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Numerical Modeling for Prediction of Compression Index from Soil Index Properties

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Abstract: *Expansive Clays known for its vulnerability pose numerous problems to builders. Compression index is a clay dependant parameter which can be evaluated from the consolidation test data. Evaluation of compression index from the consolidation test is time consuming and laborious. Prediction of compression index from the index properties of soil is attempted. In this study, a correlation between compression index (C_c) with liquid limit (W_L) and plasticity index (I_P) is aimed at. Remoulded clay samples were collected from twenty locations of Coimbatore for experimental study. Clay was for its liquid limit, plastic limit and consolidation properties in the laboratory. Correlations of compression index in terms of liquid limit and plasticity index was arrived from Regression model and Artificial Neural Network (ANN). From these correlations, the best fit linear equation is found to be ANN which is having higher accuracy. This correlation will be helpful for the geotechnical engineer to predict the compression index value of clay from index properties.*
Keywords: *Regression model, Artificial Neural Network, liquid limit, plasticity index, compression index, correlation*

I. Introduction

Compressibility of soil is an important engineering properties and is related to settlement of the foundation or structures. If the compressibility was high, settlement will also be high. Settlement was calculated from the compression index. Compression index was a clay dependent parameter computed from the consolidation test .The process of consolidation test take longer durations. So it was beneficial if the value of compression index can be related with index properties such as liquid limit and plasticity index. Atterberg's Reliable correlations between the engineering and index properties of soils will reduce the work load of a soil investigation program, in case of urgency.

Study Area was Coimbatore city, covered with black cotton soils.. In this work, twenty locations namely Government College of Technology (GCTCampus), Rathinapuri, Sitra and Government Polytechnic College (GPT), Peelamedu, Thudiyalur, Pudhur, Saravanampatti, Vadakovai, Vadavalli, Agri University(campus), Forest college quarters, Telungupalayam, Saibabacolony, Venkittapuram, GCT(girls hostel), Periyanaikenpalayam, Sivanantha colony , Neelambur, Veerakeralam in the city were identified for soil sampling and laboratory .Samples collected from the twenty locations are analyzed for its grain size distribution, Atterberg's limit, Standard Proctor Compaction, Consolidation and Differential Free Swell. An attempt was made to establish a correlation between compression index Vs plasticity index and compression index Vs liquid limit. In these investigations the observed value of the compression index compared with predicted value of the compression index using MATLAB with the help of Artificial Neural Network and Regression analysis.

Amith Nath and S.S Dedalal was collected clay samples from West Bengal and artificially mixed soil samples were prepared. A correlation was achieved to determine the compression ratio in terms of liquid limit, plastic limit,void ratio. **Arpan Laskar and Sujit Kumar Pal (2008)** carried out a detailed study on Geotechnical Characteristics of two different soils and their mixture and relationships between parameters. The two soil samples collected from NIT Agartala campus and Howrah were investigated and the particle size distribution of NITA sample was determined. Then NITA sample was replaced with different proportions of the Howrah soil. The mixture of both the soils (Mixed Soil) was also investigated to study the variations in properties and to establish correlations of soil parameters**. Slamet Widodo and Abdelazim Ibrahim** collected 20 samples in Supadio Airport in Pondianak, Indonesia.The soil specimens were tested in the laboratory and proposed three different equations to estimate the compression index of the soils. The summary equations of the literature was given below in the table 1

