DEVELOPMENT OF MODELS FOR PREDICTING CALIFORNIA BEARING RATIO OF LATERITIC SOIL USING SELECTED SOFT COMPUTING TECHNIQUES

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ABSTRACT
Models for predicting the California bearing ratio values of lateritic soil was developed using soft computing techniques. Soft computing techniques are algorithm which find provably correct and optimal solutions to problem. The Soaked CBR values used in pavement design takes about 96 hours to complete the test process. This can be time-consuming and expensive, Hence the need for researches to seek for alternate means of obtaining it. Several researchers have employed the use of Artificial Neural network (ANN), Gene expression programming (GEP), Support Vector machine (SVM) and Deep neural network (DNN) to predict CBR values, these models have inherent limitations such as sensitivity to hyper-parameters, limited flexibility and lack of interpretability. This study proposes a new model to address this challenge, Artificial Neural Networks (ANN) and its hybrid (ANFIS) were considered. Soil samples were collected from a burrow pit and required tests were conducted on the collected soil samples, Tests carried out are index, compaction and California bearing ratio. The experimental result data was augmented from data gotten from previous research work (unpublished) in same study area. The result gotten was used for training the models. 70% of the data was used for training and the remaining for the validation of the models. Two different models were developed and the performance of each model was measured by the coefficient of determination (R^2), Mean Square Error (MSE) and Root mean square Error (RMSE). Upon analyzing the result, the both models ANN and ANFIS demonstrated high accuracies but ANFIS model gave a higher predictive accuracy of 0.98 as R^2, RMSE of 0.11 and MSE of 0.33. ANFIS Model demonstrated exceptional accuracy and precision in capturing complex relationships within the data and hence should be adopted in the prediction of CBR values of lateritic soil.

Keywords: *Soft Computing Techniques, California Bearing Ratio, Index Properties, Lateritic soil*

Introduction

Soft computing Techniques have significantly gained popularity in recent years due to their ability to handle complex and non-linear problems. one domain where these techniques have been successfully employed is the prediction of California bearing ratio values [22]. CBR test is a strength test used worldwide by civil Engineers in the design of flexible pavements, in order to design this pavement, there is need to assess the strength of the

material underneath (subgrade soil). The process of pavement design focuses on estimating the required thickness of every layer to safely transfer the load to the soil without exceeding the soil strength in order to avoid failure.[24, 23]

The subgrade layer serves as the foundation of a road pavement and the wheel load from the pavement surface is distributed to the sub-grade [24]. The value of the California bearing ratio (CBR) test is an index making it possible to evaluate the load of the foundation soil and the resistance of the pavement materials [7]. The strength characteristics of this soil reveals it response when use as a construction material. The failure of some engineering infrastructures such as road pavement, retaining walls have been attributed to this strength behavior [4].

The subgrade must be able to support loads transmitted from the pavement structure. This load-bearing capacity is often affected by degree of compaction, moisture content, and soil type. A subgrade having a California Bearing Ratio (CBR) of 10 or greater is considered essential and can support heavy loads and repetitious loading without excessive deformation. [25].
Since CBR value is typically obtained through laboratory tests, which can be time-consuming and expensive. Therefore, it is very important for geotechnical engineers to quickly predict the behavior of geo-materials used in the infrastructure [28].

Index properties of soil are used to characterize soils and determine their basic properties such as moisture content, specific gravity, particle size distribution, consistency and moisture-density relationship. Index property like particle size distribution which gives the percentage of various sizes of particles in a dry soil sample affects the CBR in such a way that as the percentage of gravel increases CBR value also increases since bearing capacity of granular soil will be more, but as the percentage of silt & clay increases CBR value decreases since it may easily undergo settlement and bearing capacity of soil will be lesser compare to granular soil. Liquid limit of cohesive soil will be more because in cohesive soil percentage of silt & clay will be more which increases the surface area available for binding moisture, meanwhile it decreases the CBR value, and it is vice versa in case of granular soils. Hence in general we can say that liquid limit as well as plastic limit of soil inversely affects its CBR value. Dry density is one of the main index properties which affects CBR value directly, i.e., as dry density increases CBR value also increases. Dry density is a measure of degree of compaction, at maximum compaction bearing capacity of soil will be more, which increases CBR value as well as dry density. Increase in moisture content will increases dry density to maximum and it tends to decrease as water content increases, hence water content at which maximum dry density occurs is termed as optimum moisture content which will be used to measure CBR of soil.

