



## THE USE OF ARTIFICIAL NEURAL NETWORK (ANN) IN EVALUATING SOAKED CALIFORNIAN BEARING RATIO OF LATERITIC SOILS

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### ARTICLE INFO

### ABSTRACT

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The soaked California Bearing Ratio (CBR) of soil is an important parameter for the design of flexible pavements. Although the traditional method of obtaining the soaked CBR value is time consuming. In this work Artificial Neural Network (ANN) is adopted to estimate the soaked CBR of soils from the soils index properties. Six soil samples were obtained from different borrow pits in Wudil and Ungoggo local government areas of Kano state. The samples were prepared and their Fraction of Fines (FF), Plastic Limit (PL), Liquid Limit(LL), Plasticity Index(PI), Optimum Moisture Content (OMC), Maximum Dry Density (MDD), and the soaked CBR values were measured in the laboratory. Four neural network models were developed, in which three are of dynamic neural network and one model is of static neural network. Each of the models was trained with different number of soils data for training, testing, and validating the network. Out of the four models, dynamic neural network with Non-linear input-output model with a regression equation of  $0.99 \cdot T + 0.053$ , correlation coefficient of 0.998 network architecture of 6~10~1, training performance of  $3.83 \cdot 10^3$  and mean square error of 0.45585 gives the best predicted result.

### 1.0 INTRODUCTION

The intricacy of most of the engineering problems has made experts of this field use the new mathematical and modeling methods for solving these type of problems. Intelligent systems for identifying complex problems can be used as suitable tools due to their capability of adaptation and learning,(Isma'il 2015, and Vahid 2009). California Bearing Ratio test is an important field/laboratory test in geotechnical engineering. It is performed to assess the resistance offered by sub-grade layer of soil or in the foundation of a structure viz. earth dams, highway embankments, bridge abutments and retaining wall fills. The strength of soil can be considered to be indexed by its CBR values,(Craig 2004).

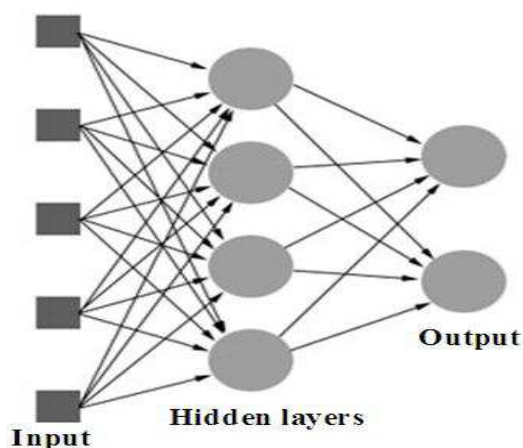
CBR test is a time consuming and expensive test in addition to the difficulty encountered in

conducting the test. As such these problems were overcome through the use of other methods such as regression based models (both single and multiple) and ANN models. Soil properties like LL, PL, OMC, MDD and percentage passing 75micron sieve are determined and used to develop models for correlating the soaked CBR value (Rakaraddi and Gomarsi, 2015).

An artificial neuron is a computational model inspired in the natural neurons. ANN is a mathematical model of human intelligence that intimates the human nervous system. They are structured in the same pattern as the human brain. It consist of a series of processing elements called nodes which are arranged in input, output, and one or more hidden layers.

The input layer is the node where the propagation of information begins and where the networks input data are presented, the hidden layer is the node at which the network modifies its weights on the presentation of data and the processing of the data to produce an output with the smallest possible error, and the output layer is where the processed data is presented as the fit back of the network (Cheung and Cannons, 2002). The structure consist of many neurons connected to each other and each neuron is a processing unit that performs a calculation on the input signal and outputs the result to the next neuron via connections. The connections indicate the flow of information from one neuron to another as shown in **figure1** below (Sudhir and Pradeep 2014). The neural network is classified into; dynamic and static groups. Static neural network have no feed

back elements and contain no delay, the output is calculated directly from the input through feed forward connections. The response of this network last as long as the input pulse. The sequence of inputs does not affect the simulated response of the network but might affect the way in which the network is trained. While in dynamic neural networks, the network is divided into two categories; those that have only feed forward connections and those that have feed back. Its response at any given time depends not only on the current input but on the history of the input sequence. The response of the dynamic network lasts longer than the input pulse. They are more powerful than static neurons and posses memory which makes it capable of learning time varying patterns when trained (Dhinakaram and Venkatasubramanian, 2011).