Table 1 Literature Summary

Equation	Author
$C_c'=0.0021W_L+0.0587$	Amith Nath and S.S Dedalal
$C_c'=0.0888\ e_0+0.0525$	Amith Nath and S.S Dedalal
$C_c'=0.0025\ I_P+0.0866$	Amith Nath and S.S Dedalal
PI = 0.7785 (LL 18.623)	Arpan Laskar and Sujit Kumar Pal
OMC = 0.43 (PI + 30)	Arpan Laskar and Sujit Kumar Pal
Cc = 0.0046(LL –1.39)	Arpan Laskar and Sujit Kumar Pal
$C_c=0.0058(PI-13.76)$	Arpan lascar and Sujit Kumar Pal
$C_c=0.5217(e_o-0.20)$	Slamet Widodo and Abdelazim Ibrahim
$C_c=0.5217(W_n+11.57)$	Slamet Widodo and Abdelazim Ibrahim
$C_c=0.5217(W_L-1.30)$	Slamet Widodo and Abdelazim Ibrahim
$C_c = 0.002\ w_L + 0.0025I_p - 0.005$	Amardeep Singh

II. Materials And Methods

Collection of soil samples:

Twenty soil samples collected from Coimbatore city. The soil samples are disturbed and collected in plastic bag from the depth of 0.5-1.0 m below the ground level. The collected samples are tested in the laboratory .Their physical properties and index properties namely grain size distribution, specific gravity, liquid limit, plastic limit, maximum dry density and optimum moisture content and their classification are determined as per Indian Standard code of practice. The samples are represented as S1, S2, S3 ……S20. Here, S denotes soil samples and the number refers the order of sample taken. Properties of soil samples are shown in table 2.

Table 2 Soil Properties

Sample no	Specific gravity	% Gravel	% sand	% Silt	% clay	Soil classification	Free Swell %	OMC %	MDD g/cc	W_l (%)	W_P (%)	I_P (%)	C_c
S1	2.72	0	38.7	19.3	40	CI	70	14	1.787	37.8	24	13.8	0.12
S2	2.67	20.25	43.9	20	15.85	CL	45	12	1.948	31.2	20	11.2	0.08
S3	2.77	0.1	19.3	23.6	57	CH	80	20	1.592	66.2	30	36.2	0.62
S4	2.78	0.01	17.26	27.74	55	CH	80	25	1.487	58.5	25	33.5	0.44
S5	2.702	0	36.3	18.47	45.23	CH	60	23	1.659	65.83	22	43.83	0.57
S6	2.78	1.1	26	31.47	41.33	CH	80	30	1.549	63.33	23.5	42.68	0.5
S7	2.82	1.1	33.5	24.85	40.55	CH	70	22	1.598	67.48	20.7	46.78	0.76
S8	2.79	0.2	24	29.8	45.25	CH	80	26	1.492	75	27.3	47.68	0.9
S9	2.78	0.6	24.6	28.43	46.47	CH	70	24	1.55	61.8	21.4	40.4	0.46
S10	2.778	0.1	24.7	32.33	42.86	CH	95	24	1.590	54.8	19.2	35.6	0.29
S11	2.84	0.2	20.8	33.97	45.03	CH	100	22	1.492	72	20.1	51.9	0.74
S12	2.68	0.4	19.6	27	53	CH	100	25.3	1.47	57	20	37	0.3
S13	2.76	0.3	30.41	29.19	40.10	CH	85	22	1.625	74.3	18.8	55.5	0.86
S14	2.758	0.6	29.4	30.1	39.9	CH	80	20	1.605	53.3	20.1	33.2	0.2
S15	2.69	1.7	32.9	30.7	34.7	CI	75	18	1.78	44.5	18.2	26.3	0.18
S16	2.72	1.3	32.1	20.6	46	CH	80	20	1.69	57.3	20.8	36.5	0.34
S17	2.82	0.4	14.8	14.4	70.4	CH	100	24	1.481	77.8	23.5	54.3	0.96
S18	2.68	0	20	37.5	42.5	CL	70	16	1.79	29	19	10	0.067
S19	2.824	0.5	16.67	18.23	64.6	CH	100	24	1.427	65	30	35	0.56
S20	2.79	0.5	4.5	20	75	CH	100	22	1.458	59	19	40	0.46

Consolidation test

One dimensional consolidometer having brass ring 60mm in diameter and 20mm height was used. The specimen for Consolidation test was prepared in optimum moisture content and maximum dry density. The prepared sample was shown in figure 1

