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# SUITABILITY ASSESSMENT OF LATERITE SOIL AS ALTERNATIVE TO SHARP SAND IN CEMENT BLOCK PRODUCTION: PERFORMANCE EVALUATION AND PREDICTIVE ANALYSIS

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## Abstract

*To address the growing need for alternative building materials, this study investigated laterite soil as a partial replacement for sharp sand in cement block production, aiming to provide a sustainable and cost-effective building material. Laterite soil and sharp sand were characterized, and cement blocks with 0-30% laterite replacement were produced. Particle size distribution test was carried out to determine the grading characteristics of the aggregates. In addition, water absorption, bulk density, and compressive strength tests were evaluated at 7, 14, 21, and 28 days of curing. Statistical and predictive analysis, including ANOVA and machine learning models, was performed. Results showed laterite had a higher Coefficient of Uniformity (15.40) than sand (9.47), indicating better grading. Water absorption increased with laterite replacement, reaching 2.95% at 30% compared to 1.88% for the control mix. Bulk density decreased linearly from 2448 kg/m³ to 2180 kg/m³ at 30% replacement. Compressive strength declined with increased laterite, with significant reductions beyond 25%. ANOVA revealed significant differences in compressive strength ($p < 0.000157$), and Scheffé post-hoc analysis identified significant strength reductions at 25% and 30% laterite replacement. Predictive modeling using Artificial Neural Networks (ANN) achieved the highest accuracy ($R^2 = 0.982$, RMSE = 0.118), outperforming polynomial ($R^2 = 0.962$) and linear regression ($R^2 = 0.854$). The study concluded that laterite replacement up to 20% maintains acceptable block quality, balancing sustainability with structural performance.*

## 1.0 INTRODUCTION

The growing demand for construction materials, especially sharp sand, has intensified pressure on natural resources and contributed to environmental challenges such as riverbank erosion, loss of biodiversity, and groundwater depletion [1]. This concern is particularly critical in developing countries where rapid urbanization and rising construction costs make conventional materials increasingly unsustainable. As a result, researchers have shifted focus toward locally abundant and environmentally friendly alternatives such as laterite soil, which is widely available across tropical regions and has shown significant potential as a replacement for fine aggregates in cement-based products [2], [3].

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Several studies have demonstrated the feasibility of partially substituting natural sand with laterite to develop sustainable and cost-effective construction materials. For instance, research on laterized concrete shows that incorporating laterite scraps or soil can reduce virgin sand demand while maintaining adequate strength and durability when properly optimized [4]. Similarly, investigations into lateritic concrete and mortar performance indicate that lower replacement levels, typically between 10% and 25%, enhance or maintain compressive strength, while higher replacement levels may reduce strength due to clay minerals and increased water demand [4], [5]. Such findings support the controlled use of laterite to balance performance and sustainability outcomes.

Durability considerations also strengthen the case for laterite use. Studies have shown that lateritic blends demonstrate acceptable long-term behavior when subjected to water absorption, permeability, and wetting–drying cycles, especially at optimal replacement levels or when used with stabilizing additives such as cement, lime, or pozzolanic materials [1], [3], [6]. Furthermore, microstructural analyses reveal the formation of cementitious compounds such as Calcium Silicate Hydrate (CSH), Calcium Aluminate Hydrate (CAH), and Calcium Aluminosilicate Hydrate (CASH), contributing to improved bonding and reduction in pore spaces in stabilized lateritic materials [6], [7].

Beyond mechanical and durability performance, the integration of laterite as a fine aggregate offers significant environmental and economic advantages. For example, embodied energy in laterized mixes has been shown to reduce by over 20%, demonstrating clear sustainability benefits [4]. The use of industrial or agricultural by-products alongside laterite, such as sawdust ash [8] or recycled concrete material [7], further enhances circular-economy practices, reduces waste, and offers cost-effective alternatives for construction. Recent advancements also highlight the potential of biological and optimization techniques, such as microbially induced calcite precipitation (MICP) and swarm-based algorithms, to improve lateritic soil performance in engineering applications [9].

Predictive analysis frameworks are increasingly being integrated into material design, particularly using machine learning models to estimate mechanical properties such as compressive strength based on material proportions and curing parameters. For example, artificial neural network (ANN) models have been successfully employed to predict the strength of lateritic soils treated with cement and pozzolanic additives, achieving high accuracy and offering reliable tools for material optimization [8]. Similarly, regression-based models for laterized concrete have demonstrated their usefulness in forecasting performance and guiding mix design decisions [2], [10].

Given this context, assessing laterite soil as a sustainable alternative to sharp sand in cement block production is both timely and essential. While studies have explored laterite in concrete, mortar, pavement layers, and stabilized soils, limited research has specifically focused on its application in sandcrete block production with integrated predictive modeling. Therefore, this study seeks to evaluate the engineering, durability, and sustainability performance of lateritic soil when used as a partial substitute for sharp sand in cement block production and to develop predictive models capable of accurately estimating block strength characteristics.
The findings will contribute to sustainable construction practices, cost reduction, and environmentally responsible material sourcing across developing regions.

## 2.0. MATERIALS AND METHOD

Dangote cement was sourced from Timber market Ahiaeke, Abia State while lateritic soils were obtained from Umudike metropolis. The conventional fine aggregate, sand, were sourced from Timber Market Ahiaeke, and water samples were collected from the College of Engineering and Engineering Technology (CEET) borehole. The sandy and lateritic soils were tested for particle size distribution test and hence made ready for manual block production. Furthermore, bulk density, water absorption, and compressive strength tests were conducted at 7, 14, 21, and 28 days of curing. The obtained results were analyzed using appropriate statistical analysis and predictive modeling to assess the variation in compressive strength between blocks produced solely with sand and those incorporating different proportions of lateritic soils.

### 2.1 Sample Preparation

The required quantity of cement was measure using a scale and measuring container. For lateritic soils, samples were collected from Umudike metropolis using suitable tools like shovels and soil auger at the depth of 0.5m. The soil samples were air-dried to eliminate excess moisture and sieved through a 4.75mm sieve to remove large particles or debris, and


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store the prepared samples in labeled containers to prevent contamination. Regarding conventional fine aggregate (sand), samples were obtained from Timber market Ahiaeke. It was ensured to be free from impurities such as clay or organic matter. The sand was sieved to eliminate coarse particles or debris, and stored in labeled containers to prevent contamination. For water samples, it was collected from the CEET borehole using clean containers. The containers were ensured to be sterile to avoid contamination; the water samples were labeled with pertinent information including location and collection date, and transported to the testing facility while maintaining appropriate storage conditions to preserve water quality.

