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Study of ANN Program for Prediction of California Bearing Ratio of Fine-Grained Soils

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Abstract: ***Expansive soils, popularly known as black cotton soils in India, undergo swelling by absorbing water and shrinking by loss of moisture. Expansive soils are a boon to former but problematic to civil Engineers as they are prone to high volume changes even due to natural processes of climatic and environmental changes. The shear strength of an expansive soil is very high in dry state and it reduces considerably upon wetting. So statistical models (i.e., Regression Analysis, ANN, Fuzzy Logic and Genetic Algorithm) are developed to assess or estimate the engineering properties from basic soil properties. In this paper study both Regression Analysis and Artificial Neural Networks are used for estimating CBR of fine-grained soils can be determined by carrying out laboratory CBR test on undisturbed samples; however, the test is quite time-consuming and laborious. Therefore, many empirical formulas based on regression analysis have been presented for estimating the CBR by using soil Index properties. In the present study a statistical regression model is developed for estimating CBR of soils. Artificial Neural Network (ANN) model is suggested for prediction of CBR, considering basic soil properties like W_L, P_L and MDD, OMC of the soils as the input parameters. An NN Code is developed for prediction of output parameter by using Back-Propagation Algorithm. Also a model is developed for predicting Compression Index of soils neural fitting tool which is part of MATLAB Software. For development of this model, Levenberg-Marquardt (LM) Back-propagation Algorithm (trainlm) is considered. Comparative studies were done between the observed and predicted values obtained using MR Model, developed Program, and Neural Fitting tool (NF tool), using same input parameters and to predict same output parameter. The predicted values of CBR obtained from the developed code model is found closer to actual/observed values of CBR when compared to that of from Neural Fitting tool (NF tool). So the developed NN Program is successfully executed for the prediction of CBR of fine-grained soils.***

Keywords: Expansive Soils, CBR, ANN, ANF, MATLAB Software

1. Introduction

Safe and Economic design of Civil Engineering structures is the prime concern of a civil engineer. The domain of Civil Engineering involves extensive use of Timber, Soil, Rock, Plain and Reinforced concrete as construction materials. Use of new materials such as Geosynthetics, Reinforced Earth, Blends of soil, Cement, Lime and Industrial waste materials such as Fly Ash, Rice husk ash and Iron slag etc. Response of these materials to different types of loading (axial compression, tension, bending, torsion and shear) and unloading as well as the engineering properties like as Strength, Toughness, Hardness, Resistance to Scour, Resistance to Wear and Tear are of primary concern to the Civil Engineer in order to evolve a safe and economical design of a structure. Engineering behavior of these materials is generally expressed by the properties and/or parameters like Compressive Strength, Tensile Strength, Shear Strength, Permeability, Compressibility, Deformation Modulus, Shear modulus, Poisson's ratio etc. These properties and/or parameters are extensively used in the analysis and design of Civil Engineering structures. Most often the required properties are obtained by conducting laboratory tests on selective sample specimens. Further, analysis and design also involves several simplifying assumptions and idealization of materials in order to reduce the complexity of mathematical computations. In all types of problems, the engineer is often dealing with incomplete information or uncertain conditions. Hitherto empirical safety factors based on experience are widely being used to handle uncertainties giving raise to subjectivity in the analysis, design and decision making. It is necessary for the engineer to be aware of many assumptions and idealizations. There is a felt need to quantify the uncertainties and to develop a more rational analysis and design methods. Soil properties are mainly divided into two categories they are i) Index Properties ii) Engineering Properties. In this above engineering properties Compressibility is the one of the most important property of the soil to predict the settlement of soils.

Pavement is a hard crust constructed over the natural soil for the purpose of providing a stable and even surface for the vehicles. The pavement supports and distributes the wheel loads and provides an adequate wearing surface.
Pavements are basically three types:
1) Flexible pavements
2) Rigid pavements and
3) Semi-flexible pavements.

2. Literature Review

Datta and Chottopadhyay (2011) proposed correlation between CBR and index properties of soil. Value of CBR is often required for geotechnical solutions of engineering road structures. But due to high cost and time requirement for such testing it generally becomes difficult to map the variation in their value along the alignment. Correlations of CBR from different index properties have been made by different researchers. However the validity and applicability of such correlation need to be established for their acceptances in general practice. The predicted and tested values of CBR of various soils have been used to check the applicability and limitations of available methods and are presented in this paper.

