Assessment of Soaked California Bearing Ratio of Clay-Gravel Mixtures Using Artificial Neural Network Modeling

K. L. Timani [1[0000-1111-2222-3333]] and R.K. Jain[2[1111-2222-3333-4444]]

[1] Ph. D. Scholar, Civil Engineering, Gujarat Technological University & Associate Professor, Vishwakarma Govt. Engineering College Ahmedabad, (Gujarat), India,382424

[2] Professor and Head, Civil Engineering Department, S. S. Engineering College, Bhavnagar, Gujarat, India, 344060

E-mail: ketantimani12@gmail.com; rajkjain7@gmail.com

Abstract. The Flexible pavement consists of different thickness of layers of different materials. CBR, elastic modulus, moisture condition, unit weight are the basic characters of subgrade for the design of pavement components. Characterization of CBR is of primary importance for all flexible pavement related tasks. CBR is a laborious and time consuming test, therefore many researchers have suggested ANN techniques to predict CBR because it provides much better alternative. As per the IRC recommendation, CBR should be found for a soaked specimen of subgrade soil. The study presents the application of ANN for estimation of CBR of clay-gravel mixture under soaked condition. Nine different clay percentage and five different moisture range were selected for conducting CBR tests. In the analysis, dry unit weight parameter was made standardized using mean particle size of the mixtures and surcharge weight which was kept on the mould to provide vertical confinement while penetration of the plunger during testing. To determine the contribution of each independent variable, many methods have been proposed for sensitivity analysis. In the present study, Garson,Olden and Lek's profile models were developed using neural network to assess the influence of the parameters. From both the models contribution of independent variables is visualized. CBR values are found to reduce continuously when blending with clay fraction, but moisture content has more negative impact than clay on CBR values. The unit weight has strongest relationship with CBR. The strength of model that was developed has been examined in terms of standard error and co-efficient of determination.

The standard error is 0.08800434 and R^2 values are 0.9316485 of the generated model. It shows that ANN technique is able to learn the relation between CBR and soil mass.

Keywords: Artificial neural network, California bearing ratio, Sensitivity analysis, Subgrade soil.

1 Introduction

The behavior of soil depends on amount and type of soil, shape and size of particles, moisture content, gradation and unit weight. Clay particles produce important soil type and type of mineral present in clay has dominating effect on entire soil mass. Water in soil acts both as a lubricant and as a binding agent among the soil particulate materials, thereby influencing the structural stability and strength of soil. The physico-chemical reaction between clay particle and moisture affect many soil properties. The suitability of soil for a particular use should be determined based on its engineering characteristics. Generally, fine grained soils have a relative smaller capacity in bearing of load than the coarser grained soils. Clay-gravel mixtures are frequently used in engineering applications. Materials which form the base and subbase courses in flexible pavements generally consist of crushed stone or selected gravels. Clay is mixed with gravel which fills the voids and acts as a binder. The contact mechanism varies by the change in the amount of clay. Therefore amount of clay fraction is crucial in determining properties required for all engineering applications. The pavement construction requires proper construction of subbase and base layers.CBR is one of the frequently used index test to assess the strength of subgrade. The CBR test is not only expensive but also time consuming. With the increase in growth of statistical modeling, researchers are using more and more complex method like artificial neural network. T.Taskiran (2010), Suneet Kaur et.al (2011), Akshaya Sabat (2013) and many other have developed ANN models to predict CBR with a reasonable degree of accuracy. The present study is an attempt to quantify effect of clay fraction on the compaction characteristics and behavior of soaked CBR.

2 Experimental Program

2.1 Materials

The materials used in the experiments to form the mixtures were clay and gravel. Clay was obtained from a depth of 0.5 to 0.6 m from the ground surface of BHAL area. It was a disturbed sample with grey color, in dry state and was converted in to powder form before used in the analysis. Gravel used was collected from Sabarmati river basin. The range of the gravel size was from 4.75 mm to 10 mm. The median size of clay was 0.0014 mm and of gravel was 7.1 mm.Clay was classified as CH type on plasticity chart with liquid limit 54% and plasticity index 27%. For gravel, value of C_c was less than 2, which indicate that it is a uniformly graded material and classified as GP.