## 2.2 Block Molding And Testing Procedure

Particle size distribution for sand and lateritic soils was determined via sieve analysis following BS 812 [11], using balances, sieves, an oven, and a mechanical sieve shaker. Dried samples were sieved, and the percentage passing or retained was calculated. Manual block molding followed a systematic process. First, materials (1:6 cement-sand mix) were precisely measured and thoroughly blended. Molds were prepared with a release agent, and the mixture was compacted within them to ensure density. Following initial setting, blocks were demolded and cured for 7-28 days, kept moist and protected from extreme conditions. Quality control checks were performed throughout the process to monitor dimensions and finish. Finally, cured blocks were stored in a dry, ventilated area to prevent damage.

Water absorption of 28-day cured cubic cement block specimens (150mm x 150 mm x 150mm) was measured per BS 1881 [12] by comparing oven-dried and water-saturated weights. Bulk density was assessed at 7, 14, 21, and 28 days by calculating volume from dimensions and weighing the blocks. Compressive strength testing, following BS 1881 [13], was performed on blocks with varying sand and lateritic soil content (0–25%) at 7, 14, 21, and 28 days. Dried cubes were immersed in water before testing, loaded until failure, and compressive strength was calculated.

## 2.3 Machine Learning And Statistical Analyses Methodology

Statistical and machine learning analyses, including multiple linear regression (MLR), polynomial regression, and an artificial neural network (ANN), were performed using Python (version 3.12.12). The analyses were executed in the Google Colab environment, utilizing the scikit-learn and stats models libraries. The methodology begins with preparing a dataset of concrete samples collected from the tests carried in the laboratory as discussed in section 2.2, where key input features (water/cement ratio, cement content, sand content, laterite content, laterite replacement percentage, and curing days) are compiled into a Data frame along with compressive strength as the target variable.

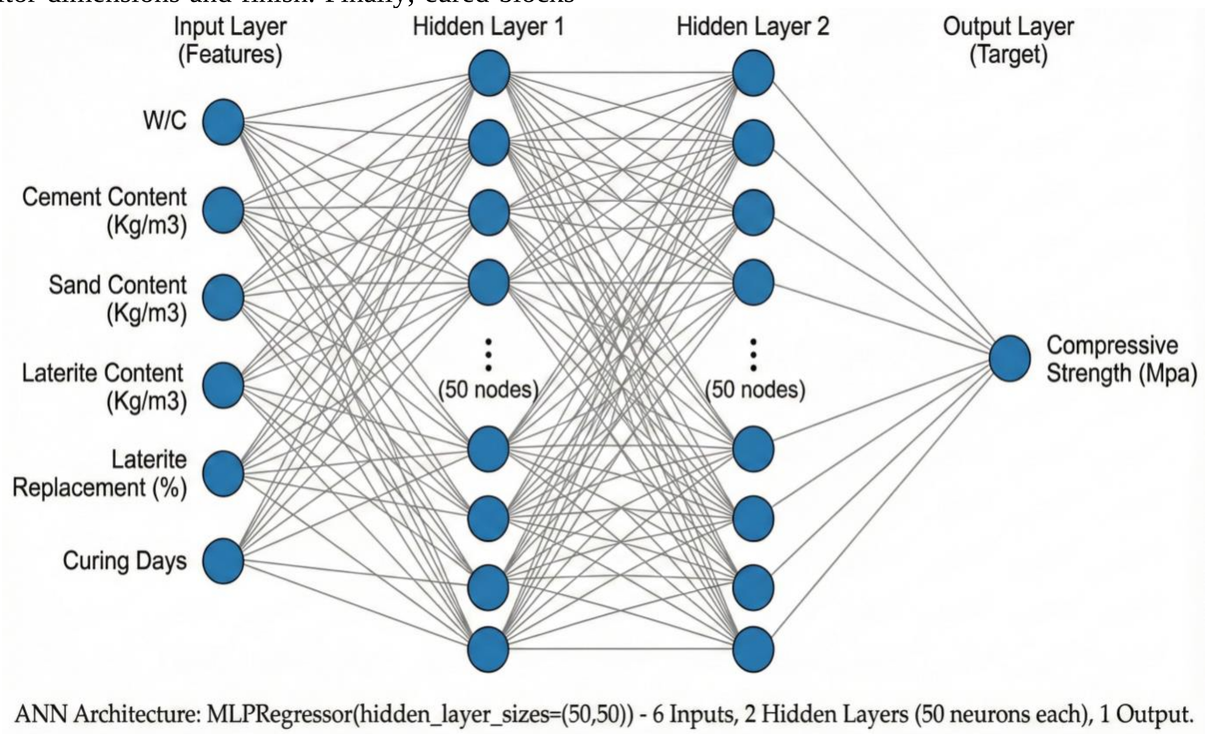


**Figure 1**: ANN architecture


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Exploratory data analysis is then performed using correlation heatmaps, histograms with statistical annotations, scatter plots with $R^2$ values, violin plots, and contour plots to reveal variable distributions and relationships. Next, the dataset is split into a training set containing 25 samples and a testing set containing 11 samples, after which the data is standardized, and three models are developed: a linear regression model to capture basic relationships, a degree-2 polynomial regression model to address non-linearities, and an MLP neural network for learning complex patterns; Ridge regression with hyperparameter tuning further refines the polynomial model. Finally, model performance is evaluated using metrics like $R^2$, RMSE, and MAE, with parity plots comparing predicted versus actual values and an ANN loss curve to monitor convergence, while regression equations are derived for the linear and polynomial models to clearly illustrate how each feature influences compressive strength. The predictive methodology applied in this study is related to the method utilized by [14] and [15] to predict the compressive strength of concrete and CBR of lateritic soil respectively. Figure 1 presents the architecture of the artificial neural network (ANN) used in the model.