An Artificial neural network (ANN), also known as Neural Network (NN), is a machine-learning technique that was developed with the purpose of creating machines that can mimic the brain. A neural network is a collection of artificial neurons that are linked together (Artificial neural network, [10, 9]. They are physical cellular systems that are capable of acquiring, storing, and applying experiential knowledge. The ANN, like the human brain, learns from the instances it encounters. The learning process in the human brain system includes changes to the synaptic connections between neurons [14]. During the learning phase, artificial neural networks modify their structure in response to input and output data, a process that resembles the information processing system in the human brain [15].

An adaptive neuro-fuzzy inference system or adaptive network-based fuzzy inference system (ANFIS) is a kind of artificial neural network that is based on Takagi–Sugeno fuzzy inference system. The technique was developed in the early 1990s. [13,14]

Since it integrates both neural networks and fuzzy logic principles, it has potential to capture the benefits of both in a single framework.

Its inference system corresponds to a set of fuzzy IF–THEN rules that have learning capability to approximate nonlinear functions. [1] Hence, ANFIS is considered to be a universal estimator.

The training algorithm uses a combination of the least-squares and backpropagation gradient descent methods to model the training data set. fis = anfis (trainingData, options) tunes an FIS using the specified training data and options

ANFIS is a framework of neuro-fuzzy model that can integrate human expertise as well as adapt itself through learning

The Artificial Neural Network (ANN) is a computational model inspired by the functioning of biological nervous systems, such as the human brain. ANNs have the ability to learn and generalize from input data, even when it contains errors or is incomplete. Similar to how humans learn through examples, ANNs are powerful tools for solving complex engineering problems. The processing elements in a neural network resemble neurons in the brain and consist of simple computational elements organized in layers. [8,19]. They typically include an input layer, one or more hidden layers, and an output layer.

One effective estimation technique for complex problems is the Adaptive Neuro-Fuzzy Inference System (ANFIS). ANFIS combines the capabilities of fuzzy logic and neural networks and offers the learning ability of ANNs to establish and utilize correlations between input and output elements. Supervised learning is employed in ANFIS, which consists of a learning algorithm, multilayer feed forward networks that incorporate input/output variables, and fuzzy rules [15].

Literature Review

Several researchers have carried out experimental studies on the use of soft computing techniques for predicting the California bearing ratio (CBR) values of lateritic soil. For instance, Taskiran [26] used artificial neural network (ANN) and gene expression programming (GEP) for the prediction of CBR of fine-grained soils from Southeast Anatolia Region/Turkey. The study results have shown that both ANN and GEP are able to learn the relation between CBR and basic soil properties.

Another study carried out by Ho and Tran [11]. Used twelve machine learning techniques (6 single models and 6 hybrid models). The single models include artificial neural network (ANN), gradient boosting (GB), extreme gradient boosting (XGB), random forest (RF), support vector machine (SVM), and K-nearest neighbors (KNN), while the six hybrid models are a combination of these single models and random restart hill-climbing optimization (RRHC) to estimates the CBR of stabilized soil. The study models were constructed based on eleven input variables, including cement, Atterberg's limits, optimum moisture content (OMC), maximum dry density (MDD), and dust and ashes.

Furthermore, Al-Busultan *et al.* [5] applied Artificial Neural Networks in Predicting Subbase CBR Values Using Soil Indices Data and the results showed that the ANN model successfully predicted the CBR value using soil index data.

The result of Various machine learning methods including artificial neural network (ANN), deep neural networks (DNN) and gene expression programming (GEP) that have been previously employed to predict CBR values has inherent limitations such as sensitivity to hyper-parameters, limited flexibility, lack of interpretability which raise concerns in critical decision-making applications.

Chukwuemeka [6] also applied Artificial Neural Networks in Predicting CBR Values of Soils in Nigeria from their index properties and the result showed that the ANN model successfully predicted the CBR value using soil index data.

Materials and Method

Materials

The material for this study is lateritic soil which was gotten from Taliba farm and maikukenle area of Minna, Niger state. The samples collected was prepared in accordance with [2,3] Prior to preparing the test specimens, the materials were air – dried and broken into smaller fragments. Test was done at the Engineering Laboratory of the Federal University of Technology, Minna.

Methods

Grain size analysis

For coarse grained materials, the grain size dispersion is controlled by passing soil specimen each by wet or dry shaken through a progression of sieves putted in direction of decreasing standard opening sizes plus a pan at the bottom of the stock. At that point the percent passing on each sieve is utilized for additional distinguishing the distribution and gradation of various grain sizes. In this study, the test was done in accordance to [3]

Atterberg limits

The three Atterberg limits which are liquid limit, plastic limit point and shrinkage limits are the limit between every one of the two sequential states of the soil water stages. The test is performed uniquely on that segment of a soil which passes the 425mm. in this study, it was done in accordance according to the system of [3].