Ramasubbarao and Siva Sankar (2013) have critically reviewed some of correlations and models developed by predecessors and have proposed a simple correlation equation for predicting of soaked CBR of compacted soils. The equation is as follows:

$$CBRs = 0.064F+0.082S+0.033G-0.069LL+0.157PL-1.81MDD-0.061OMC \ldots (1)$$

Where, F=% fines, S= Sand, G= Gravel, LL= Liquid limit, PL=Plastic limit, MDD= Maximum dry density, OMC= Optimum moisture content.

Shirur and Hiremath (2014) established relationship between CBR value and physical properties of soil. Sub-grade strength is mostly affected by thickness of pavement, in highway design. CBR is the one of the method to determine the sub grade strength.CBR test is laborious and time consuming, hence a method is proposed for correlating CBR value with the liquid limit, plastic limit, shrinkage limit, plasticity index, optimum moisture content and maximum dry density. Various laboratory tests including Atterberg limit, specific gravity, gradation analysis, CBR and compaction were performed on the samples. Linear relation exists between plasticity index and CBR value with a coefficient of correlation of R2=0.72. The empirical relation is:

CBR= -4.8353–1.56856(wopt) +4.6351* (Max .dry density) with R2= 0.82

3. Materials and Methodology

3.1 Test procedures

1) Index properties (IS:2720 Part-5-1985)
2) Grain size distribution (I.S: 2720 Part-IV-1965)
3) Sieve analysis (IS: 2720 Part-IV-1985)
4) Compaction Characteristics (IS: 2720 Part-VII-1980)
5) CBR test (IS: 2720 Part -16-1979)

3.2 Methodology Used In Present Study

In the present work to determine California bearing ratio (CBR) of soil Fine Fraction are taken as independent parameters. In this study actual CBR of soil was not considered. So by using Regression Analysis we developed an equation for prediction of CBR. For this, CBR is considered as dependent variable in terms of MDD, OMC, Plasticity Index and Fine Fraction as independent parameters an equation was developed for prediction of CBR of soils. Regression analysis was done for selecting the most influencing parameters. Eliminating each of the independent variables, it was found from the analysis that Liquid Limit is most influencing parameter for PI. So

After predicting FSI by using Regression Models, the next is to predict the Compression Index of soils by using developed ANN code and In-built neural fitting App (nftool). An equation was developed for predicting Compression Index of soils by using Multiple Linear Regression Analysis.
From the 60 soil samples 46 is used for Training, Validation and Testing for both code and In-built ANN Tool. The remaining 14 soil samples are used to checking purpose for developed equation.

4. Development of Regression Models For Prediction of CBR

4.1 Steps Involved In Development of Regression Model

1) First step in the model development is the determination of influencing input variables.
2) In second step all the dependent and independent variables data should enter in the Excel sheet.
3) In third step we go to Data Analysis and select the Regression, a new window will appear on the desktop as below.
4) In the Y-axis we have to select the dependent variable i.e. CBR.
5) In the X-axis we have to select the independent variables i.e. MDD, OMC, Fine Fraction (FF) and Plasticity Index (Ip). After selecting the data we have to run the Regression.

Equation:
CBR=0.134*%FF-0.108*PI-2.949*MDD-7.197*OMC+111.24
(R^2=0.92)

5. Development of ANN Program for Prediction of California Bearing Ratio of Soils

5.1 Procedure For Training And Testing Supervised Neural Networks:

Step1:- Randomly sampling the data in three sessions to form three independent data sets: training set, validation set, and test set (i.e., independent – sample testing).

Step2:- Import total soil data, inputs and output (CBR) to define our fitting problem. For fitting problem only Predicted CBR and % fines are taken as inputs and CBR is taken as output.

Step3:- In nftool soil data is divided randomly as mentioned in the 4.2 section. Here we have a option to change the training, validation and testing ratios. From various journals it was noted that 60 to 75% of total soil data is used for training purpose, remaining data is used for validation and checking purpose. In this present study 70% of data is used for training, remaining 30% of soil data was equally divided (15% and 15%) for validation and testing purpose.

