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(RESEARCH ARTICLE)

# Investigating the competency of some selected soft computing techniques for modeling of lateritic soil strength based on index properties

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## Abstract

This study aims to assess the capability of some soft computing techniques including ANN, M5P and RF to accurately predict the strength of selected lateritic soils in southwestern Nigeria from index properties including specific gravity, linear shrinkage, liquid limit, plasticity index, fine sand content, and fines content. To achieve this goal, the experimental dataset obtained from the laboratory analysis of three hundred soil samples taken from thirty different lateritic deposits within southwestern Nigeria was divided into model and gaging dataset. The model dataset contains two hundred and forty data points, which were divided into 70% for training and 15% each for testing and validation of the proposed models. The gaging dataset contains sixty data points, which were used to validate the proposed models against prominent existing models in the literature. The models performances were evaluated using various statistical estimators. Based on the statistical estimators, the proposed models outperformed the existing models in the literature and provided satisfactory performances, thus, they are validated. The obtained $R^2$ values using the ANN model are 0.9967, 0.9963, 0.9989, and 0.9852 for training, testing, validation, and gaging dataset, respectively; the $R^2$ values obtained for M5P model are 0.6676, 0.5501, 0.636 and 0.6727; and the $R^2$ values for RF model are 0.8346, 0.6380, 0.7564, and 0.7901. This implies that ANN provided the most reliable model for the prediction of the soil strength. Thus, ANN is strongly recommended for prediction of lateritic soil strength.

**Keywords:** Lateritic soil; Shear strength; Index properties; Soft computing techniques

## 1. Introduction

Laterite is an important construction material that is used as foundation fill, road subgrade, subbase, base course [1], [2], landfill liners [3], [4] among others. However, key geotechnical properties determine the suitability of laterite for the aforementioned purposes such as shear strength (SS), which determines the resistance to failure of lateritic soil when used for engineering construction [5]. Many engineering structures have failed due to insufficient information about the geotechnical characteristics of this important construction material [6]. Therefore, accurate determination of these properties is highly imperative for ensuring the safety of life and property.

Nevertheless, the tests used to determine SS are cumbersome, expensive, and time-consuming. Therefore, it is important to develop model to predict SS based on index properties, which are less tedious and less expensive. Several regression-based models have been developed in the literature to estimate SS of soil based on index properties [7]. Regression-based analysis is used to establish the relationship between a dependent variable and one or more independent variables [8]. Regression-based models can be classified into two types: single-parameter or multi-parameter regression-based models. The models proposed by [9], [10], [11] in the literature fall under the first category. Apart from the fact that limited index properties are considered in the existing empirical models, regression-based models are less reliable; they cannot capture the inherent variability in geomaterial properties [12], [13]. Therefore, to

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design effective predictive models for prediction of SS of lateritic soil, there is need for a more robust method that is capable of capturing the inherent variability in soil properties. A good example of such method is soft computing method. Soft computing is an important branch of computational intelligence in which fuzzy logic, neural networks, and genetic algorithms are synergistically used to mimic the reasoning and decision making of a human [14]. Soft computing methods such as artificial neural network, (ANN), adaptive neural fuzzy inference systems (ANFIS), particle swarm optimization-artificial neural networks (PSO-ANN) and gene expression programming (GEP) have been used to solve various difficult geoengineering problems [13], [14], [15]. [16] used hybrid ANFIS, support vector regression and ANN to predict the SS of lateritic soil and they concluded that soft computing models performed excellently. However, apart from the fact that limited research developed models to predict SS from index properties, all the previous studies were performed on soil outside the study area; there is no soft computing technique that has been specifically used to predict SS of lateritic soil in the study area (Southwest Nigeria) as at the time of writing this paper, and soil has inherent variability in its properties, which necessitates domestic-based research on the applications of soft computing methods to predict SS of lateritic soils. Hence, this research aims to develop soft computing models using ANN, random forest (RF) and M5P for prediction of SS of lateritic soils from index properties.

## 2. Description of the proposed models

### 2.1. Artificial neural network

ANN is defined according to [17] as a computing system that is made of an extremely interconnected set of simple information processing elements, analogous to a neuron, called a unit. ANN is a soft computing method that imitates the human brain in the processing of information through the series of interconnected structures comprising several simple processing neurons having the ability to perform large parallel computations for data processing and information representation nodes [14]. The processing ability of the ANN is stored in the weights that interconnect the nodes. The way in which the nodes are connected is known as the ANN architecture. The artificial neural network architecture is determined by the number of layers, the number of nodes in each layer and the weighted connections between the nodes [13]. There are different ANN architectures, but feed forward, FF was used in this research. However, ANN requires training of the network before it can be used to construct a model. Various learning algorithms are used in training multilayer perceptron feed forward, MLP-FF but the back-propagation, BP algorithm is commonly used by past researchers [13], [14], [15].

In BP, signals are propagated from the input layer through the hidden layer to the output layer, known as the forward pass, after which the obtained values are compared to the actual values. The resulting errors are subsequently returned to the system to update the weights, known as backward-pass. In this process, the errors in both the training and testing datasets are reduced. The procedure is repeated in the feed-forward-back-propagation, FF-BP ANN until the resulting errors have converged to the threshold level specified by the system's error function, such as the mean squared error.

