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Predicting CBR Value from Index Properties of Soils using Expert System

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Abstract- The sub grade gives an establishment to supporting the asphalt structure. The sub review regardless of whether in cut or fill ought to be all around compacted to use its full quality and to conserve consequently on the general thickness of asphalt required. For plan, the sub review quality is evaluated regarding the CBR of the sub review soil in both fill and cut areas. For deciding the CBR esteem, the static entrance test method ought to be entirely clung to. The test should dependably be performed on formed specimens of soils in the research center. CBR test is difficult and tedious; yet once in a while the outcomes are not precise due to the poor laboratory conditions. Advance if the accessible soil is of low quality, appropriate added substances are blended with soil and the subsequent quality of the dirt will be evaluated by CBR esteem, which is unwieldy. In this paper we proposed a new expert system (Multi Layer Perceptron (MLP) neural network) to be working as computer decision maker and predicate the precise CBR value based upon the data.

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Ahmad Taha Abdulsadda[α] & Dhurgham Abdul Jaleel[σ]

Abstract- The sub grade gives an establishment to supporting the asphalt structure. The sub review regardless of whether in cut or fill ought to be all around compacted to use its full quality and to conserve consequently on the general thickness of asphalt required. For plan, the sub review quality is evaluated regarding the CBR of the sub review soil in both fill and cut areas. For deciding the CBR esteem, the static entrance test method ought to be entirely clung to. The test should dependably be performed on formed specimens of soils in the research center. CBR test is difficult and tedious; yet once in a while the outcomes are not precise due to the poor laboratory conditions. Advance if the accessible soil is of low quality, appropriate added substances are blended with soil and the subsequent quality of the dirt will be evaluated by CBR esteem, which is unwieldy. In this paper we proposed a new expert system (Multi Layer Perceptron (MLP) neural network) to be working as computer decision maker and predicate the precise CBR value based upon the data.

I. Introduction

Sub grade quality is generally influenced by thickness of asphalt, in Highway plan. California Bearing Ratio (CBR) is the one of the technique to decide the sub level strength [[1]– [3]].CBR test is relentless and tedious Value of CBR is regularly required for geotechnical arrangements of building street structures. For region advancement ventures utilizing fillings requires position of such fillings in appropriate request for high quality and low compressibility [[4]– [6]]. Gigantic amount of filling material is utilized for development of sub review and CBR esteem for every single such fill is essential parameter and should be surveyed. However, because of high cost and time prerequisite for such testing it for the most part ends up plainly hard to outline variety in their incentive along the alignment [7].A few number of specialists anticipated exact equations displayed in the geotechnical writing that were produced to assess the socked CBR value for coarse grained soils from the physical properties and compaction attributes of soil [8].These models were create to gage CBR value contingent upon minimal effort, less time utilization premise. Such these experimental writing are recipe introduced by NCHRP [9];it where proposed best-fitted condition to associated CBR esteem with D60 for spotless, coarse-grained soil;In [10] they utilized two sorts of soil tests (CL-ML) to setting up connection between's dirt parameters. The soil utilized examples was blend differed sand content (SP).A basic and different linear regression were develop to connect amongst MDD and rate sand content.In [11] they proposed associating between CBR esteem and some list properties. They utilized twenty quantities of plastic and non-plastic soil tests were gather from various areas in India. Set of lab tests were leading on the dirt examples. A basic and different direct relapse examination between record properties and socked CBR esteem.In [12], they applying straightforward and numerous direct relapse investigation to create connection models. Physical and mechanical testicles result like dampness thickness relationship, consistency points of confinement, and CBR tests were utilized as an informational collection. They utilized 387 informational indexes of soil properties and relating CBR values. The groups in [13] they utilized simple and different relapse examination models to associate between some of soil properties and CBR esteem. The experimental formula that associate CBR esteem with sifter investigation and compaction qualities.

In ANN side,In [14], they have detailed the practicality of utilizing ANN for evaluating the Optimum dampness content and Most extreme dry thickness values for various sorts of soil subjected to various similar endeavors.Other group in [15] built up the ANN based model to foresee the shear parameters of the dirt regarding distinctive soil parameters, for example, dry thickness and versatility record, gravel, rate sand, rate sediment, rate dirt as input parameters gotten through research center tests for soil tests from various parts of India and union and edge of inner rubbing as yield parameters. In [16] the group created ANN model to foresee the building properties of soil, for example, Porousness, Compressibility and Shear Strength parameters as far as Fine Fraction, Liquid Limit, Plasticity Index, Most extreme Dry Density, and Optimum Moisture Content as input parameters acquired through lab tests for soil tests.

