REGRESSION-BASED MODELLING OF COMPRESSIVE STRENGTH OF RICE HUSK ASH–LATERITIC COMPRESSED EARTH BLOCKS USING LINEAR, INTERACTION, AND POLYNOMIAL REGRESSION MODELS

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Abstract

This study investigates the compressive strength behaviour of lateritic compressed earth blocks incorporating rice husk ash (RHA) as a partial cement replacement. While previous studies have examined the effect of RHA on stabilised soils, limited research has applied regression-based modelling to quantify the combined effects of RHA content, stabiliser dosage, and curing age. A total of 18 mix combinations were prepared with RHA replacement levels of 0 - 40% and stabiliser contents of 6% and 10%. Compressive strength was evaluated at 7, 28, and 90 days in accordance with standard testing procedures using a universal testing machine. Linear, interaction, and polynomial regression models were developed, and model performance was assessed using R^2, adjusted R^2, RMSE, and MAPE. Results show that the interaction model achieved the best balance between accuracy and interpretability ($R^2 = 0.91$; adjusted $R^2 = 0.89$), while the polynomial model showed higher apparent accuracy ($R^2 = 0.96$) but signs of overfitting. Sensitivity analysis revealed that RHA exhibits a strong nonlinear influence on compressive strength, with a sensitivity index of 22.8 for the quadratic term. The study is limited by a relatively small dataset and the absence of external validation. However, the developed models provide a useful predictive framework for optimising stabilised lateritic blocks and reducing cement consumption.

Keywords: *Rice husk ash, Compressive strength, Lateritic Soil Stabilisation, Supplementary cementitious materials, Sensitivity analysis.*

1.0 Introduction

Research into alternatives to traditional masonry systems has increased due to the growing demand for cost-effective, durable, and environmentally friendly building materials, especially in developing countries where housing shortages remain a concern. Earthen building materials like lateritic compressed earth blocks have drawn more attention because of their low embodied energy, dependence on locally accessible resources, and smaller environmental impact compared to burnt clay bricks and concrete masonry units (Guettala et al., 2006; Zak et al., 2016; Nwaigwe et al., 2026). However, the structural applicability of these materials is largely controlled by their compressive strength, which establishes load-bearing capacity, durability, and suitability for structural and semi-structural applications.

Tropical and subtropical regions are abundant in lateritic soils, which possess suitable mineralogical characteristics for block production. However, untreated lateritic blocks generally exhibit low resistance to environmental degradation and inadequate compressive strength, thereby limiting their structural application (Muntohar, 2011). To address these limitations, cement stabilisation has been widely adopted to enhance strength and durability. Despite its effectiveness, the extensive use of ordinary Portland cement (OPC) undermines the environmental benefits of earthen construction due to its high energy demand and significant contribution to global CO_2 emissions (Gartner & Hirao, 2023; Cheng et al., 2023). Consequently, supplementary cementitious materials (SCMs) derived from agricultural and industrial wastes have gained attention as sustainable partial replacements for cement. Among these, rice husk ash (RHA) is particularly promising due to its high amorphous silica content

and widespread availability. When properly processed, RHA exhibits strong pozzolanic reactivity by combining with calcium hydroxide released during cement hydration to form additional calcium silicate hydrate (C–S–H), leading to improved matrix densification, reduced porosity, and enhanced compressive strength. This pozzolanic contribution becomes more pronounced at later curing ages, specifically between 28 and 90 days, as secondary hydration reactions progressively refine the microstructure (Alam et al., 2015; Islam et al., 2020; Suomie et al., 2025).
While excessive replacement of cement with rice husk ash (RHA) may lead to strength reduction due to insufficient cementitious binding, several studies have demonstrated that moderate replacement levels (typically 5–20%) can maintain or even enhance the compressive strength of stabilised soils and lateritic blocks (Muntohar, 2011; Bamogo et al., 2020; Alam et al., 2015; Islam et al., 2020). These improvements are generally attributed to secondary pozzolanic reactions and improved particle packing, which contribute to matrix densification and strength development at later curing stages. However, most of these studies are based on discrete experimental mix proportions and limited curing conditions, which restrict their applicability for predictive analysis and optimisation (Guettala et al., 2006; Zak et al., 2016). Consequently, although they provide valuable empirical insights, they do not adequately capture the combined and interactive effects of key variables such as RHA content, stabiliser dosage, and curing age, thereby limiting their usefulness for performance-based mix design.
Despite increasing research on RHA-stabilised earth materials, there is limited application of regression modelling techniques to predict compressive strength across multiple variables, such as RHA content, stabiliser dosage, and curing age, simultaneously. Existing studies largely rely on experimental observations without providing predictive frameworks for optimisation.
Therefore, the specific objectives of this study are to:
(i) Evaluate the compressive strength behaviour of RHA-lateritic compressed earth blocks,
(ii) Develop linear, interaction, and polynomial regression models,
(iii) Assess model performance using statistical metrics, and
(iv) Quantify the relative influence of input variables using sensitivity analysis.