## 3.0 RESULTS AND DISCUSSION

### 3.1 Grading Characteristics of Sand And Laterite

The grading characteristics of sand and laterite were evaluated using the Coefficient of Uniformity (CU) and Coefficient of Curvature (CC). Figure 2 shows that sand exhibited a CU of 9.47 and a CC of 0.95, while laterite showed a CU of 15.40 and a CC of 1.04. The higher CU value for laterite indicates a wider range of particle sizes, suggesting it is better graded than sand. Both materials displayed CC values within acceptable ranges for well-graded soils, though sand's CC suggests slightly better grading.

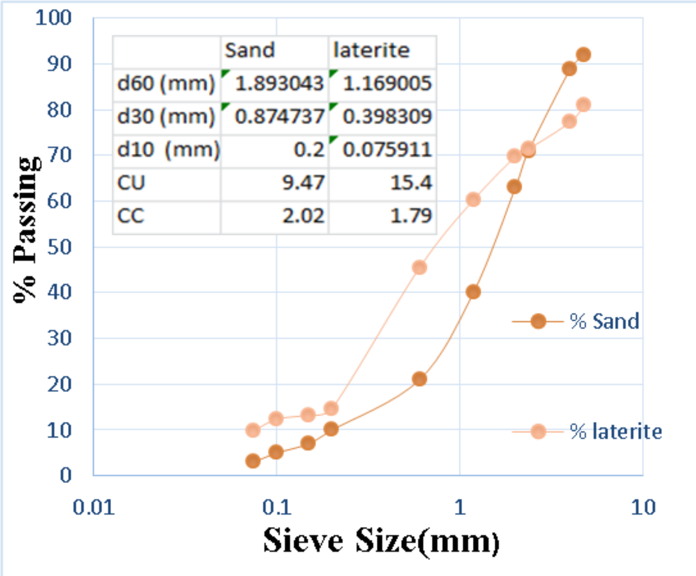


**Figure 2**: Particle size distribution of natural fine aggregates

### 3.2 Water Absorption Characteristics of Laterite-Sand Mixtures

The control mix exhibited low water absorption (1.95-1.88%). Laterite replacement increased absorption, reaching 2.95% at 30% (Table 1), indicating higher porosity and potential durability concerns in wet environments. Table 3 compares the current study's findings with the previous related works.

**Table 1**: Water absorption (WA) of the block mix

| S/N | % Replacement | 7 days WA (%) | 14 days WA (%) | 21 days WA (%) | 28 days WA (%) |
|---|---|---|---|---|---|
| **1** | 0% | 1.95 | 1.92 | 1.90 | 1.88 |
| **2** | 2% | 2.05 | 2.02 | 1.99 | 1.96 |
| **3** | 5% | 2.15 | 2.11 | 2.08 | 2.04 |
| **4** | 7% | 2.23 | 2.19 | 2.16 | 2.13 |
| **5** | 10% | 2.35 | 2.30 | 2.26 | 2.22 |
| **6** | 15% | 2.50 | 2.45 | 2.40 | 2.36 |
| **7** | 20% | 2.68 | 2.63 | 2.58 | 2.54 |
| **8** | 25% | 2.80 | 2.75 | 2.70 | 2.65 |
| **9** | 30% | 2.95 | 2.89 | 2.83 | 2.78 |


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### 3.3 Effect of Laterite Replacement on Bulk Density

Higher laterite content enhances sustainability by reducing dependence on processed quarry materials, lowering cost, and minimizing environmental impact, it simultaneously leads to reduced bulk density and potential strength loss due to the lower specific gravity and higher porosity associated with laterite. This is reflected in Figure 3, the linear decrease in density from 2448 kg/m³ at 0% laterite to 2180 kg/m³ at 30% replacement suggesting that although laterite improves the eco-friendliness of the mix, excessive replacement can compromise compactness, mechanical performance, and overall structural reliability, making it essential to identify an optimal balance between environmental benefits and engineering requirements.

**Table 2**: Experimental data

| W/C | Cement content (Kg/m$^3$) | Sand content (Kg/m$^3$) | Laterite content (Kg/m$^3$) | Laterite replacement (%) | Curing days | Compressive Strength (Mpa) |
|---|---|---|---|---|---|---|
| 0.5 | 274 | 1824 | 0 | 0 | 7 | 4.14 |
| 0.5 | 274 | 1824 | 0 | 0 | 14 | 4.98 |
| 0.5 | 274 | 1824 | 0 | 0 | 21 | 5.66 |
| 0.5 | 274 | 1824 | 0 | 0 | 28 | 6.42 |
| 0.5 | 274 | 1787.52 | 36.48 | 2 | 7 | 3.98 |
| 0.5 | 274 | 1787.52 | 36.48 | 2 | 14 | 4.66 |
| 0.5 | 274 | 1787.52 | 36.48 | 2 | 21 | 5.19 |
| 0.5 | 274 | 1787.52 | 36.48 | 2 | 28 | 6.02 |
| 0.5 | 274 | 1732.8 | 91.2 | 5 | 7 | 3.22 |
| 0.5 | 274 | 1732.8 | 91.2 | 5 | 14 | 4.21 |
| 0.5 | 274 | 1732.8 | 91.2 | 5 | 21 | 4.96 |
| 0.5 | 274 | 1732.8 | 91.2 | 5 | 28 | 5.83 |
| 0.5 | 274 | 1696.32 | 127.68 | 7 | 7 | 3.21 |
| 0.5 | 274 | 1696.32 | 127.68 | 7 | 14 | 3.65 |
| 0.5 | 274 | 1696.32 | 127.68 | 7 | 21 | 4.63 |
| 0.5 | 274 | 1696.32 | 127.68 | 7 | 28 | 5.43 |
| 0.5 | 274 | 1641.6 | 182.4 | 10 | 7 | 3.02 |
| 0.5 | 274 | 1641.6 | 182.4 | 10 | 14 | 3.61 |
| 0.5 | 274 | 1641.6 | 182.4 | 10 | 21 | 4.25 |
| 0.5 | 274 | 1641.6 | 182.4 | 10 | 28 | 5 |
| 0.5 | 274 | 1550.4 | 273.6 | 15 | 7 | 2.87 |
| 0.5 | 274 | 1550.4 | 273.6 | 15 | 14 | 3.31 |
| 0.5 | 274 | 1550.4 | 273.6 | 15 | 21 | 3.84 |
| 0.5 | 274 | 1550.4 | 273.6 | 15 | 28 | 4.67 |
| 0.5 | 274 | 1459.2 | 364.8 | 20 | 7 | 2.57 |
| 0.5 | 274 | 1459.2 | 364.8 | 20 | 14 | 2.88 |
| 0.5 | 274 | 1459.2 | 364.8 | 20 | 21 | 3.21 |
| 0.5 | 274 | 1459.2 | 364.8 | 20 | 28 | 3.28 |
| 0.5 | 274 | 1368 | 456 | 25 | 7 | 2.55 |
| 0.5 | 274 | 1368 | 456 | 25 | 14 | 2.68 |
| 0.5 | 274 | 1368 | 456 | 25 | 21 | 2.87 |
| 0.5 | 274 | 1368 | 456 | 25 | 28 | 3.2 |
| 0.5 | 274 | 1276.8 | 547.2 | 30 | 7 | 2.02 |
| 0.5 | 274 | 1276.8 | 547.2 | 30 | 14 | 2.54 |
| 0.5 | 274 | 1276.8 | 547.2 | 30 | 21 | 2.64 |
| 0.5 | 274 | 1276.8 | 547.2 | 30 | 28 | 2.89 |