In this paper, we proposed a computer decision maker to predicate the value of the CBR as accurate results as what we can be found in the linear and nonlinear regression equations that many researcher have been done in literature. The paper is organized as follow: the experimental data is presented in section 2, the Multi Layer Perceptron (MLP) predicate structure has

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explain in section 3, the verification simulation results details is listed in section 4, finally, the conclusion and future works remark presents in section5.

II. Experimental Data

The soil samples that utilized as a part of this paper were arranged from various size of materials, One hundred number of bothered soil tests were tried from various areas in Al-Najaf city that utilized for asphalt development ventures amid 2010 to 2016. The chose soil tests were tried for Socked CBR esteem, optimum water content, maximum dry unit weight, grain size distribution. These tests were led in Al-Najaf specialized foundation lab. as shown in Fig. 1. Every one of these

Figure 1: Experimental data setup.

tests were performed by ASTM standard. Most of the materials contained non-plastic union less materials that utilized as fill material for street dikes and sub base and base courses material. The Soil parameters utilized as a part of the database were optimum water content (OWC), maximum dry unit weight (MDU),Effective size (D10), The diameter of particles meet 60%, The diameter meet 30%, The coefficient of curvature (Cc), The coefficient of uniformaity (Cu), % Gravel (G), % Sand (S), % Fines (F),. With a specific end goal to survey the sufficiency of the database, clear measurements of every informational index exhibit in the database were resolved.

Table 1 and table 2 present the descriptive statistics of each variable which will be fed to the neural network, where the neural network proposed in this paper has input layer with an 12 input nodes. According to the results, appear in the tables (1and 2), it can be obviously shown that the database consists of a wide range of data.

III. CBR Predication Using Neural Network Processing

As illustrated in Fig. 2, we adopt the multilayer perceptron (MLP) architecture for the neural network. AnMLP network consists of an input layer, a hidden layer, and an output layer, and is the most widely used network structure for nonlinear classification and prediction applications [17].

Table 1: Statistical parameters of database

	Percentage Passing per sieve opening (mm)							Compaction characteristics		CBR value
	25	9.5	4.75	2.36	1.18	0.3	0.075	OMC	MDD	
NO. of tests achieved	100	100	100	100	100	100	100	100	100	100
Maximum ratio gained	100	90	75	75	63	29	17	15	2.280	44
Minimum ratio gained	75	40	28	28	17	8	5	4	2.070	30
Range	25	50	47	47	46	21	12	11	0.210	14
Mean	86.3	64.5	52.2	51.8	41.6	16.3	10.8	9.8	2.201	36.3
Median	86	66	54	53	43	15	11	10	2.202	36
Standard dev.	5.56	7.77	7.30	7.05	7.06	2.08	2.65	2.8	0.017	0.67

Table 2: Result of recalculating the parameters database

	Percentage Passing per sieve opening (mm)							
	G	S	F	D10	D30	D60	Cc	Cu
Maximum ratio gained	72	64	17	0.75	4.75	17	16.29	300
Minimum ratio gained	25	22	5	0.04	0.18	0.55	0.02	7.33
Range	47	42	12	0.71	4.57	16.45	16.27	292.66
Mean	48.37	41.31	10.78	0.09	1.17	8.26	2.91	113.92
Median	48	42	11	0.07	1	7.3	1.87	100
Std. deviation	7.25	7.42	2.65	0.05	0.58	2.78	2.40	56.72
Units	%	%	%	mm	mm	mm	%	%

One could use different features extracted from the experimental output data as the input to the neural network. The number of inputs is the same as the number of experimental data (12) considered. The number of the hidden-layer nodes is chosen through a genetic algorithm (GA)-based

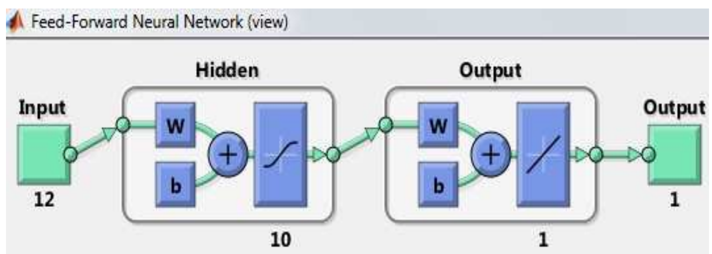

Figure 2: Schematic of the MLP neural network for signal processing of the features

optimization process. Each hidden layer node represents the operation of nonlinear activation, which takes the form of a sigmoid function. The output layer has one nodes, representing the y predicted CBR of value.

