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Artificial Neural Networks (ANNS) For Prediction of California Bearing Ratio of Soils

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ABSTRACT: *The behaviour of soil at the location of the project and interactions of the earth materials during and after construction has a major influence on the success, economy and safety of the work. Another complexity associated with some geotechnical engineering materials, such as sand and gravel, is the difficulty in obtaining undisturbed samples and time consuming involving skilled technician. Knowledge of California Bearing Ratio (C.B.R) is essential in finding the road thickness. To cope up with the difficulties involved, an attempt has been made to model C.B.R in terms of Fine Fraction, Liquid Limit, Plasticity Index, Maximum Dry density, and Optimum Moisture content. A multi-layer perceptron network with feed forward back propagation is used to model varying the number of hidden layers. For this purposes 50 soils test data was collected from the laboratory test results. Among the test data 30 soils data is used for training and remaining 20 soils for testing using 60-40 distribution. The architectures developed are 5-4-1, 5-5-1, and 5-6-1. Model with 5-6-1 architecture is found to be quite satisfactory in predicting C.B.R of soils. A graph is plotted between the predicted values and observed values of outputs for training and testing process, from the graph it is found that all the points are close to equality line, indicating predicted values are close to observed values.*

Keywords: *Artificial Neural Networks, California Bearing Ratio, Fine fraction, Liquid limit, Optimum Moisture content, Maximum Dry density and plasticity index.*

I. INTRODUCTION

The tests required for determination of California Bearing Ratio value are generally elaborate and time-consuming. Sometimes, the geotechnical engineer is interested to have some rough assessment of the C.B.R value without conducting elaborate tests. This is possible if index properties are determined. Simple tests which are required to determine the index properties are known as classification tests. The soils are classified and identified based on the index properties. The main index properties of course- grained soils are particle size and relative density. For fine- grained soils, the main index properties are Liquid limit and the Plasticity Index. In order to cope with the above complexities, traditional forms of engineering modeling approaches are justifiably simplified. An alternative approach, which has shown some promise in the field of geotechnical engineering, is Artificial Neural Networks (ANN).In these investigation the California Bearing Ratio (C.B.R) values for soils are predicted using Artificial Neural Networks (ANN). ANN model is developed using NN tool in MATLAB software (7.0.1).

In the paper an attempt has been made to model the California Bearing Ratio in terms of Fine Fraction (FF), Liquid Limit (WL), Plasticity Index (IP), Maximum Dry Density (MDD), and Optimum Moisture Content (OMC). A multi-layer perceptron network with feed forward back propagation is used to model the California Bearing Ratio varying the number of hidden layers. The best neural network model is identified by analyzing the performance of different models studied.

II. ARTIFICIAL NEURAL NETWORK MODELS DEVELOPMENT

Artificial neural networks (ANN) are developed by the structured arrangement of simple processing unit called “neurons”. Each neuron is a processing unit that performs a calculation on the input signal and outputs the result to the next neuron via “connections”. Connections indicate flow of information from one neuron to another. A weight is assigned to each connection and therefore, the resulting “weighted signal” is passed to the nextneurons. In a Multilayer Preceptron Network (MLP) the neurons are organized in the form of layers. It consists of an input layer, a hidden layer (or hidden layers), and an output layer, as shown in Fig. 1. In this type of network, each neuron has full connection to all neurons of the next layer but there is no connection between the neurons within the same layer. The neurons in the input layer represent number of input variables considered, while the output neurons identify the desired outputs. Each neuron in the network has an activation function, usually expressed by sigmoid function through other types of activation functions, such as linear and hyperbolic tangent functions, and may be used as well. Weights are assigned randomly to all of the connections inside the network so that optimum values of these are attained for minimizing the network error measure (the difference between the actual and computed outputs gives the error) which will be back propagated through hidden layers for all training sets until the actual and calculated outputs agree with some predetermined tolerance.