Figure 1 sample preparation

Filter papers placed between the specimen and saturated porous stones to prevent from movement of particles into the porous stone.A seating pressure of 0.05 kgf/cm^2 was applied to the specimen and was allowed to reach equilibrium for 24 h. The test was continued using a loading sequence which would successively apply stress of 0.1, 0.2 and 0.4 kgf/cm^2 on the soil specimen. The readings of the dial gauge were taken using a time sequence such as 0, 1/4, 1/2, 1, 2, 4, 8, 15, 30, 60 min and 2, 4, 8, 24 h. The graph plotted between the void ratio (e) and logarithmic value of applied pressure (σ_{ef}) is shown in figure 2. The slope of the straight line portion was called as compression index. The compression index values from the consolidation test are shown in table 1

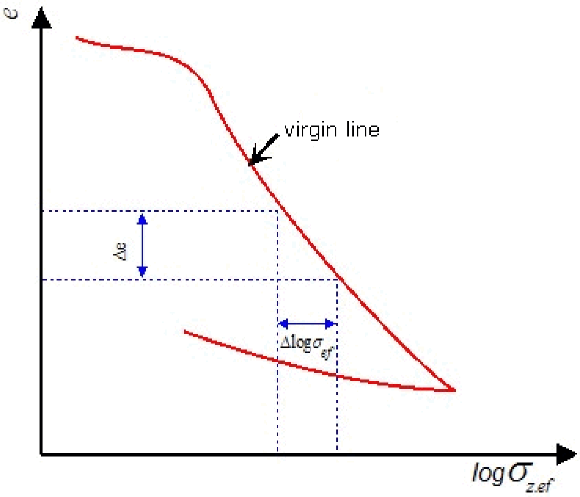

Figure 2 void ratio (e) Vs applied pressure (σ_{ef})

$$C_C = \frac{\Delta e}{\Delta \mathrm{Log}\,(\sigma_{ef})}$$

Δe = changing void ratio

σ_{ef} = changing applied pressure

Mathematical Modelling: Two different approaches namely Regression analysis and Artificial Neural Network to obtain the correlation between compression index and liquid limit. Similar approaches are also applied to predict the correlation between compression index and plasticity index.

Regression analysis

Regression analysis uses more sophisticated equations to analyze larger sets of data and translates them into coordinates on a line or curve. In the not-so-distant past, regression analysis was not widely used because of the large volume of calculations involved. Since spreadsheet applications, such as Excel, began offering built-in regression functions, the use of regression analysis has become more widespread.

The equation $y = mx + b$ algebraically describes a straight line for a set of data with one independent variable where x is the independent variable, y is the dependent variable, m represents the slope of the line, and b represents the y-intercept. If a line represents a number of independent variables in a multiple regression analysis to an expected result, the equation of the regression line takes the form $y=m_1x_1+m_2x_2+...+m_nx_n+b$ in which y is the dependent variable, x_1 through x_n are n independent variables, m_1 through m_n are the coefficients of each independent variable, and b is a constant.

Linear regression produces the slope of a line that best fits a single set of data based on a year's worth of sales figures. By following the line forward in time, we can estimate future sales, if we can safely assume that growth will remain linear.

Exponential regression produces an exponential curve that best fits a set of data that we suspect does not change linearly with time.

Multiple regression is the analysis of more than one set of data, which often produces a more realistic projection. We can perform both linear and exponential multiple regression analyses.

Using multiple regression analysis the correlations are obtained. In this approach, the values of liquid limit, compression index and plasticity index were taken as inputs to derive the correlations. The figure 7.3 shows the data analysis process for the input values of compression index and liquid limit.