### 2.2. M5P

M5P algorithm also known as M5 model tree is a machine learning method used for regression task. It is used to predict values of numerical response which is a decision tree with linear regression functions at terminal nodes; it builds a decision tree where each leaf node contains a linear regression model, and due to this, it can predict a range of values at each leaf. M5P algorithm trains a linear regression model on each leaf nodes during the process of trying to construct the model tree [18].

Leaf analysis technique which divides data into numerous categories by engaging linear regression at each node enables the achievement of good results [19]. Furthermore, what make M5P outstanding machine learning is that the error for the linear model is computed at each node from the bottom of the tree. Unlike ANN which learns by reducing the error of prediction through the adjustment of weight values at each node until the resulting errors have converged to the threshold level specified by the system's error function, M5P learn by trimming the sub-tree of a node until the errors is smaller than the model sub-tree held by the node itself [20]. Standard deviation is employ to analyze the error of class values reaching each node [19]. Generally, the M5P algorithm put together the interpretability of decision trees with litheness of linear regression models to make accurate prediction.

### 2.3. Random forest

Random forest, RF is a supervised machine learning method which learns through building of trees of decision using samples of data and gathered predictions on each of the sample data and chooses the best prediction. Random forest is an advance version of random decision. It can be used for both classification and regression problems using voting method and average value, respectively [21]. For the case of classification, the predictions of every single decision tree are evaluated to determine the class of the data item and the most voted class is chosen as the class of the data item. For the case of regression, the RF repressor predict based on the average of the predictions produced by the trees in the forest; thereby improving RF accuracy and reduces over fitting. The RF technique consists of three major steps: the first step involves building of trained regression trees using a training dataset; the second does the calculation of the mean value of a single regression tree; and lastly, the third step involves the calculation of the mean value of multiple regression trees [19]. The RF regression model can be evaluated using root mean square.

## 3. Materials and methods

### 3.1. Sample collection and analysis

Three hundred lateritic soil samples were collected from thirty different deposits in southwestern Nigeria within the following coordinates: latitude 6°30'10.01'' to 8°41'33.36'' and longitude 3°9'34.87'' to 5°44'44.70''. Ten samples were randomly collected from each laterite deposit. Approximately 10–15 kg of each sample was collected and taken to the laboratory for analysis.

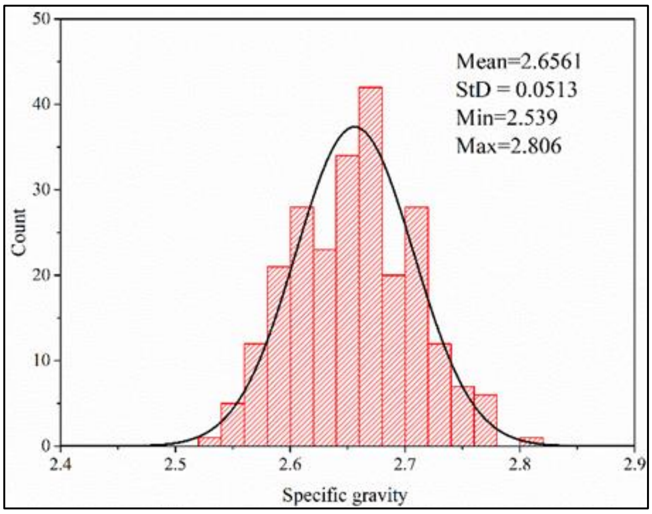
The obtained samples were subjected to various tests in the laboratory for the determination of specific gravity (SG), linear shrinkage (LS), liquid limit (LL), plastic limit (PL), fine sand content (FSC), fines content (FC), and SS. The SG of the samples was determined using a pycnometer according to the standard procedure of [22]. The Atterberg limits test was carried out on the samples in accordance with the standard procedure of [23] to determine the PL and LL. The plasticity index, PI was estimated using Eq. (1).

$$PI = LL - PL \quad \ldots\ldots\ldots\ldots (1)$$

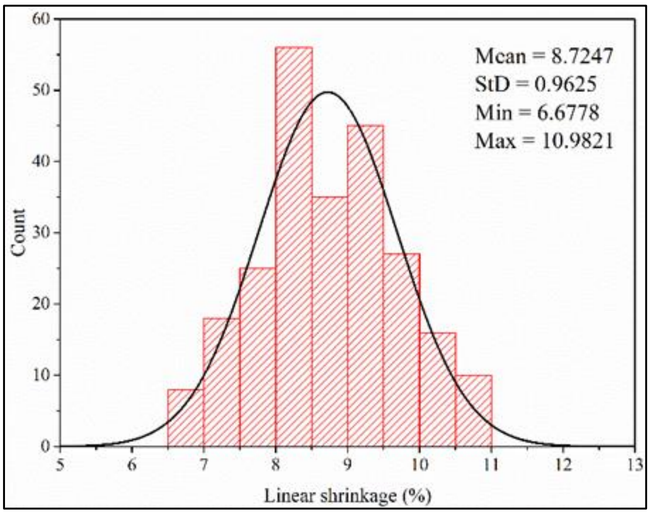
The LS of the samples was determined according to the standard procedure of [24]. A sieve analysis was performed on the samples to determine FSC and FC according to [25] standard procedure. Unconfined compression test was conducted on the samples in accordance with the standard procedure of [26]. The SS of the samples was calculated from the unconfined compressive strength (UCS) using Eq. (2).

