

Multivariate regression models for predicting the compressive strength of bone ash stabilized lateritic soil for sustainable building

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HIGHLIGHTS

- Samples containing 6% bone ash cured for 28 days had the best compressive strength.
- Multivariate regression models were used for strength prediction and analysis.
- Non-linear and mixed models performed better than linear models.
- The best-fit statistical models were identified for the compressive strength prediction at the highest R^2 value of 97%.
- The effects of individual independent variables in predicting the strength of stabilized lateritic soil indicated that bone ash content had the most significant effects.

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ABSTRACT

Substantial amount of time, financial resources and energy are required to obtain experimental data on the compressive strength of building components. Application of multivariate regression models in predicting the strength of stabilized lateritic soil has the potential of reducing the time and cost of construction projects in Nigeria. This study is aimed at developing multivariate models for predicting the strength of lateritic soils stabilized with bone ash for sustainable construction. Different percentages of bone ash were used to stabilize lateritic soil. The lateritic brick samples obtained were cured at different temperatures and ages. The samples were tested to obtain their compressive strength. Multivariate and non-linear models were used to predict the compressive strength of the lateritic bricks. A mixed model with R^2 of 97% was identified as the best-fit statistical model. The usefulness of the models is limited to the range of variables used but for a more universal application, wider ranges of variables can be explored. This model has practical application for the prediction of compressive strength of stabilized lateritic soil for sustainable housing construction in Nigeria.

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1. Introduction

Lateritic soils are among the topmost local building materials used in the construction industry in Nigeria for the provision of sustainable and affordable housing and other infrastructure [1]. The high cost of conventional building materials such as cement and asphalt which has resulted in housing deficits in Nigeria has

led researchers to seek how to utilize the abundant local materials such as lateritic soil in the country by improving its strength to make it more suitable for sustainable housing materials. Recent research works in construction materials are focused on finding a sustainable alternative capable of reducing the consumption of cement and concrete in the construction industry [2–5]. Lateritic bricks have been used since ancient times for the provision of affordable housing and other infrastructure such as roads, dams and monuments [6]. However, a structure constructed with lateritic soil has lower compressive strength compared to that of cement and concrete resulting in low bearing capacity and durability [7].

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Conversely, there have been several tons of agro-wastes generated [8] due to the consistent increase in population with its attendant socio-economic activities. Cattle bone is one of the major agro-wastes from meat production [9]. In the quest to turn wastes to wealth, different ways of utilization of these wastes in many economic sectors especially the construction industries are of paramount importance. This will not only add economic value to the wastes but will also provide new job opportunities for individuals who may be involved in waste collection and utilization.

In order to strengthen lateritic soil for sustainable building applications, researchers have been exploring different waste materials including agro-wastes materials as admixtures or soil stabilizers for improving the mechanical properties of lateritic soil [10]. Obianyo et al. [11] explored the possibility of using bone ash in place of hydrated lime in stabilizing lateritic soil for sustainable buildings. It was found that the bone ash improved the compressive strength of the lateritic soil significantly after 28 days of curing. An adequate understanding of the soil compressive strength is crucial in construction projects such as buildings, earth dams, and road and railway embankments [12].

However, a substantial amount of time, financial resources and energy are required to run tests in the laboratory to obtain the compressive strength of lateritic soil. Therefore, the application of mathematical or statistical models in predicting the strength of earth-based materials such as lateritic soil is crucial. Presently, there is limited systematic data on the properties and multivariate regression models for strength prediction of stabilized lateritic bricks. Jin et al. [13] expressed the need for using multiple independent variables (IVs) in a proper data analytical method for predicting the targeted response random variable (RRV) of cementitious materials. Artificial Neural Network (ANN) and linear regression method have been used by various researchers to predict the properties of stabilized earth-based materials [14,15]. There is no empirical model available for predicting the compressive strength of bricks made from lateritic soil stabilized with bone ash.

This study aimed to develop multivariate stochastic models for predicting the compressive strength of bricks made from lateritic soils stabilized with bone ash for sustainable building purposes. The statistical models were used to predict the compressive strength of stabilized lateritic soil. The implication of the formulated models on the effects of bone ash stabilizer, curing age and curing temperature on the compressive strength of stabilized lateritic soil was quantitatively demonstrated in this work. Also, the application of these proposed statistical models has the potential of reducing the cost and time in acquiring experimental data.

2. Background

2.1. Lateritic soil as a sustainable building material

Sustainable building materials are those materials that have the capacity of meeting the building needs of the present generation without having a negative effect on the capability of future generations to meet their own needs [16]. Lateritic soil is regarded as a sustainable building material because it can be recovered 100% when recycled or deconstructed. Although the advantages of sustainable building materials are well known, the use of conventional and high-impact building materials such as cement is still on the rise [17]. In order to achieve sustainable construction, efforts must be targeted at improving local building materials production processes, materials recycling/reuse, materials substitution, as well as the utilization of eco-friendly and innovative materials.