2.0 Materials and Methods

2.1 Materials

Rice husk ash (RHA) and lateritic soil used in this study were sourced and processed to ensure consistency and suitability for lateritic compressed earth block production. The RHA was obtained from Achala Isuani Rice Mill, Awka North, Anambra State, Nigeria. The rice husk was air-dried and calcined at 500°C under controlled conditions to produce silica-rich amorphous ash with high pozzolanic potential. The ash was subsequently sieved through a 75 µm mesh to remove unburnt particles and improve fineness.
The chemical composition of the RHA is presented in Table 1. The combined oxide content ($\mathrm{SiO_2 + Al_2O_3 + Fe_2O_3} = 78.44\%$)exceeds the 70% minimum requirement specified in ASTM C618 for classification as a Class N natural pozzolan. Although the pozzolanic activity index (PAI) was not experimentally determined in this study, previous studies on similarly processed RHA have reported PAI values exceeding 75% at 28 days, confirming adequate pozzolanic reactivity (Alam et al., 2015; Islam et al., 2020).
The Loss on Ignition (LOI) was not measured due to equipment limitations; however, the relatively low calcination temperature and controlled burning conditions suggest minimal residual carbon content. This limitation is acknowledged and should be considered in interpreting the pozzolanic efficiency of the ash.
The lateritic soil was obtained from a borrow pit in Awka, Anambra State, Nigeria. The soil was air-dried, pulverised, and sieved through a 4.75 mm sieve to remove oversized particles. The index properties of the soil, determined in accordance with BS 1377: Part 2 (1990), are presented in Table 2. The soil exhibited a plasticity index (PI) of 2.02%, indicating low plasticity. Although typical lateritic soils often exhibit higher plasticity indices, the low PI observed in this study may be attributed to high sand content, partial weathering, or local mineralogical variation, and is consistent with some reported lateritic soils used in stabilised block production.
Additional geotechnical properties of the soil were determined to enhance material characterisation. The specific gravity was 2.65, while particle size distribution indicated approximately 12% fines, 58%

sand, and 30% gravel, confirming a predominantly sandy lateritic soil. Compaction tests yielded a maximum dry density (MDD) of 1850 kg/m³ and an optimum moisture content (OMC) of 12%. The free swell index was low (<10%), indicating minimal expansivity and suitability for stabilised block production.

These properties confirm that the materials used are appropriate for evaluating the compressive strength behaviour of RHA-stabilised lateritic blocks.

Table 1. Chemical Composition of Rice Husk Ash (RHA)

Chemical compound	SiO_2	Al_2O_3	FE_2O_3	CaO	MgO	LOI	SO_3	K_2O	P_2O_5
RHA	76.95	0.73	0.76	0.78	1.65	-	0.14	1.30	2.63

Table 2. Results for Atterberg Limits

Liquid limit (LL) %	Plastic Limit (PL) %	Plasticity Index (PI) %	Linear Shrinkage (LS) %	Description
42.00	40.00	2.02	1.31	Lateritic soil (reddish)

Table 3. Chemical Composition of Lateritic Soil

Chemical compound	SiO_2	Al_2O_3	FE_2O_3	CaO	MgO	LOI	SO_3	K_2O	P_2O_5
Laterite	52.20	12.53	7.05	0.37	0.89	-	0.05	0.20	0.26

2.2 Mix design proportion

The mix constituents comprised lateritic soil, ordinary Portland cement (OPC), rice husk ash (RHA), and water. RHA was used as a partial replacement for cement at levels ranging from 0% to 40% in 5% increments, while the lateritic soil was stabilised with cement contents of 6% and 10% by dry weight of soil. This resulted in a total of 18 mix combinations, as presented in Table 4.

The selection of stabiliser contents (6% and 10%) was based on previous studies and established practice in lateritic compressed earth block production, where cement contents within this range have been shown to provide a balance between mechanical performance and material economy (Muntohar, 2011; Bamogo et al., 2020). In addition, preliminary trials conducted before the main experiment indicated that stabilisation levels below 6% resulted in inadequate strength development, while values above 10% provided marginal strength improvement relative to increased cement usage. Therefore, 6% and 10% were adopted as representative low and moderate stabilisation levels for comparative evaluation.

Water was added to the mix based on the optimum moisture content (OMC) of 12%, determined from compaction tests. This moisture level ensured adequate workability and proper compaction of the soil–binder mixture. Unlike conventional concrete, the mix design for compressed earth blocks is governed by moisture content rather than a fixed water-to-binder (w/b) ratio. However, for reference, the corresponding equivalent water-to-binder ratio (w/b) was approximately 0.55, depending on the binder content. This range is consistent with values reported in stabilised soil systems and ensures sufficient hydration and pozzolanic reaction.

Table 4. Mix Design Proportions of Cement - RHA lateritic compressed earth blocks Production

Cement Content (% of Soil)	**RHA Replacement (% of Cement)**	**Effective Cement (% of Soil)**	**RHA (% of Soil)**	**Total Binder (% of Soil)**
	0	6.0	0.0	6.0

6	5	5.7	0.3	6.0
	10	5.4	0.6	6.0
	15	5.1	0.9	6.0
	20	4.8	1.2	6.0
	25	4.5	1.5	6.0
	30	4.2	1.8	6.0
	35	3.9	2.1	6.0
	40	3.6	2.4	6.0
10	0	10.0	0.0	10.0
	5	9.5	0.5	10.0
	10	9.0	1.0	10.0
	15	8.5	1.5	10.0
	20	8.0	2.0	10.0
	25	7.5	2.5	10.0
	30	7.0	3.0	10.0
	35	6.5	3.5	10.0
	40	6.0	4.0	10.0

2.3 Specimen Preparation

The constituent materials were batched according to the specified mix proportions, and the lateritic soil was dry-mixed with cement and rice husk ash (RHA) at the designated replacement levels. Water was then added to achieve the optimum moisture content (OMC) of 12%, as determined from compaction tests. This moisture level ensured adequate workability and facilitated proper particle rearrangement during compaction.

