

Prediction of CBR Value of Coarse Grained Soils by Soft Computing Techniques

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ABSTRACT

California Bearing Ratio (CBR) value is an indicator of subgrade soil strength and is used often for design of flexible pavements. The conventional soaked CBR testing method is expensive and time consuming. To overcome this situation, it is appreciable to predict CBR value of subgrade soil with simple properties of soils such as index properties which include grain size analysis (% Gravel, % Sand, % Fines), Liquid Limit (LL), and Maximum Dry Density (MDD) and Optimum Moisture Content (OMC) from Modified Compaction test.

This paper presents the application soft computing techniques like Artificial Neural Network (ANN) tool of MATLAB and Multiple Regression Analysis (MLR) tool of STATISTICA to build models to help predict California Bearing Ratio value of Coarse grained soils from the basic properties of soil viz. optimum moisture content and maximum dry density, liquid limit and Coarse fraction. Out of total Fifty-four soil data sets, 38 were used for training and 16 were used for testing. It was observed that prediction of CBR from the properties of soil was better through ANN than MLR. The performance of the developed ANN model has been validated by actual laboratory tests and a good correlation of 0.9 was obtained.

Keywords: ANN, CBR, LL, MLR, Modified OMC, MDD, Coarse Fraction, Soils.

I. INTRODUCTION

Engineering projects that involve earthwork such as road embankments, airport runways and pavement constructions require construction of a proper foundation. The subgrade layer acts as a foundation for these structures. The subgrade should meet strength requirements. California Baring Ratio (CBR) is widely used as an index test to assess the strength characteristic of subgrade in such earth structures.

Characterizing subgrade material by using laboratory tests is involves many inherent problems. For instance, collection and testing of representative samples is a difficult process. Because of the large variability of typical subgrade materials, a large number of random samples are required to be collected and tested to generate results with good statistical significance.

A laboratory test generally takes four days to measure the soaked CBR value for each soil sample. The result of the tests is actually an indirect measure, which represents comparison of the strength of sub grade material to the strength of standard crushed rock referred in percentage values. Civil engineers generally encounter difficulties in obtaining representative CBR values for design of pavement. The CBR tests performed in lab are time consuming. Instead it can be predicted from the index properties of soil which are easily determined and measured in laboratories. Several studies have been conducted to estimate CBR from liquid limit, plasticity index, clay content and standard proctor compaction parameters. MLR and ANN are the most common methods adopted to develop relationships between parameters.

Multiple linear regressions (MLR) determine the relationship between two or more independent

variables and a dependent variable by fitting a linear equation to observed data. Every value of the independent variable is associated with a value of the dependent variable. The equations are expressed as:

$$(Y = ax_1 + bx_2 + cx_3 + \dots)$$

Where X_n is an independent variable, Y is a dependent variable and a, b, c, \dots are coefficients.

The ANN is one of the computing methods copied from the animal neuron network system which tries to identify the innate correlation among the data and provide a network between the input spaces (input layer/s) and the desired space (output layer/s) through the processor named neuron. This network is composed of at least three: input, hidden and output layers. The hidden layers receive the data from the input layer and deliver them to the output layer after training. Training is a process that ends in learning. The network learning occurs when the communicational weights among the layers change in a manner where the differences between predicted and computed values are at the acceptance level.

By obtaining these conditions, the learning process is materialized. These weights express the memory and the knowledge of the network. The trained neuron network can be applied in predicting the outcomes fit to the new data collection.

Fig. 1 shows the configuration of a feed forward three-layer ANN. In this figure, X is a system input vector composed of a number of causal variables that influence system behavior, and Y is the system output vector composed of a number of resulting variables that represent the system behavior.

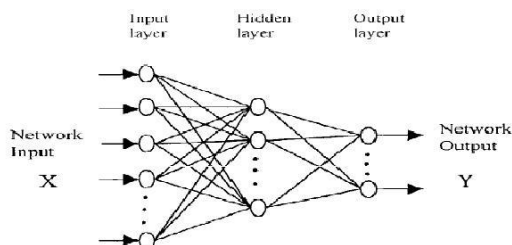


Figure 1. Structure of feed forward ANN

II. LITERATURE REVIEW

Most researchers found that ANN performs better than MLR. Many models were developed by several researchers to predict CBR based on index properties or on the standard proctor compaction parameters of the soils for local region.

Mehrjardi [1] evaluated soil properties using artificial neural network and multiple regression analysis for 125 soil samples from the Gorgan Province, North of Iran. Results showed that ANN with two neurons in hidden layer had better performance in predicting soil properties than multivariate regression.