2.2. Agro-waste ash as soil stabilizer

Environmental pollution from heaps of agro-wastes littered in the streets has been a nuisance to the society. Efforts have been made on how to either recycle or re-use these wastes to reduce their implications and health hazards [18]. One of the diverse ways of managing agro-wastes is its use in the construction industry. Several researchers have used agro-wastes in the form of ash or fibre as a soil stabilizer or an admixture to improve the geotechnical and mechanical properties of soil.

Some representative studies on the use of agro-waste ash for stabilization of earth-based materials are shown in Table 1. It is evident that each of the agro-waste ash used in the previous studies shown in Table 1 improved the geotechnical and mechanical properties of soil. This indicates that agro-waste ash is a viable material for the stabilization of soil for building applications.

2.3. Prediction methods linking lateritic brick mix design to compressive strength

Selected existing studies on prediction of compressive strength of stabilized lateritic bricks using different regression models are represented in Table 2. Some of the input variables used in the models represented in Table 2 include age, cement content, index properties (consistency and Atterberg's limit), field density, moisture content, specific gravity, sand, particle size, and laterite. These input variables were used to successfully predict the strength of lateritic bricks to a certain extent depending on the model and type of input variables employed.

3. Materials and methods

3.1. Materials

In this study, the sustainable building material used is lateritic soil and it was obtained from Tunga-Maje, Gwagwalada Area Council, Abuja. The study area, Abuja in Nigeria with Global Positioning System (GPS) coordinates of 9° 4' 20.1504" N and 7° 29' 28.6872" E is in the subtropics with seasonal heavy rainfalls that promote laterization which is a process that widely occurs in the middle Niger, Benue and Upper Benue areas [30]. The cattle bones for the production of bone ash used shown in Fig. 1 was obtained from a meat vendor shop. The chemical compositions of the lateritic soil sample (LSS) and bone ash are shown in Table 3 and 4 respectively were obtained via XRF analysis using Thermo Scientific X-ray Fluorescence (XRF) Epsilon Spectrometer. The summation of the oxides percentage of SiO₂, Al₂O₃ and Fe₂O₃ for the LSS is greater than 70% and this implies that the soil sample is pozzolanic [31]. The chemical composition of bone ash indicates that it contains predominantly oxides of calcium and phosphorus. Clean tap water that is free from contamination and good for drinking was used for the mixing of the raw materials as specified in BS EN 1008 [32]. The particle size distribution of the lateritic soil sample used for this study was obtained using Sieve analysis as presented in Fig. 2. The distribution curve indicated that the soil sample mainly contains silt.

3.2. Experimental design

The lateritic soil samples (LSS) were collected and air-dried for two weeks at the AfDB laboratory of African University of Science and Technology, Abuja. The bone ash (BA) used for the soil stabilization was obtained from the cattle bones, which were washed, sun-dried, calcined at 650 °C, crushed and passed through a 75 µm sieve. The experimental mix design for the lateritic brick

Table 1

Previous studies on the use of agro-waste for stabilization of earth-based materials.

Reference	Agro-waste type	% Content of stabilization	Curing age	Type of earth-based materials	Properties of soil improved
Akinwumi & Aidomojie [19]	Corn cob ash	0–12%	1 day and 28 days	Lateritic soil	Geotechnical properties
Ayinuola & Sogunro [20]	Bone ash	3%, 5%, 7%, 10%, 15% and 20%	–	Sandy & Clayey soil	Shear strength
Okonkwo et al. [21]	Bagasse ash	from 0% to 20% at 2% intervals	7 days	Lateritic soil	Compressive strength and California bearing ratio
James [22]	Saw-dust or wood ash	5%, 10% and 20%	2 h, 7, 14 and 28 days	Expansive soil	Unconfined compression strength (UCS)
Beigh & Lone [23]	Bone ash	2%, 4%, 6%, 8% and 10%	–	Clayey soil	Shear strength
Ayinuola & Denloye [24]	Bone ash	0, 3, 5, 7, 10, 15 and 20%	–	Sandy & Clayey soil	California bearing ratio

Table 2

Previous studies on compressive strength prediction of the lateritic brick using regression models.

Reference	Input variables	Curing age	Adopted model	Achieved R ²
Jafer et al. [25]	Age and Ordinary Portland Cement (OPC).	1, 3, 7, 14, 28 and 90 days	Non-linear multi-regression model	0.8534
Attoh-Okine & Fekpe [26]	Index properties, field density and moisture content.	–	Adaptive neural networks model	–
Iyke et al. [27]	plasticity index, percentage of particles passing sieve No.200, specific gravity, liquid limit and plastic limit	–	Artificial neural network model	–
Ezeh & Anya [28]	Water, cement, sand and laterite	28 days	Scheffe's simplex model	–
Jaritngam et al. [29]	Cement content and curing time	3, 7, 14 and 28 days	Multiple regression models	0.97