$$SS = \frac{UCS}{2} \quad \ldots\ldots\ldots\ldots\ldots (2)$$

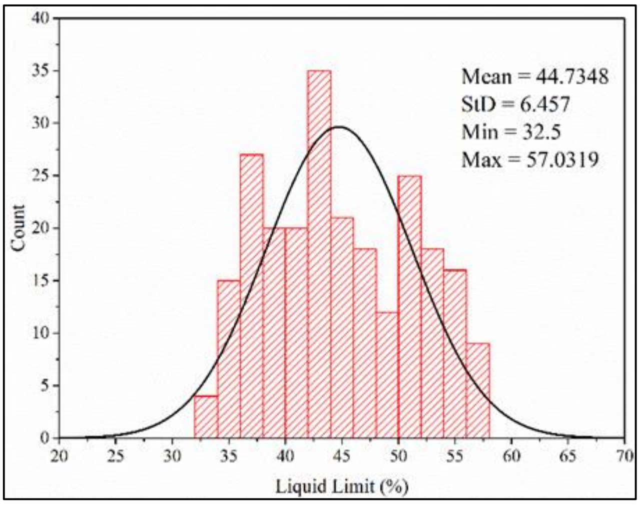
The statistical descriptions of the experimental dataset are presented in Fig. 1, showing the mean, standard deviation, minimum, and maximum values of each of the variable. The SG of the samples varied between 2.54 and 2.8; LS varied between 6.7% and 11%; LL varied between 32.5% and 57%; PL varied between 17.4% and 37.1%; PI varied between 3.8% and 30.3%; FSC varied between 35.1% and 63.2%; and FC varied between 36.4% and 60.9%. The distributions of the data are largely close to normal. The results of grain size analysis, liquid limit and plasticity index tests indicated that the soils are silty sand to clayey soils based on the AASHTO soil classification [27].


Mean=2.6561
StD = 0.0513
Min=2.539
Max=2.806
Count
Specific gravity

(a)


Mean = 8.7247
StD = 0.9625
Min = 6.6778
Max = 10.9821
Count
Linear shrinkage (%)

(b)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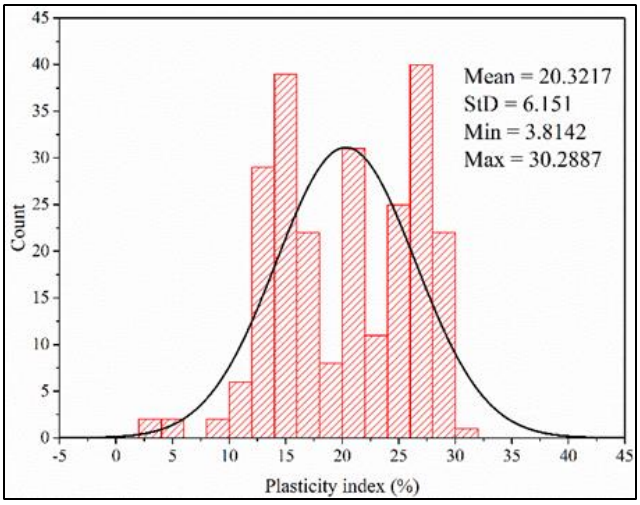
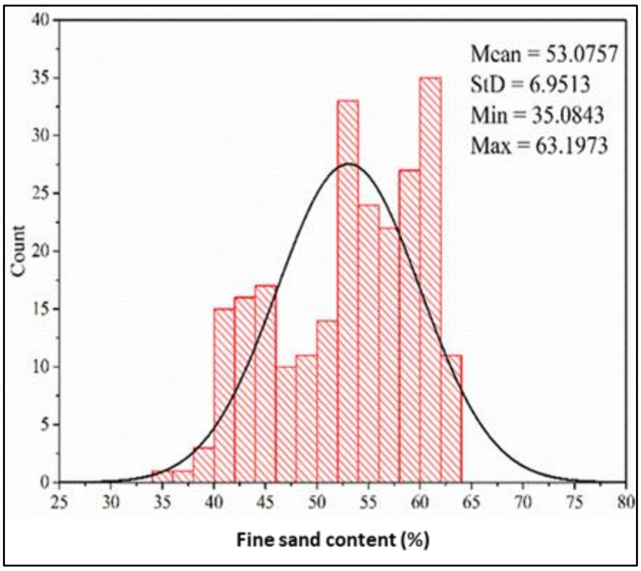
StD = 6.457
Min = 32.5
Max = 57.0319
Count
Liquid Limit (%)