2.2 Experimental program

The Clay in various proportions by weight was mixed with gravel. Nine different mixtures were prepared by varying clay content from 10% to 50 % at the increment of 5% by weight. Maximum dry density and optimum moisture content of clay- gravel mixtures were found out following the procedure of modified Proctor test as per the IS: 2720 (Part-8).Samples for CBR testing were prepared at these maximum dry density and optimum moisture content, above 2 and 3.5 and below 2 and 3.5 of mdd and omc. Thus total 45 samples were prepared. The compaction of soil mixture in CBR mould was achieved by pressing in the spacer disc using a compaction machine. Thus prepared mould were kept in water for 96 hours to achieve soaked conditions. California Bearing ratio test was conducted on this specimen as per the IS: 2720 (Part-16).samples were loaded under a constant strain of 1.25mm/ minute. In dry condition, the absence of water results in the absence of diffused double layer in clay, thus mainly mechanical forces act on clay particles. soaking results in the formation of diffused double layer results in both mechanical and electrostatic forces acting on the particles. A scalar plot shown in fig. 1 gives the idea of relationship between CBR and clay percent.

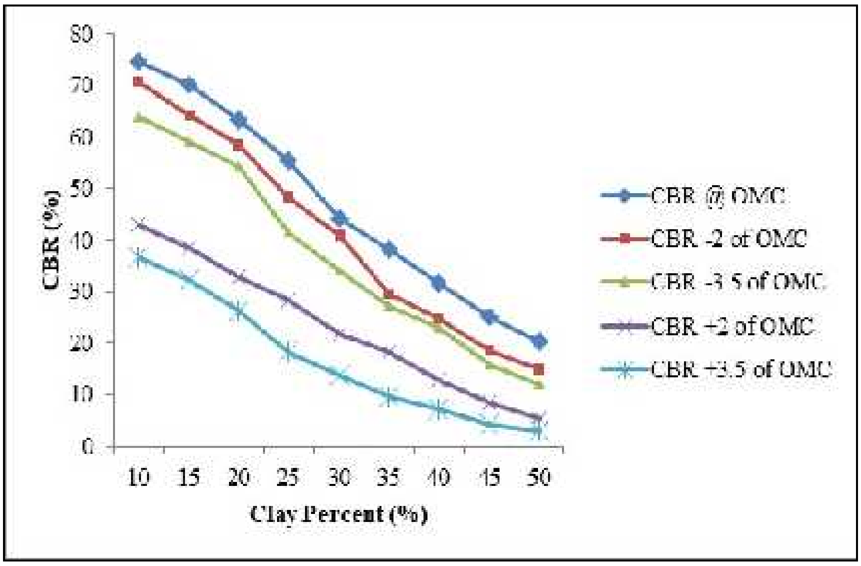

Fig.1. Variation in CBR with clay percent under soaked condition

3 Dimensional Consideration

3.1 Soaked Condition

The following functional relationship can be written to compute CBR in case of clay-gravel mixtures under soaked conditions.

$$CBR = f(P_c, \gamma_d, w, PI, G, C, \phi, S, d_a) \quad (1)$$

Here S is the surcharge pressure applied on the mould during soaking period wherein surcharge weight was kept 2.5 kg. It is difficult to compute the shear strength parameters under soaked conditions of specimen in tri-axial apparatus. Therefore C and ϕ have been dropped from further analysis. PI and G have minimal variation, also been dropped. Therefore, new functional relationship for CBR is written as

$$CBR = f(P_c, w, ¥_d, S, d_a) \tag{2}$$

Using dimensional analysis, the variables of Eq. (2) can easily be arranged into the following non-dimensional form (Peerless, 1967):

$$CBR = f\left[P_c, w, \frac{¥_d d_a}{S}\right] \tag{3}$$

The functional relationship in the form of Eq. (3) can be used to develop an expression for the computation of California bearing ratio of clay-gravel mixtures under soaked conditions. In analysis of CBR data, two different modeling techniques are used Multiple Linear Regression Analysis and Neural Network using neural-net-tools package to predict the value of soaked CBR values.

4 Analysis of Results

4.1 Multiple Linear Regression Model

The general-purpose of the MLR is to discover the relationship between some predictor variables or independent and a dependent variable.

Table 1. Regression Statistics.