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### 3.4 Experimental/Analytical Data

Table 2 contains the experimental data used for all subsequent statistical and machine learning analyses, including histograms; scatter plots, contour plots, violin plots, and predictive models.

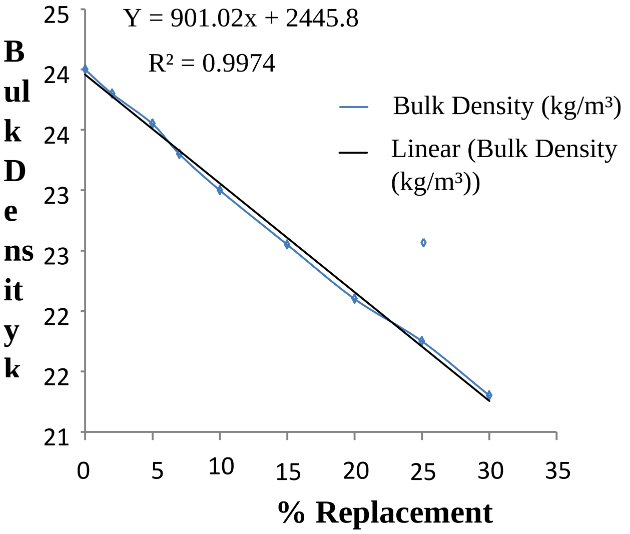


**Figure 3**: Bulk density result visualization

### 3.5 Effect of Laterite Replacement on Compressive Strength

Compressive strength tests (Figure 4) revealed a decrease in strength with increasing laterite replacement, tested at 7, 14, 21, and 28 days. The control mix (0% laterite) exhibited the highest strength, which steadily increased over time. Higher laterite content resulted in significant strength reduction, limiting load-bearing applications.

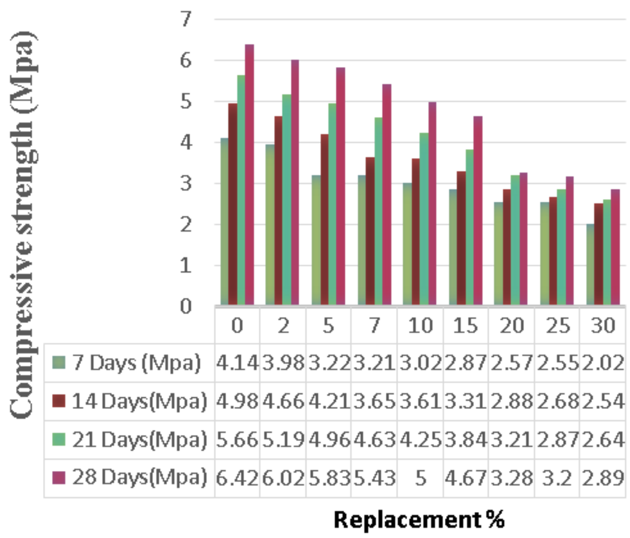


**Figure 4**: Compressive strength visualization

**Table 3**: Short comparative table

| **Finding (current)** | **Matches which prior work?** | **Key difference / reason** |
|---|---|---|
| ↑ water absorption with more laterite (to 2.95% at 30%) | Ewa [16] | Differences in absolute numbers depend on grading and mix ratio; Consoli [3] shows stabilization can reverse effect |
| Linear ↓ bulk density with laterite; eqn $y = -901.02x + 2445.8$, $R^2=0.9974$ | Ewa ([16], Akinyemi [17] | High $R^2$ indicates strong, consistent effect for your material; Consoli [3] demonstrates density can be raised via grain-size modification and compaction |
| ↓ compressive strength with increased laterite (7–28 d) | Ofuonu [18], Ewa [16] | Ofuonu [18] saw linear decline up to 12.5% replacement; Ibrahim [19] and Consoli [3] show strength can be recovered with cement stabilization and grading control |

### 3.6 Statistical Analysis Using ANOVA

Analysis of variance (ANOVA) was conducted to determine if there are statistically significant differences in compressive strength between the different replacement levels. The analysis of variance was done in Excel 2010 using the values of compressive strength shown in Figure 4 and the following result were obtained as shown in Table 4.

Since the p-value is **0.000157**, which is less than 0.05, there is enough evidence to reject the null hypothesis. This indicates that there are statistically significant differences in compressive strength between the different replacement levels.