**Fig. 1: The Architecture of Neural Network**

California bearing ratio test is a penetration test of compressive nature. It was initiated by Caltrans California department of transportation after world war II in the late 1930s. The test is mainly used to examine the mechanical strength as well as the potential strength of road subgrades and base course materials including the recycled material used for road and air field pavements (Civil Engineering Blog, 2013). The test can be performed in the laboratory on undisturbed or compacted remoulded specimens in water soaked or unsoaked conditions, however CBR values are highly dependent on the condition of the material at the time of testing. In the

field, the test can be performed at ground surface or in a test pit, trench, on a level surface. The test on crushed stone is defined to have a CBR value of 100 percent and the corresponding load is called Standard Load. 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 (AIJRSTEM, 2014). ANN model with levenberg Marquardt (LM) algorithm was found to be able to learn the relationship between CBR and subgrade soil properties; Optimum Moisture Content, Maximum Dry Density, Liquid Limit, Plastic Limit, and Plasticity Index.

The LM algorithm with an architecture of 5-6-1 and transfer function (Tanh Axon) was found to possess a correlation coefficient of 0.933 and root square value of 0.87. The CBR predicted from this algorithm and the laboratory obtained CBR were compared, the relation showed a correlation coefficient of 0.998 and root square value of 0.996. The LM was recommended as an alternative method for determining CBR as it is precise, economical and rapid than laboratory methods (Saklecha et al 2013). CBR test is a time consuming and expensive test in addition to the difficulty engaged in conducting the test. As such these problems were overcome through other methods such as regression based models (both single and multiple). Soil properties like LL, PL, OMC, MDD and percentage passing 75micron sieve are determined and used to develop models for correlating the soaked CBR value. In the study LL was considered to have higher priority for predicting soaked CBR value followed by OMC,PI,MDD based on assessment from root-square  $R^2$ . From the correlation  $CBR = 0.275LL + 0.118PL + 0.033F + 5.106G$  and  $R^2 = 0.961$  (Rakaraddi and Gomarsi, 2015). The neural network is classified into; dynamic and static groups. Static neural network have no feed back elements and contain no delay, the output is calculated directly from the input through feed forward connections. The response of this network last as long as the input pulse. The sequence of inputs does not affect the simulated response of the network but might affect the way in which the network is trained. Dynamic neural network is divided into two categories; those that have only feed forward connections and those that have feed back. Its response at any given time depends not only on the current input but on the history of the input sequence. The response of the dynamic network lasts longer than the input pulse. They are more powerful than static neurons and possess memory which makes it capable of learning time varying patterns when trained. (Beale et al, 2015). ANN is a multilayer perception network with feed forward back propagation. The network is used to cope up the complexities in solving Engineering problems. The network was used

on 50 soils test data obtained from the laboratory and was found to be quite satisfactory in predicting the soils CBR after being fed with OMC, MDD, LL, PI, and FF. In this research, 30 soils data were used for training the network and the remaining 20 soils data were used for testing the network using 60-40 distribution. The architectures developed were 5-4-1, 5-5-1 and 5-6-1. The 5-6-1 architecture was observed to be adequate (Vaddi et al, 2015). ANN was used in predicting the soaked CBR of a stabilized expansive soil. Three models (BRNN, LMNN, DENN) of the neural network were developed. The models were developed using different training algorithms, the BRNN was observed to possess a correlation coefficient of 0.99 and 0.98 in training and testing phase of the network respectively and a root mean square error of 0.98 and 0.90 in training and testing phase respectively, DENN was found to possess a correlation coefficient of 0.91,0.93 in its training testing phases respectively and root mean square error of 0.87,0.82 in the training and testing phases respectively. The predicted values and laboratory CBR values were correlated and a correlation coefficient of 0.99 and 0.98 were observed for training and testing data respectively (Sabat 2015). Before the advancement of Artificial neural network, regression models were used for predicting CBR values in flexible pavement. The neural network model has the ability to predict output precisely even for unseen new data. This characteristic of neural network is termed as generalization, in that by means of the modeling process . ANN detects the general pattern (hidden relation) between input and output using the data only without requiring any prior knowledge on the problem. As such neurons are non linear calculation units. (Rani et al, 2013). The CBR of fine grained soil was estimated by applying artificial neural network(ANN) and multiple linear regression(MLR) in which the CBR was correlated with soil properties such as optimum moisture content(OMC) and maximum dry density(MDD) of modified proctor compaction test, liquid limit(PL), plastic limit(PL), plasticity index(PI), and percentage of fines.

