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Correlation of Mechanical Properties of weathered Basaltic Terrain for strength Characterization of foundation using ANN

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ABSTRACT

This paper presents the application of artificial neural network (ANN) to study the strength characterization of a foundation soils in a basaltic terrain. The prediction models were developed for foundation strength characteristic California Bearing Ratio (CBR) using correlations with mechanical properties of foundation soil viz. optimum moisture content (OMC), maximum dry density (MDD), liquid limit (LL), plastic limit (PL), and plasticity index (PI). For this study, 387 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. The results indicated a strong correlation (r = 0.87). The performance of the developed ANN model has been validated by actual laboratory tests and a good correlation r = 0.9971 was obtained.

General Terms

Optimum moisture content (OMC), Maximum dry density (MDD), Liquid limit (LL), Plastic limit (PL), Plasticity index (PI,) California bearing ratio (CBR), Artificial neural network (ANN).

Keywords

Prediction, Correlation, Foundation soil, Subgrade, Feed forward backpropagation neural network (FFBP).

1. INTRODUCTION

The study of strength characteristics of a foundation is very important for geotechnical and earth structures such as pavements, bridge abutments, earth dams, and the fills behind retaining walls. Subgrade acts as a foundation for these structures. The strength characteristic of a foundation soil for these structures is commonly represented by California Bearing Ratio (CBR). The strength characteristics of a foundation soil in a weathered zone vary rapidly as the extent of weathering changes from place to place. Many methods for obtaining the strength aspects of the heterogeneous litho units especially in the basaltic terrain are adopted through field investigations and laboratory tests. These methods are time consuming, cumbersome and costly. Hence, to overcome these problems and to minimize the lab tests for estimation of the strength aspect of the subgrade material, a computational method viz. Artificial Neural Network (ANN) was explored. In recent times, artificial neural networks (ANNs) have been applied to many geotechnical engineering tasks and have demonstrated some degree of success. For example, ANNs have been used in pile bearing capacity prediction [1-2], stress-strain modeling of sands [3], interpretation of site investigation [4], and in seismic liquefaction assessment [5]. There were attempts to develop prediction models, considering that the strength characteristic CBR of subgrade soils are affected by the soil index properties. Many researchers have conducted studies to show the effect of soil types and characteristics on CBR values. Black [6] developed a correlation between CBR and PI for cohesive soils. deGraft-Johnson and Bhatia [7] suggested a correlation for CBR using the concept of suitability index, which varies with plasticity and grading characteristics. Agarwal and Ghanekar [8] tried to develop a correlation equation between CBR and either LL, PL or PI. National Cooperative Highway Research Program of United States of America NCHRP [9] suggested some correlations that described the relationship between soil index properties and CBR. Kin [10] calculated the CBR values by correlating the soil index properties and measured CBR values. T. Taskiran [11] successfully used ANN for the prediction of CBR of fine grained soils. . Yildirim and Gunaydin [12] studied the estimation of the compaction parameters with soil index properties by using statistical analysis and ANN.

In the course of this study, ANN models were applied to predict the CBR value of foundation soils from a set of foundation soil properties viz. OMC, MDD, LL, PL and PI. It was observed that ANN models can be an alternate method for strength characterization of a foundation soil. ANN models are more precise, economical and rapid than other methods.

2. STATISTICAL PARAMETERS OF DATA USED

The statistics of the collected data sets of foundation soils are given in Table 1.

3. DEVELOPMENT OF ANN MODELS

The type of ANN adopted was multilayer Feedforward backpropagation neural network (FFBP) with supervised learning. A typical model of FFBP neural network is shown in Fig. 1. To get the successful network, five models of FFBP neural network with diverse topologies were developed. These models are presented in table 2. In order to get the most appropriate network topology of each model, the models were trained and cross validated until the convergence was achieved in the mean sum of squares of the network errors

(MSE). The most appropriate network topology of each model (table 3) was obtained on the basis of relative performance during training and cross validation. The most appropriate network topology of each model was assumed to represent their corresponding model. Subsequently each model was tested for their predictability of strength characteristic CBR; the evaluation criteria was linear correlation coefficient (r), MSE, NMSE, MAE, Min Abs Error and Max Abs Error. On the basis of performance in testing, the best ANN model was obtained. The test results are presented in (table 4).