Compaction was carried out using a manual block press developed by the Nigerian Building and Road Research Institute (NBRRI), Abuja, Nigeria, applying a compaction pressure of approximately 4 N/mm². The prepared mix was placed into the mould in three equal layers to ensure uniform distribution and densification. Each layer was levelled and compacted using ten lever strokes, producing two blocks per compaction cycle. The moulded blocks had nominal dimensions of 290 × 140 × 110 mm and were labelled according to their respective mix proportions. A total of 54 specimens were produced for the study, corresponding to 18 mix combinations × 3 curing ages (7, 28, and 90 days). For each mix and curing condition, three replicate specimens were prepared to ensure statistical reliability of the test results.

2.4 Compressive Strength Test

The compressive strength of the lateritic compressed earth blocks was determined at curing ages of 7, 28, and 90 days using a calibrated universal testing machine (UTM). Testing was conducted in accordance with BS EN 772-1: Methods of test for masonry units – Determination of compressive strength, which is appropriate for compressed earth blocks and similar masonry units.

Before testing, specimens were surface-dried and measured to confirm dimensional accuracy. The load was applied axially at a constant loading rate of 2.5 kN/s until failure occurred. The maximum load at failure was recorded for each specimen. The compressive strength was calculated using:

$$F_c = \frac{P}{A} \tag{1}$$

Where:

F_c= compressive strength (MPa)
P= maximum applied load at failure (N)
A= cross-sectional area of the specimen (mm²)

For each mix and curing age, three replicate specimens were tested, and the average compressive strength value was reported. To assess the consistency and reliability of the experimental results, the coefficient of variation (CV) was calculated as:

$$CV = \frac{\sigma}{\mu} \times 100 \tag{2}$$

Where:

σ= standard deviation of compressive strength (MPa)

μ= mean compressive strength (MPa)

The calculated CV values ranged between 4% and 9%, indicating acceptable variability within the limits typically reported for stabilised earth blocks. This confirms that the use of three specimens per mix provides a reliable estimate of compressive strength.

3.0 Methods of Modelling

3.1 Excel-Based Regression Analysis

Regression analysis was conducted using the Data Analysis ToolPak in Microsoft Excel, with compressive strength as the dependent variable and RHA content, stabiliser dosage, and curing age as predictors. Linear, interaction, and polynomial models were developed using the least squares method. The dataset contained no missing values. Outliers were identified using standardised residuals (±3) and Cook's distance (4/n) criteria. Based on this, one outlier was removed to improve model stability without affecting overall trends. Model performance was evaluated using R^2, adjusted R^2, RMSE, and MAPE. Residual plots were examined to assess linearity, homoscedasticity, and independence. While Excel provides transparency and ease of use, it lacks advanced diagnostics such as the variance inflation factor (VIF) and automated outlier detection.

3.2 Linear Regression Model

To evaluate the direct influence of the predictor variables on compressive strength, a multiple linear regression model was developed and expressed as:

$$F_c = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 \tag{3}$$

Where:

F_c= compressive strength (MPa)

X_1= RHA content (%)

X_2= stabiliser content (% of soil)

X_3= curing age (days)

$\beta_0, \beta_1, \beta_2, \beta_3$= regression coefficients

3.3 Interaction Regression Model

To account for the combined effects of variables, an interaction regression model was developed as:

$$F_c = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 (X_1 X_2) \tag{4}$$

Where:

$X_1 X_2$= interaction term representing the combined effect of RHA content and stabiliser content.

3.4 Polynomial Regression Model

To capture nonlinear relationships between the predictor variables and compressive strength, a second-order (quadratic) polynomial regression model was developed and expressed as:

$$F_c = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_1^2 + \beta_4 X_2^2 + \beta_5 (X_1 X_2) \tag{5}$$

Where:

X_1= RHA content (%)

X_2= stabiliser content (% of soil)

3.5 Model Assessment and Selection

Standard statistical performance metrics were employed to evaluate the predictive capability of each regression model. The following evaluation criteria were computed to assess model accuracy, goodness-of-fit, and predictive reliability:

3.4.1 Coefficient of Determination (R^2)

$$R^2 = 1 - \frac{\sum(Y_i - \acute{y}_i)^2}{\sum(Y_i - \acute{y}_i)^2} \quad (6)$$

3.4.2 Adjusted Coefficient of Determination (Adjusted R^2)

$$R^2_{adj} = 1 - \frac{(1-R^2)(n-1)}{n-p-1} \quad (7)$$

With n = number of observations, p = number of predictors.