Moisture content (MC)

The moisture content (MC) of a material refers to the proportion of water present in that material, expressed as a percentage of its dry weight.

To determine the moisture content, the material is subjected to an oven-drying process, and the loss of water is measured. In this study, the moisture content test is done in accordance to the systems of AASHTO T 265 Equation 3.1 was used to calculate the moisture content of the lateritic soil

$$\text{Moisture content} = \left[\frac{W2-W3}{W3-W1}\right] \text{x } 100 \qquad (3.1)$$

Weight of empty moisture can = W1
Weight of moisture can + sample (wet) = W2
Weight of moisture can + sample (oven – dried) = W3

Natural Moisture content			
Trial No	**1**	**2**	**3**
Wt. of Can	19.7	19.1	15.9
Wt. of Can + Wet sample (g)	34.8	30.7	27.2
Wt. of Can + Dry sample (g)	32.7	29.1	25.6
Moisture content (%)	16.15	16.00	16.49
Avg. Moisture content (%)		**16.22**	

California bearing ratio (CBR)

The California bearing ratio (CBR) test is done to measure the strength characteristic of soil. For this study soaked CBR value is used and was determined using Modified AASHTO T-180 method The loads for 2.5mm and 5mm are recorded, and the CBR value is calculated by expressing this load as a percentage of the standard load value at each deformation level as presented in Equation 3.2

$$\text{CBR (\%)} = \frac{test\ unit\ load}{standard\ load} * 100 \qquad (3.2)$$

Moisture - Density relationship

Compaction of a soil improves the construction properties, for example it expands the shear strength of the soil therefore, the bearing capacity increases. In this study, the laboratory standard proctor and modified proctor tests are proceeded according to [2,3] correspondingly. The tests are done on disturbed specimen of soil particles passing sieve sizes 4.75mm conducted on aggregates with sizes larger than 14 mm.

Model development for ANN

In this study, the MATLAB (2015) software from [18] was employed to develop the model utilizing various Artificial Neural Network (ANN) architectures. The aim was to determine the most suitable architecture for the task at hand. The developed ANN was trained to recognize and interpret inputs, generating corresponding outputs based on the input data.

The process of developing the ANN architecture involved several steps. These steps included selecting the number of layers, which consisted of the input layer, one or more hidden layers, and the output layer. Additionally, the number of neurons in each layer was determined, the appropriate activation function was chosen, weights and biases were assigned, and a training algorithm was selected.

In this particular study, five input parameters were utilized: max dry density (MDD), Optimum Moisture content (OMC), Plastic Limit (PL), Liquid Limit (LL) and plasticity index. The output of the model focused solely on the California Bearing Ratio (CBR).

The network underwent multiple training, retraining, and simulation iterations until the smallest error between the actual experimental data and the model output was achieved. The performance of the trained model was evaluated using metrics such as Mean Square Error (MSE), Root Mean Square Error (RMSE), and Regression (R).

The specific architecture employed in this study consisted of a single hidden layer comprising 100 neurons. Table 3.1 shows the parameters utilized in the ANN models

Table 1 - Input parameters for the ANN models

Parameter	Configurations
Input data	MDD, OMC, LL, PL, PI
Output data	California Bearing Ratio
Max. number of epochs	100
Training function	TrainLM
Activation function	Hidden layer – Logsig and Tansig; Output Layer-Purelin
ANN architectures tried	5:100:1

Development of ANFIS

The development of the adaptive neuro fuzzy inference system (ANFIS) model for predicting the California bearing ratio of lateritic soil involved the following steps:

(i) Preparation of Datasets: Data gotten from the experimental work which was used to train the ANN Model was used for the ANFIS model.

(ii) Training the Model: The training dataset was utilized to train the ANFIS model using the ANFIS-based Grid partition algorithm. As there are multiple input neurons, this algorithm was employed to effectively train the model.

(iii) Validation of the Model: The testing dataset, which is a percentage of the total dataset used in the training process, was used to validate the ANFIS model. Several error criteria such as Root Mean Square Error (RMSE) and R-squared (R^2) were employed for model validation.

To analyze and defuzzify the implemented data, a fuzzy algorithm was utilized to classify the data and assign values representing the degree of truth or membership function. The membership function (MF) captures the degree of truth in the classification, and its type and shape are determined based on the data type and related uncertainties. Triangular or trapezoidal-shaped MFs are suitable for data with accelerated dynamic variation, while Gaussian types are used for analytical data requiring high accuracy. The bell-shaped MF is commonly employed for data related to construction and construction materials [27].