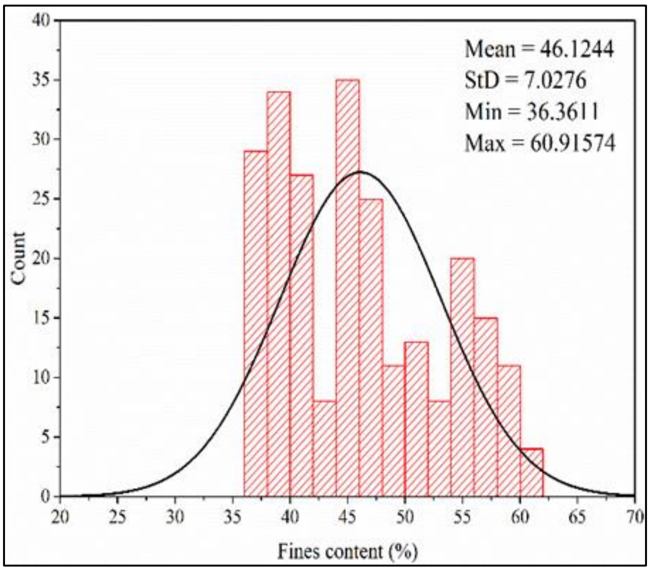
(c)


Mean = 20.3217
StD = 6.151
Min = 3.8142
Max = 30.2887
Count
Plasticity index (%)

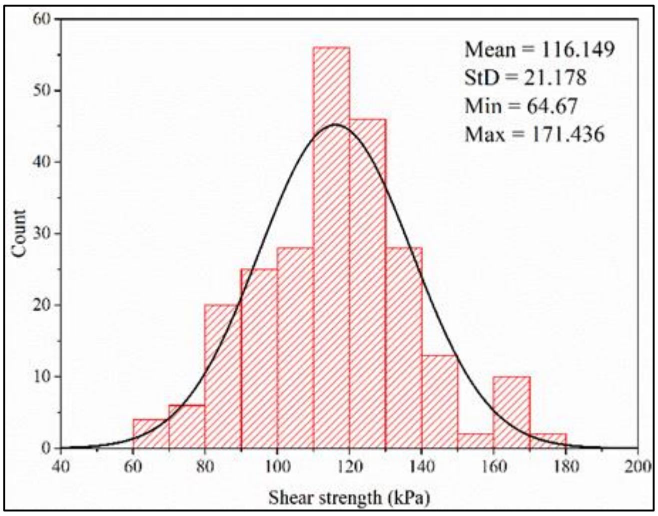
(d)


Mean = 53.0757
StD = 6.9513
Min = 35.0843
Max = 63.1973
Count
Fine sand content (%)

(e)


Mean = 46.1244
StD = 7.0276
Min = 36.3611
Max = 60.91574
Count
Fines content (%)

(f)




(g)

**Figure 1** Statistical descriptions of the experimental dataset

The experimental dataset was divided into a model dataset containing two hundred forty data points that were used to develop and evaluate the proposed models, and a gaging dataset of sixty data points that were used to compare and validate the proposed models against the existing model.

## 3.2. Model development

### *3.2.1. ANN model*

The ANN model described above was developed for the prediction of the SS of lateritic soil obtained from different locations described in the previous section. The ANN was implemented in MATLAB software. The model dataset comprises two hundred forty data points, which are part of the experimental dataset statistically described in Fig. 1. The model dataset were divided into training, testing and validation datasets, with 70% for training and 15% each for testing and validation. The data were preprocessed by normalizing them within the range of -1 to 1. The model predictors are SG, LS, LL, PI, SC, and FC, while the targeted output is SS. The backpropagation training algorithm with the Levenberg Marquardt training algorithm was used in training the ANN. Three-layer ANN structures were simulated for the SS. The transfer function at the hidden and output layers was the hyperbolic tangent. The performance of each of the simulated ANN structure was evaluated with the coefficient of correlation (R). The optimum ANN structure with the highest R value was subsequently selected for the SS models. A total of nineteen (19) ANN simulations were performed for SS as shown in Table 1. ANN architecture 6-13-1 was the optimum for SS as shown in Fig. 2.

**Table 1** ANN simulated for SS

| Networks | Training | Testing | Validation | Whole |
|---|---|---|---|---|
| | **R** | | | |
| 6-2-1 | 0.81588 | 0.86786 | 0.84282 | 0.82956 |
| 6-3-1 | 0.86875 | 0.92454 | 0.84981 | 0.87385 |
| 6-4-1 | 0.88843 | 0.86593 | 0.82519 | 0.87487 |
| 6-5-1 | 0.95156 | 0.94295 | 0.95475 | 0.95006 |
| 6-6-1 | 0.95434 | 0.95964 | 0.95335 | 0.95507 |
| 6-7-1 | 0.9828 | 0.97372 | 0.96193 | 0.97931 |
| 6-8-1 | 0.9956 | 0.83354 | 0.96162 | 0.97203 |
| 6-9-1 | 0.99201 | 0.98153 | 0.99339 | 0.99081 |

| | | | | |
|---|---|---|---|---|
| 6-10-1 | 0.99193 | 0.99517 | 0.99454 | 0.99272 |
| 6-11-1 | 0.98501 | 0.98845 | 0.94094 | 0.98196 |
| 6-12-1 | 0.99777 | 0.99929 | 0.9986 | 0.9981 |
| **6-13-1** | **0.99834** | **0.99817** | **0.99892** | **0.9984** |
| 6-14-1 | 0.99392 | 0.86417 | 0.99843 | 0.97964 |
| 6-15-1 | 0.99742 | 0.99785 | 0.99813 | 0.99758 |
| 6-16-1 | 0.9803 | 0.98805 | 0.97578 | 0.98112 |
| 6-17-1 | 0.99706 | 0.99465 | 0.996 | 0.99653 |
| 6-18-1 | 0.99803 | 0.99528 | 0.99533 | 0.99749 |
| 6-19-1 | 0.9779 | 0.967 | 0.94557 | 0.97007 |
| 6-20-1 | 0.99695 | 0.99749 | 0.99761 | 0.99715 |