**Fig. 1.** Cattle bones used for the production of bone ash used for the study [1:127].

used consisted of four different matrices with bone ash content of 0, 3, 6 and 9% of the weight of lateritic soil. The water used for the mix design was 20% of the weight of the combination of bone ash and lateritic soil contents for the four matrices. Each of the matrices was made up of a three-component composite obtained by mixing lateritic soil, bone ash and water. These constituents were mixed in varying proportions aimed at achieving a desired compressive strength of the stabilized bricks. Both the bone ash and lateritic soil were first mixed with respect to the mix design before adding the required calculated amount of water. A homogenous mixture of lateritic soil, bone ash and water were then placed in a 50 mm × 50 mm × 50 mm mould after which the moulded bricks were cured for 3, 14 and 28 days using room-drying, sun-drying and oven-drying methods at temperatures of 23 ± 2 °C, 37 ± 2 °C and 600 °C respectively. Compressive strength tests were conducted on the cured lateritic bricks and the results were presented

in Table 6. The effects of curing age and curing temperature on each of the design mixes were analyzed with respect to compressive strength (CS). The independent variables (IVs) employed in predicting the response random variable (RRV) are X_1 , X_2 , and X_3 denoting percentage of bone ash, percentage of lateritic soil, curing age, and curing temperature respectively.

3.3. Defining IVs in estimating the behaviour of stabilized lateritic bricks

The various IVs for predicting the targeted RRV (CS) are defined in Table 5. Comprehensive experimental data of the compressive strength data and the potential IVs that could influence the RRV are shown in Table 6. The CS was determined based on monitoring of the force or load at the point of failure and the initial cross-sectional surface area during the compressive strength tests. These IVs were chosen according to their effects on the compressive strength of stabilized lateritic soil in previous studies [11]. In order to clearly understand the effects of bone ash content, curing age and curing temperature on the compressive strength of bone ash stabilized lateritic soil, bar graphs of comparison of the compressive strength of these parameters are shown in Fig. 3. It was observed from Fig. 3 that the samples containing 6% bone ash cured at a temperature of 23 °C for 28 days gave the best compressive strength. Samples cured using the oven-drying method at a temperature of 600 °C were found to have lower compressive strength compared to those cured using room-drying and sun-drying methods.

3.4. Development of Non-linear and mixed regression models for predicting the behaviour of stabilized lateritic brick

The use of statistical models to examine the possible relationship between the strength of stabilized lateritic brick and input

Table 3

Chemical composition of lateritic soil samples used for the study.

Oxides	SiO ₂	Al ₂ O ₃	Fe ₂ O ₃	K ₂ O	MgO	TiO ₂	Na ₂ O	P ₂ O ₅	CaO	BaO	MnO
%Content	67.9	20.1	6.6	1.9	1.1	1.0	0.4	0.4	0.2	0.1	0.1

Table 4
Chemical composition of bone ash used for the study [11]

Oxides	CaO	P ₂ O ₅	MgO	Na ₂ O	SrO	Al ₂ O ₃	K ₂ O	Fe ₂ O ₃	ZnO
%Content	52.20	48.08	2.08	1.33	0.87	0.61	0.09	0.03	0.01

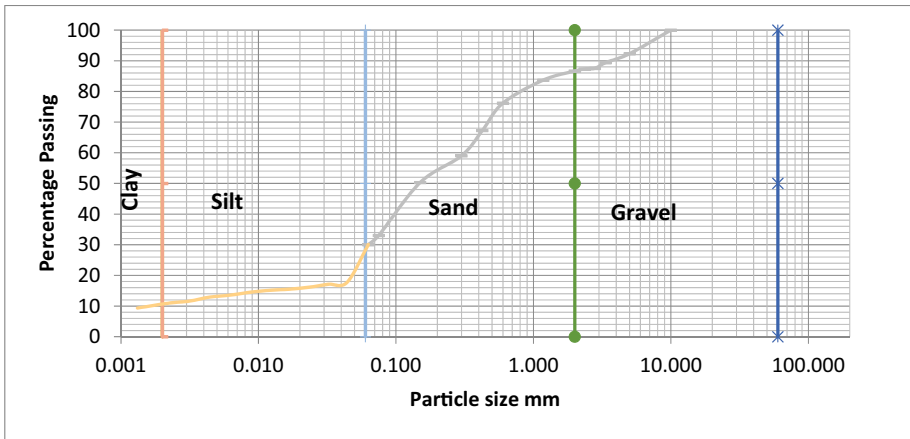


Fig. 2. Particle size distribution of lateritic soil.

Table 5
Definitions of RRV and IVs for the system.

Variables	Symbols	Definitions
Y ₁	f _{cs} (MPa)	CS (MPa): Compressive Strength of Lateritic Bricks (LB)
X ₁	W _{ba} (%)	Different Percentage of Bone Ash (BA)
X ₂	t _{ca} (days)	Curing age
X ₃	T _c (°C)	Curing temperature

variables (i.e. curing temperature, curing age and stabilized bricks mixture- based variables) were carried out. Different potential regression models were applied and their accuracies in predicting the RRV of stabilized lateritic brick were assessed. The model I described in Eq. (1) is from the conventional linear regression model whereas the non-linear and mixed models which are represented in Eqs. (2) - (5) were initiated [33].