Gunaydin [2] presented the application of different methods (simple–multiple analysis and artificial neural networks) for the estimation of the compaction parameters (maximum dry unit weight and optimum moisture content) for soils from Turkey. Results showed that correlation equations obtained as a result of regression analyses are in satisfactory agreement with the test results.

Zelalem [3] developed a correlation between CBR and index properties of granular soil and silty clayey soils. For granular soils the properties considered were Optimum Moisture Content, Maximum Dry Density, and 60% passing sieve size. CBR had best correlation with OMC and MDD with coefficient of determination 0.863. For Silty-clayey soils, the properties considered were LL, PL, PI, OMC, Percent passing 0.075mm sieve no, MDD. Correlation was not strong as granular soils.

Mehmet Saltan[4] successfully used Artificial Neural Network for Flexible Pavement Thickness Modeling. ANN approach was used for the elimination of this drawback of time consumption and indirect measurements by Benkelman Beam dynaflect, road rater and falling weight deflectometer (FWD). Results indicate that the ANN can be used for back calculation of the thickness of layers with great improvement and accuracy

Taskiran, et.al,[5] successfully used Artificial Neural Network (ANN) and Gene Expression Programming (GEP) for the prediction of CBR from the properties of fine grained soils like plasticity properties, compaction properties and gradation properties

collected from Anatolia Region/Turkey. The results showed that maximum dry unit weight is the most effective parameter influencing CBR.

Venkatasubramanian, et.al,[6] developed a method for predicting CBR values from liquid limit, plasticity index, OMC, Maximum dry density, and UCC of soil samples from south India using ANN and MLR and found that MLR performed better and the value could be further improved by modifying the parameters

Patel, et.al,[7] developed correlation for alluvial soils of various zones of Surat city of Gujarat state, India using SPSS software. The correlation is established in the form of an equation of CBR as a function of different soil properties.

Saklecha, et.al,[8] suggested a Correlation between Mechanical Properties of weathered Basaltic Terrain and strength Characterization of foundation using ANN. Laboratory test data sets were collected for different locations in Wardha district in the state of Maharashtra, India. It has been shown that ANN was able to learn the relations between strength characteristic CBR and mechanical properties of foundation soil

Harini H.N et.al,[9] successfully used Artificial Neural Network (ANN) and Multiple Linear Regression(MLR) for the prediction of CBR from the properties of fine grained soils like plasticity properties, compaction properties and gradation properties collected in and around Bangalore city. The results showed that ANN model gives better correlation than MLR and hence can be used.

In the present study, ANN and MLR models were developed to predict the CBR value of Coarse grained soils from its basic properties such as LL, Coarse fraction, Modified OMC, and MDD. It was observed that ANN models can be an alternate method for estimation of CBR. ANN models are more precise, economical and rapid than MLR.

III. MATERIALS AND METHOD OF ANALYSIS

Fifty four soil samples in and around Bangalore were collected. Experiments were conducted and the data obtained was first analyzed for the relationship between parameters. The potential of using MLR and ANNs for the estimation of CBR were investigated by

developing various models .The variables which appear to be potentially influential to CBR value were used for prediction models. Totally four basic soil parameters Liquid Limit (WL), Coarse Fraction, Optimum Moisture Content (OMC), and Maximum dry density(MDD), were taken into consideration as input parameters for the models. To obtain the best model that governs CBR, ten different models were established by proper combination of input data with CBR as output. The input scenarios of different models used in the study is given in Table 1. Out of total 54 soils sample data, 38 were used for training and 16 were used for testing. 60% of data was used for training, 10% for cross validation and 25% for testing in ANN analysis.

Table 1. Input and Output For The Different Model

Model	Input	Output
Model 1	W _L , CF, OMC, MDD,	
Model 2	W _L , MDD, CF,	
Model 3	W _L , OMC, MDD	
Model 4	W _L , OMC, CF	
Model 5	W _L , CF	CBR
Model 6	OMC, CF	
Model 7	W _L , OMC	
Model 8	W _L , MDD	
Model 9	OMC, MDD	
Model 10	MDD, CF	

MLR was carried out using STATISTICA software and ANN analysis was performed using MATLAB, which includes various training algorithms. Feed forward back propagation algorithm was made use of to obtain the models with 2 hidden layers. The statistics of the training and testing data set are given in Table 2.