In this study 40 soils data were used for the research and was found that the predicted CBR from ANN was better than that from MLR. Also ANN is more accurate and efficient than MLR.(Harini and Naagesh, 2014). ANN models have been developed using multilayer perception neural network (MLPN) and general regression neural network (GRNN) algorithms with elementary soil parameters; fraction of fines, liquid limit, plasticity index, optimum moisture content, and maximum dry density as inputs and California bearing ratio as output. The MLPN posses varying learning rate moments of 0.01,0.03,0.05 and momentum coefficients of 0.5 and 0.7. The developed MLPN algorithm also posses root square ( $R^2$ ) and mean square error (MSE) values of 0.97 and 0.52 respectively during its training phase, and  $R^2$  and MSE value of 0.71 and 3.88 respectively during the testing phase of the network, and this algorithm was regarded as fairly good in predicting CBR. GRNN algorithm posses a varying radius of (0.1 to 0.5). It posses  $R^2$  and MSE value of 0.99 and 0.02 during the training phase and  $R^2$  and MSE of 0.98 and 0.22 respectively during the testing phase of the network. GRNN was regarded as a more precise tool than MLPN. It was concluded that GRNN better predict CBR for remoulded soil (Saxena et al 2013).

## **2.0 METHODOLOGY AND MATERIALS**

Data were collected through experimental works and with the data obtained, the design and training of the neural network was the first phase of neural network development process using Matlab 2013 version. At this phase the network was with a set of known input-output patterns.

The dissemination of information in artificial neural network begins at the input layer

where the input data are presented. The neural network modify its weights on the presentation of a data set, the network uses its learning rule to find a set of weights that will produce the input/output mapping that has the minimal possible error, this process is called the training phase. After this phase (the training phase), the performance of the model is validated using an independent data set, this process is called the training phase. The weight factors of the nodes were adjusted until the inputs yield the desired output.(Gersheson 1997). The California bearing ratio of the different soil samples used was predicted from the inputs(fraction of fines, liquid limit, plastic limit, plasticity index, optimum moisture content, maximum dry density) and a target data (Laboratory obtained CBR).The prediction was conducted using both the static and dynamic categories of the neural network, in which the neural fitting tool which is of static feed-forward neural network.. The neural times series posses three activation functions namely; Non-linear aggressive regression with external input (NARX), Non-linear auto regressive (NAR) and the Non-linear Input-Output functions. Both networks and activation functions were used in the work. In order to obtain the predicted CBR of soil using artificial neural network, numerous soil data are required to achieve such an aim (Saklecha et al 2013). In this research 50 soils data were used, in which 6 soils data were obtained from KUST geotechnical engineering laboratory and 44 soils data were obtained from the international journals (JMCE,2014), (IJETA,2014), (JEES,2014) and (IJCSE,2013) in order to facilitate and obtained accurate results.