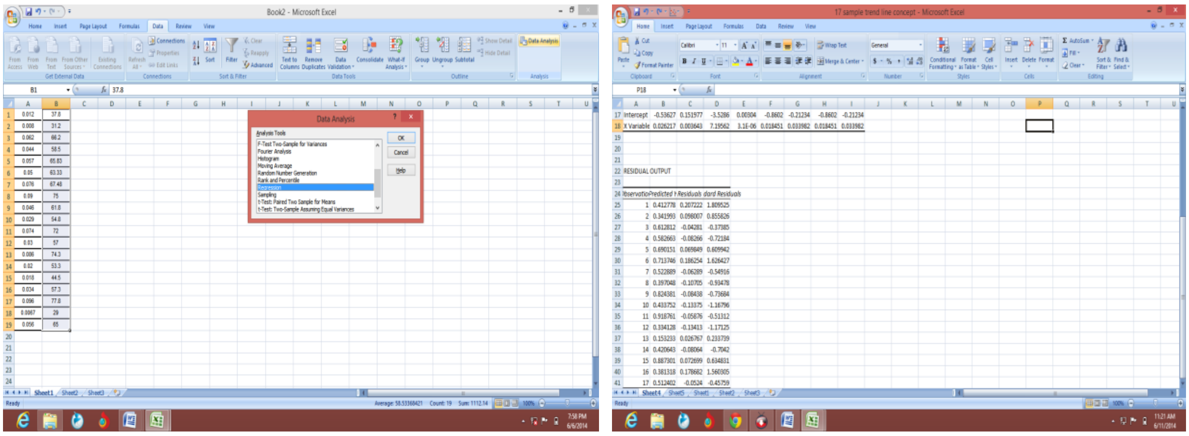

Figure 3 Regression analysis input and output diagram

Two different values of compression index predicted when liquid limit is given as input and plasticity index given as input are shown in Table 3

Table 3 Predicted Values Of Compression Index Using Regression Model (W_l As Input)

S.No	C_O	C_P liquid limit as input	C_P Plasticity index as input	S.No	C_O	C_P liquid limit as input	C_P Plasticity index as input
S1	0.62	0.619959	0.412778	S10	0.3	0.836844	0.433752
S2	0.44	0.413785	0.341993	S11	0.86	0.27455	0.918761
S3	0.57	0.610052	0.612812	S12	0.2	0.038922	0.334128
S4	0.5	0.543112	0.582663	S13	0.18	0.381654	0.153233
S5	0.76	0.654233	0.690151	S14	0.34	0.93056	0.420643
S6	0.9	0.855588	0.713746	S15	0.96	0.587828	0.887301
S7	0.46	0.502145	0.522889	S16	0.56	0.427173	0.381318
S8	0.29	0.314714	0.397048	S17	0.46	0.836844	0.512402
S9	0.74	0.77526	0.824381				

7.3 Artificial Neural Network (Ann)

Neural networks are typically organized in layers. Layers are made up of a number of interconnected 'nodes' which contain an 'activation function'. Patterns are presented to the network via the 'input layer', which communicates to one or more 'hidden layers' where the actual processing is done via a system of weighted 'connections'. Artificial neural networks are computational methodologies that perform multi factorial analyses. Inspired by networks of biological neurons, artificial neural network models contain layers of simple computing nodes that operate as nonlinear summing devices. These nodes are richly interconnected by weighted connection lines, and the weights are adjusted when data are presented to the network during a “training” process. Successful training can result in artificial neural networks that perform tasks such as predicting an output value, classifying an object, approximating a function, recognizing a pattern in multi factorial data, and completing a known pattern. Many applications of artificial neural networks have been reported in the literature, and applications in medicine are growing.

The methodology of ANNs is based on the learning procedure from the data set presented it from the input layer and testing with other data set for the validation. A network is trained by using a special learning function and learning rule. In ANNs analyses, some function called learning functions is used for initialization; training, adaptation and performance function. During the training process, a network is continuously updated by a training function which repeatedly applies the input variables to a network till a desired error criterion is obtained. Adapt functions is employed for the simulation of a network, while the network is updated for each time step of the input vector before continuing the simulation to the next input. Performance functions are used to grade the network results.