A multilayer perceptron neuron network is identified by its architecture, the way the neurons are arranged inside the network, and a learning rule. The learning rule is an algorithm used to determine the optimum values of the unknown weights that minimize the error measure of the network. A database is also required for training and testing the network. Feed-Forward-error-back-propagation network with supervised learning is currently used in applications relating to science and engineering. Fig.1. Shows typical three-layered network. In most of the neural networks the number of inputs, hidden nodes and the output in different layers has to be predetermined before feeding the data to the network based on the input considered and desired output from the model network. The number of hidden layers and neurons in each hidden layer are determined in contrast to the known output obtained from a known set of data used for training and this network topology can be generalized for prediction.

The objective of the present investigation is to develop a neural network model output being Compression index. The input parameters, for the networking should be those basic soil parameters, which has significant influence on Compression index. The details of the database used for training input parameters are presented in the following section.

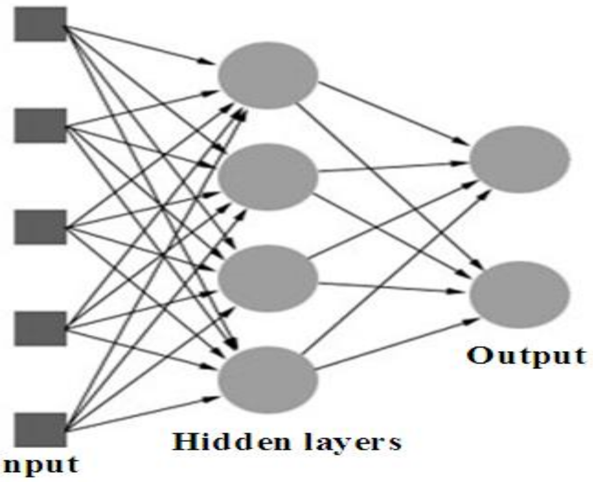

Fig. 1: The Architecture of Neural Network

A. Normalization of Data

Ideally a system designer wants the same range of values for each input feature in order to minimize bias within the neural network for one feature over another. Data normalization can also speed up training time by starting the training process for each feature within same scale. It is especially useful for modeling applications where the inputs are generally on widely different scales. The normalized data is determined by min-max normalization and is expressed as

$$X= 0.1+0.8*(x_i/x_{max})$$

Where

X = normalized value

x_i= input parameter

x_{max}= maximum in input parameter

B. Data used for Training and Testing

The soil test data is divided into 2 parts using 60:40 mode of distribution. A total of 50 soils which is obtained from different parts of chitter district with wide range of W_L from laboratory tests. Among 30 soils data is used for testing and remaining 20 soils data is used for training. The typical normalized data used for training phase is presented in Table 1 and inTable 2 presents the typical normalized data used for testing phase.

C. Network Training and Testing

30 soils test data was used for training the neuron, training data is presented in Table I. Remaining 20 soils test data was used for testing the network modeldeveloped for prediction of Compression index of soils. Testingdata ispresented in Table II. The feed forward back propagation training network models have been coded into a MATLAB program using neural network toolbox. The MATLAB software enables training with different convergence criteria, tolerance level, activation functions and number of epochs. The neural network models studied in this investigation uses transfer function 'LOGSIG' as activation function. A constant value of learning rate equals to 0.001 was assigned for all the models. The network training/learning halts automatically once the mean square error value converges to a tolerances value of 0.5 or the Number epochs become equal to 2000 whichever is earlier. After this the network model is ready for prediction of desired output.