**4.0 RESULTS AND DISCUSSION**

The laboratory obtained and predicted soaked CBR are as shown below:

**Table 1:** Summary of Soil index properties, laboratory and predicted soaked CBR results

FF(%)	LL(%)	PL(%)	PI(%)	OMC(%)	MDD (Kg/m <sup>3</sup> )	Lab CBR	NNFIT	NARX	NAR	NIO
64	49.4	27	22.4	18.2	1.74	3.28	3.41	3.8676	5.052	3.3002
71	61	26	35	23.1	1.45	1.06	1.19	1.8252	3.054	1.1024
72	64	39	25	26	1.45	2.03	2.16	2.7176	3.927	2.0627
31	34	24	10	12.12	1.98	4.18	4.31	4.6956	5.862	4.1912
77	57	30	27	22	1.59	2.79	2.92	3.4168	4.611	2.8151
63	45	25	20	21.05	1.6	3.2	3.33	3.794	4.98	3.221
64	52	28	24	23.2	1.6	1.56	1.69	2.2852	3.504	1.5974
72	58	30	28	19.8	1.63	2.54	2.67	3.1868	4.386	2.5676
71	66	40	26	22.1	1.61	2.05	2.18	2.736	3.945	2.0825
42	39	22.5	16.5	15.82	1.8	3.45	3.58	4.024	5.205	3.4685
72.85	28.46	20.24	8.22	14.56	1.65	5.56	5.69	5.9652	7.104	5.5574
68.71	34.62	26.65	7.97	15.11	1.7	5.62	5.75	6.0204	7.158	5.6168
68.71	34.92	27.4	7.52	15.2	1.71	5.77	5.9	6.1584	7.293	5.7653
169.22	35.2	27.51	7.69	15.35	1.69	5.69	5.82	6.0848	7.221	5.6861
58.77	34.42	27.47	6.95	15.62	1.72	5.81	5.94	6.1952	7.329	5.8049
62.38	29.35	23.23	6.12	14.39	1.77	6.12	6.25	6.4804	7.608	6.1118
63.55	30.34	23.78	6.56	14.92	1.76	6.1	6.23	6.462	7.59	6.092
70.21	36.78	28.32	8.46	15.82	1.64	5.72	5.85	6.1124	7.248	5.7158
68.71	32.21	25.69	6.52	14.42	1.75	6.2	6.33	6.554	7.68	6.191
71.21	34.25	27.53	6.72	14.16	1.74	6.05	6.18	6.416	7.545	6.0425
54.1	85.5	18.3	67.2	18.2	1.74	11	11.13	10.97	12	10.943
50.1	50.5	12	38.5	14.2	1.85	26	26.13	24.77	25.5	25.793
68.3	88.5	31.4	57.1	17.4	1.55	8	8.13	8.21	9.3	7.973
38.1	46	14.2	31.8	10.2	2.03	30	30.13	28.45	29.1	29.753
57.9	71.5	9.8	61.7	17.2	1.5	16	16.13	15.57	16.5	15.893
4	36	29	7	12	14.53	2.77	2.9	3.3984	4.593	2.7953
25	38	32	6	11	17.27	1.05	1.18	1.816	3.045	1.0925
9.97	49	43	6	12	15.5	3.44	3.57	4.0148	5.196	3.4586
5	30	25	5	12	14.22	3.17	3.3	3.7664	4.953	3.1913
21	28	22	6	11	16.19	2.37	2.5	3.0304	4.233	2.3993
27	42	36	6	10	15.69	1.58	1.71	2.3036	3.522	1.6172
12	60	54	6	11	15.79	1.19	1.32	1.9448	3.171	1.2311
26	35	27	8	9.09	14.22	3.08	3.21	3.6836	4.872	3.1022
9.99	30	21	9	10	14.23	2.14	2.27	2.8188	4.026	2.1716
12.6	26	17	9	10	14.13	1.45	1.58	2.184	3.405	1.4885
19.96	29	18	11	12.6	2.2	9.2	9.33	9.314	10.38	9.161