In the learning stage, network initially starts by randomly assigning the adjustable weights and threshold values for each connection between the neurons in accordance with selected ANNs model. After the summation of weighted inputs and added the threshold values, they are passed through a differentiable non-linear function defined as a transfer function. This process is continued, until a particular input captures to their output (i.e., target) or as far as the lowest possible error can be obtained by using an error criterion. In other words the network training is the determination of the weights and the biases.

The observed values of the liquid limit, compression index and plasticity index from the experimental results were taken as an input and the ANN mechanism was processed in the hidden layer and outputs was obtained in the form of compression index. The mechanism of ANN modeling is shown in Figure 4

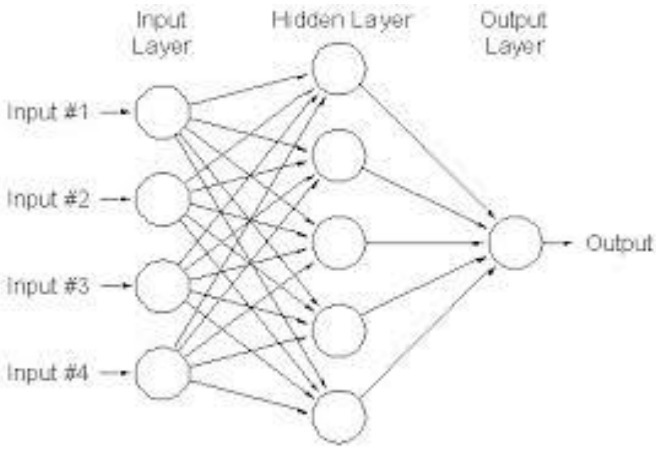

Figure 4 Mechanisms of ANN

The observed liquid limit and plasticity index are given as input and observed compression index is given as target for the ANN modeling. After the values are given as input, the training process will takes place in the developed hidden layer to predict the R value. From the trained results the output values are obtained. Figure 5 shows the R value after training process.

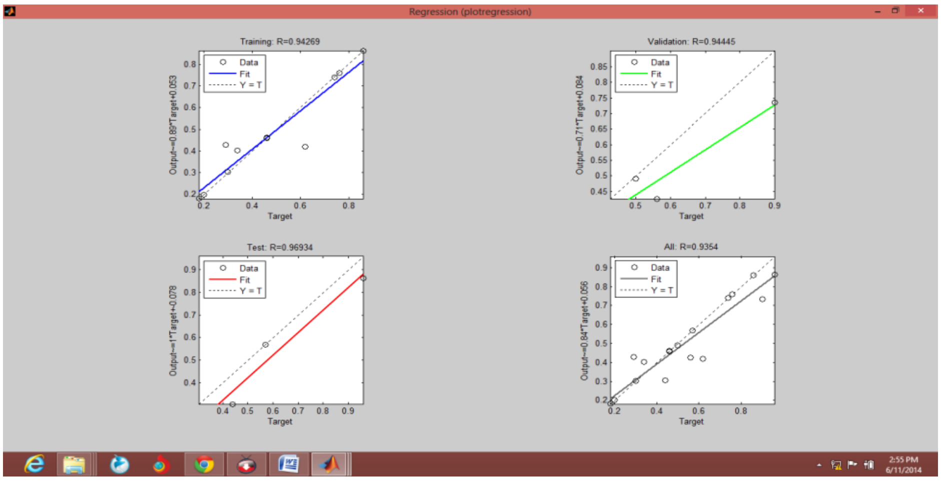

Figure 5 Output after training

By changing the number of hidden layers the R value changes. The maximum R value is obtained by giving 20 hidden layers for the ANN modeling. The correlation coefficient value (R^2) obtained from the output is 0.949. After predicting R value, simulation process is carried out to determine the output values. The simulation diagram of current problem where liquid limit and plasticity index are given as input variables is given in Figure 6.

