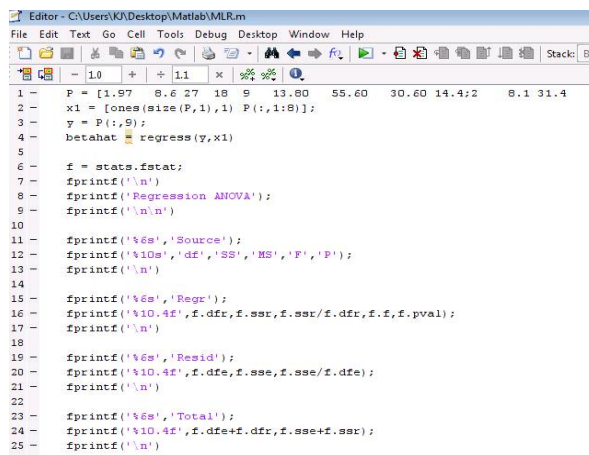
$Y = \text{CBR}$ ,  $X_1 = \text{MDD}$ ,  $X_2 = \text{OMC}$ ,  $X_3 = \text{Plastic limit}$ ,  $X_4 = \text{Liquid limit}$ ,  $X_5 = \text{Plasticity index}$ ,  $X_6 = \text{Gravel}$ ,  $X_7 = \text{Sand}$ ,  $X_8 = \text{Silt \& Clay}$ .  $\beta_0, \beta_1, \beta_2, \dots, \beta_8$  are partial regression coefficients.

**MLR Model 1 :**  $Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \beta_8 X_8$

**MLR Model 2 :**  $Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5$

**MLR Model 1 :**  $Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_6 X_6 + \beta_7 X_7 + \beta_8 X_8$

**MLR Model 1 :**  $Y = \beta_0 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \beta_8 X_8$



```

Editor - C:\Users\KA\Desktop\Matlab\MLR.m
File Edit Text Go Cell Tools Debug Desktop Window Help
1 - P = [1.97 8.6 27 18 9 13.00 55.60 30.60 14.4:2 8.1 31.4 ;
2 - x1 = [ones(size(P,1),1) P(:,1:8)];
3 - y = P(:,9);
4 - betahat = regress(y,x1);
5
6 - f = stats.fstat;
7 - fprintf('\n')
8 - fprintf('Regression ANOVA');
9 - fprintf('\n\n')
10
11 - fprintf('%s','Source');
12 - fprintf('%10s','df','SS','MS','F','P');
13 - fprintf('\n')
14
15 - fprintf('%s','Reg');
16 - fprintf('%10.4f',f.dfr,f.ssr,f.ssr/f.dfr,f.f,f.pval);
17 - fprintf('\n')
18
19 - fprintf('%s','Resid');
20 - fprintf('%10.4f',f.dfe,f.sse,f.sse/f.dfe);
21 - fprintf('\n')
22
23 - fprintf('%s','Total');
24 - fprintf('%10.4f',f.dfe+f.dfr,f.sse+f.ssr);
25 - fprintf('\n')

```

Figure 3

Figure 3: Algorithm used for MLR analysis in matlab

In matlab statistical toolbox regress and regstat are used for MLR analysis and the algorithm written for MLR model is as shown in Figure 3. In that algorithm, P indicates data matrix which contains 8 input parameter starts from 1<sup>st</sup> to 8<sup>th</sup> column and the last 9<sup>th</sup> column has the target data. The first three lines of algorithm for actual regression i.e. to obtain regression coefficients and it was given by betahat, remaining lines were used to construct annova table for error analysis.

Four MLR models were created for prediction of CBR with different input combinations as same as done in the case of ANN. Performance of the models were measured for both training and testing and the model.

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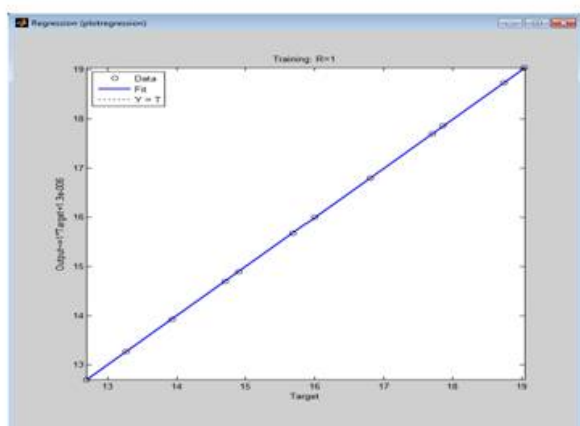
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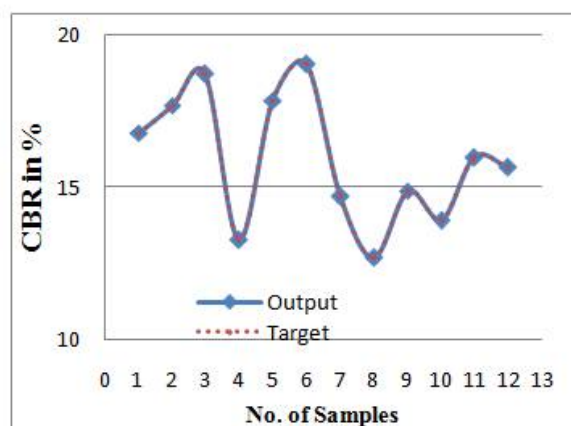
## VI. RESULTS AND DISCUSSIONS