Table 1 continue

FF(%)	LL(%)	PL(%)	PI(%)	OMC(%)	MDD (Kg/m <sup>3</sup> )	Lab CBR	NNFIT	NARX	NAR	NIO
85.12	78	43	35	29.8	1.42	0.48	0.61	1.2916	2.532	0.5282
70.27	72.5	28	44.5	28.6	1.45	1.33	1.46	2.0736	3.297	1.3697
42.05	47	21.5	25.5	20	1.66	3.16	3.29	3.7572	4.944	3.1814
90.04	37	16.14	20.86	16.2	1.85	8.82	8.95	8.9644	10.038	8.7848
54.8	59	22	37	25	1.54	2.26	2.39	2.9292	4.134	2.2904
38.24	26	15.5	10.5	9.2	1.27	2.11	2.24	2.7912	3.999	2.1419
61	60	54	6	22.1	2.05	4	4.13	4.53	5.7	4.013
40	29	17	12	11	2	6.11	6.24	6.4712	7.599	6.1019
0.11	39.65	27.2	12.45	16.4	1.88	25.35	25.48	24.172	24.915	25.1495
7.49	41.4	35.6	5.8	15.2	2.232	43	43.13	40.41	40.8	42.623
2.09	36.13	31.5	4.63	16.6	1.81	40.75	40.88	38.34	38.775	40.3955
3.07	27.89	25.2	2.69	11.7	2.01	77.75	77.88	72.38	72.075	77.0255
4.7	22	20.7	1.3	11.9	2.03	22.5	22.63	21.55	22.35	22.328
2.4	36.22	35.7	0.52	12.7	1.94	26	26.13	24.77	25.5	25.793

The table above shows a summary all the input data used in developing the neural network models and the predicted results of each network model developed. In NNFIT is the result for neural network fitting tool

model, NARX is the result for nonlinear autoregressive with external output model, NAR is the result for non linear autoregressive model, and NIO is the result for the nonlinear input output model.

Table 2: Performance of the Neural Network models

Models	MSE		Network Structure	Correlation Coefficient
	Training	Testing		
NNFIT	7.16769e-2	601.86712e-0	6~10~1	0.99975
NARX	9.31312e0	786.75483e-0	6~10~1	0.98211
NAR	18.65530e-0	22.25506e-0	1~15~1	0.96357
NIO	4.5585e-1	119.59304e-0	6~10~1	0.99806

The above table shows the network properties of the used models. In which the MSE is the mean square error for each model during the training and testing phase of the

network. The network structure shows the number of inputs to number of neurons used by the network during prediction and the number of output.

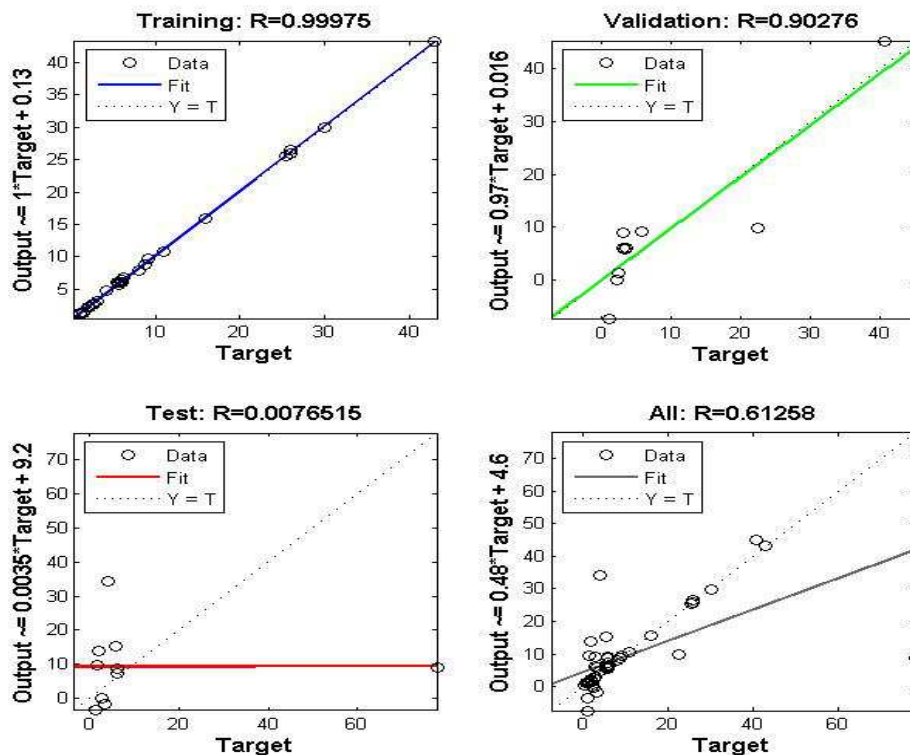


Figure 1: Neural fitting tool regression plot (NNFIT)