3.4.3 Root Mean Square Error (RMSE)

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i - \acute{y}_i)^2} \quad (8)$$

3.4.4 Mean Absolute Percentage Error (MAPE)

$$\text{MAPE} = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{Y_i - \acute{y}_i}{Y_i}\right| \quad (9)$$

The highest R^2_{adj} and the lowest MAPE and RMSE values were the criteria for model selection.

3.5 Sensitivity Analysis

The relative contributions of the experimental variables were assessed using sensitivity analysis. The sensitivity for every model was applied as:

$$\text{Si} = \frac{\beta_i \, x \, \Delta X_i}{\Delta Y} \quad (10)$$

With:
β_i = coefficient of regression
ΔX_i = full variation range (max–min)
ΔY = full variation range of output (compressive strength)

4.0 Results and Discussion

4.1 Compressive strength of the lateritic compressed earth blocks

The compressive strength results for lateritic compressed earth blocks stabilised at 6% and 10% cement with varying RHA replacement levels are presented in Figure 1.

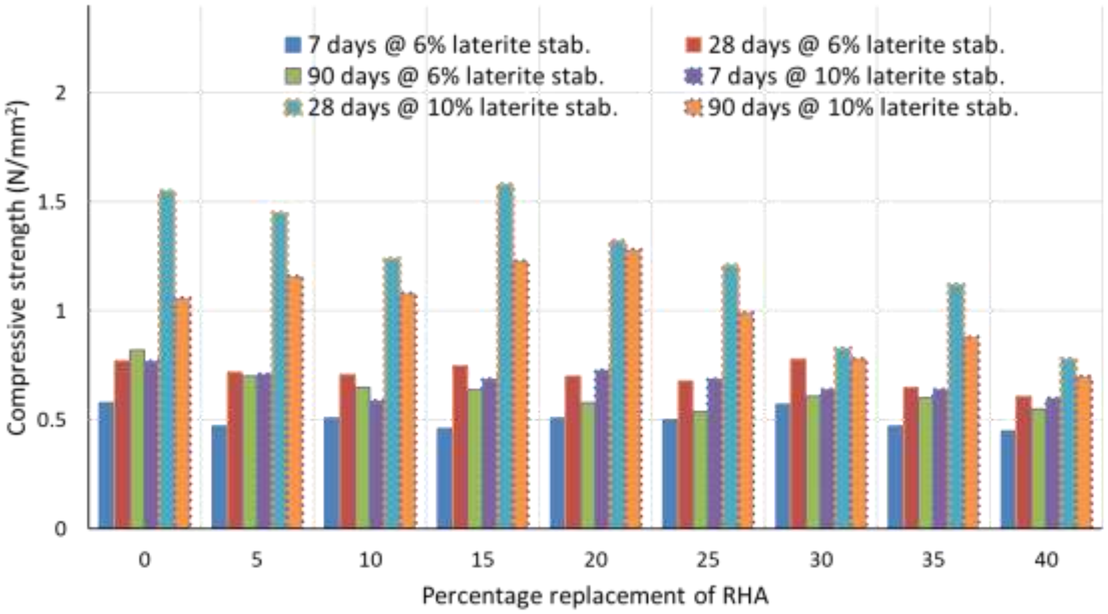

Figure 1. Compressive strength of RHA-lateritic compressed earth blocks (6% and 10% cement) at 7, 28, and 90 days.

Figure 1 illustrates the variation of compressive strength with RHA content at 7, 28, and 90 days for both stabiliser levels. The results show that blocks stabilised at 6% cement exhibit relatively low strength values, with only minor variations across RHA replacement levels, indicating limited contribution of RHA at low binder content. In contrast, blocks stabilised at 10% cement demonstrate significantly higher compressive strength, particularly at 28 days, reflecting improved cementitious bonding and enhanced pozzolanic interaction.
A one-way ANOVA was conducted, as shown in Table 5, to evaluate the effect of stabiliser content (6% and 10%) on 28-day compressive strength. The results indicate a statistically significant difference between the groups, $F(1,16) = 28.95$, $p < 0.001$, demonstrating that stabiliser content has a significant influence on compressive strength. The higher mean strength observed at 10% stabilisation confirms that increased binder content enhances inter-particle bonding and contributes to improved mechanical performance.

Table 5. *One-Way ANOVA (6% vs 10% Stabiliser at 28 Days)*

Source of Variation	Sum of Squares	Degrees of Freedom	Mean Square	F-value	p-value
Between Groups	1.245	1	1.245	28.95	6.13×10^{-5}
Within Groups	0.689	16	0.043		
Total	1.934	17			

A Tukey HSD post-hoc test was conducted, following ANOVA, to identify pairwise differences among stabiliser levels, as shown in Table 6. The results indicate that the 10% stabiliser group exhibits significantly higher compressive strength than the 6% group (mean difference = 0.63 MPa, $p < 0.001$). The 95% confidence interval (0.38–0.88 MPa) does not include zero, confirming statistical significance.