### Training output of ANN models

All ANN models with network of type feed forward back-propagation network, with 2 hidden layers having 16 neurons were trained for best training performance to meet the goal. Hence trained network gives the predicted output values same as the target of training data and the regression plot for predicted output and targets of training is as shown figures below.



**Figure 4**



**Figure 5**

**Figure 4:**Regression plot of training output of ANN models, **Figure 5:**Line graph for training output of ANN models.

Regression plot and line graph between output and target shows that the ANN models were trained for a performance of zero error.

### Testing output and Error analysis of ANN models

The trained network was tested with new inputs, obtained outputs were compared with actual values and error analysis was made.

**Table 3: Testing Output of ANN Models**

No. of Samples & Errors	Actual CBR Value of Testing samples	Predicted CBR Value of Testing samples			
		NNM1	NNM2	NNM3	NNM4
1	13.54	14.74	13.15	14.36	12.72
2	16.5	16.64	16.99	15.53	17.11
3	18.05	17.57	18.07	16.89	18.83
Errors	MAE	-0.29077	-0.04467	1.3007	-0.5826
	MSE	0.564696	0.133163	0.984275	0.555698
	CC	0.999841	NAN	NAN	NAN
R <sup>2</sup> Value from scattered graph	R <sup>2</sup>	<b>0.9997</b>	<b>0.9818</b>	<b>0.951</b>	<b>0.9954</b>

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Testing results of NNM1 shows that all predicted values follows observed values and the correlation between observed and predicted is also good for predicting CBR of subgrade soil. MSE value of 0.56 and CC of 0.999 shows there is a positive correlation between input and output.  $R^2$  value obtained from the scattered graph plotted against actual and predicted CBR values, which is very nearer to 1 show that ANN model 1 is a better model for prediction of CBR.

### MLR Models

MLR equation formed by using the same data set used for training the ANN models and tested with the same testing data as well. The equations got after finding coefficients of regression were as shown below and errors of the models were tabulated in Table 2.

**MLR 1:**  $Y = -73.412 + 7.8239X_1 + 0.1579X_2 - 0.2356X_3 + 0.0483X_4 + 0X_5 + 0.9193X_6 + 0.7802X_7 + 0.6981X_8$

**MLR 1:**  $Y = 13.6076 + 15.7164X_1 + 0.2572X_2 - 0.2553X_3 + 0.1371X_4 + 0X_5$

**MLR 3:**  $Y = 163.8357 + 10.0418X_1 - 0.3455X_2 - 1.5302X_6 - 1.6714X_7 - 1.7005X_8$

**MLR 4:**  $Y = 84.4013 - 0.2709X_3 + 0.0001X_4 + 0X_5 - 0.3861X_6 - 0.5794X_7 - 0.7863X_8$

**Table 4: Errors of Testing and Training output of MLR models**

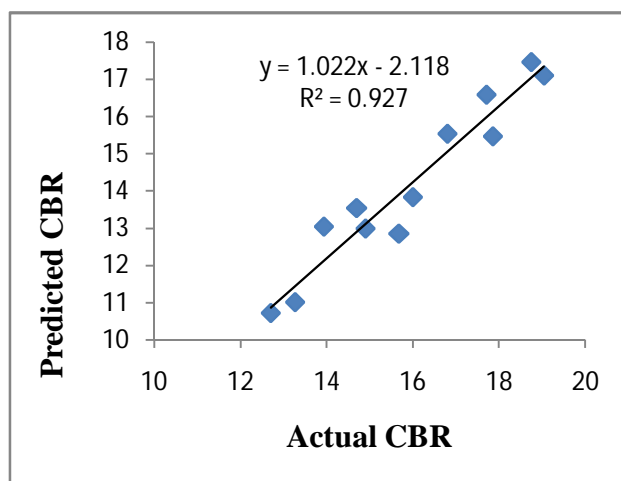
Models	For	MAE	MSE	CC	$R^2$
MLR 1	Training	1.761235	3.441324	0.9422	<b>0.9272</b>
	Testing	1.122372	2.943502	0.995989	<b>0.9788</b>
MLR 2	Training	-0.00096	0.410018	NAN	0.9003
	Testing	-0.65223	2.177341	0.995398	0.7891
MLR 3	Training	0.001601	0.343189	NAN	0.9165
	Testing	-0.26469	2.448936	0.993884	0.6583
MLR 4	Training	-0.01098	0.336767	NAN	0.9181
	Testing	-0.42231	2.963693	0.992837	0.5584