Step4:- Select the number of neurons in the fitting networks in hidden layer's. Generally to select number of neurons this formula is used. Number of neurons = 60 to 90% (no. of inputs + no. of outputs)

Step 5:- Train the network to fit the inputs and outputs (targets).

Step 6:- Check the MSE and R^2 for Training, Validation and Testing data sets. For engineering problems range of R^2 should be $\mathbf{0.75 \leq R^2 < 1}$

Table 1: Soil data for ANN Programme

Sl.No	FF	PI	MDD	OMC	CBR
1	72.85	8.22	1.65	14.56	5.56
2	68.71	7.97	1.7	15.11	5.62
3	68.71	7.52	1.71	15.2	5.77
4	69.22	7.69	1.69	15.35	5.69
5	58.77	6.95	1.72	15.62	5.81
6	62.38	6.12	1.77	14.39	6.12
7	63.55	6.56	1.76	14.92	6.1
8	70.21	8.46	1.64	15.82	5.72
9	68.71	6.52	1.75	14.42	6.2
10	71.21	6.52	1.74	14.16	6.05
11	74.06	7.15	1.73	15.62	5.95
12	79.23	8.11	1.62	15.76	5.67
13	71.11	7.35	1.68	15.52	5.92
14	69.27	7.25	1.68	15.62	5.88
15	83.21	8.12	1.71	15.4	5.98
16	69.41	7.02	1.74	14.65	6.02
17	26.4	19.9	1.95	11.3	3.5
18	32.1	21.8	1.86	12.3	9.1
19	30.3	19.4	1.89	13.7	5.4
20	32.8	30.2	1.84	13.9	3.2
21	41.1	32.4	1.82	13.8	3.8
22	36.9	27.4	1.75	16	3.5
23	16.9	10.9	1.94	10	12.5
24	26	25.1	1.92	12	16.1
25	38.4	21.9	1.82	14.8	12.1
26	29.4	10.1	1.83	13.7	5.6
27	18.9	9.5	1.92	11.3	16.7
28	18.4	8.7	1.92	11.5	16.3
29	19.1	9.9	1.96	11	16.9
30	29.3	20	1.89	12	18.3
31	39.9	20.2	1.76	16	3.7
32	35.2	28.7	1.7	15.5	5
33	25.7	36	1.89	13	16.4
34	42.5	28.2	1.68	16.4	5.5
35	23	25.9	1.87	12.8	8.9
36	20.4	16.2	1.79	12.8	30.5
37	15	7	2.21	5.5	59
38	16	7	2.15	5	59
39	10	3	2.24	4.5	79
40	11	2	2.23	4.5	78
41	9	3	2.23	4.9	79
42	8	3	2.24	4.6	78
43	9	3	2.23	5	77
44	10	4	2.22	4.9	79
45	10	2	2.22	4.6	81
46	9	4	2.12	4.6	81
47	31	1	2.1	8.5	20
48	14	4	2.24	5.8	63
49	54	8	1.71	15	5
50	9	1	2.12	5.5	54
51	14	4	2.24	5.8	63
52	49	11	1.98	11.5	11
53	42	3	1.73	15	13
54	49	11	1.74	13	10
55	49	11	1.75	13	24
56	15	11	2.25	8	47
57	11	11	2.22	7	46
58	21	13	1.93	12	13
59	11	4	2.17	7	59
60	7	2	2.13	9	32

Step 7:- If R^2 value should not meet the above range retrain the network.

Step8:- Adjust the network size if retraining didn't help.

Step9:- If adjustment of network also doesn't meet the target, then we may use a larger data set to train and meet the Targets.

Step10:- After completion of above process save the results.

In present study developing ANN model Inputs and Outputs are not normalized. This is the beauty in the nftool that we can use both normalized and un-normalized values.