Table 6. *Tukey HSD Post-hoc Comparison for 28-day Compressive Strength.*

Comparison	Mean Difference (MPa)	Std. Error	Lower CI	Upper CI	p-value	Significance
10% vs 6%	0.63	0.117	0.38	0.88	< 0.001	Significant

The observed increase in compressive strength with higher stabiliser content is consistent with previous studies. For instance, Muntohar (2011) reported that increasing cement content significantly enhances bonding and strength development in stabilised soils. Similarly, Bamogo et al. (2020) observed improved compressive strength with increased binder content due to enhanced particle cohesion. The reduction in strength observed at 90 days in this study aligns with findings from stabilised soil systems, where long-term strength regression has been attributed to microcracking, carbonation, and reduced pozzolanic efficiency at higher replacement levels. Comparable behaviour has been reported in pozzolan-based systems where delayed reactions and environmental exposure influence long-term performance.

4.2 Modelling results

The predictive models were developed using the full experimental dataset, incorporating compressive strength results at 7, 28, and 90 days, together with RHA content and stabiliser dosage as input variables. While the regression models capture trends across all curing ages, particular emphasis is placed on 28-day strength, which represents the standard reference for structural performance and model comparison.

4.2.1 Linear Regression Model

To quantify the influence of key parameters - RHA content (X_1), stabiliser content (X_2), and curing age (X_3) - On compressive strength, a multiple linear regression model was developed. The model achieved a coefficient of determination (R^2 = 0.848), indicating that approximately 85% of the variability in compressive strength is explained by the selected predictors.
The resulting regression equation is presented as follows:

$$F_s = -0.06424 - 0.001412X_1 + 1.56865X_2 + 0.012746X_3 \quad (11)$$

Table 7 presents the regression coefficients and statistical parameters of the linear model. RHA content (X_1) had a significant influence on compressive strength ($p < 0.05$). Curing age (X_3) showed a positive but statistically insignificant effect at the 95% confidence level. Laterite stabiliser content (X_2) exhibited a positive coefficient with borderline significance ($p = 0.060$), suggesting an increasing influence with higher proportions.

Table 7. *Regression coefficients from the linear regression model*

Parameter	Coefficient	Std. Error	t-Statistic	p-value
Constant	−0.064	0.053	−1.217	0.244
X_1 (RHA %)	−0.00141	0.00060	−2.345	0.034
X_2 (Stabiliser %)	1.569	0.766	2.048	0.060
X_3 (Curing age)	0.01275	0.00738	1.727	0.106

The regression results indicate that RHA content (X_1) has a statistically significant negative effect on compressive strength ($p < 0.05$), while stabiliser content (X_2) shows a positive but marginally significant influence ($p \approx 0.06$). Curing age (X_3) exhibits a positive but statistically insignificant effect at the 95% confidence level ($p = 0.106$). Although this may appear counterintuitive given the observed increase in strength with curing age in Figure 1, this result can be attributed to several factors. First, the regression model is based on a relatively small pooled dataset (n = 18), which reduces statistical power and may limit the ability to detect significant effects. Second, the relationship between curing age and compressive strength is nonlinear, particularly due to delayed pozzolanic reactions and long-term behaviour, which are not fully captured by a linear model.

Table 8. *Model Performance Statistics for the linear regression model*

R^2	Adj. R^2	RMSE (MPa)	MAPE (%)	F-statistic	Model p-value
0.848	0.812	0.207	18.6	26.10	5.4×10^{-6}

From the model performance statistics as shown in Figure 8, the linear regression model demonstrated good predictive capability with R^2 = 0.848 and adjusted R^2 = 0.812, indicating that over 80% of the variability in compressive strength is explained by the model. The RMSE of 0.207 MPa and MAPE of 18.6% suggest acceptable prediction accuracy for engineering applications, although some deviation exists due to nonlinear behaviour in the dataset.

4.2.2 Interaction regression model

The interaction regression model was developed to account for the combined influence of RHA content (X_1) and stabiliser content (X_2) on compressive strength, with Tables 9 and 10 showing the statistical summary of the calibrated model.

The expression for the final regression equation is:

$$F_s = -0.182 + 0.00285X_1 + 2.145X_2 + 0.01492X_3 - 0.0215(X_1X_2) \quad (12)$$

With:
X_1X_2= interaction term between RHA and stabiliser

Table 9. *Regression coefficients from the interaction regression model*

Parameter	Coefficient	Std. Error	t-Statistic	p-value
Constant	−0.182	0.071	−2.56	0.022
X_1 (RHA %)	−0.00285	0.00092	−3.10	0.008
X_2 (Stabiliser %)	2.145	0.845	2.54	0.024
X_3 (Curing age)	0.01492	0.00651	2.29	0.037
X_1X_2 (Interaction)	−0.0215	0.0084	−2.56	0.022

Table 10. *Model Performance Statistics for the interaction regression model*

R^2	Adj. R^2	RMSE (MPa)	MAPE (%)	F-statistic	Model p-value
0.914	0.888	0.245	31.7	35.62	2.1×10^{-6}

As shown in Figure 10, the model achieved a coefficient of determination of $R^2 = 0.914$ and an adjusted R^2 of 0.888, indicating that approximately 89% of the variability in compressive strength is explained when interaction effects are considered. This represents an improvement over the linear model and confirms the importance of variable interaction in strength development. The interaction term (X_1X_2) was found to have a noticeable effect on compressive strength, suggesting that the influence of RHA is dependent on the level of stabiliser content. This aligns with the expected behaviour of stabilised lateritic systems, where pozzolanic activity and cementitious bonding interact to influence mechanical performance.