3.1 Best Performing Network Model

A comparative study of above results showed that model 1 with relatively less complex structure 5-6-1, produced best performance amongst all the tried models. This model was successfully trained in 370 epochs. For this best performing model, the final MSE after training was found to be 0.001615. The test reports showed a good coefficient of relationship (r) = 0.88. The average MSE was 18.6816216, normalized mean squared error (NMSE) was 0.241242072, and mean absolute error (MAE) was 1.946510441. These are reasonable values and indicate good learning of model 1.

3.2 Performance of predicted CBR vs. desired CBR

The correlation coefficient between predicted CBR and desired CBR was found to be 0.88, which showed a good learning of the ANN model 1. Fig.2 shows the correlation between desired CBR (exemplar) and CBR predicted by model 1 (output). It was observed that CBR values predicted by the model 1 satisfactorily follow the desired CBR values.

4. VALIDATION OF NETWORK OUTPUTS BY LABORATORY TESTS

Soil samples (27 no.) were collected from different locations and were tested in the laboratory for CBR values. Subsequently, the values of inputs viz. OMC, MDD, LL, PL, and PI obtained during the laboratory tests were fed into the trained network (best performing model 1) to get the predicted values of the CBR. A linear correlation graph was plotted between predicted CBR and Laboratory CBR (fig. 3) and a good coefficient of correlation r = 0.9971 was obtained. Hence, the performance of model 1 was considered to be validated.

5. SUMMARY AND CONCLUSION

The objective of this study was to investigate the applicability of ANN for correlation of mechanical properties of weathered basaltic terrain for strength characterization of foundation soil. CBR was used as an index property to evaluate the strength characteristic of foundation soil. The correlation coefficient between predicted CBR and desired CBR was found to be 0.88, which showed a good learning of the ANN model. It could be concluded that the ANNs were found to be able to learn the relation between the CBR and mechanical properties of foundation soil and could be used for the prediction of CBR values. In the present study, five models of multilayer feedforward backpropagation neural networks were analyzed. The models were trained, cross validated and tested with varying network topologies and having various structures ranging from a simple 5-2-1 to a complex structure 5-8-8-8-1. It was found that a comparatively less complex structure 5-6-1 of model 1 with transfer functions TanhAxon for hidden layer and TanhAxon for output layer and with learning rule LevenbergMarquardt converged successfully. The comparison of CBR values obtained in laboratory tests with the predicted CBR by ANN model validated the results of ANN model 1 (r= 0.9971). Therefore ANN model 1 can be treated as an optimized model for prediction of strength parameter CBR values of foundation soils. Consequently, it can be concluded that the ANNs are found to be able to learn the relation between the strength parameter CBR and mechanical properties of foundation soil. Considering the strength characterization of foundation soil to be fairly difficult, time consuming and expensive, it can be emphasized that the ANN modeling for correlation of mechanical properties with strength parameter CBR could be a helpful tool to be used as a base of judgment for the validity of characterization of a foundation on a weathered basaltic terrain.

Table 1: Statistical parameters of data used

Statistical Parameters	OMC %	MDD gm/cc	LL%	PL %	PI %	CBR %
Lab. Data sets	387	387	387	387	387	387
Min value	8.40	1.46	20.30	15.60	3.60	1.80
Maximum value	25.50	2.31	79.70	45.48	52.60	52.60
Range	17.10	0.85	59.40	28.88	49.00	50.80
Mean value	15.52	1.82	35.57	25.08	10.49	7.81
Median	15.26	1.79	33.64	25.30	7.88	3.70
Mode	18.16	1.72	35.10	26.92	6.92	3.15
Std deviation	3.01	0.15	8.77	5.73	6.50	8.28

Table 2: ANN Models used in the study.