**Table 4**: ANOVA single factor results

| Groups | Count | Sum | Average | Variance |
|---|---|---|---|---|
| 0 | 4 | 21.2 | 5.3 | 0.944 |
| 2 | 4 | 19.85 | 4.9625 | 0.742292 |
| 5 | 4 | 18.22 | 4.555 | 1.2303 |
| 7 | 4 | 16.92 | 4.23 | 0.992267 |
| 10 | 4 | 15.88 | 3.97 | 0.7238 |
| 15 | 4 | 14.69 | 3.6725 | 0.599492 |
| 20 | 4 | 11.94 | 2.985 | 0.106967 |
| 25 | 4 | 11.3 | 2.825 | 0.079767 |
| 30 | 4 | 10.09 | 2.5225 | 0.133892 |

| Source of Variation | SS | df | MS | F |
|---|---|---|---|---|
| **Between Groups** | 30.292718 | | 3.786588 | 6.137345 |
| **Within Groups** | 16.6583327 | | 0.616975 | |
| **Total** | 46.9510335 | | | |

### 3.7 Post HOC Analysis

The p-value corresponding to the F-statistic of one-way ANOVA is lower than 0.05, suggesting that one or more treatments are significantly different. Scheffe multiple comparison tests follow. These post-hoc tests would likely identify which of the pairs of treatments are significantly different from each other, the analysis was computed using the online version of Scheffe multiple comparison tests. The results obtained are shown in Table 5 where A, B, C, D, E, F, H and I represents 0%, 2%, 5%, 7%, 10%, 15%, 20%, 25% and 30% respectively and the treatment data used for this analysis is captured in Figure 4. Scheffé post-hoc analysis revealed no significant compressive strength differences between most laterite replacement levels ($p > 0.05$). However, significant strength reductions ($p < 0.05$) were observed when comparing the 0% control mix to 25% and 30% replacements. Replacements from 2% to 20% showed no significant deviation from the control, indicating acceptable strength maintenance within that range.

**Table 5:** Scheffé results for compressive strength of samples

| Treatments pair | Scheffé Tt-statistic | Scheffé p-value | Scheffé inferfence |
|---|---|---|---|
| A vs B | 0.6077 | 0.999 | Insignificant |
| A vs C | 1.3413 | 0.983 | Insignificant |
| A vs D | 1.9265 | 0.870 | Insignificant |
| A vs E | 2.3946 | 0.675 | Insignificant |
| A vs F | 2.9302 | 0.410 | Insignificant |
| A vs G | 4.1680 | 0.063 | Insignificant |
| A vs H | 4.4561 | 0.037 | $p<0.05$ |
| A vs I | 5.0008 | 0.012 | $p<0.05$ |

### 3.8 Concrete Strength And Material Composition Analysis

This analysis explores concrete mix design and compressive strength. The correlation matrix (Figure 5) shows that cement and curing time positively correlate with strength, while sand/laterite negatively correlate; the water-cement ratio is independent. Figure 6 reveals constant water-cement and cement content, while sand and laterite show wider, similarly spread distributions. Figures 7 and 8 show that compressive strength is strongly influenced by aggregate composition and curing age. Figure 7

reveals no trend with water–cement ratio due to its uniformity across all mixes, while sand content shows a positive correlation with strength and laterite content shows a corresponding negative correlation, indicating that higher sand improves packing and higher laterite increases porosity. Figure 8 confirms that strength increases steadily with curing time, with wider distributions at later ages reflecting the influence of varying mix proportions. Finally, Figure 9's contour plots indicate higher strength with lower water-cement ratios and optimal sand/laterite content ranges.


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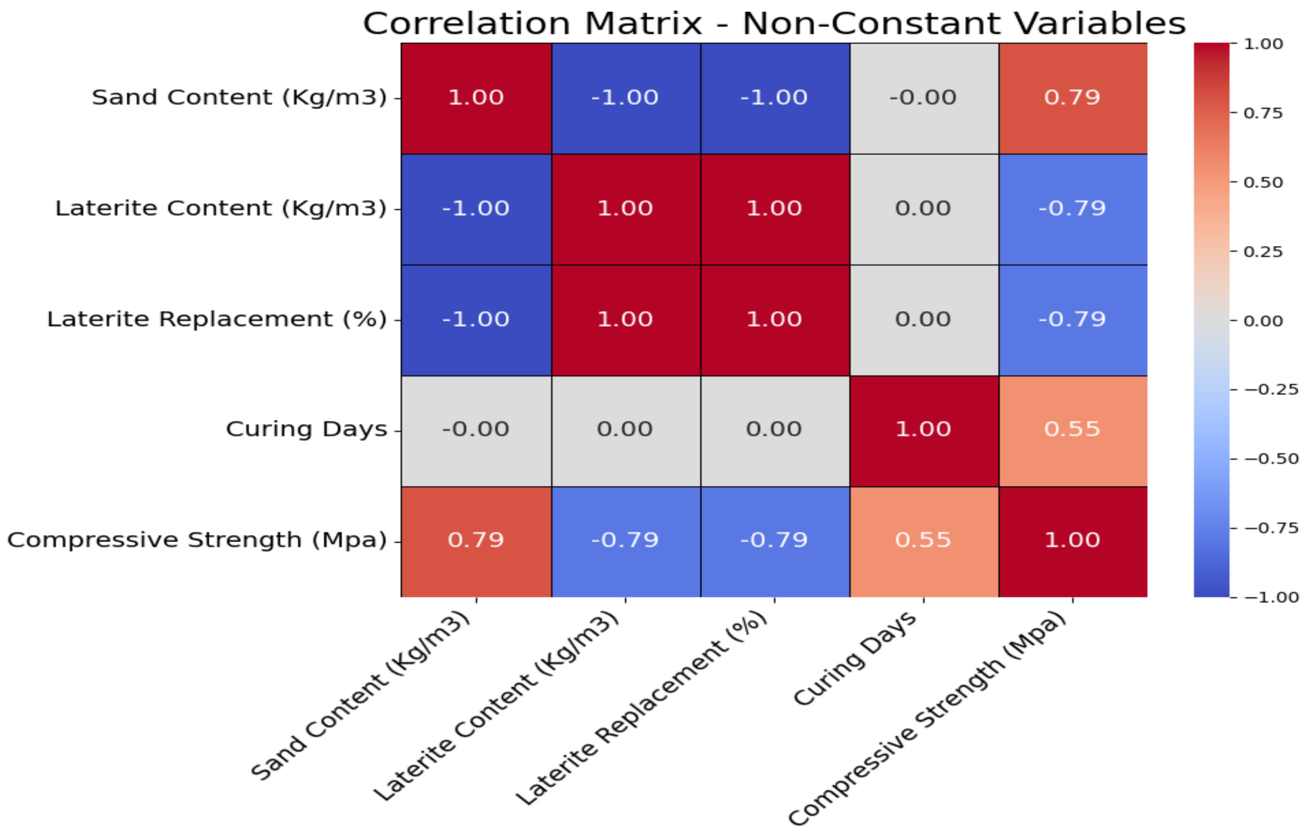