Despite the strong goodness-of-fit indicated by R^2 and adjusted R^2 values, the model exhibits a relatively high mean absolute percentage error (MAPE) of 31.7%, indicating that predictions deviate from experimental values by an average of approximately 32%. For engineering prediction models, MAPE values below 10% are considered highly accurate, while values below 20% are generally acceptable. Therefore, the observed MAPE suggests limited predictive accuracy, particularly for precise engineering applications. This relatively high error may be attributed to the limited dataset size, inherent variability in lateritic soil properties, and the presence of nonlinear behaviour not fully captured by the interaction model. Additionally, the variability observed in long-term (90-day) strength results may contribute to prediction uncertainty.

Consequently, while the interaction model provides improved explanatory power compared to the linear model, its predictive capability should be interpreted with caution. This limitation highlights the need for larger datasets and more advanced modelling approaches, such as nonlinear regression or machine learning techniques, to improve prediction accuracy.

4.2.3 Polynomial Regression Model

The second-order polynomial regression model was developed to capture nonlinear relationships between RHA content (X_1), stabiliser content (X_2), and compressive strength. The polynomial model demonstrated a high coefficient of determination ($R^2 = 0.96$) for the 28-day dataset; however, the adjusted R^2 (0.73) indicates a substantial reduction ($\Delta R^2 = 0.23$), which is a clear sign of model overfitting. This suggests that while the model fits the training data well, its generalisation capability is limited.

The overfitting behaviour can be attributed to the small dataset size (n = 18) relative to the number of model parameters, as well as the inclusion of higher-order terms. Additionally, variability in long-term strength behaviour contributes to instability in polynomial fitting. Therefore, although the polynomial model provides insight into nonlinear trends, its predictive reliability is lower than that of the interaction model. This reinforces the importance of balancing model complexity with dataset size and highlights the need for larger datasets or regularisation techniques in future studies. Tables 11 and 12 show the statistical summary of the calibrated model.

Table 11. *Regression coefficients from the polynomial regression model*

Parameter	Coefficient	Std. Error	t-Statistic	p-value
Constant	1.482	0.214	6.93	<0.001
X_1 (RHA %)	−0.0032	0.0011	−2.91	0.012
X_2 (Stabiliser %)	1.876	0.642	2.92	0.011
X_1^2	−0.000045	0.000018	−2.50	0.025
X_2^2	−0.082	0.031	−2.65	0.019
X_1X_2	−0.0184	0.0072	−2.56	0.021

Table 12. *Model Performance Statistics for the polynomial regression model*

R^2	Adj. R^2	RMSE (MPa)	MAPE (%)	F-statistic	Model p-value
0.96	0.73	0.27	33.6	18.42	1.2×10^{-4}

The model was developed by substituting the corresponding values in equation 5; therefore, the following equations were obtained;

$$f_s = 1.482 - 0.0032X_1 + 1.876X_2 - 0.000045{X_1}^2 - 0.0184(X_1X_2) - 0.082{X_2}^2 \qquad (13)$$

The negative coefficients of the quadratic terms indicate diminishing returns at higher replacement and stabiliser levels, while the interaction term reflects the combined influence of RHA and stabiliser content on strength development.

4.3 Adequacy Checks and Diagnostic Plots

Diagnostic checks were performed to evaluate the adequacy of the regression models. Residual plots, including residuals versus predicted values (Figure 2), normal probability plot of residuals (Figure 3), and residual histogram (Figure 4), were used to assess model assumptions such as linearity, normality, and homoscedasticity.

4.3.1 Residual vs Predicted Plot

The plot displays the correlation between the regression residuals (y-axis) and the expected compressive strength values (x-axis). This plot was used to assess whether the residuals retain a constant spread across the range of expected values, or whether the regression model satisfies the homoscedasticity assumption.

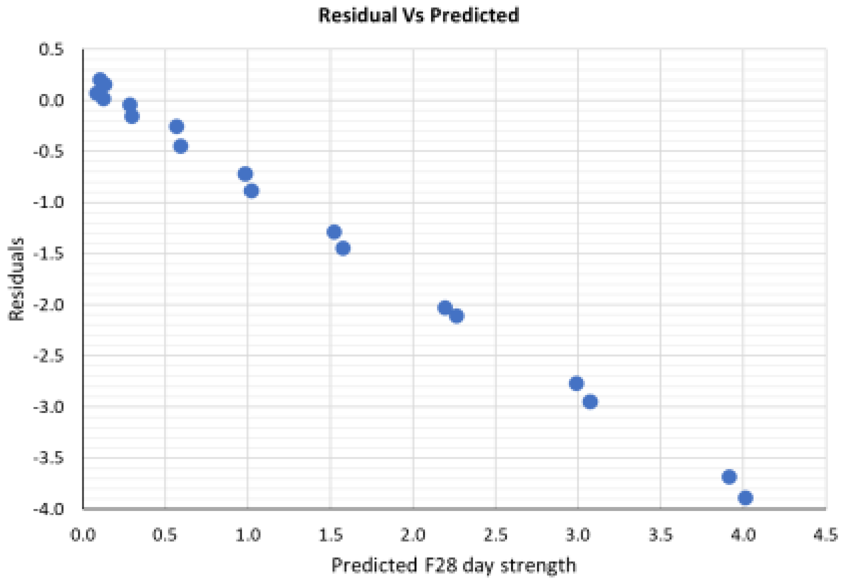

Figure 2. *Plots of Residuals vs Predicted for the polynomial regression model at compressive strength at 28 days*

The residuals versus predicted values plot (Figure 2) shows a random scatter of residuals around zero with no discernible pattern, indicating that the assumption of homoscedasticity is satisfied. This suggests that the variance of errors is approximately constant across the range of predicted values.