Topology	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Algorithm	FFBP	FFBP	FFBP	FFBP	FFBP
Input parameters	LL, PL, PI, OMC, MDD	LL, PL, PI, OMC, MDD	LL, PL, PI, OMC, MDD	LL, PL, PI, OMC, MDD	LL, PL, PI, OMC, MDD
Output parameters	CBR	CBR	CBR	CBR	CBR
Training data sets	232	232	232	232	232
No. of hidden layers	1	1	2	3	3
Neurons in hidden layer 1	2 to 8	2 to 8	2 to 8	2 to 8	2 to 8
Neurons in hidden layer 2	nil	nil	4	4	4
Neurons in hidden layer 3	nil	nil	nil	4	4
Transfer function layer1	TanhAxon	Sigmoidal Axon	sigmoidal Axon	TanhAxon	SigmoidAxon
Learning rule layer1	Levenberg Marquardt	Levenberg Marquardt	Levenberg Marquardt	Levenberg Marquardt	Levenberg Marquardt
Transfer function layer2	nil	nil	Sigmoidal Axon	TanhAxon	SigmoidAxon
Learning rule layer2	nil	nil	Levenberg Marquardt	Levenberg Marquardt	Levenberg Marquardt
Transfer function layer3	nil	nil	nil	TanhAxon	SigmoidAxon
Learning rule layer3	nil	nil	nil	Levenberg Marquardt	Levenberg Marquardt
Transfer function output layer	TanhAxon	Linear Axon	LinearAxon	TanhAxon	LinearAxon
Learning rule output layer	Levenberg Marquardt	Levenberg Marquardt	Levenberg Marquardt	Levenberg Marquardt	Levenberg Marquardt

Max epoch	1000	1000	1000	1000	1000
Training runs	3	5	1	1	1
Training data	60%	60%	60%	60%	60%
Cross validation data	15%	15%	15%	15%	15%
Testing data	25%	25%	25%	25%	25%

Table 3. Most appropriate network topology of each model.

Training report	Model 1	Model 2	Model 3	Model 4	Model 5
Neurons in hidden layer 1	6	10	8	4	4
Neurons in hidden layer 2	nil	nil	4	4	4
Neurons in hidden layer 3	nil	nil	nil	4	4
Run #	1	1	1	1	1
Epoch #	370	777	638	510	511
Minimum MSE during training	0.001615	0.00494	0.0017	0.00204	0.00166
Final MSE during training	0.001615	0.00494	0.0017	0.00204	0.00166
Minimum MSE during cross validation	0.007062	0.007834	0.00705	0.03736	0.00522
Final MSE during cross validation	0.007849	0.0365898	0.18134	0.0797	0.15139
Structure of best performing network	5-6-1	5-10-1	5-8-4-1	5-4-4-4-1	5-4-4-4-1

Table 4. Test results.

Performance	**model 1**	**model 2**	**model 3**	**model 4**	**model 5**
Linear correlation coefficient (r)	0.879121	0.3234433	0.876520204	0.74698	0.826128646
MSE	18.68162	130.64759	15.06588948	18.7687	10.68631011
NMSE	0.241242	3.1988888	0.251210685	0.44937	0.146847954
MAE	1.94651	3.6287159	1.782308215	2.62334	1.818042312
Min Abs Error	0.005182	0.0127181	0.015149669	0.00212	0.052627998
Max Abs Error	31.13906	98.68019	27.3721845	17.7934	18.1911437
Structure of best performing network	5-6-1	5-10-1	5-8-4-1	5-4-4-4-1	5-4-4-4-1

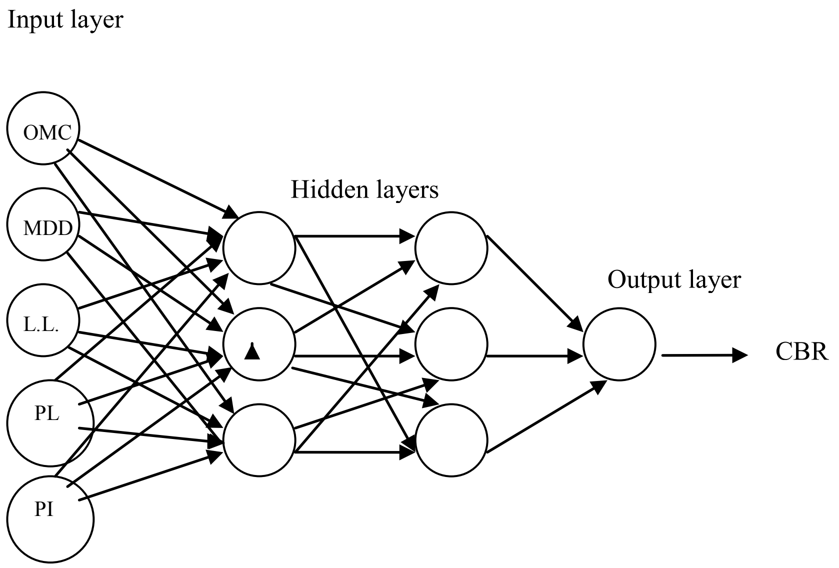

Fig. 1. A typical model of FFBP neural network used in this study.