**Figure 5**: Correlation matrix of concrete mix design variables

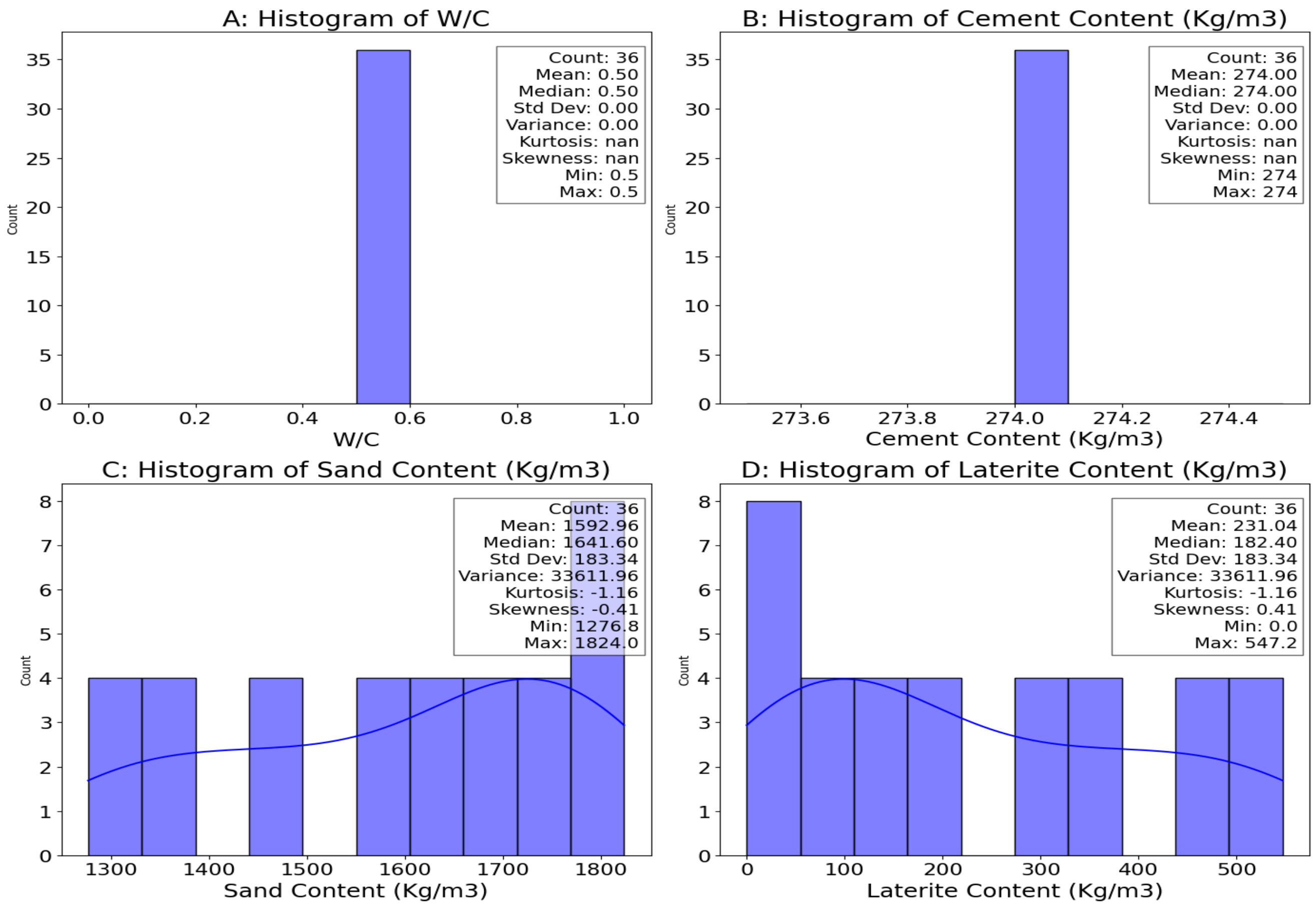


**Figure 6**: Histogram distribution and statistical analysis of concrete properties



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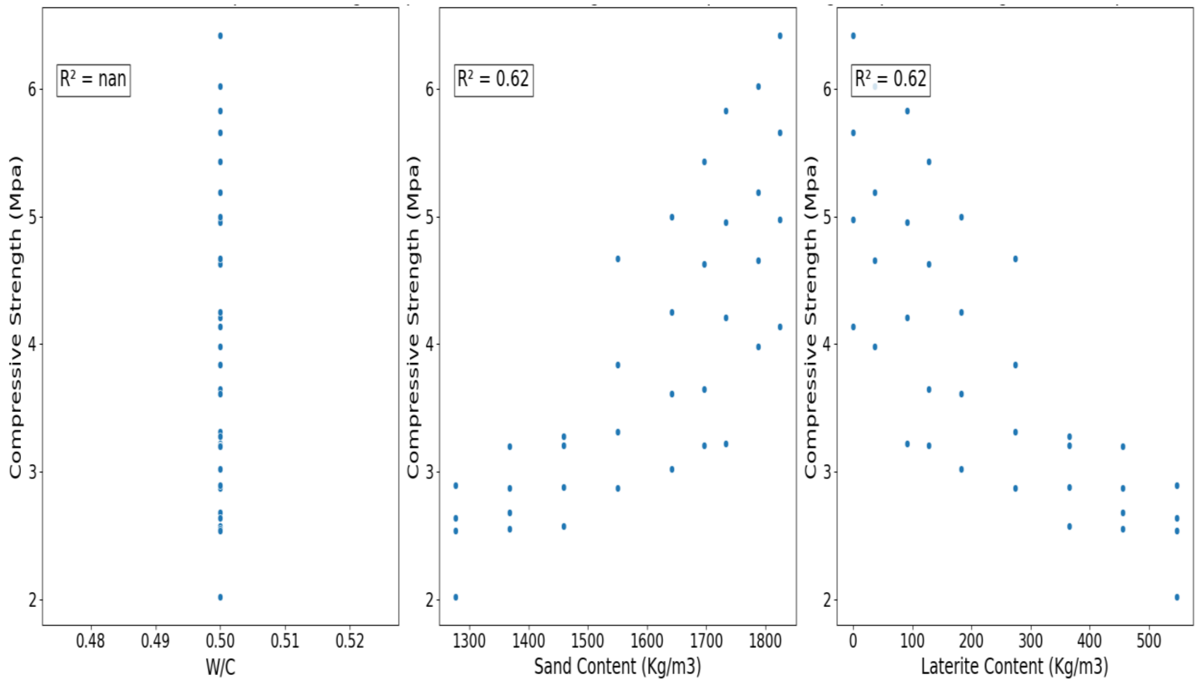