This network model uses 60% (30) of the soils data for training the network, and 20% (10) each for training and testing the network. An architecture of 6~10~1 meaning six inputs in the input layer, 10 neurons within the hidden layer were used to generate the network, and one output was produced in the output layer of the network. From figure 1 above; it consists of four plots, the plot at the top left hand corner is a plot displaying the relationship between the network training

data and the target data (laboratory CBR), the plot at the bottom left corner displays the relationship between the network’s testing data and the target data (laboratory CBR). Also the plot at the top right and bottom right corner of the figure displays the relationship between data used for validating the tested data of the network and the target data (laboratory CBR). And the predicted results were presented in table 1 above.

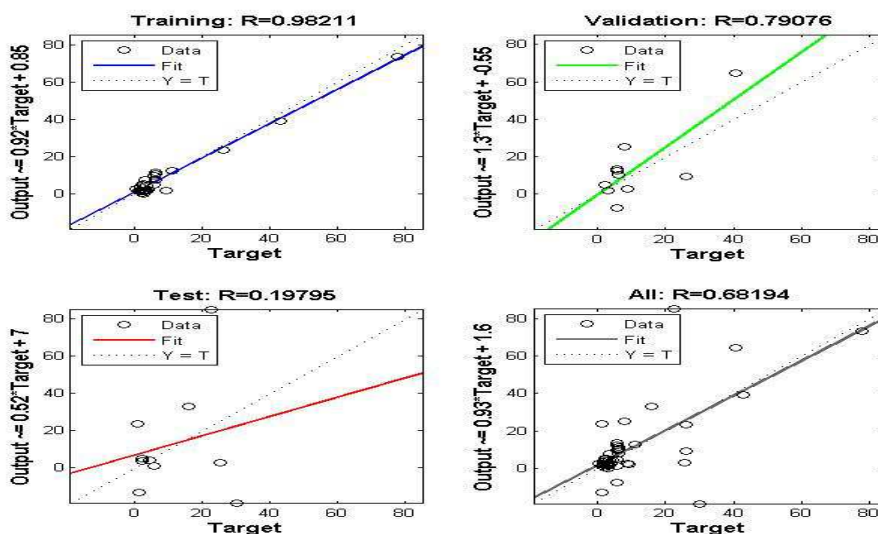


Figure 2: NARX regression plot

This network model uses 60% (30) of the soils data for training the network, and 20% (10) each for training and testing the network. An architecture of 6~10~1 meaning six inputs in the input layer, 10 neurons within the hidden layer were used to generate the network, and one output was produced in the output layer of the network. From figure 1 above; it consists of four plots, the plot at the top left hand corner is a plot displaying the relationship between the network training

data and the target data (laboratory CBR), the plot at the bottom left corner displays the relationship between the network’s testing data and the target data (laboratory CBR). Also the plot at the top right and bottom right corner of the figure displays the relationship between data used for validating the tested data of the network and the target data (laboratory CBR). And the predicted results were presented in table 1 above.