The number of hidden-layer nodes and the connective weights between the layers are determined through a two-phase training procedure, using the software simulink matlab. The training data are obtained by in Al Njafa Technical Institute as explained in experimental data section. The objective function is defined as:

$$J = \frac{1}{2M}\sum_{i=1}^{M}(y_i - \hat{y}_i)^2, \qquad (1)$$

where ($\hat{y}_i$) denotes the predicted value for (yi) under the current network structure and weights. The values of the connective weights obtained in the first training phase then serve as the initial condition for weights refinement in the second phase, where the network structure is fixed as determined in the first phase. Delta-bar-delta learning [5], with adaptive learning rate, is used for weights optimization. Let K be the total number of weights. For each weight w_k, $1 \leq k \leq K$, the update rule is

$$w_k^{\text{new}} = w_k^{\text{old}} - \eta_k^{\text{new}} \frac{\partial J}{\partial w_k^{\text{old}}}, \qquad (2)$$

where the adaptive learning rate hk is updated as

$$\eta_k^{\text{new}} = \begin{cases} \eta_k^{\text{old}} + a, \; if \; \frac{\partial J}{\partial w_k^{\text{old}}} > 0 \\ b\eta_k^{\text{old}}, \; if \; \frac{\partial J}{\partial w_k^{\text{old}}} \leq 0 \end{cases}, \qquad (3)$$

and a,b are constants satisfying $0 < a,b < 1$.

IV. Simulation Results

In traditional proposed methods which were presented in literature as multiple nonlinear regression models to predicate the CBR value based upon the soil properties, for example, rate passing, G, S, F, D_{10}, D_{30}, D_{60}, Cc, Cu, MDU and OWC are considered as the needy factors. Five models, with various soil properties chosen from database were produced for connections. Measurable parameters like relationship coefficients (R^2) qualities is ascertained. The anticipated CBR values with genuine CBR values picked up from database are plotted and best direct fit bends are attract to discover the variety between the anticipated values and the correct value as shown in Fig. 3. Fig. 3 shows obviously that the empirical formula proposed by the CBR results governed from the

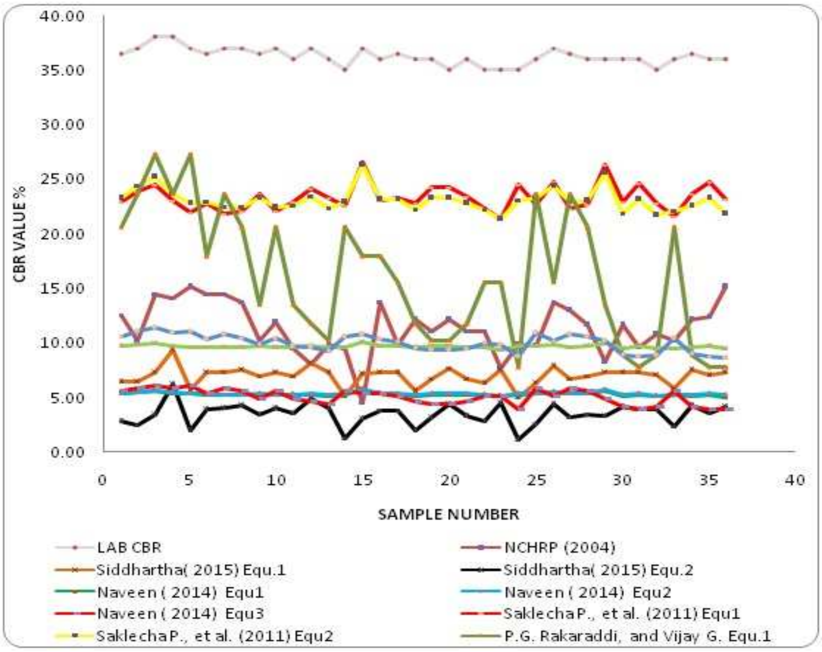

Figure 3: Multiple linear regression schemes

effort of the researchers are smaller than what the laboratory CBR results. In addition that, some of the empirical formula proposed were based on very limited materials while others were based on a good number of materials, that effect on the deviation between the estimated value and calculated value.