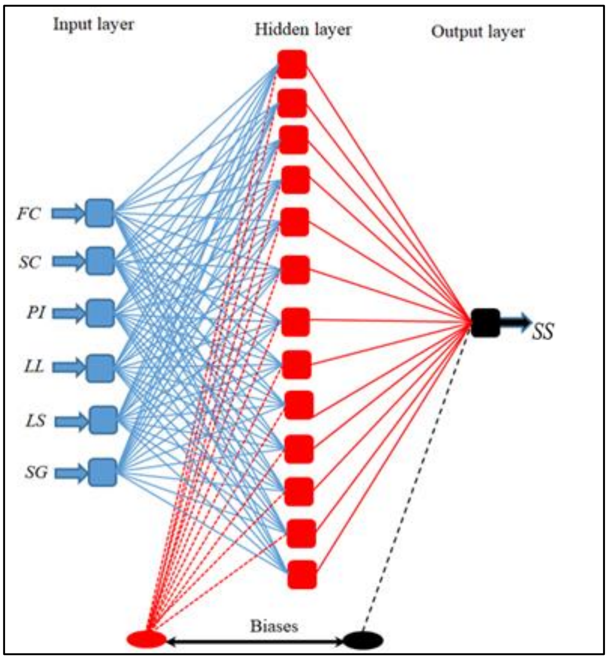



**Figure 2** Optimum ANN architectures for SS

*3.2.2. M5P model*

As described in the previous section (see 2.2), M5P was also used to predict the SS. The model dataset in this case was also preprocessed by normalizing it within the range of 0 to 1 and then divided into the same training, testing and validation datasets, with 70% for training and 15% each for testing and validation as ANN. M5P was implemented in Weka software with a smoothed linear model. The obtained M5P pruned regression tree presented for the SS is shown in Fig. 3 with their corresponding rule values presented in Table 2 which indicates 16 rules. The M5P model seems to eliminate majority of the model parameters in the SS as shown in Fig. 3.