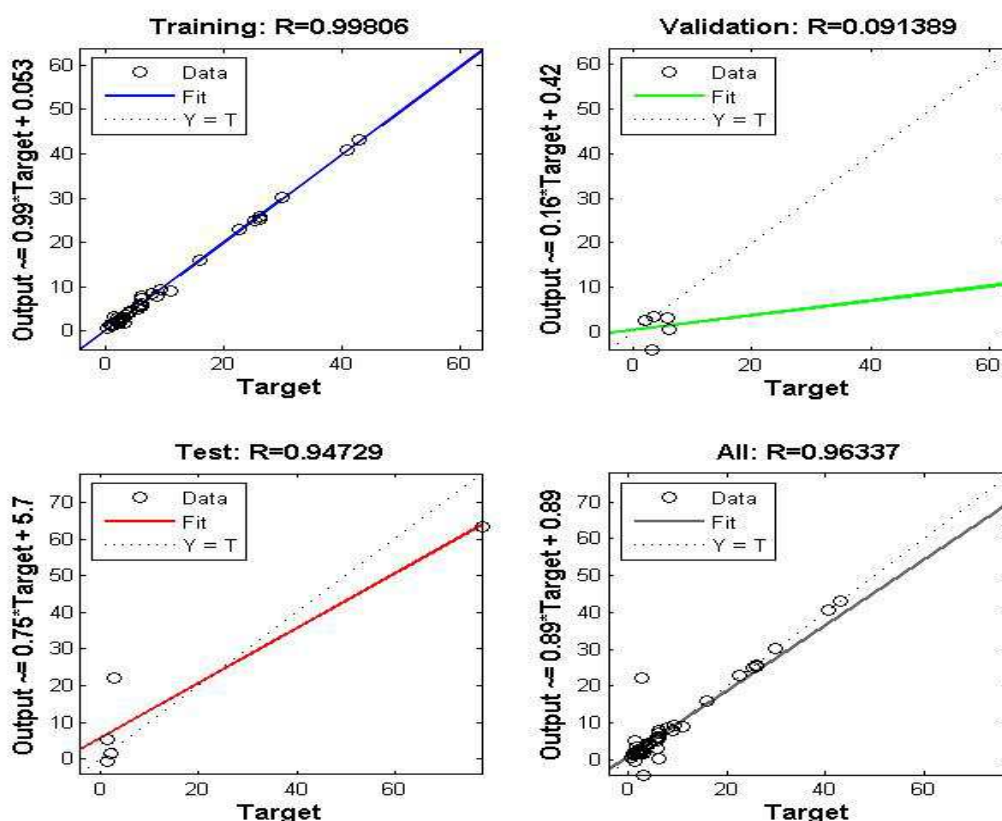


Figure 3: Non-linear input-output time series (NIO) regression plot

This network model uses 80% (40) for training the network, and 10% (5) each for training and testing the network. An architecture of 6~10~1 meaning six inputs in the input layer, 10 neurons within the hidden layer were used to generate the network, and one output was produced in the output layer of the network. From figure 3 above; it consists of four plots, the plot at the top left hand corner is a plot displaying the relationship between the network training data and the target data

(laboratory CBR), the plot at the bottom left corner displays the relationship between the network’s testing data and the target data (laboratory CBR). Also the plot at the top right and bottom right corner of the figure displays the relationship between data used for validating the tested data of the network and the target data (laboratory CBR). And the predicted results were presented in table 1 above.