**Figure 7**: Scatter plot analysis of compressive strength factors

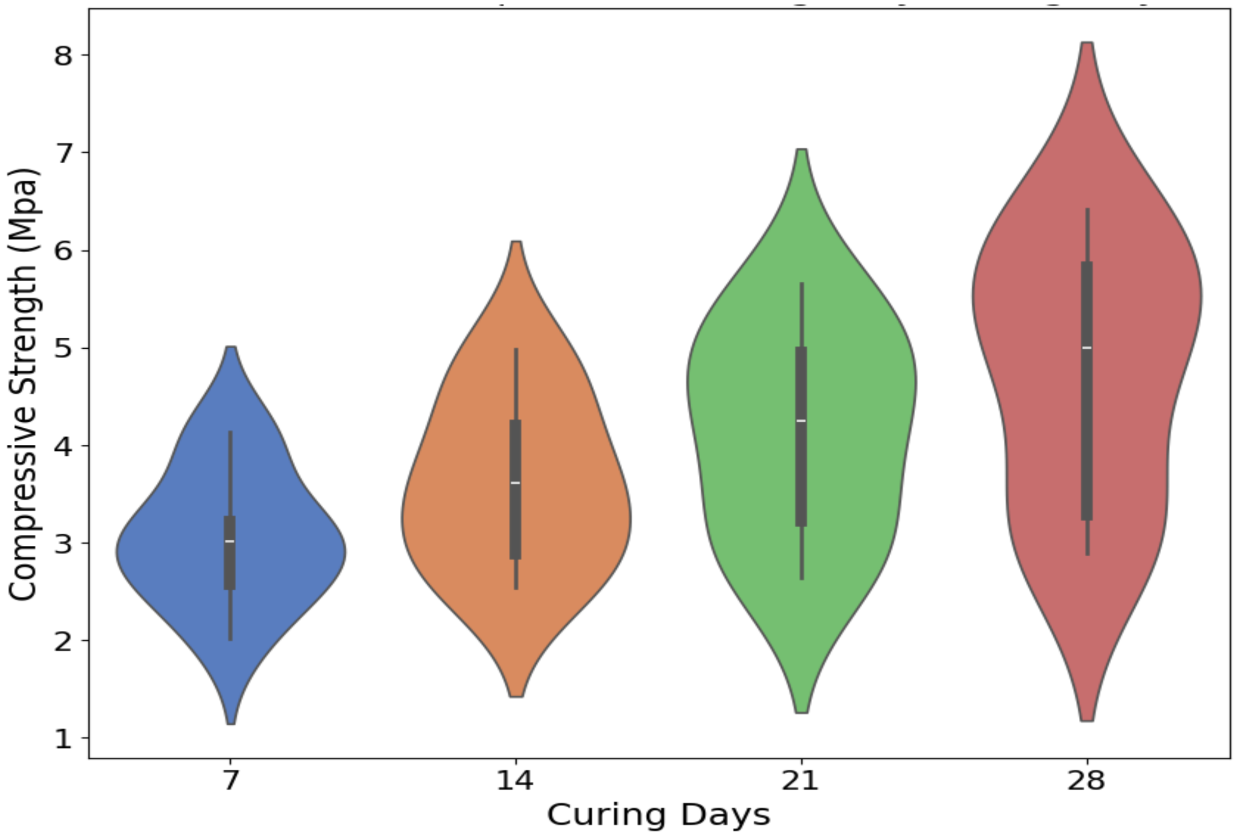


**Figure 8**: Violin plot of compressive strength over time

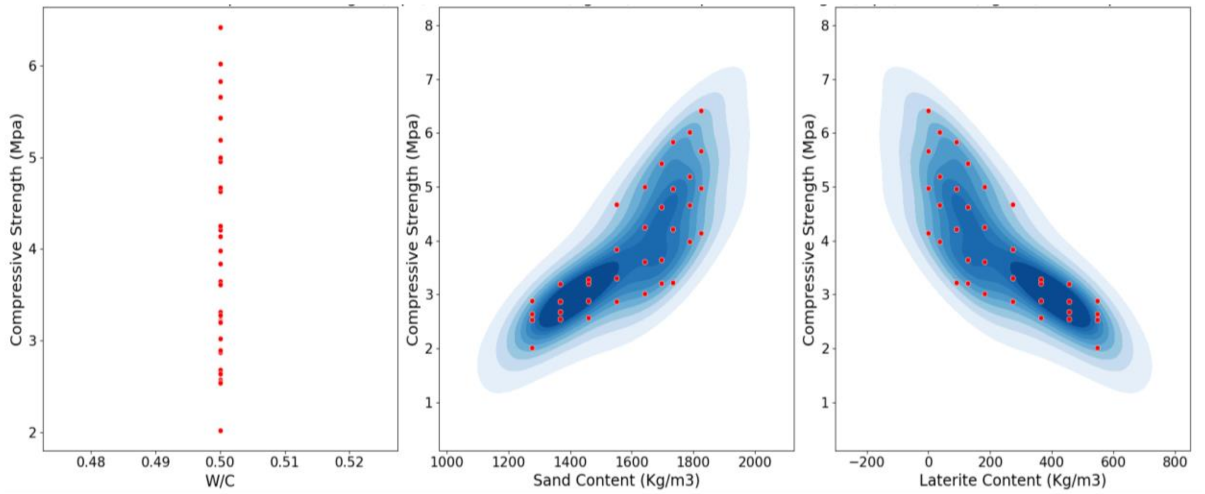


**Figure 9**: Contour plots of compressive strength and material ratios

### 3.9 Linear Regression Model

Figure 10 shows the correlation between measured and predicted compressive strength using linear regression. Linear regression is a simple and interpretable model used to predict compressive strength (CS) based on independent variables such as sand content (A), laterite content (B), laterite replacement percentage (C), and curing days (D). The positive coefficient for sand content (0.2093A) signifies that increasing sand enhances strength. Conversely, negative coefficients for laterite content (-0.2093B) and replacement (-0.2093C) indicate a strength reduction. Notably, curing days (0.7196D) exhibit the strongest positive impact on compressive strength. A collinearity assessment was performed using Variance Inflation Factors (VIF). The results showed that sand content, laterite content, and laterite replacement percentage exhibited perfect multicollinearity (VIF → ∞) because these variables are mathematically dependent. Water–cement ratio and cement content showed no variance across the samples (VIF = 0), while curing days was the only independent variable (VIF = 1). The full VIF table is provided in Table 6.