Model I: *Multivariate linear regression analysis*

$$Y_i = \alpha + \sum_{j=1}^k \beta_j X_{ij}, i = 1, \dots, n \quad (1)$$

Model II: A non-linear model involving natural logarithms

$$\ln Y_i = \alpha + \sum_{j=1}^k \beta_j X_{ij}, i = 1, \dots, n \quad (2)$$

Model III: The second type of non-linear model involving natural logarithms

$$\ln Y_i = \alpha + \sum_{j=1}^k \beta_j \ln X_{ij}, i = 1, \dots, n \quad (3)$$

Mixed models from (4) to (k + 3)

$$\frac{X_{ij}}{Y_i} = \alpha + \sum_{l=1}^k \beta_l X_{il}, i = 1, \dots, n; j = 1, \dots, k \quad (4)$$

Mixed models from (k + 4) to (2k + 3)

$$\frac{\ln X_{ij}}{Y_i} = \alpha + \sum_{l=1}^k \beta_l \ln X_{il}, i = 1, \dots, n; j = 1, \dots, k \quad (5)$$

where k IVs such as curing temperature and age are represented by X_{ij}, and the response random variables (RRV) which is CS is

denoted by Y₁, and α, β₁...β_k are constants associated with the jth IV.

All the models proposed for the RRVs are (2 k + 3) models. The analysis of each of the (2 k + 3) models was performed using Minitab statistical software. In order to compare the accuracy of these models in predicting the target RRVs, the values of the residual standard deviation (RSD) and R² were generated from the regression analysis. Analysis of Variance (ANOVA) was used to generate the F and p values from the data samples which were used to test the significance of the selected regression models at a 95% significance level. The null hypothesis to be tested was that the target RRV with the chosen IVs cannot be predicted using the selected models. When the p-value was less than 0.05, the null hypothesis would be rejected and this indicated that the selected regression model fitted the data. Conversely, if the p-value was greater than 0.05, the null hypothesis would be accepted and this indicated that the selected regression model does not fit the data. According to Durbin-Watson statistical analysis which is based on the null hypothesis, residuals from a least-squares regression are not autocorrelated. The value of the Durbin-Watson varies from 0 to 4. An ideal Durbin-Watson value ranges from 1.5 to 2.5 [34] whereas, a value less than 2 indicates positive serial correlation; a value equals 2 indicates non-autocorrelation and a value greater 2 indicates negative correlation [35].

In order to study the differences between the predicted RRV and experimental data, the residual analysis was also conducted using Minitab software to obtain the values and distribution of residuals. Some of the k IVs will certainly have more significant effects on the target RRV than others. To test the significance of the effect of each independent variable (IV) on the RRV, t-test of correlation analysis was conducted. Each IV has a p-value corresponding to each t value. A p-value less than 0.05 at 95% level of confidence implies that the selected IV significantly contributed to the RRV while p values greater than 0.05 indicate that the IVs do not contribute to the RRV significantly. The redundancies caused by the internal correlations among IVs probably resulted in some IVs having higher significance than others. This implies that the regression analysis could be repeated by eliminating the redundant IVs which will automatically shorten the regression equation by including only the significant IVs.

Table 6

Average Results of the tested lateritic bricks.

No. of specimens	W_{ba} (%)	t_{ca} (days)	T_c (°C)	f_{cs} (MPa)
3	0	3	23	1.941
3	3	3	23	2.320
3	6	3	23	3.131
3	9	3	23	2.807
3	0	14	23	2.147
3	3	14	23	2.399
3	6	14	23	3.391
3	9	14	23	3.002
3	0	28	23	2.333
3	3	28	23	2.846
3	6	28	23	3.572
3	9	28	23	3.338
3	0	3	37	1.794
3	3	3	37	2.270
3	6	3	37	3.057
3	9	3	37	2.772
3	0	14	37	2.029
3	3	14	37	2.310
3	6	14	37	3.271
3	9	14	37	2.937
3	0	28	37	2.306
3	3	28	37	2.800
3	6	28	37	3.612
3	9	28	37	3.209
3	0	3	600	1.684
3	3	3	600	2.105
3	6	3	600	2.948
3	9	3	600	2.655
3	0	14	600	1.621
3	3	14	600	1.932
3	6	14	600	2.896
3	9	14	600	2.575
3	0	28	600	1.542
3	3	28	600	1.868
3	6	28	600	2.702
3	9	28	600	2.511

4. Results and discussion

The evaluation of the performance of the different models used in predicting the compressive strength of lateritic bricks was carried out to ascertain their accuracies in predicting the RRV. A total of 9 multivariate models were evaluated in this study. The best-fit model was obtained by conducting a residual analysis. The effects of the individual factors (IVs) on the RRV were also analyzed. The regression analysis was conducted in such a way that the internally correlated IV among the shortlisted IVs was automatically removed before the analysis.