Table 4 shows errors of testing and training output of MLR models which clears that MLR 1 is more reliable model than any other MLR models.

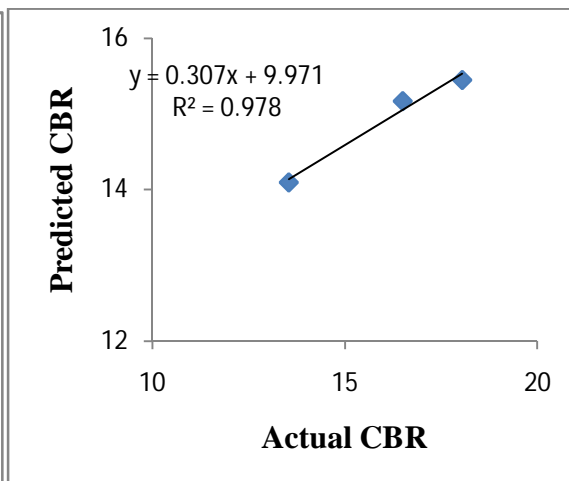
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**Figure 6**



**Figure 7**

**Figure 6:** Scattered graph for the training output of MLR1, **Figure 7:** Scattered graph for the testing output of MLR1.

From the scatter graph of testing MLR model 1 the value of  $R^2$  is nearer to 1 and lesser error values shows that model 1 is a better model for prediction of CBR than all other MLR models.

### Comparison

**Table 5: Comparison of testing output of ANN & MLR with actual CBR**

Models	Sample	1	2	3	$R^2$
	Actual	13.54	16.5	18.05	
Model 1	ANN	14.7425	16.646	17.5738	<b>0.9997</b>
	MLR	14.1003595	15.170287	15.452238	<b>0.9788</b>
Model 2	ANN	13.1511	16.9976	18.0753	<b>0.9818</b>
	MLR	15.76374	17.2472	17.03575	<b>0.7891</b>
Model 3	ANN	14.3638	15.5311	16.8944	<b>0.951</b>
	MLR	15.95023	16.03224	16.90161	<b>0.6583</b>
Model 4	ANN	12.7215	17.1122	18.8389	<b>0.9954</b>
	MLR	16.25964	16.24241	16.85488	<b>0.5584</b>

As observed from above table, result obtained from the models NNM3, MLR 2, MLR 3 and MLR4 were highly unpredictable and misleading in nature. By comparing results of ANN and MLR models, it shows that ANN models predicts more accurately than MLR models. Results of MLR models were not satisfactory and these models not good for prediction except MLR1 which shows better results than all other MLR models. Coefficient of determination  $R^2$  value of scattered plot 0.9997 which is very nearer to 1 show that NNM1 predicts CBR of subgrade soil more accurately than any other model. It indicates that all eight were needed for accurate prediction of CBR. From above results it was observed that CBR estimation highly depends on consistency and plasticity of fine-grained soil as well as textural classification of soils.



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## VII. CONCLUSIONS

The following conclusions can be drawn from this work:

- The Feed-forward back propagation type of neural networks with 2 hidden layers having 16 neurons in the 1<sup>st</sup> and one neuron in 2<sup>nd</sup> layer, trained by trainlm algorithm using tansig activation function could predict the CBR value of subgrade from its index properties with satisfactory performance.
- The ANN models are more suitable in modelling of complex problems and save a lot of computational effort compared to conventional methods significantly. The use of these networks will help in solving more complex problems.
- In both techniques, models having all eight input parameters show good performance than all other models, hence it proves that all eight parameters are essential for predicting CBR of subgrade soil from its index properties.
- ANN predicts more accurately when input range of training data set was well established. Hence it is very important to select input and target data used for training, so that input of testing data set was well within range of training data set.
- These types of ANN models which take less time and easier to perform as compared to the standard procedure of CBR testing, can be used to predict the CBR of a various type of subgrade soil using their index properties.

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