Table I. Normalized Data for Training the Neural Network Models

S.No	FF	W_L	I_P	OMC	MDD	C.B.R
1	0.87	0.90	0.90	0.60	0.69	0.26
2	0.67	0.57	0.42	0.55	0.59	0.24
3	0.82	0.55	0.34	0.63	0.73	0.20
4	0.77	0.63	0.43	0.56	0.69	0.28
5	0.83	0.79	0.58	0.53	0.63	0.26
6	0.90	0.55	0.41	0.87	0.77	0.26
7	0.77	0.76	0.53	0.80	0.74	0.20
8	0.73	0.55	0.36	0.55	0.70	0.36
9	0.71	0.46	0.30	0.42	0.79	0.53
10	0.78	0.65	0.41	0.64	0.67	0.25
11	0.75	0.60	0.33	0.56	0.63	0.30
12	0.80	0.55	0.34	0.44	0.82	0.34
13	0.75	0.58	0.35	0.50	0.69	0.30
14	0.74	0.57	0.33	0.55	0.68	0.35
15	0.77	0.55	0.34	0.58	0.90	0.33
16	0.76	0.56	0.33	0.53	0.69	0.32
17	0.72	0.57	0.34	0.55	0.70	0.35
18	0.79	0.66	0.37	0.60	0.76	0.32
19	0.70	0.64	0.35	0.45	0.61	0.45
20	0.85	0.46	0.32	0.36	0.59	0.76
21	0.80	0.53	0.27	0.88	0.81	0.29
22	0.82	0.60	0.30	0.54	0.66	0.55
23	0.83	0.53	0.33	0.71	0.67	0.38
24	0.73	0.69	0.36	0.51	0.63	0.46
25	0.85	0.54	0.40	0.90	0.77	0.29
26	0.75	0.69	0.38	0.72	0.67	0.32
27	0.80	0.61	0.35	0.64	0.66	0.35
28	0.74	0.50	0.26	0.55	0.63	0.48
29	0.78	0.58	0.29	0.41	0.59	0.77
30	0.77	0.71	0.34	0.37	0.58	0.90

Table II. Typical Normalized Data for Testing the Neural Network Models

S.No	FF	W_L	I_P	OMC	MDD	C.B.R
1	0.80	0.90	0.90	0.75	0.77	0.16
2	0.83	0.60	0.31	0.90	0.79	0.22
3	0.89	0.84	0.68	0.71	0.74	0.20
4	0.88	0.59	0.48	0.68	0.69	0.22
5	0.90	0.44	0.23	0.78	0.72	0.25
6	0.84	0.54	0.56	0.73	0.81	0.22

7	0.89	0.42	0.33	0.66	0.67	0.18
8	0.71	0.50	0.34	0.48	0.82	0.37
9	0.78	0.54	0.32	0.55	0.81	0.33
10	0.74	0.45	0.35	0.46	0.83	0.47
11	0.77	0.47	0.34	0.59	0.73	0.31
12	0.81	0.32	0.31	0.38	0.87	0.66
13	0.72	0.39	0.34	0.42	0.90	0.62
14	0.89	0.51	0.43	0.63	0.76	0.27
15	0.71	0.47	0.36	0.53	0.79	0.29
16	0.68	0.59	0.43	0.71	0.71	0.18
17	0.86	0.48	0.40	0.52	0.79	0.35
18	0.76	0.34	0.27	0.34	0.75	0.90
19	0.82	0.36	0.28	0.40	0.83	0.57
20	0.88	0.50	0.30	0.57	0.77	0.33

III. VALIDATION AND COMPARISON OF NETWORK PREFORAMANCE

After training the ANN models were used to predict California Bearing Ratio value of soil of 20 soils reported in the literature. Data used for testing is shown in the Table II. The model developed for predicting the California Bearing Ratio value are 5-4-1(inputs-hidden layers-output), 5-5-1, and 5-6-1. Among these models the best model proposed is 5-6-1 network model. The CORR or (R^2) values for the developed models are presented in TableIII.The ratio normalized observed values to the normalizedpredicted values in training are shown in Table IV and testing values are shown in Table V. The model performance is given in Fig.3.1. Since graphical representation gives a clear idea, the same values are shown in Fig.3.2 during training and Fig.3.3 during testing respectively.

Table III ANN Model Statistical Parameter Performance Indices

Stastical parameter	Models	During training	During testing
		C.B.R	C.B.R
CORR	5-4-1	0.716	0.707
	5-5-1	0.924	0.881
	5-6-1	0.986	0.932

Table VIComparison of Normalized Observed and Normalized Predicted values of C.B.R for Trained Data