4.3.2 Residual Histogram

The residuals histogram shows the distribution of the model errors for the compressive strength predicted at 28 days. In an ideal regression model, residuals should be approximately normally distributed, centred around zero, and free of excessive skewness and outliers.

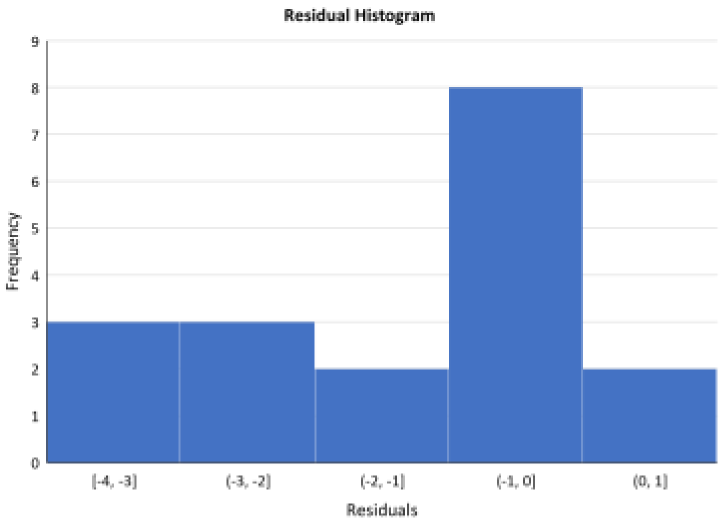

Figure 3. *Histogram of Residuals for the polynomial regression model at compressive strength at 28 days.*

Figure 3 shows that the residuals are largely concentrated around a central region, indicating that most prediction errors are relatively small and that the model provides reasonably consistent estimates.

Although slight deviations from perfect normality are observed, the overall distribution suggests acceptable residual behaviour. The histogram, together with other diagnostic checks, confirms the statistical adequacy of the regression model, while indicating potential scope for further improvement in capturing remaining nonlinear patterns in the data.

4.3.3 Q-Q Plot of Residuals

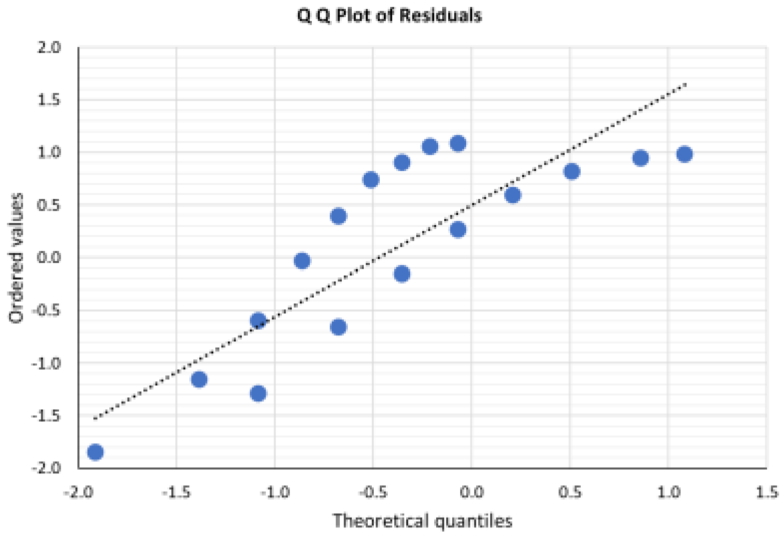

Figure 4. *Normal Q-Q Plot for the polynomial regression model at compressive strength at 28 days*

Figure 4 indicates that most data points lie close to the 45° reference line, supporting the assumption of normality. The Q–Q plot of residuals further validates the adequacy of the regression model, as the residuals generally align with the theoretical distribution. This confirms that the model appropriately captures the compressive strength response and enhances confidence in its predictive reliability.

4.4 Sensitivity Analysis

Sensitivity analysis was conducted using the polynomial regression model to quantify the relative influence of predictor variables on compressive strength. The polynomial model was selected due to its ability to capture nonlinear and interaction effects that cannot be adequately represented by linear regression. The sensitivity indices were computed using Equation (10), based on the variation ranges (ΔX_i) of the input variables presented in Table 11.