4.1. Comparison of the different models

The nine (9) different statistical models used for the multivariate regression analysis for predicting the RRV with their prediction performance measured by R^2 values are summarized in Table 7. Non-linear models performed better than the linear model whereas numerous mixed models outperformed both linear and non-linear models as shown in Table 7. Models 4, 6, and 9 were found to be superior with higher R^2 values in predicting the RRV. The multivariate regression equations of Model 4, which exhibits superior performance compared to other models explored, is presented in Eq. (6). All the mixed models performed better with R^2 above 90%. The Eqs. of models 6 and 9 are shown in Eqs. (7) and (8).

$$W_{ba}/f_{cs} = 0.0500114 + 0.336052 W_{ba} - 0.00477305 t_{ca} + 0.000485692 T_c \quad (6)$$

$$T_c/f_{cs} = 20.4685 - 6.063 W_{ba} + 0.275179 t_{ca} + 0.47155 T_c \quad (7)$$

$$(T_c)/f_{cs} = 160.631 - 2.39097(W_{ba}) - 34.5628(W_{ls}) - 0.0201418(t_{ca}) + 0.492081(T_c) \quad (8)$$

The Durbin-Watson statistical test result was incorporated in Table 7. Durbin-Watson value of the majority of the 9 statistical models fell within the ideal value range except for Models 3, 5, and 7. It was observed that the Durbin-Watson values for Models 1, 2, 4, and 9 were greater than 2, which indicated negative correlation whereas that of Models 6 and 8 were less than 2, which indicated positive serial correlation.

4.2. Regression analysis using the Best-fit model

According to Table 7, the obtained best-fit model (Model 4) was further analyzed with respect to the experimental and predicted values from the multivariate regression analysis. Model 1 and Model 4 were used to establish the linear correlation between the experimental and modelled RRV values as shown in Fig. 4. Model 1's regression equation is represented in Eq. (9).

$$f_{cs} = 2.05029 + 0.122063 W_{ba} + 0.0106128 t_{ca} - 0.000843747 T_c \quad (9)$$

The conventional linear regression as represented in Model 1 was compared with the best-fit model (Model 4) in Fig. 4. Model 4 was found outperforming Model 1 for the predicted RRV. In addition to the comparison of R^2 value between Model 1 and Model 4, a residual analysis was conducted as shown in Figs. 5 and 6. The linear regression model (Model 1) in Fig. 5 indicated normally distributed residual values. However, its residual values were not uniformly or symmetrically distributed around the neutral line representing the zero residuals. Mixed model (Model 4) shown in Fig. 6 indicated a significantly higher frequency of residuals at 0 when compared to Model 1. The Fitted Value and Observation Order of the two distribution plots in Figs. 5 and 6 further showed that Model 4 has a better distribution of residual values which are more uniformly and symmetrically distributed around the neutral line.

4.3. Individual factor analysis

The assessment and the interpretation of the effects of the different parameters measured from the 108 mixes require the use of statistical techniques. Two-way ANOVA and regression analysis were used to analyze the data using Minitab software developed by Minitab Incorporation [36]. Statistical models presented have a confidence limit of 95%. Individual effects of each of the IV on the targeted RRV (compressive strength) based on the linear regression model (Model 1) were represented in Table 8. The correlational relationship and the level of significance of the effects of the IVs (factors) are shown by the t-values and p-values in Table 8. The bone ash content (X_1 or W_{ba}) had the highest positive significant effect (t-value = 6.22; p-value = 0.00), followed by curing temperature (X_3 or T_c) with t-value of -2.58 and p-value of 0.014. These effects were as a result of the cementitious content (CaO) of bone ash that facilitated the pozzolanic reaction that occurred in the stabilized lateritic soil which further led to the observed improved compressive strength due to the cementitious compounds formed. However, bone ash content had a significant positive impact on the compressive strength of the bone ash stabilized lateritic soil whereas curing temperature had a negative effect. The negative effect of curing temperature identified by the regression models could be attributed to the lower improvement in compressive strength gain of lateritic soil with respect to curing temperature. Curing age (X_2 or t_{ca}) had the least effect on compressive strength with t-value of 1.15 and p-value of 0.258. This implies