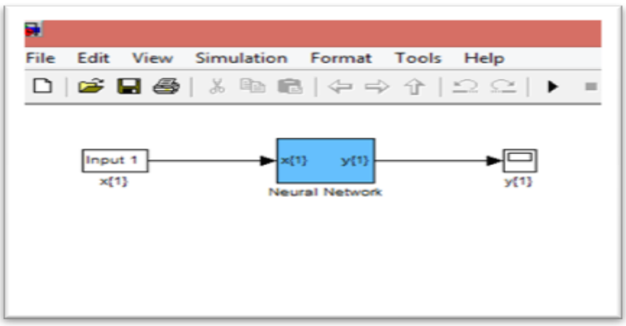

Figure 6 Simulation Diagram in ANN

The output value of simulation process is given in Figure 7 which shows the predicted compression index (c_p).

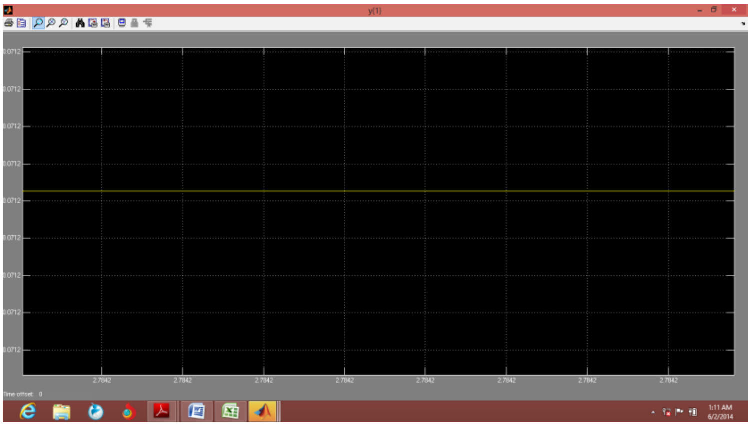

Figure 7 Output after Simulation

Two different type of predicted values of compression index (c_p) using regression model when liquid limit as input and plasticity index as input are shown in Table 3

Table 3 Predicted Values Of Compression Index Using Ann Model

S.No	C_C	C_P liquid limit as input	C_P Plasticity index as input	S.No	C_C	C_P liquid limit as input	C_P Plasticity index as input
S1	0.62	0.5786	0.4189	S10	0.3	0.26	0.303
S2	0.44	0.431	0.305	S11	0.86	0.86	0.86
S3	0.57	0.5692	0.569	S12	0.2	0.2105	0.2
S4	0.5	0.4765	0.4895	S13	0.18	0.18	0.18
S5	0.76	0.848	0.76	S14	0.34	0.3135	0.4015
S6	0.9	0.9	0.7355	S15	0.96	0.9586	0.8635
S7	0.46	0.4674	0.4898	S16	0.56	0.56	0.4264
S8	0.29	0.29	0.4273	S16	0.46	0.495	0.458
S9	0.74	0.797	0.74				

III. Result And Discussions

Correlations from the Regression analysis

The Figure 8 shows the relation between the observed and predicted compression index with liquid limit as input

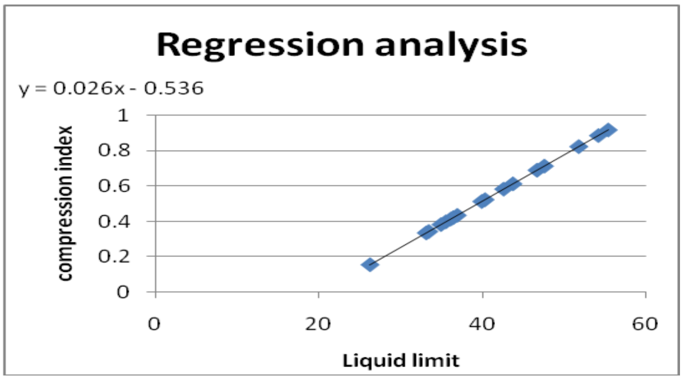

Figure 8 predicted and observed compression index from regression analysis using W_L

The correlation developed for predicted compression index based on liquid limit is given in equation 1

$$C_C=0.0026w_L-1.152 \text{ ------------ } 1$$

The Figure 9 shows the relation between the observed and predicted compression index with plasticity index input.