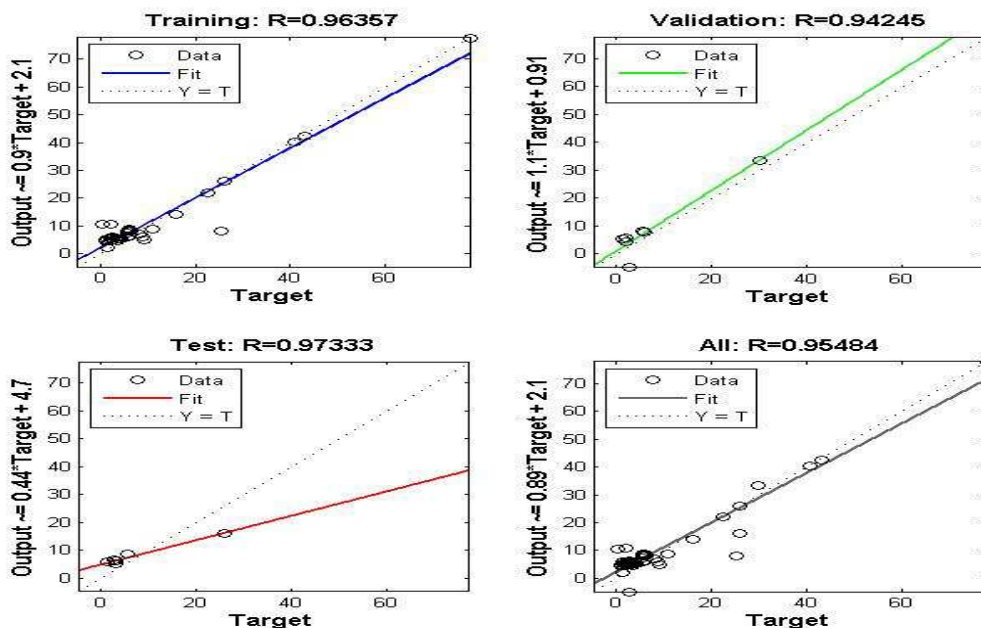


Figure 4: NAR regression plot

This network model uses 70% (34) of the data for training the network, and 15% (8) each for training and testing the network. An architecture of 1~15~1 meaning one input in the input layer, 15 neurons within the hidden layer were used to generate the network, and one output was produced in the output layer of the network. From figure 4 above; it consists of four plots, the plot at the top left hand corner is a plot displaying the relationship between the network training data and the target data (laboratory CBR), the plot at the bottom left corner displays the

relationship between the network’s testing data and the target data (laboratory CBR). Also the plot at the top right and bottom right corner of the figure displays the relationship between data used for validating the tested data of the network and the target data (laboratory CBR). And the predicted results were presented in table 1 above. This neural network tool (NAR) has a different feature from the other three(3) tools used, as in its case only the target data is required to predict the required result.

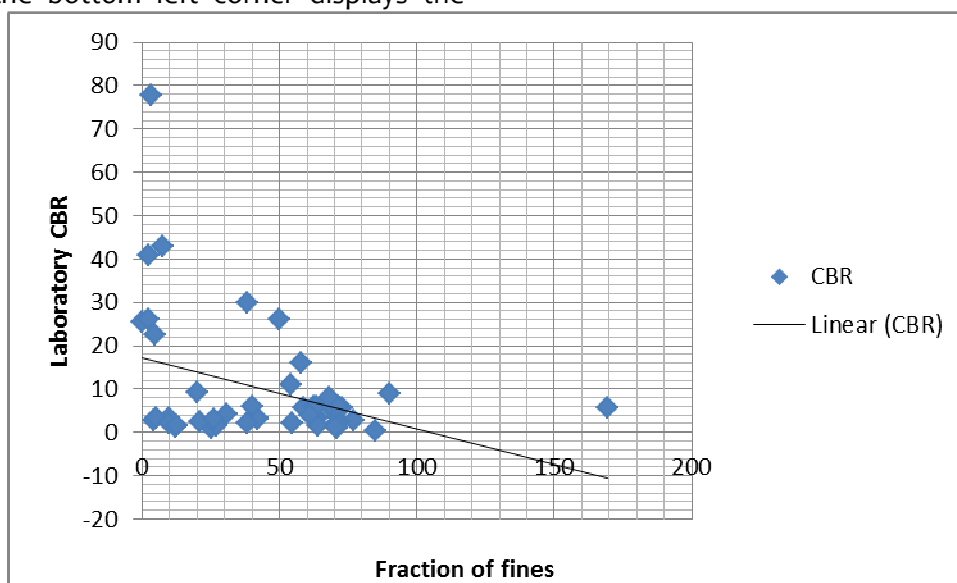


Figure 5: Correlation between CBR and Fraction of fines

From results obtained, it was observed that the liquid limits and plastic limits were less than 50%, the fraction of fines (FF) for all samples were observed to be less than 10%, the Maximum dry density of sample A, C and F was observed to be less than  $200\text{kg/m}^3$  and that of B, D and E are greater than  $200\text{kg/m}^3$ . Optimum Moisture Content and plasticity index for all samples were observed to be less than 20%. Also the relationship between the laboratory obtained CBR and the fraction of fines shows that the CBR decreases with increase in the fraction of fines.

From **figure 5** above, it was observed that the soaked CBR increases with decrease in fraction of fines of the soils. This is because soils with finer particles possess less strength than those with larger particles.

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#### 5.0 CONCLUSION

It was concluded that four models were used for the prediction of California bearing ratio each with six independent variables (inputs) and one dependent variable (target CBR). From the developed neural network models, three (3) are of dynamic neural network and one model is of static neural network. Each of the models was trained with different number of soils data for training, testing, and validating the network. Out of the four models, dynamic neural network with Non-linear input-output (NIO) model gives the best predicted result with best regression of  $0.99T+0.053$ , mean square error of 0.45585, 34 iterations and training performance of  $3.83 \times 10^3$  predicts the best result.

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