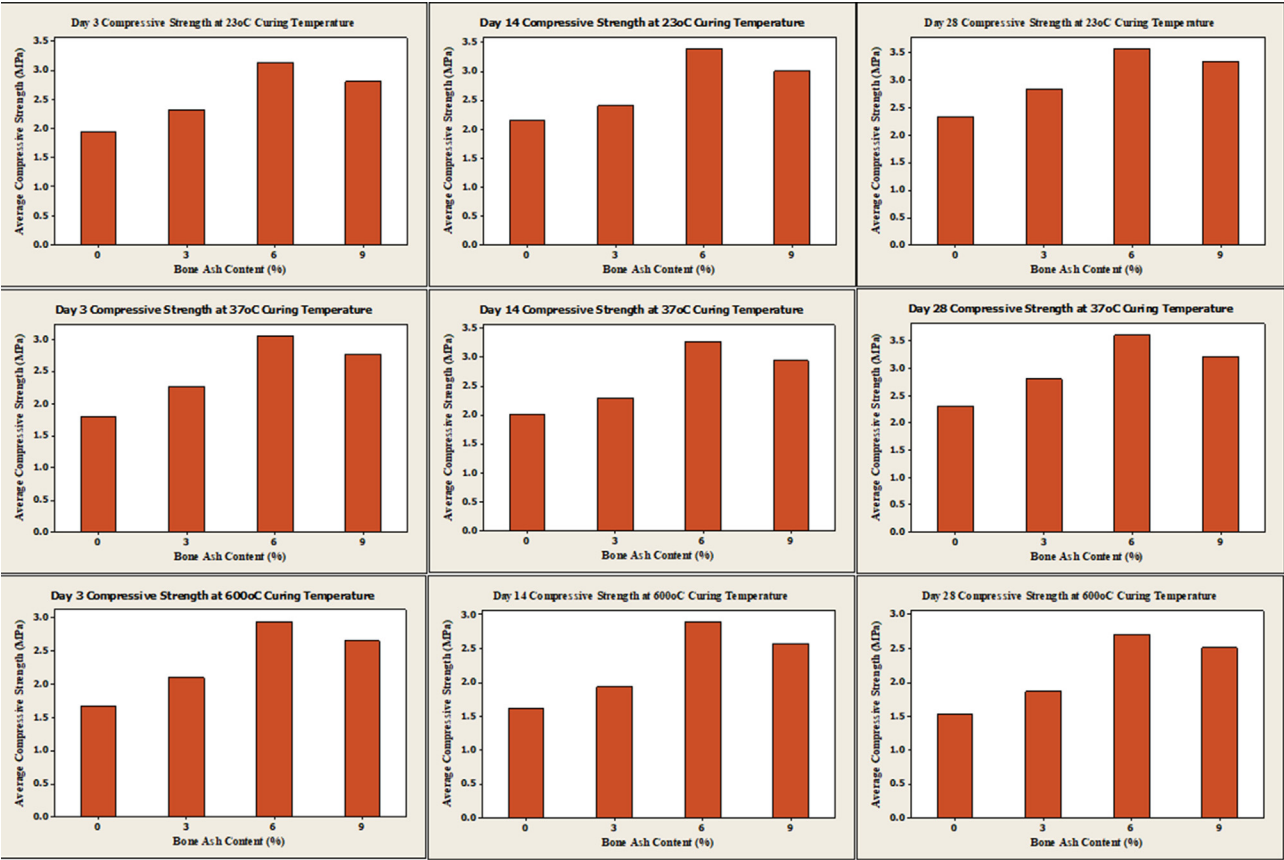


Fig. 3. Comparison of compressive strength of different parameters.

Table 7
Multivariate regression results in predicting the compressive strength of lateritic bricks.

Model type	Model Number	RRV	R ²	Durbin-Watson value
Linear	1	f_{cs}	0.733	2.29527
Non- linear	2	$\ln(f_{cs})$	0.756	2.19061
Non- linear	3	$\ln(f_{cs})$	0.883	1.21519
Mixed models	4	W_{ba}/f_{cs}	0.969*	2.57512
Mixed models	5	t_{ca}/f_{cs}	0.911	1.27837
Mixed models	6	T_c/f_{cs}	0.945*	1.90797
Mixed models	7	$\ln(W_{ba})/f_{cs}$	0.944	0.72111
Mixed models	8	$\ln(t_{ca})/f_{cs}$	0.928	1.49368
Mixed models	9	$\ln(T_c)/f_{cs}$	0.953*	2.43035

*Models that achieved the best R² are highlighted.