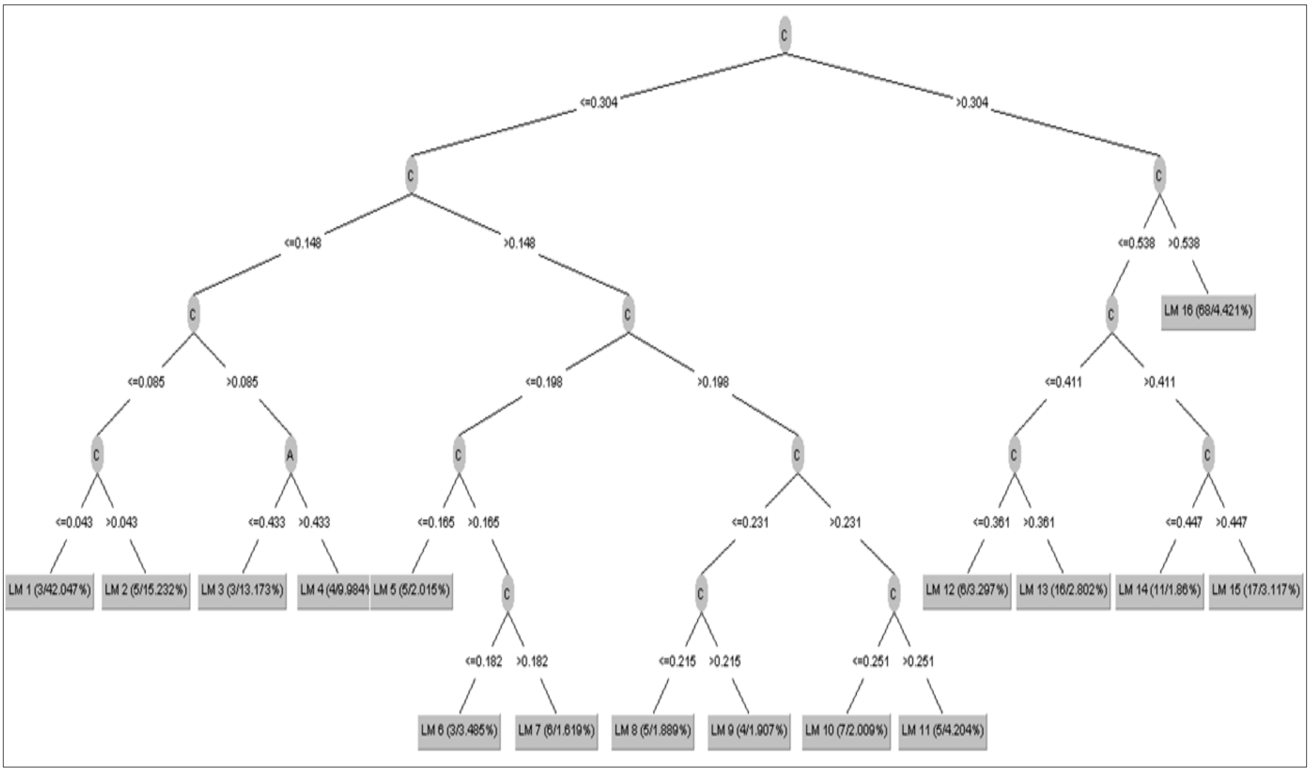



**Figure 3** M5P tree for SS

**Table 2** Values of LM in Fig. 3 for SS

| LM | Values |
|---|---|
| LM num: 1 | 0.4022 |
| LM num: 2 | 0.394 |
| LM num: 3 | 0.3627 |
| LM num: 4 | 0.3608 |
| LM num: 5 | 0.2488 |
| LM num: 6 | 0.2449 |
| LM num: 7 | 0.2443 |
| LM num: 8 | 0.2228 |
| LM num: 9 | 0.2223 |
| LM num: 10 | 0.217 |
| LM num: 11 | 0.2159 |
| LM num: 12 | 0.0729 |
| LM num: 13 | 0.0699 |
| LM num: 14 | 0.0591 |
| LM num: 15 | 0.0554 |
| LM num: 16 | 0.026 |

*3.2.3. Random forest model*

RF, which is also a type of regression tree, is similar to M5P and was also used to predict the SS in this study. Background information about the RF algorithm is presented in section 2. The model dataset in this case was also preprocessed by normalizing it within the range of 0 to 1 and then divided into the same training, testing and validation datasets, with 70% for training and 15% each for testing and validation as ANN. RF was implemented in Weka software. The results were compared with those of the other proposed models as shown in the next section.

## 4. Results and discussion

### 4.1. Performance comparison of the proposed model

The SS predicted by the proposed models and the laboratory measured values were compared as shown in Fig. 4 for the training, testing and validation cases. The + or – 5% error bars are also included in the figures. For the training case, the model with a seemingly zero intercept performed better than the model with the highest intercept value. In this case, the M5P model has the highest intercept value, and as a result, its predicted data points are largely outside the error bars. The obtained coefficients of determination (R2) values for M5P are 0.6676, 0.5501, and 0.636 for the training, testing and validation dataset, respectively. The RF model's intercept is the next best to that of the M5P model. Its predicted data points also fall largely outside the error bars; consequently, its predicted $R^2$ values are 0.8346, 0.6380, and 0.7564 for the training, testing and validation dataset, respectively. For the ANN model, the inclination is approximately 45°, and virtually all the predicted data points using this model fall within the error bars. The obtained $R^2$ value using the ANN are 0.9967, 0.9963, and 0.9989 for the training, testing and validation dataset, respectively; thus, the ANN outperformed the other models. This observation is similar to the results of the testing and validation. The performances of the models are proportional to the interception of the fitted and error bars to the vertical axis.