Table 2. Statistics Of The Training And Testing Data Sets

	Statistical Parameters	W _L	CF	OMC %	MDD g/cc	CBR %
Training	Minimum	18	66	8	1.77	5.6
	Maximum	38	86	14	1.9	11.48
	Mean	25.94	75.92	10.10	1.83	7.105
	SD					

		5.46	5.48	1.37	0.033	1.469
Testing	Minimum	18	65	9.0	1.78	5.46
	Maximum	38	84	13	1.89	9.19
	Mean	25.18	76	10.68	1.83	6.64
	SD	5.833	5.046	1.195	0.037	0.938

IV. RESULTS AND DISCUSSION

Analysis by Multiple Linear Regressions (MLR):

The regression analysis was performed using STATISTICA software and yielded the relation equations as shown in Table 3

Table 3. Performance Indices For Coarse Grained Soil By MLR

Model No.	RMSE	CC		Equations generated
		Training	Testing	
1	0.272	0.68	0.70	$CBR = ((W_L * 0.0797) + (CF * 0.0902) + (OMC * 0.03103) + (MDD * 7.145) - 15.5367)$
2	1.077	0.6	0.68	$CBR = ((W_L * 0.0822) + (MDD * 7.1136) + (CF * 0.08586) - 14.8805)$
3	1.1	0.67	0.58	$CBR = ((W_L * 0.1025) - (OMC * 0.2372) + (MDD * 6.3021) - 4.8798)$
4	0.84	0.59	0.63	$CBR = ((W_L * 0.0687) + (OMC * 0.017) + (CF * 0.084) - 1.586)$

5	2.188	0.44	0.63	$CBR = ((W_L * 0.0702) + (OMC * 0.089) - 1.24631)$
6	0.619	0.13	0.51	$CBR = ((OMC * 0.2247) + (CF * 0.115) - 4.44137)$
7	0.619	0.52	0.51	$CBR = ((W_L * 0.0914) - (OMC * 0.2303) + 6.908)$
8	0.75	0.60	0.52	$CBR = ((W_L * 0.0835) + (MDD * 6.187) - 6.69021)$
9	0.972	0.4	0.12	$CBR = ((OMC * 0.048) + (MDD * 2.570) + 2.5584)$
10	0.94	0.4	0.48	$CBR = ((MDD * 3.7069) + (CF * 0.0873) - 6.6829)$

A comparative study of above results showed that model 1 with relatively high Correlation coefficient (CC) = 0.70 with least RMSE value works out to be the best performing model among other models.

This indicates CBR is well correlated with Liquid limit, Coarse fraction, Optimum moisture content and Maximum dry density. These are reasonable values and indicate good learning of model 1. The scatter plot for Coarse grained soils by MLR is obtained by considering the CBR values obtained by feeding the inputs of testing data to the obtained equations and the CBR values obtained from the laboratory for the same set of data as shown in Figure 2

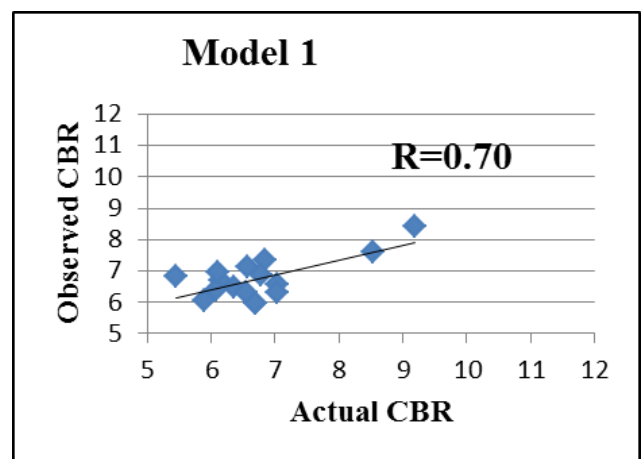


Figure 2. Scatter plot for Coarse grained soils of observed v/s predicted CBR for the best model by MLR

Analysis by Artificial Neural Network (ANN):

Analysis by ANN was carried out by feed forward back propagation technique using tansig transfer functions and two hidden layers. On the basis of performance in testing, the best ANN model was obtained. The test results are presented in Table 4.

Table 4. Performance Indices for Coarse Grained Soil Group by ANN

Model	RMSE	CC		No of neurons
		Training	Testing	
1	0.43	0.81	0.90	04
2	0.43	0.69	0.70	07
3	0.54	0.86	0.70	05
4	0.49	0.78	0.84	05
5	0.50	0.65	0.59	06
6	0.60	0.55	0.61	03
7	0.60	0.76	0.64	04
8	0.60	0.68	0.55	06
9	0.81	0.75	0.37	05
10	0.63	0.52	0.35	04

The results indicate that a strong correlation was obtained for model 1 with structure 4-2-1 with correlation coefficient (CC) of 0.9. This model was successfully trained in 14 epochs. The test reports showed a good coefficient of relationship (r) = 0.81 during training and 0.90 during testing. RMSE was found to be 0.43. This indicates CBR is well correlated with Liquid limit, coarse fraction, OMC and MDD from modified proctor test.