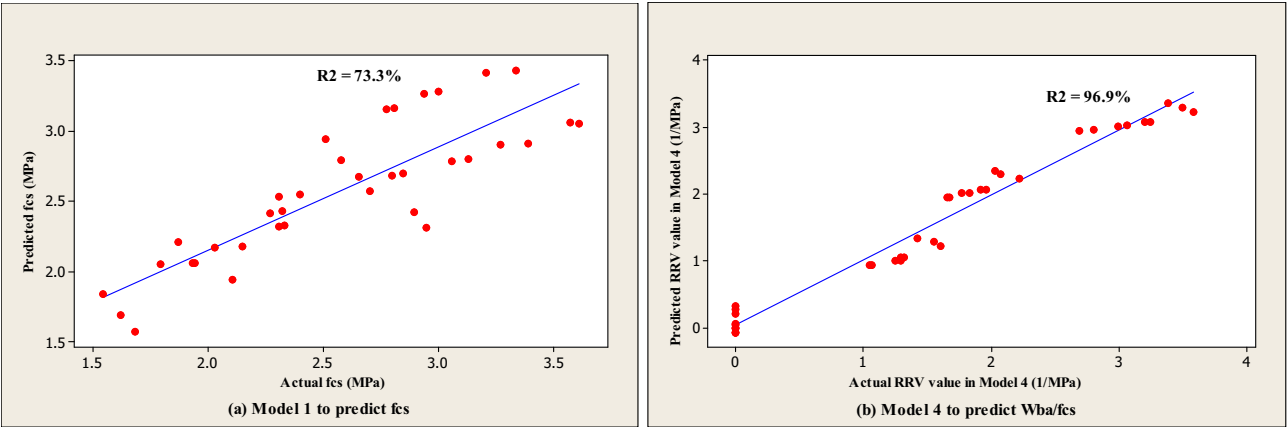
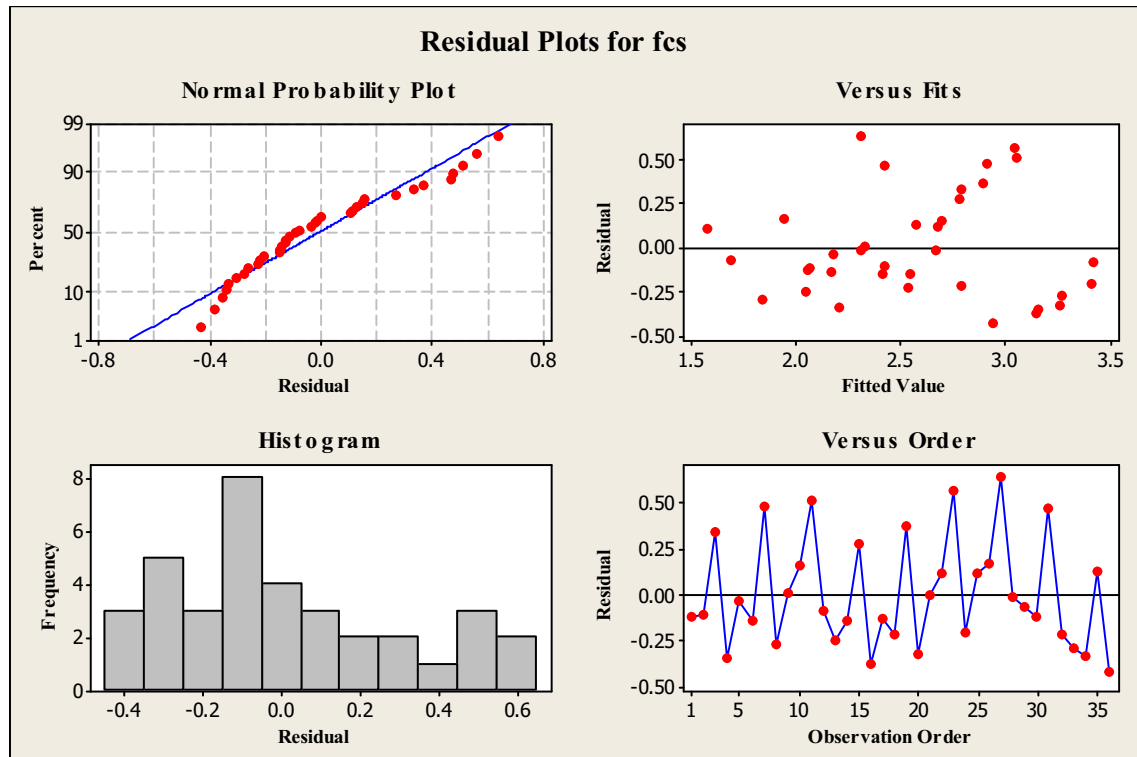
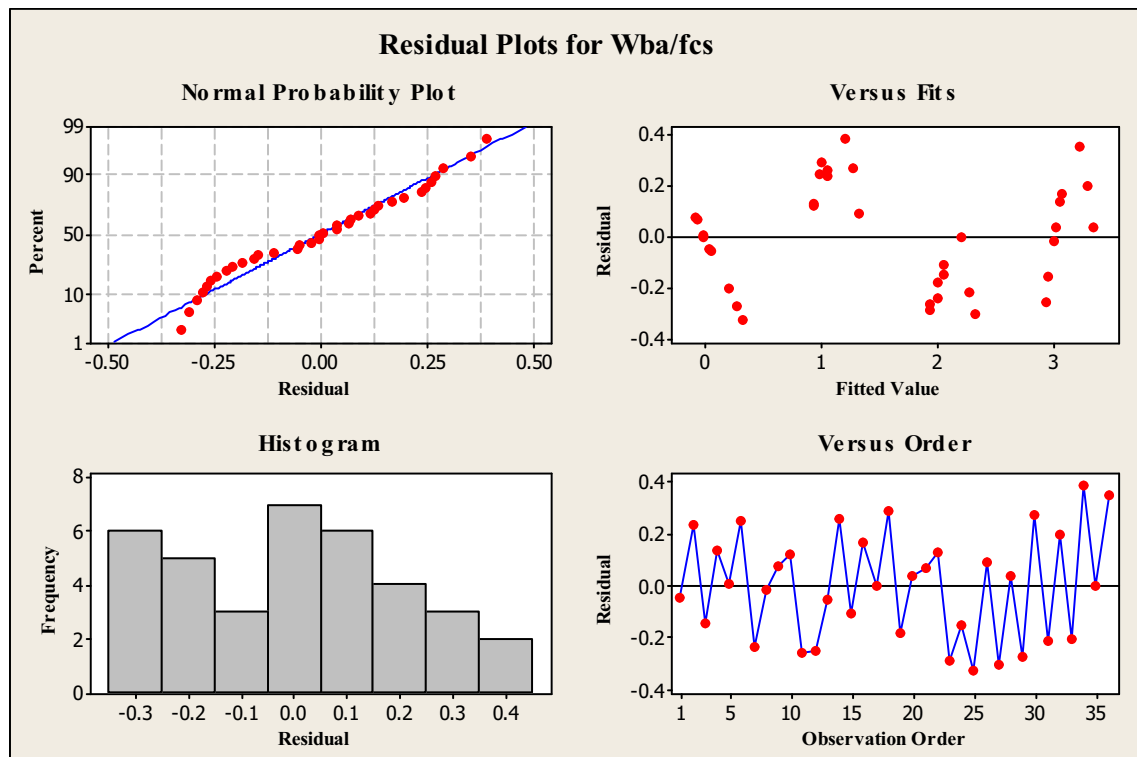


Fig. 4. Comparison between the predicted RRV and experimental data using Model 1 and Model 4.