Identifying the most influential input parameters on the output involved developing and training ANFIS models based on each individual input parameter. The precision of training the ANFIS model focusing on a single input parameter indicates its potential as a sole predictor of the output. The impact of each input parameter on the output can then be evaluated using statistical error indices such as Root Mean Squared Error (RMSE) and Coefficient of Determination (R^2).

For a visual representation of the ANFIS models' flowchart, please refer to Figure1, which outlines the sequential steps in the ANFIS modeling process.

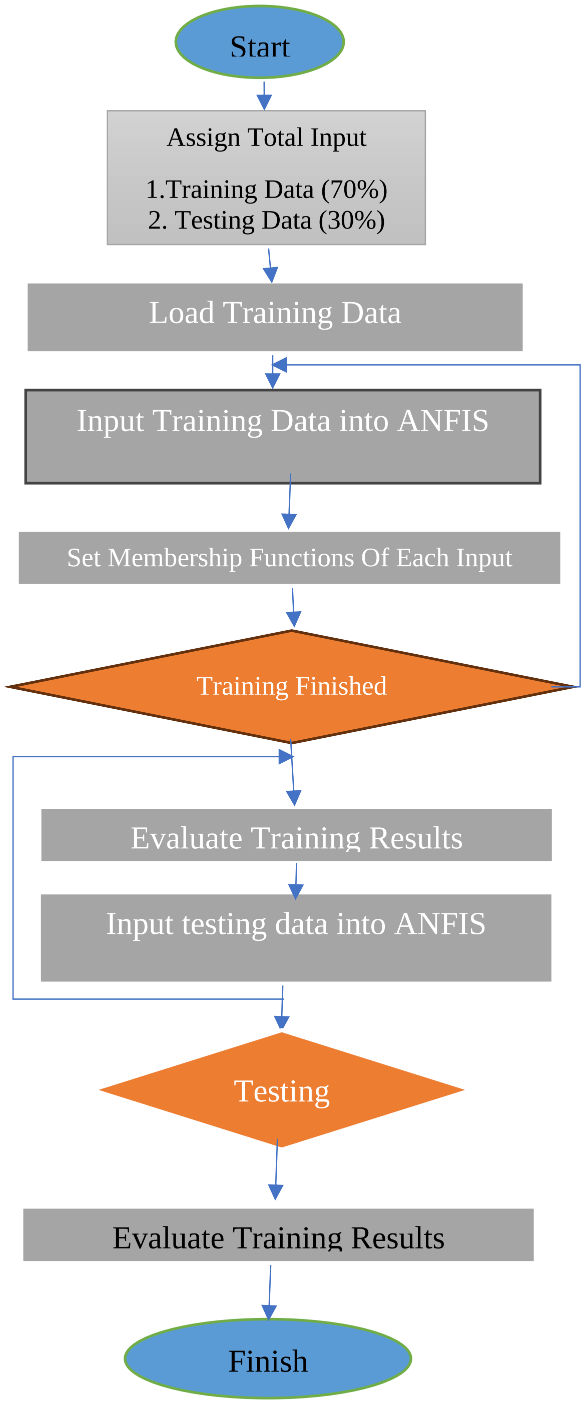

Figure 1 – ANFIS flowchart for prediction purposes.

Results and Discussion

RESULTS

Table 1: Summary of Result

Nos	Actual CBR	ANN Predicted	ANFIS Predicted
1	12.3	12.30	12.32
2	10.65	10.65	10.65
3	12.2	12.31	12.20
4	5.2	5.61	5.21
5	7.87	7.87	7.87
6	2.3	2.30	2.30
7	4.75	4.75	4.75
8	7.86	7.87	7.87
9	12.28	12.28	12.28
10	2.89	2.89	2.89
11	12.35	12.35	12.33
12	12.19	12.19	12.20
13	6.7	6.70	6.70
14	10.37	10.37	10.37
15	2.45	1.56	2.45
16	2.5	3.03	2.50
17	1.26	1.26	1.27
18	2.75	11.26	2.75
19	5.4	5.40	5.40
20	2.6	2.60	2.59
21	2.41	2.41	2.41
22	5.96	6.37	5.43
23	11.7	8.51	11.89
24	8.68	2.59	6.77
25	1.48	2.48	1.73
26	10.94	11.47	11.16
27	11.92	12.35	12.18
28	8.95	12.33	8.67
29	9.87	12.30	9.75
30	5.6	5.60	4.29