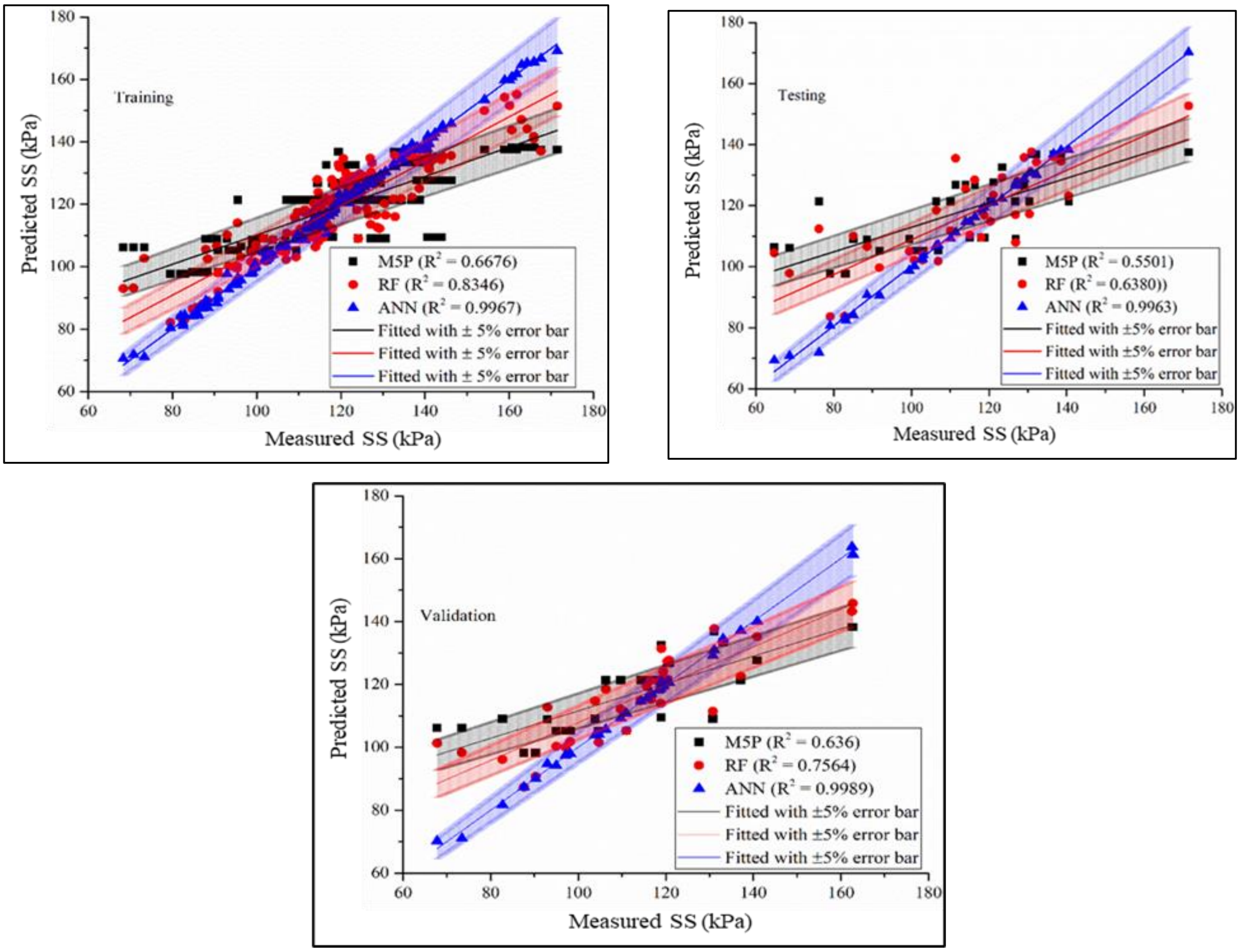



Figure 4 Performance of the proposed models for the training, testing and validation

### 4.2. Performance comparison of the proposed and exiting models

Prior to this study, several existing empirical models were proposed in the literature for predicting soil SS, the performance of the prominent among them shown in Eqs. (3) to (5), listed in Table 3, were compared to that of the proposed models in this study. It is important to compare their performances with the proposed models in this study to validate and identify the best model suitable for accurate prediction of the SS.

**Table 3** Existing empirical models in the literature for predicting soil SS

| S/N | Existing Model | Reference | Eq/N |
|---|---|---|---|
| 1. | SS = 185.778 – 3.807 PI | [9] | (3) |
| 2. | SS = $0.923e^{-0.013PI}$ | [10] | (4) |
| 3. | SS = $191.4/e^{0.03\ LL}$ | [11] | (5) |

To achieve this goal, the proposed ANN, RF and M5P models and the existing regression-based models proposed by [9], [10], and [11] in the literature were made to predict SS based on index properties using the gaging dataset and their performances were evaluated using statistical indices, namely, $R^2$; root mean squared error (RMSE), mean absolute percentage error (MAPE), and mean absolute error (MAE) as presented in Eqs. (6) to (10) and the results are summarized in Table 4.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(E-P)^2}{\sum_{i=1}^{n}(E-\overline{Y})^2} \quad \text{......................(6)}$$

$$\overline{Y} = \frac{1}{n}\sum_{i=1}^{n} E \quad \text{...................... (7)}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(E-P)^2} \quad \text{...................... (8)}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{(E-P)}{E} \times 100 \quad \text{......................(9)}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|E - P| \quad \text{.................. (10)}$$

where *n* is the number of sample data points used for the models development, $\overline{Y}$ is the mean of the measured values, and E and P represent the measured and the predicted value of the SS, respectively.

**Table 4** Error analysis for SS models

| Models | Error analysis | | | |
|---|---|---|---|---|
| | $R^2$ | RMSE | MAPE | MAE |
| ANN | 0.9852 | 2.6846 | 1.2147 | 1.4189 |
| M5P | 0.6727 | 13.9199 | 9.1879 | 10.3688 |
| Radom forest | 0.7901 | 10.8657 | 6.6358 | 7.6576 |
| Bakala *et al.* (2021) | 0.4738 | 15.7133 | 10.816 | 12.2606 |
| Senoon and Hussein (2018) | 0.2654 | 51.8782 | 38.88 | 48.1682 |
| Edil *et al.* (2009) | 0.4767 | 69.0346 | 55.8478 | 67.0342 |

The results obtained using the models suggested by [9], [10], [11] presented lower $R^2$ values than did the ANN, M5P and RF models (Table 4), indicating that the proposed soft computing models explained the variability in the measured SS better than did the empirical models suggested by [9], [10], [11]. Furthermore, the RMSE, MAPE and MAE values presented by [9], [10], [11] are greater than those of the proposed ANN, M5P and RF models, indicating that the models' prediction errors are greater for the [9], [10], [11] empirical models than for the proposed ANN, M5P and RF models.

For all the comparisons (Table 4), the proposed ANN, M5P and RF models outperformed the existing empirical models in the literature for the prediction of SS. Thus, the proposed ANN, M5P and RF models are validated. Also, the ANN model presented the highest $R^2$ and the lowest RMSE, MAPE and MAE values, followed by RF and then the M5P for the prediction of SS. Thus, the ANN is the most reliable model for prediction of lateritic soil.