The scatter plot for Coarse grained soils by ANN is obtained by considering the CBR values obtained by feeding the inputs of testing data to the trained networks and the CBR values obtained from the laboratory for the same set of data as shown in Figure 3

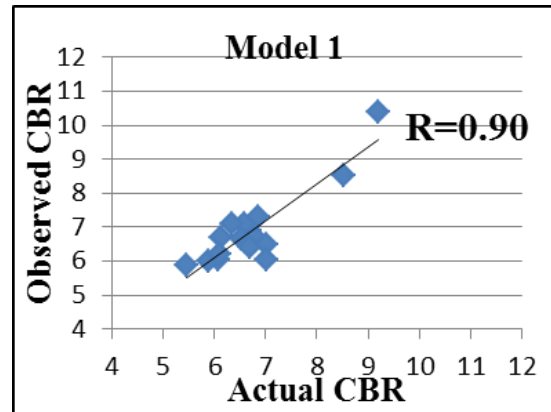


Figure 3. Scatter plot for coarse grained soil of observed v/s predicted CBR of Model 1

V. COMPARISON BETWEEN ANN AND MLR

The variation of RMSE and CC with different models for ANN and MLR Analysis are as shown in figure 4, 5 and 6 respectively. The Figure 4 shows that RMSE is more for most of the MLR models when compared with ANN models

It is evident from figures 5 and 6 that the correlation coefficient is more for ANN models during training and testing indicating the better learning and predicting ability of ANN models.

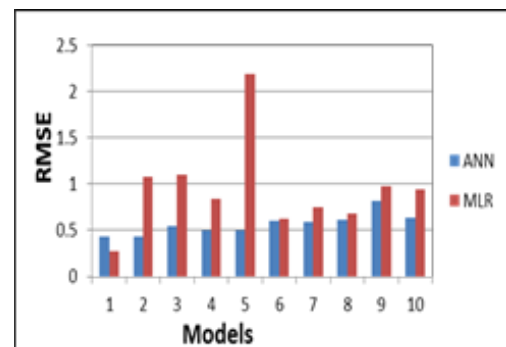


Figure 4. Different models v/s RMSE

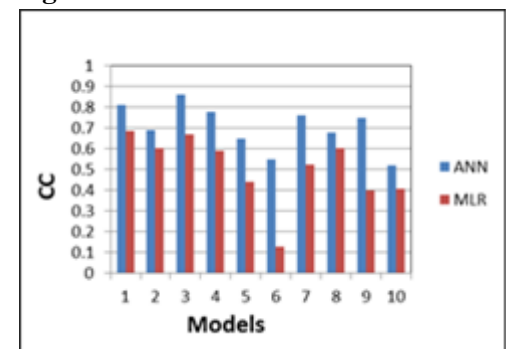


Figure 5. Different models v/s CC during Training

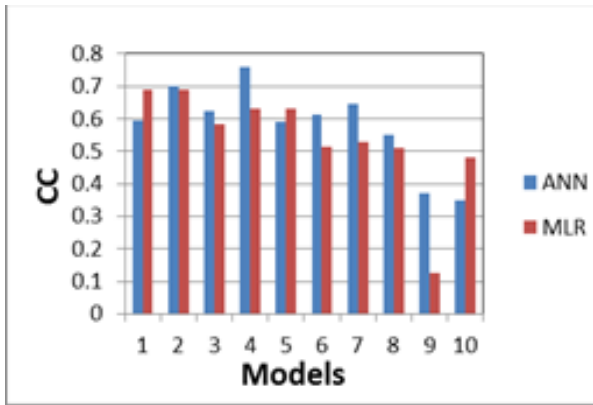


Figure 6. Different models v/s CC during Testing

VI. CONCLUSION

ANN and MLR analysis on Coarse grained soil was performed and following conclusions are drawn

1. Neural network models trained by feed forward back-propagation algorithm, with two hidden layers, perform reasonably well for correlating CBR with properties of soil.
2. Neural network models, which can easily incorporate additional model parameters, give less scattered predicted values than those given by MLR.
3. ANN analysis indicated that Liquid limit, Coarse fraction, OMC and MDD have been found to be the most sensitive parameters in correlating CBR with Correlation coefficient (CC) of 0.9
4. MLR method showed that Liquid limit, Coarse fraction, OMC and MDD strongly correlated with CBR value with Correlation coefficient (CC) value of 0.70
5. The CC values obtained by MLR are less than that obtained from ANN for most of the models. Hence it can be concluded that ANN model using Feed Forward Back Propagation Network algorithm with two hidden layers gives better correlation than MLR and hence can be used.

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