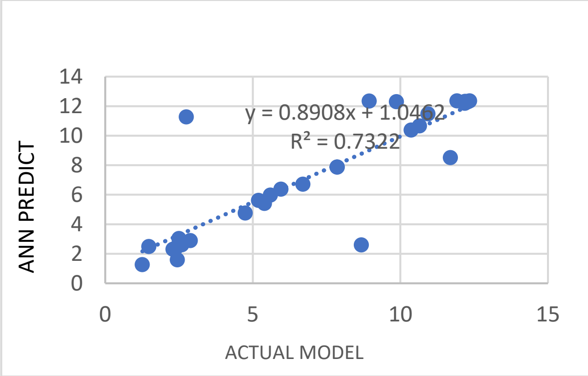

Figure 2: Regression Chart for the chosen ANN model result

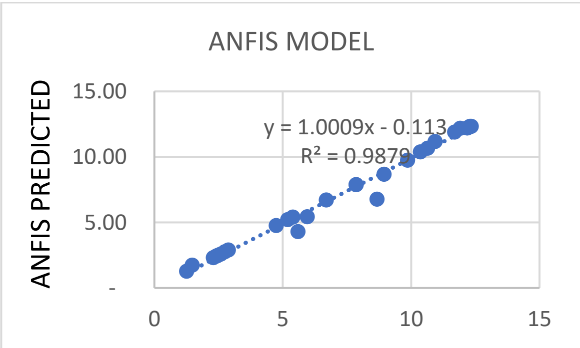

Figure 3: Regression chart for the ANFIS model result

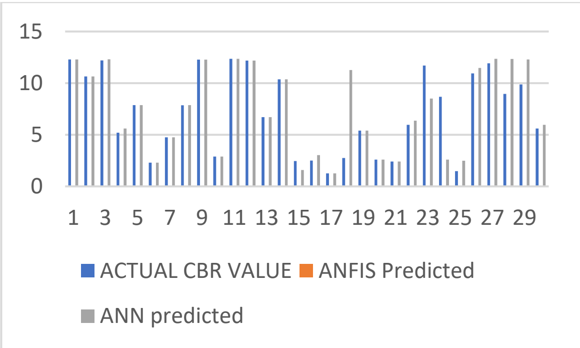

Figure 4: comparison between Actual and predicted CBR Values

Table 4: The statistical evaluation for all the CBR models

Statistical Evaluators/ Models	ANN	ANFIS
R^2	73%	98%
RMSE	2.16	0.33
MSE	4.67	0.11

Discussion of results

In comparing the performances of both models, it was observed that ANFIS models outperformed the ANN model in predicting the CBR Values of lateritic soil. The ANN models achieved high R-squared (R^2) values and low Root Mean Square Error (RMSE) values, indicating a robust predictive performance. Similarly, the ANFIS model demonstrated a stronger predictive capability with perfect R^2 values and significantly lower RMSE values which implies that both the ANN and ANFIS models are highly suitable algorithms for accurately predicting the CBR Values of lateritic soil.

Figure 4 illustrates the comparison between the actual experimental CBR data and the predicted values obtained from the ANN and ANFIS models using both training and testing data. The predicted values of both the ANN and ANFIS models align closely with the actual data, indicating their strong agreement.

Conclusion

The following conclusions can be drawn from this work:

1. The Feed-forward back propagation type of neural networks with 2 hidden layers having 100 neurons trained by trainlm algorithm using tansig activation function could predict the CBR value of lateritic from its index properties with satisfactory performance.
2. Soft Computing Techniques models are more suitable in modelling of complex problems and save a lot of computational effort compared to conventional methods. significantly, the use of soft computing technique will help in solving more complex problems.
3. ANN predicts more accurately when input range of training data set was well established. Hence it is very important to select input and target data used for training, so that input of testing data set was well within range of training data set.
4. Both ANN and ANFIS take less time and easier to perform as compared to the standard procedure of CBR testing, thus can be used to predict the CBR of a various soil using their index properties.
5. ANFIS models outperformed the ANN model in predicting the CBR Values of lateritic soil

Recommendations

The research findings and conclusions provide the basis for the following recommendations:

- ANN predicts more accurately when input range of training data set was well established. Therefore, it is recommended that, input and target data used for training be set within wide range.
- Researchers and geotechnical engineers are encouraged to utilize the ANFIS Models which demonstrated predictive capabilities in this study. The ANFIS model can be relied upon for accurate predictions of CBR values of lateritic soil.
- It is suggested to conduct comparative studies involving additional soft computing techniques such as Support Vector Machines (SVM), Random Forests, Deep Learning and Genetic Algorithm.

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