Regression Statistics (clay-gravel mixture, soaked condition)				
Multiple R	0.9677			
R Square	0.9364			
AdjustedR Square	0.9318			
Standard Error	0.0887			
Observations	45			
ANOVA				
	df	*SS*	*MS*	*F*
Regression	3	4.7555	1.5852	201.3617
Residual	41	0.3228	0.0079	
Total	44	5.0783		
	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	5.5194	0.2937	18.7900	0.0000
Clay (%)	0.4390	0.1888	2.3249	0.0251
Moisture Content (%)	-0.7892	0.0885	-8.9126	0.0000
Dimensional	3.5573	0.4620	7.7003	0.0000

Density	
γ_d*da /surcharge	

4.2 Artificial Neural Network Model

$$CBR = 5.51 - 0.43P_c - 0.78w + 3.55\frac{\gamma_{d}.d_a}{S}$$

After dimensional consideration, three basic parameters such as clay fraction, moisture content and dry unit weight were taken as input parameters for the ANN model. In this study the Neural-Net-Tools package is used for the interpretation of supervised neural network models created in R Programming. Functions in the package are used to visualize a model using a neural network interpretation diagram, evaluate variable importance by the model weights, and performed sensitivity analysis of the response variables to changes in the input variables. To obtain the knowledge of relationship between input and output variables in a model, bar plots are developed by Garson and Olden methods. It is important to note that Garson algorithm uses absolute value of connection weight and Olden algorithm accounts for negative and positive signs of the weights. Lek Profile method produces profile plots of each output variable with respect to a range of one input variable. This method differs fundamentally from the variable importance algorithms by evaluating the behavior of response variables across different values of the input variables. The method evaluates the effects of input variables by generating a plot of model predictions across the range of values for each variable. The remaining explanatory variables are held constant when evaluating the effects of each input variable.

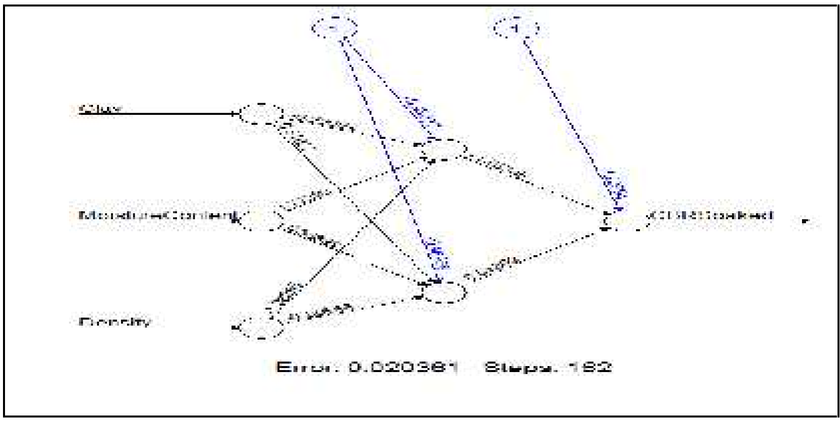

Fig.2 Neural Network architecture for prediction of CBR

Table 2. Matrix containing input-hidden-out put Connection Weights and Biases of ANN model.

	Weights					Bias	
Neuron	Intercept	Clay	Moisture content	Density	CBR	b_{hk}	b_0
Hidden neuron (k=1)	-0.930	-0.220	1.7793	-1.9628	-1.033	-0.930	1.2299

Hidden neuron (k=2)	0.464	0.818	0.5889	-0.8956	-0.543	0.464

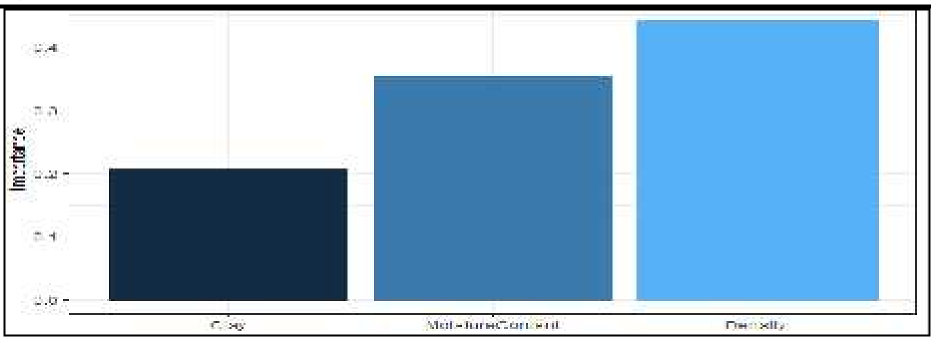

Fig.3. Bar plots showing percentage relative importance of input variables for predicting CBR based on Garson's method