6. Results and Discussions

1) In the present study total 60 soils tested data was collected for modeling in nftool, development for code, and developing equation in both MLRA & ANN model shows in table 1.
2) The network model is developed taking Fine Fraction, Plasticity Index and predicted CBR as inputs, and CBR as output.
3) The network is selected with 2 neurons.
4) The model proposed is 2-2-1 network and the soil data is trained, tested and equation developed for this model.
5) The results are given in table.
6) The comparison of the observed values from laboratory with the predicted values using this ANN model and developed code are given in tables 2 along with observed/predicted in fig 1.
7) Since graphical representation gives a clear idea, the same is shown in fig 2.

Table 2: Comparison of Normalized Observed and Normalized Predicted Values of CBR for Trained Validation and Testing results generated by In-Built App

%NFF	NPI	NMDD	NOMC	NCBR	NPCBR	RATIO (ob/pre)
0.800	0.283	0.687	0.810	0.155	0.169	0.916
0.761	0.277	0.704	0.837	0.156	0.169	0.918
0.761	0.267	0.708	0.841	0.157	0.169	0.927
0.765	0.271	0.701	0.849	0.156	0.169	0.923
0.665	0.254	0.712	0.862	0.157	0.171	0.921
0.700	0.236	0.729	0.802	0.160	0.171	0.941
0.711	0.246	0.726	0.828	0.160	0.170	0.942
0.775	0.288	0.683	0.872	0.156	0.169	0.925
0.761	0.245	0.722	0.803	0.161	0.170	0.951
0.785	0.245	0.719	0.791	0.160	0.169	0.943
0.812	0.259	0.715	0.862	0.159	0.169	0.940
0.862	0.280	0.676	0.869	0.156	0.168	0.926
0.784	0.263	0.697	0.857	0.158	0.169	0.937
0.766	0.261	0.697	0.862	0.158	0.169	0.934
0.900	0.280	0.708	0.851	0.159	0.168	0.944
0.767	0.256	0.719	0.815	0.159	0.169	0.941
0.354	0.542	0.793	0.651	0.135	0.192	0.699
0.409	0.584	0.761	0.700	0.190	0.180	1.057
0.391	0.531	0.772	0.768	0.153	0.181	0.845
0.415	0.771	0.754	0.778	0.132	0.173	0.762
0.495	0.820	0.747	0.773	0.138	0.169	0.812
0.455	0.709	0.722	0.880	0.135	0.171	0.786
0.262	0.342	0.790	0.588	0.223	0.374	0.597
0.350	0.658	0.783	0.685	0.259	0.183	1.414
0.469	0.587	0.747	0.822	0.220	0.173	1.268
0.383	0.324	0.751	0.768	0.155	0.202	0.769

0.282	0.311	0.783	0.651	0.265	0.322	0.822
0.277	0.293	0.783	0.661	0.261	0.340	0.768
0.284	0.320	0.797	0.637	0.267	0.314	0.851
0.382	0.544	0.772	0.685	0.281	0.186	1.512
0.484	0.549	0.726	0.880	0.137	0.173	0.791
0.438	0.738	0.704	0.856	0.149	0.170	0.877
0.347	0.900	0.772	0.734	0.262	0.174	1.509
0.509	0.727	0.697	0.900	0.154	0.159	0.970
0.321	0.676	0.765	0.724	0.188	0.184	1.020
0.296	0.460	0.736	0.724	0.401	0.226	1.775
0.244	0.256	0.886	0.368	0.683	0.680	1.004
0.254	0.256	0.864	0.344	0.683	0.690	0.989
0.196	0.167	0.896	0.320	0.880	0.865	1.018
0.206	0.144	0.893	0.320	0.870	0.865	1.007
0.187	0.167	0.893	0.339	0.880	0.868	1.014
0.177	0.167	0.896	0.324	0.870	0.876	0.994
0.187	0.167	0.893	0.344	0.860	0.867	0.993
0.196	0.189	0.889	0.339	0.880	0.853	1.031
0.196	0.144	0.889	0.324	0.900	0.871	1.033
0.187	0.189	0.854	0.324	0.900	0.872	1.033
0.398	0.122	0.847	0.515	0.298	0.293	1.017
0.235	0.189	0.896	0.383	0.722	0.782	0.923
0.619	0.278	0.708	0.832	0.149	0.180	0.830
0.187	0.122	0.854	0.368	0.633	0.862	0.735
0.235	0.189	0.896	0.383	0.722	0.782	0.923
0.571	0.344	0.804	0.661	0.209	0.184	1.137
0.504	0.167	0.715	0.832	0.228	0.184	1.243
0.571	0.344	0.719	0.734	0.199	0.181	1.098
0.571	0.344	0.722	0.734	0.337	0.181	1.862
0.244	0.344	0.900	0.490	0.564	0.341	1.653
0.206	0.344	0.889	0.441	0.554	0.462	1.201
0.302	0.389	0.786	0.685	0.228	0.194	1.176
0.206	0.189	0.872	0.441	0.683	0.718	0.951
0.167	0.144	0.857	0.539	0.416	0.671	0.620
0.513	0.167	0.765	0.685	0.288	0.192	1.497