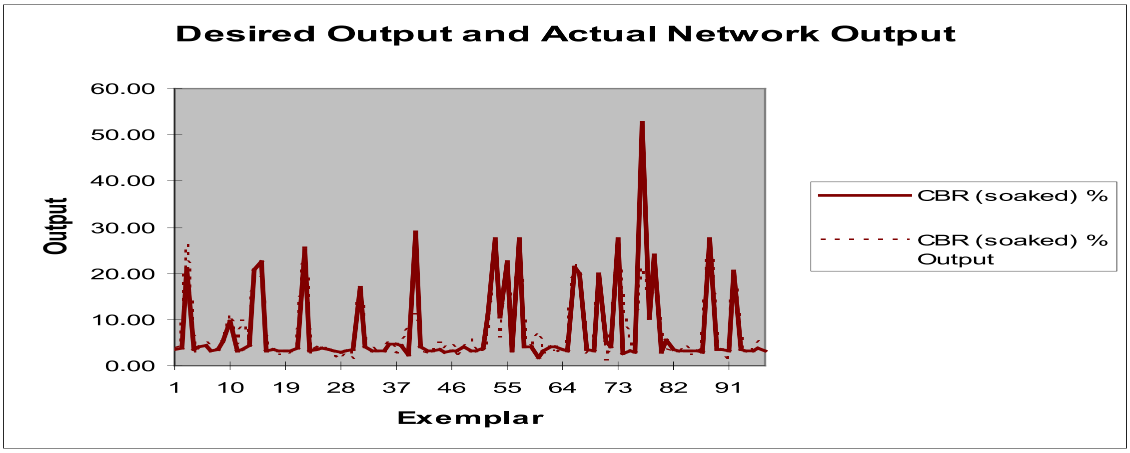

Fig.2 Predicted CBR vs. Desired CBR

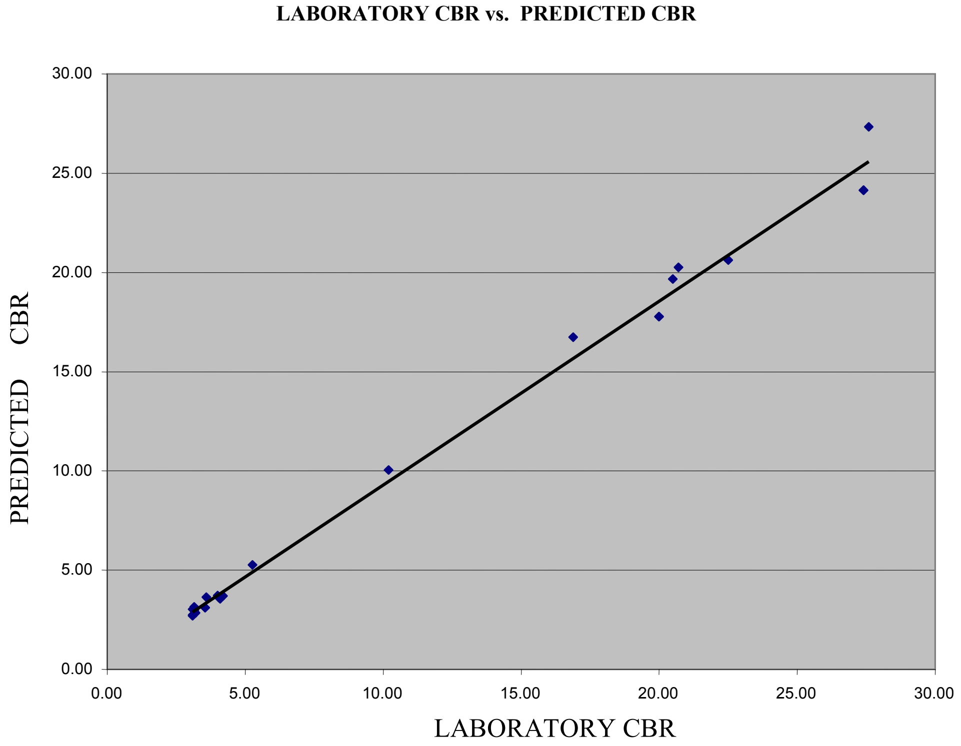

Fig 3. Linear correlation graph between predicted CBR and Laboratory CBR

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