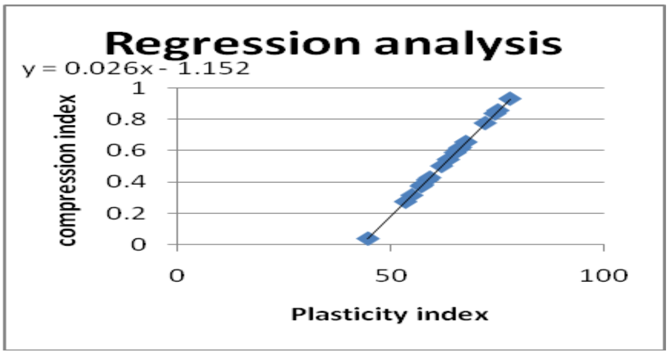

Figure 9 predicted and observed compression index from regression analysis using Plasticity index

The correlation developed for predicted compression index based on plasticity index is given in equation 2

$$C_C=0.026I_P-0.536 \text{ ---------- } 2$$

Correlations from the Artificial Neural Network

The Figure 8.3 shows the relation between the observed and predicted compression index with liquid limit as input.

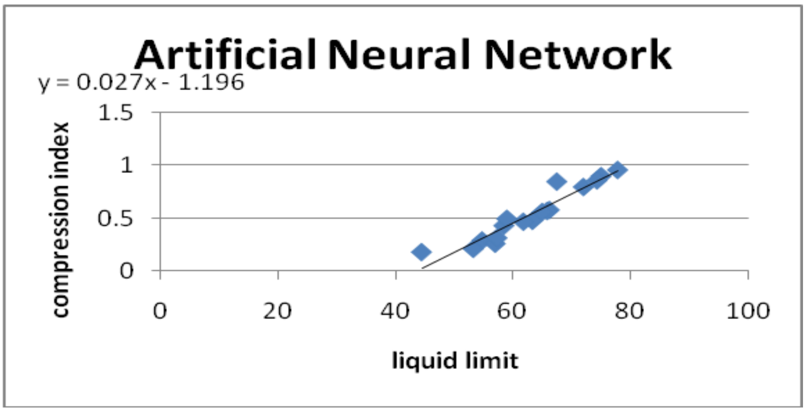

Figure 10 predicted and observed compression index from ANN model using Liquid limit (W_L)

A relationship between compression index and liquid limit was arrived based on the above plot. This is given in equation 3

$$C_c = 0.027w_L-1.196 \text{ ----------- } 3$$

The relation between the observed and predicted compression index with plasticity index as input as shown in fig

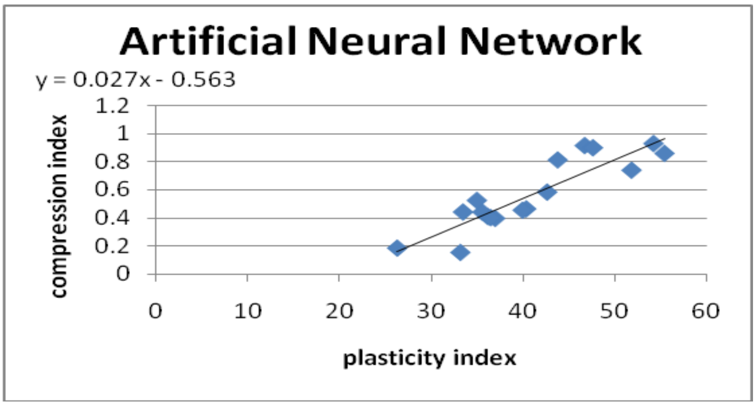

Figure 11 predicted and observed compression index from ANN model using Plasticity Index