NFF= Normalized fines, NPI= Normalized Plastic Index, NMDD= Normalized Max. Dry Density, NOMC= Normal Optimum Moisture Content, NCBR= Normal CBR, NPCBR= Normalized Predicted CBR, ob= observed, pre= predicted.

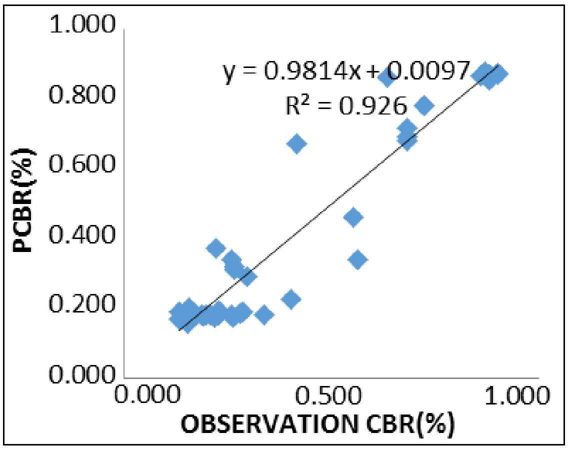

Figure 1: Predicted CBR VS Observed

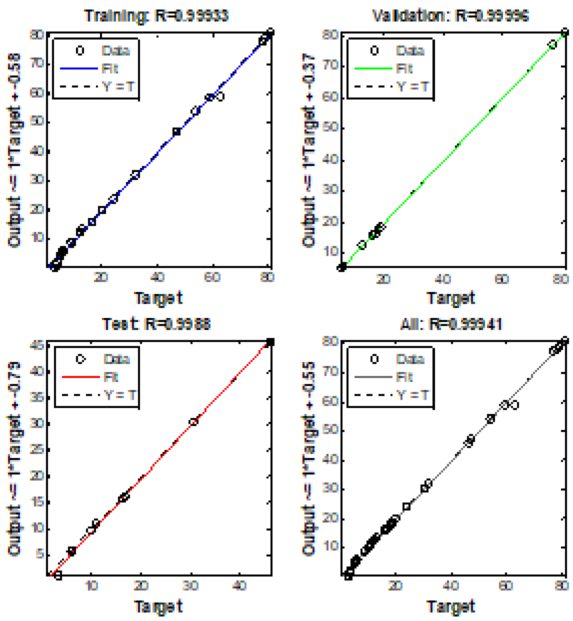

Figure 2: Training, validation and testing graphs generated from nftool

7. Conclusions

The following conclusion remarks are drawn from the present work

1) A Multiple Regression Equation is proposed for predicting CBR using PI, MDD,OMC, FF of soils.
2) Another Multiple Regression Equation is proposed for predicting CBR of fine-grained soils using Fine Fraction and MDD of Soils.
3) Due to inherent advantages like reliability, ability to learn and generalizing, Artificial Neural Networks.
4) Artificial Neural Network (ANN) Program (ANN Code Model) is developed for predicting CBR of Fine – Grained soils.
5) ANN Code Model is developed considering Fine Fraction and OMC, MDD, PI as input parameters and CBR as output parameter, Neural fitting tool (nftool), an ANN tool in MATLAB software is also used to develop a network model for predicting CBR using Fine Fraction of soils for cross checking the predicted values of CBR from both models.

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