TRAINED DATA			
Observed C.B.R	Predicted C.B.R		
	No of Neurons		
	4	5	6
0.264	0.265	0.266	0.266
0.244	0.367	0.264	0.251
0.203	0.336	0.220	0.202
0.285	0.402	0.314	0.284
0.264	0.376	0.286	0.263
0.264	0.293	0.287	0.262
0.203	0.358	0.206	0.205
0.362	0.418	0.388	0.364
0.529	0.352	0.473	0.525
0.248	0.392	0.249	0.246
0.297	0.245	0.240	0.270
0.336	0.244	0.354	0.336
0.305	0.223	0.284	0.304
0.352	0.263	0.313	0.348
0.333	0.224	0.332	0.327

0.324	0.300	0.295	0.328
0.353	0.344	0.350	0.357
0.320	0.335	0.347	0.311
0.455	0.353	0.442	0.451
0.764	0.659	0.745	0.714
0.286	0.249	0.253	0.281
0.552	0.487	0.580	0.452
0.382	0.338	0.351	0.389
0.459	0.474	0.410	0.459
0.291	0.254	0.243	0.295
0.321	0.353	0.523	0.321
0.348	0.251	0.386	0.348
0.477	0.348	0.460	0.477
0.765	0.681	0.757	0.770
0.900	0.939	0.905	0.880

Table VComparison of Normalized Observed and Normalized Predicted values of C.B.R for Tested Data

TESTED DATA			
ObservedC.B.R	Predicted C.B.R		
	No of Neurons		
	4	5	6
0.159	0.222	0.217	0.155
0.218	0.104	0.290	0.227
0.204	0.259	0.283	0.215
0.218	0.289	0.227	0.238
0.247	0.275	0.209	0.229
0.218	0.341	0.192	0.214
0.183	0.071	0.168	0.292
0.372	0.486	0.416	0.280
0.329	0.426	0.314	0.331
0.471	0.331	0.464	0.487
0.309	0.488	0.383	0.343
0.658	0.688	0.547	0.678
0.619	0.438	0.728	0.528
0.270	0.325	0.312	0.255
0.292	0.115	0.301	0.320
0.182	0.249	0.119	0.288
0.353	0.349	0.267	0.285
0.900	0.847	0.811	0.850
0.565	0.700	0.447	0.564
0.329	0.493	0.374	0.322