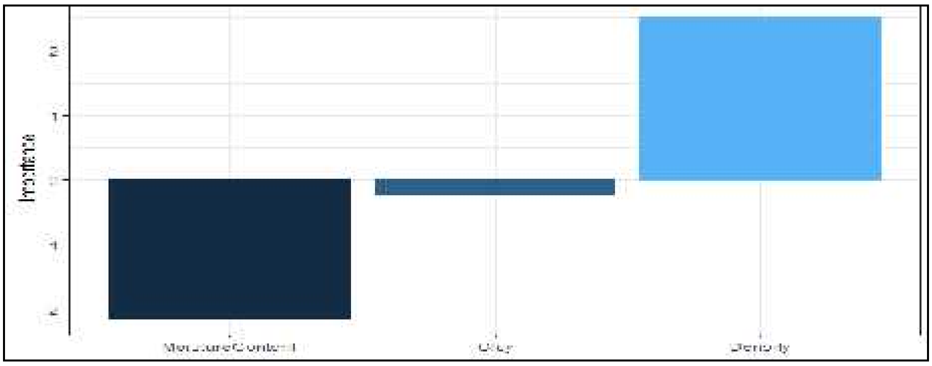

Fig.4. Bar plots showing percentage relative importance of input variables for predicting CBR based on Olden's method

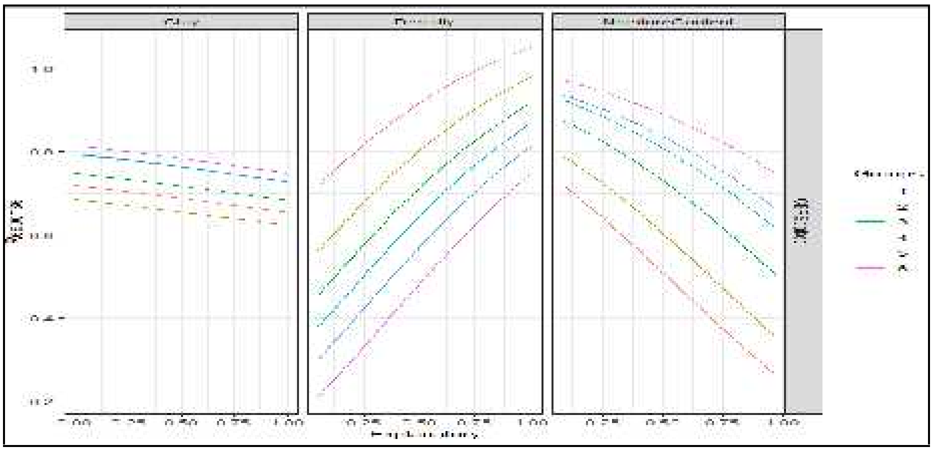

Fig.5. Contribution plots of input variables based on Lek's profile method

5 Conclusion

Functional relationships have been identified to estimate CBR of clay-gravel mixtures under soaked conditions. The weights that connect variables in a neural network are partially analogous to parameter coefficients in a standard regression model and can be used to describe relationships between variables. Using multiple linear regression analysis, relationship is proposed to estimate CBR of clay-gravel mixtures. The statistical parameters suggest that the proposed relationships very well predict the CBR. Artificial neural network (ANN) analysis using R programming was also performed to adjudge the behavior of the pertinent variables on CBR.The Neural-Net-Tools package provides a simple approach to improve the quality of information. It is evident from the contribution plot that the influence of density and moisture content has relative importance about 80% as per the Garson method. Density has strongest positive and moisture content has strongest negative relationship with soaked CBR value as per the Olden model. Clay has minimal effect on CBR. The Lek profile method shows positive effect of density and negative influence of moisture and clay fraction. Moisture has more negative effect than clay. Clay percent shows flat reduced response on soaked CBR values. These results are also confirmed with Olden method. These methods provide a means for interpreting contribution of input variables in the neural network modelling process.The presented experimental works as well as statistical results are useful in assessing and predicting the performance of subgrade layer in the pavement construction.

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