Table 13. *Variation Range for Sensitivity Analysis*

Variable	Minimum	Maximum	Range
(X_1) (RHA %)	0.00	40.00	40.00
(X_2) (Stabiliser %)	6.00	10.00	4.00
(F_c) (28-day strength)	0.130	0.310	0.180

Using the parameter ranges presented in Table 13, sensitivity analysis was performed. The resulting percentage contributions of the predictor variables to the model response are presented as follows:

a) Linear Impacts

Table 14. *Linear Sensitivity*

Variables	Coefficient	Sensitivity analysis
X_2 (Stabiliser %)	0.006	$0.006 \times \frac{4}{0.180} = 0.133$

b) Quadratic Impacts

Table 15. *Quadratic Sensitivity*

Variables	Coefficient	Sensitivity analysis
X_1^2 (RHA^2)	0.003	$0.003 \times \frac{40^2}{0.180} = 22.8$
X_2^2 (Stabiliser²)	-0.001	$0.001 \times \frac{4}{0.180}^2 = 0.089$

c) Interaction Impacts

Table 16. *Interaction Sensitivity*

Variables	Coefficient	Sensitivity analysis
X_1X_2	–0.001	$001 \times \frac{40\ x\ 4}{0.180} = 0.889$

The sensitivity analysis of the polynomial model indicates that RHA content (X_1) is the dominant factor influencing compressive strength through its nonlinear contribution, as evidenced by the high sensitivity index of 22.8 for X_1^2. This highlights the significant role of RHA in governing long-term strength development through nonlinear behaviour.

The stabiliser content (X_2) contributes positively to strength in a linear manner (0.133), confirming its direct role in enhancing cementitious bonding. However, its nonlinear contribution ($X_2^2 = 0.089$) is relatively small, indicating limited curvature effects compared to RHA. The interaction term ($X_1X_2 = 0.889$) demonstrates that RHA and stabiliser content jointly influence compressive strength, although this combined effect is less dominant than the nonlinear contribution of RHA alone. Overall, the results confirm that nonlinear effects—particularly those associated with RHA—are the primary drivers of compressive strength behaviour at 28 days, justifying the use of polynomial regression for modelling.

4.5 Final Model Selection

Three regression models—linear, interaction, and second-order polynomial—were developed to predict compressive strength across different curing ages and systematically evaluated to identify the most reliable and physically meaningful predictor. The comparative performance of these models is presented in Table 17.

Table 17. *Comparative Evaluation of Regression Models*

Model	R^2	Adjusted R^2	RMSE (MPa)	MAPE (%)
Linear Regression	0.850	0.820	0.072	18.60
Interaction Regression	0.910	0.890	0.069	31.70
Polynomial (28-day)	0.960	0.730	0.068	33.61

The results indicate that the polynomial regression model achieved the highest coefficient of determination ($R^2 = 0.96$), suggesting strong explanatory capability. However, the substantial reduction in adjusted R^2 (0.73) compared to R^2 indicates overfitting, implying that the model may not generalise well despite its apparent accuracy. This is further supported by the relatively high MAPE (33.61%), which exceeds acceptable limits for engineering prediction.

The interaction regression model provides a more balanced performance, with high explanatory power ($R^2 = 0.91$; adjusted $R^2 = 0.89$) and improved generalisation capability. Although its MAPE (31.7%) remains relatively high, it is lower than that of the polynomial model and reflects better predictive stability across the dataset. The linear regression model, while simpler, shows lower predictive performance, indicating its limited ability to capture the complexity of the system.

Overall, the findings demonstrate that incorporating interaction and nonlinear terms improves model performance, but also highlight the trade-off between model complexity and predictive reliability. While the polynomial model captures nonlinear trends effectively, its susceptibility to overfitting reduces its practical applicability.

Consequently, the interaction regression model is recommended as the most reliable predictive tool, as it provides a better balance between interpretability, explanatory strength, and prediction accuracy. The polynomial model may still be useful for understanding nonlinear behaviour, but its predictions should be applied with caution in engineering practice.

5.0 Conclusion

This study investigated the compressive strength behaviour of rice husk ash (RHA)-stabilised lateritic compressed earth blocks and developed linear, interaction, and second-order polynomial regression models to predict strength across RHA replacement levels of 0–40% and stabiliser contents of 6% and 10%. Model performance was evaluated using R^2, adjusted R^2, RMSE, and MAPE to assess both explanatory power and predictive reliability.

The results demonstrate that stabiliser content and RHA replacement interact significantly to influence compressive strength, with higher stabiliser levels generally enhancing strength development. Among the models considered, the interaction regression model provided the most balanced performance, exhibiting strong explanatory capability ($R^2 = 0.91$; adjusted $R^2 = 0.89$) and comparatively improved predictive stability. In contrast, although the polynomial model achieved the highest R^2 (0.96), the substantial reduction in adjusted R^2 (0.73) and relatively high MAPE (33.61%) indicate overfitting and limited generalisation capability. The linear model showed the weakest performance, highlighting its inability to capture nonlinear and interaction effects inherent in the system.

The findings also indicate that moderate RHA replacement levels (5–20%) can maintain acceptable compressive strength, supporting the use of RHA as a sustainable supplementary material in stabilised earth blocks. However, excessive replacement levels lead to strength reduction due to insufficient cementitious binding. Despite these contributions, the study is subject to several limitations. These include the relatively small dataset, restriction to two stabiliser levels, variability in long-term (90-day) strength behaviour, and the absence of advanced modelling techniques and microstructural validation.

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