Fig. 5. Residual analysis of Model 1 in predicting f_{cs} .Fig. 6. Residual analysis of Model 4 in predicting W_{ba}/f_{cs} .

that the effects of curing age on the compressive strength of the samples were not strong enough compared to that of the bone ash content and curing temperature. This could be as a result of lower compressive strength gain of lateritic soil with respect to curing age compared to that of cement and concrete [3].

4.4. Discussions of findings from statistical modelling

The prediction performance of all the 9 different models for the RRV (compressive strength) indicated that the mixed models generally performed better than the conventional linear regression

Table 8
Individual factor analysis of the RRV based on Model 1.

IVs	IV symbols	t value	p-value
X ₁	W _{ba}	6.22	0.000
X ₂	t _{ca}	1.15	0.258
X ₃	T _c	−2.58	0.014

* X₁ = bone ash content; X₂ = curing age; X₃ = Curing temperature

method. The non-linear regression models also performed better than the linear regression model. The introduction of the non-linear and mixed regression models yielded prediction accuracy nearly 88% and 97% respectively. The effect of the individual factor on the compressive strength was further measured using the individual factor analysis obtained from the multivariate regression analysis. The result of the individual factor analysis indicated that the bone ash content had the most significant effect on the compressive strength of RRV. This was as a result of the pozzolanic reaction that took place when the lateritic soil was mixed with bone ash and water. The stabilization mechanisms of bone ash on lateritic soil with respect to its mechanical properties, microstructural analysis and pozzolanic reaction had been comprehensively presented in previous work [11]. However, the curing age did not contribute to the improved strength of the lateritic bricks significantly as much as bone ash content and curing temperature. The statistical regression approaches used in this study can be used as a prediction tool to estimate the compressive strength of lateritic bricks for sustainable building. The proposed mixed model (Model 4) could be adopted as an alternative to other complementary methods such as artificial neural network model, Scheffe's simplex model, and adaptive neural networks model in predicting the compressive strength of lateritic bricks. This adopted statistical model has the advantages of being cost-effective and less time-consuming.

4.5. Practical implications

The practical implications of the proposed model to the construction industry would depend on the amount of time and financial resources required as well as the ability of the model to meet the requirements recommended for lateritic bricks in terms of compressive strength which is a function of optimum bone ash content, curing age and curing temperature. Based on the experimental data of this study, the optimum bone ash content that gave the best compressive strength of 3.572 MPa was 6% cured at room temperature (23 ± 2 °C) for 28 days. Room temperature being the optimum curing temperature has positive implications for low energy demand in producing the bricks. The optimum compressive strength obtained in this study met the specifications for laterite bricks of compressive strength of 1.65 MPa by the Nigerian Building and Road Research Institute (NBRI) [37]. Although the compositions of soil could vary from one location to another, lateritic soil used for moulding the brick samples has similar oxides present irrespective of the locations they were obtained. In other words, lateritic soil being a pozzolana contains oxides of silicon, aluminium and iron (SiO₂, Al₂O₃ and Fe₂O₃) up to 70% recommended by ASTM C618 [38] and will always react with the cementitious content (CaO) of bone ash in the presence of water to improve the strength of the composite (brick) formed. Hence, the model would be relevant to all lateritic soil and other pozzolanic soils.

5. Conclusions

This study successfully used newly developed multivariate regression models in predicting the compressive strength of the

bone ash stabilized lateritic bricks. Linear, non-linear and mixed models were applied in predicting the compressive strength of stabilized lateritic bricks based on the experimental results of 108 mixes. The prediction performance of the proposed multivariate models, as well as the effects of the individual factors, were compared. It was found that the non-linear models performed better than the linear model whereas the mixed models generally performed better than both the linear and non-linear models with respect to higher accuracy and symmetrical distribution of residual values. Also, the bone ash content among other predictors was found to have the most significant positive effects on the compressive strength of the lateritic bricks. However, curing age was found to have a less significant effect on the compressive strength of the samples. The usefulness of the models is limited to the range of variables used but for a more universal application, wider ranges of variables can be explored. Therefore, the proposed mixed model from this study could be further developed for the prediction of the mechanical behaviour of stabilized lateritic bricks for sustainable practical applications of housing materials in Nigeria and other developing economies.

CRedit authorship contribution statement

Ifeyinwa Ijeoma Obianyo: Conceptualization, Methodology, Writing - original draft, Software, Data curation, Resources. **Esther Nneke Anosike-Francis:** Visualization, Resources, Investigation. **Gina Odochi Ihekwe:** Visualization, Resources, Investigation. **Yang Geng:** Writing - review & editing. **Ruoyu Jin:** Methodology, Writing - review & editing. **Azikiwe Peter Onwualu:** Methodology, Writing - review & editing. **Alfred B.O. Soboyejo:** Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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