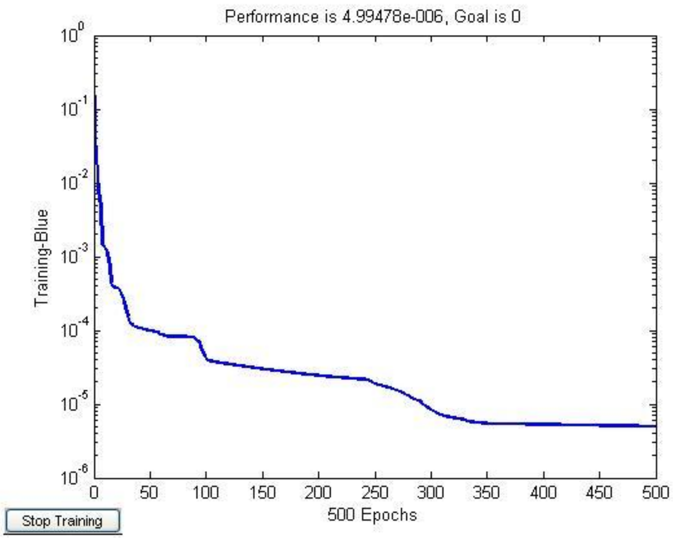

Fig.3.1 Model performance indication graph

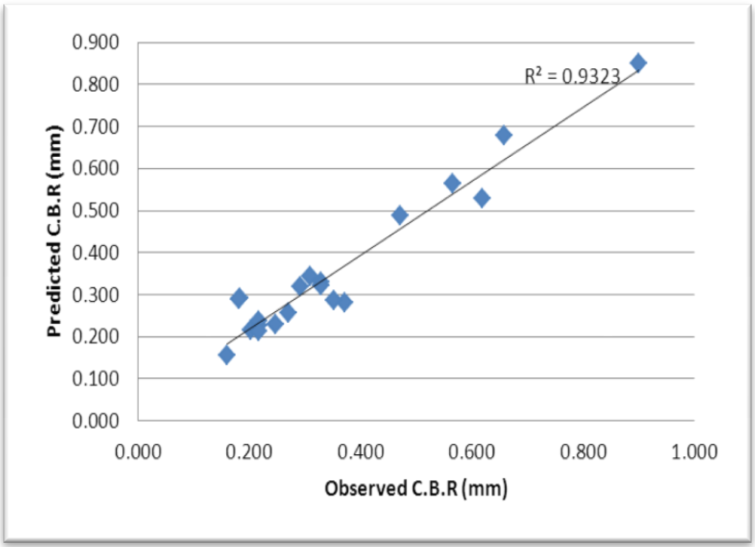

Fig.3.2Observed C.B.R Vs Predicted C.B.R during Training

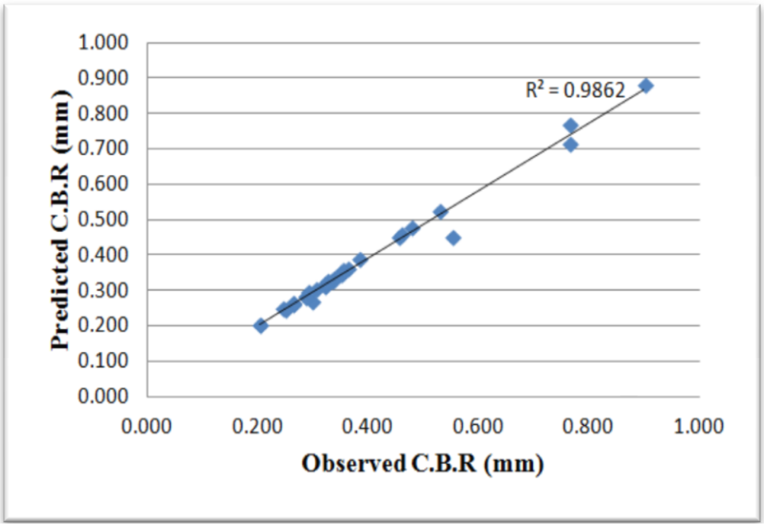

Fig.3.3Observed C.B.R Vs Predicted C.B.R during Testing

IV. CONCLUSIONS

Architecture of Proposed Model is shown in Ifig 4.1:

Inputs : 5

Neurons : 6

Outputs : 1

Transfer Function: Feed Forward Back Propagation

Activation Function: Log sigmoid

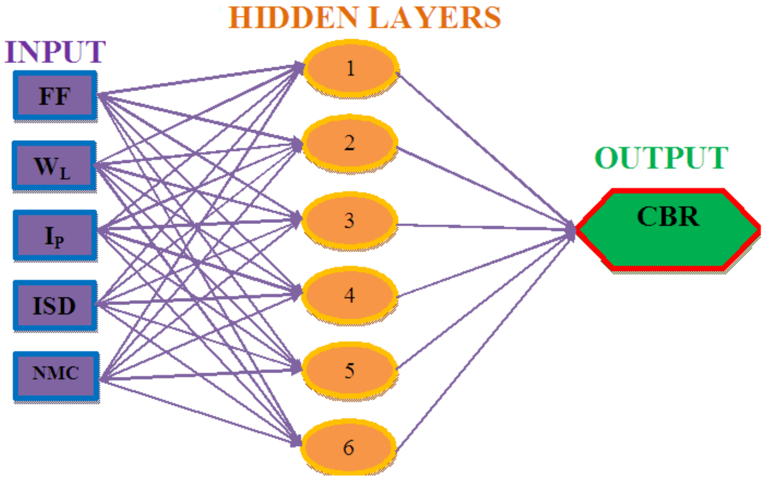

Fig.4.1. Architure of Proposed Model

An artificial neural network model with 5-6-1 architecture with a Feed Forward Back propagation using algorithm Log sigmoid activation function was developed to predictCalifornia Bearing Ratio value using basic soil properties FF(%),W_L(%),I_P(%), MDD and OMC as input parameters. The network is trained with 30 soils test data. The performance of the modal is verified for 20 soils test data. The proposed neural network model is found to be quite satisfactory in predicting desired output.

This is the foremost model for predicting the California Bearing Ratio of soils using Artificial Neural Network.

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