Otherwise, with MLP predicator the actual Lab. CBR and the predicate with the MSE are shown in Fig. 4 and Fig. 5, respectivelly. The regression is shown in Fig. 6.

V. Conclusion and Future Works

MLP neural network one of the most accurate nonlinear predicated system, to help the Lab worker to give correct response to the soil tests and make the decision is accurate we have proposed a computer expert system. In this paper we proposed a new scheme for the CBR predicate value.

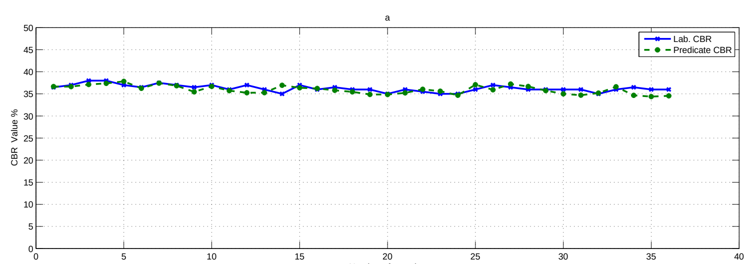

Figure 4: Simulation results: Lab. CBR and predicated responses

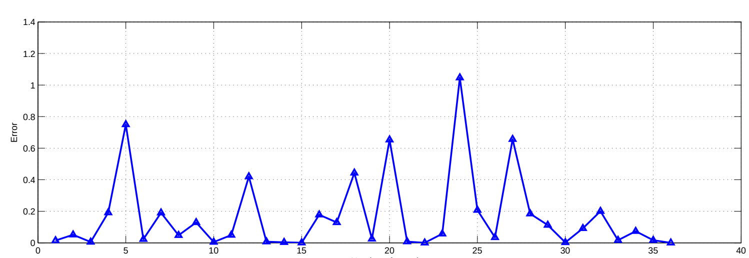

Figure 5: Simulation results: Mean square error response

The simulation results demonstrate the effectiveness of our proposed scheme to predicate the CBR value for the lab. 36 samples with efficiency factor more that 96%. In future work, we suggest to use the fuzzy rule system to determine firstly the standard that the lab. data belongs to then we use the MLP neural network to predicate the CBR value.

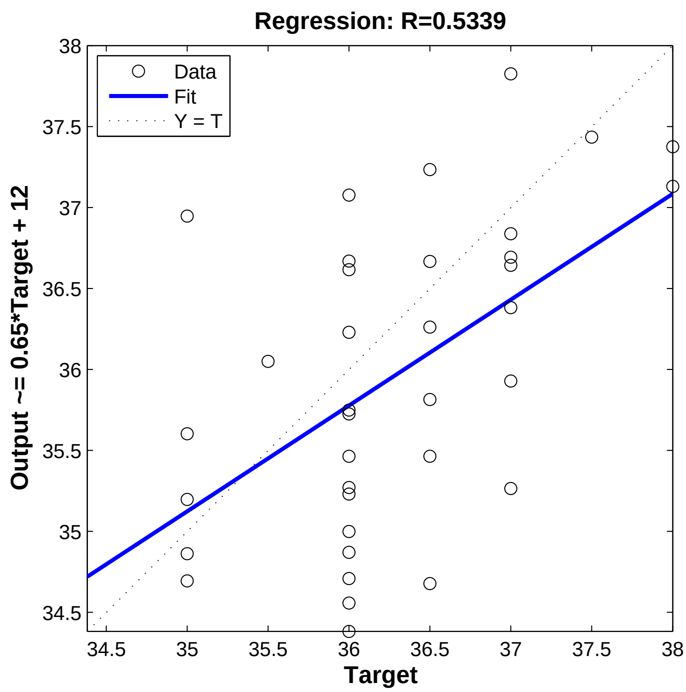

Figure 6: The predicated MLP nonlinear regression function

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