A relationship between compression index and plasticity index was arrived from the figure 8.4. This is given in equation 4

$$C_c = 0.025I_P-0.539 \text{ ----------- } 4$$

IV. Discussions

The soil samples collected from twenty locations are tested in the laboratory for its index and engineering properties. The twenty samples,17 samples are classified as CH (Clay of High compressibility
Based on the laboratory results, the compression index values are obtained for the twenty samples. Correlations between compression index, liquid limit and plasticity index are formed using Regression analysis and ANN modeling. The correlation coefficient (R^2) obtained by ANN modeling shows better accuracy than Regression analysis as shown in table 4

Table 4 R^2 Value For Regression And Ann Model

Present approach	Equation	R^2
Regression analysis	C_C=0.0026w_L-1.152	0.939
	C_C=0.026I_P-0.536	0.777
ANN	C_c = 0.027w_L-1.196	0.985
	C_c = 0.025I_P-0.539	0.872

In order to find out the compression index (c_c) value to find the C_C value for the soil, we can use these correlations. From the index properties of the soil samples, we can arrive at the compression index (c_c) value with maximum accuracy without conducting the time consuming consolidation test.

Comparison Of Correlations

The accuracy of present ANN model was checked by comparing the laboratory values of C_C with predicted values of C_C.It was found that for mean target value for input data was 0.537647 whreas the mean target value 0.5409.While the mean target value by proposed by Slamet widodo and Amardeep singh wer 1.05492 and 0.223659.The accuracy of proposed model was also checked by calculating the correlation coefficient (CORR) and it was found that for proposed model was 0.939 whereas for models proposed by Slamet widodo and Amardeep singh were 0.929 and 0.892.The values of compression index predicted using the present model and model proposed by Slamet widodo and Amardeep singh were shown in figure 12.It was found that compression index values predicted using the present model has better distribution around the trend line in comparison of other model.It can be calculated that proposed models are much accurate and are good agreement with laboratory values .

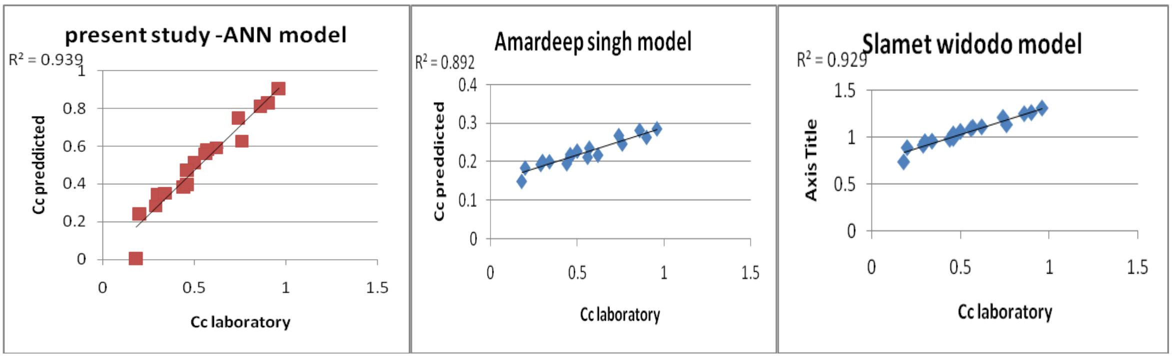

Figure 12 Comparison of Different Empirical equations

- ❖ The correlations obtained based on w_L given as below.

Regression analysis C_C =0.0026w_L-1.152
Artificial Neural Network C_c =0.027w_L-1.196

- ❖ The correlations obtained based on I_P given as below.

Regression analysis C_C=0.026I_P-0.536
Artificial Neural Network C_c = 0.025I_P-0.539

- ❖ Out these two correlations, ANN model shows more goodness of fit and it has higher reliability.

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