### 4.3. Sensitivity analysis

A sensitivity analysis was conducted to establish the contributions of each of the model parameters to the predicted values of the ANN models; the best performed models. To achieve this, the cosine amplitude method proposed by [28] was employed, as presented in Eq. (11).

$$R_{ij} = \frac{\sum_{i=1}^{m}(I_i \times O_i)}{\sqrt{\sum_{i=1}^{m}(I_i)^2 \times \sum_{i=1}^{m}(O_i)^2}} \quad \ldots\ldots\ldots\ldots\ldots\ldots(11)$$

where $R_{ij}$ is the relative contribution of each input variable, $I_i$ is the input variable, $O_i$ is the output of the ANN model and m is the number of trained data points. The results obtained with Eq. (11) using the training dataset are presented in Fig. 5.

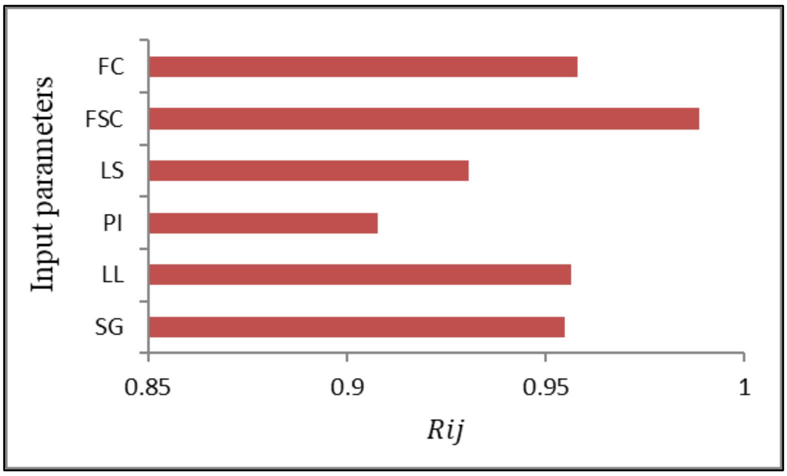



**Figure 5** Contribution of the model parameters to the ANN models

From Fig. 5, FSC seems to have the highest influence on SS followed by the SG, LS, FC, LL and PI.

*List of symbols*

- ANN: artificial neural network;
- M5P: M5P model tree;
- RF: random forest;
- ANFIS: adaptive neural fuzzy inference system;
- PSO-ANN: particle swarm optimization-artificial neural network;
- GEP: gene expression programming;
- SVR: support system regression;
- k: set of instances attain the node;
- SS: shear strength;
- SG: specific gravity;
- LL: liquid limit;
- PL: plasticity limit;
- LS: linear shrinkage;
- SC: sand content;
- FC: fine content;
- ASTM: American Society for Testing and Materials;
- AASHTO: standard specification for transportation materials and methods of sampling and testing.
- MLP: multilayer perceptron;

- FF: feed forward;
- BP: backpropagation;
- SDR: standard deviation reduction;
- R: coefficient of correlation;
- $R^2$: coefficient of determination;
- RMSE: root mean squared error;
- MAPE: mean absolute percentage error;
- MAE: mean absolute error;
- $\overline{Y}$: mean of the measured values.

## 5. Conclusions

The fitting of lateritic soil for engineering construction depends largely on its engineering properties, most especially SS. It is tedious, time consuming and costly to determine SS in the laboratory unlike index properties with simple, easy and cheap tests. To overcome this limitation, this study developed ANN, M5P and RF models to predict SS based on index properties.

In the first part of the study, three hundred lateritic soil samples, which were obtained from thirty different deposits within Southwestern Nigeria, were subjected to various laboratory tests, and the experimental dataset obtained was divided into a model dataset containing two hundred forty data points and a gaging dataset of sixty data points.

In the second part of the study, the model dataset were divided into training dataset comprising 168 data points, validation dataset comprising of 36 data points and testing dataset comprising of 36 data points, and were used to create and train predictive models using ANN, M5P and RF.

In the third part of the paper, the predictive capability of the models was tested using the training, testing and validation datasets; all the models exhibited satisfactory performance for SS, with ANN model having the lead followed by RF model and lastly, are followed by M5P model. Also, the proposed prediction models were compared with three prominent existing regression-based models in the literature using gaging dataset. The proposed models presented a higher $R^2$ and lower RMSE, MAPE and MAE values than did the existing models in the literature, with the ANN model having the lead followed by RF model and lastly, are followed by M5P model. This shows that using the prediction models established in this study leads to smaller errors than does using the existing models. Thus, it can be inferred that soft computing models capture the inherent variability in geomaterial properties better than regression-based models.

Based on all the performance comparison of the proposed models, it is obvious that the ANN model has the highest predictive capacities, thus ANN is suggested for the prediction of SS of lateritic soil.

The sensitivity analysis conducted on the predicted outputs of the best performed model, ANN model indicated that fine sand content was the most influential input variable on SS. Thus, fine sand content should not be ignored when developing SS prediction model.

## Compliance with ethical standards

### *Disclosure of conflict of interest*

The authors declare that they have no conflicts of interest.

### *Statement of ethical approval*

The authors state that the research was conducted according to ethical standards.

### *Availability of Data*

The dataset generated in this study is available at https://doi.org/10.6084/m9.figshare.26103232

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