**Table 6**: Collinearity diagnostics (VIF values) for predictor variables

| Predictor | VIF | Interpretation |
|---|---|---|
| W/C | 0.0 | Constant variable — no variance |
| Cement Content | 0.0 | Constant variable — no variance |
| Sand Content | ∞ | Perfect multicollinearity |
| Laterite Content | ∞ | Perfect multicollinearity |
| Laterite Replacement (%) | ∞ | Derived variable — perfect multicollinearity |
| Curing Days | 1.0 | No multicollinearity |

The regression equation obtained is shown in Equation 1.

$$\mathbf{CS} = 3.5450 + 0.2093A - 0.2093B - 0.2093C + 0.7196D \quad (1)$$

This model produced an $R^2$ value of 0.854, indicating that 85.4% of the variation in compressive strength is explained by the independent variables. The RMSE (0.337) and MAE (0.314) suggest moderate error levels. The correlation coefficient (0.976) indicates a strong linear relationship between the variables, though the model may not fully capture nonlinear trends.

### 3.10 Polynomial Regression Model

Figure 11 shows the correlation between measured and predicted compressive strength using polynomial regression. Polynomial regression extends linear regression by introducing squared and interaction terms to capture nonlinear relationships. The equation obtained is shown in Equation 2.

$$\mathrm{CS} = 3.26883 + 0.2493 + (B - C) + 0.4329D + 0.0236 + (A^2 - AB - AC + B^2 + BC + C^2) + 0.457 + (AD - BD - CD) + 0.0718D^2) \quad (2)$$

With $R^2$ = 0.962, polynomial regression provides a better fit than linear regression. The RMSE (0.171) and MAE (0.139) indicate lower error, and the correlation (0.997) is near perfect. This suggests


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polynomial regression effectively models the complex relationships between variables.

### 3.11 Artificial Neural Network (ANN)

ANN is a data-driven approach that captures nonlinear dependencies between variables, the correlation between measured and predicted compressive strength using artificial neural network is presented in Figure 12. The training loss curve over 175 epochs expressed in Figure 13 shows a rapid decrease initially and gradual stabilization, indicating effective learning. ANN achieved the highest $R^2$ (0.982), signifying excellent predictive power. The RMSE (0.118) and MAE (0.112) are the lowest among all models used in this study, meaning ANN has the least prediction error. With a correlation of 0.994, ANN nearly perfectly predicts compressive strength compared to the regression models.

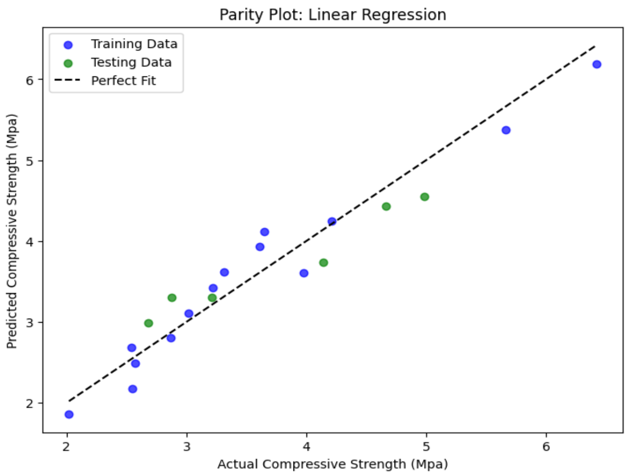


**Figure 10**: Correlation between measured and predicted compressive strength using linear regression

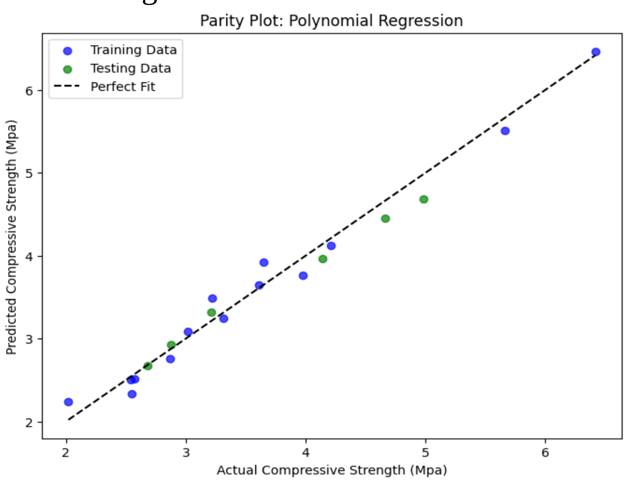


**Figure 11**: Correlation between measured and predicted compressive strength using polynomial regression

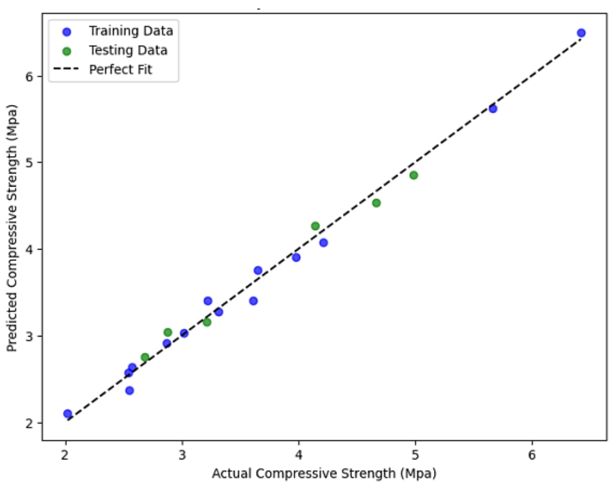


**Figure 12**: Correlation between measured andpredicted compressive strength using artificial neural network

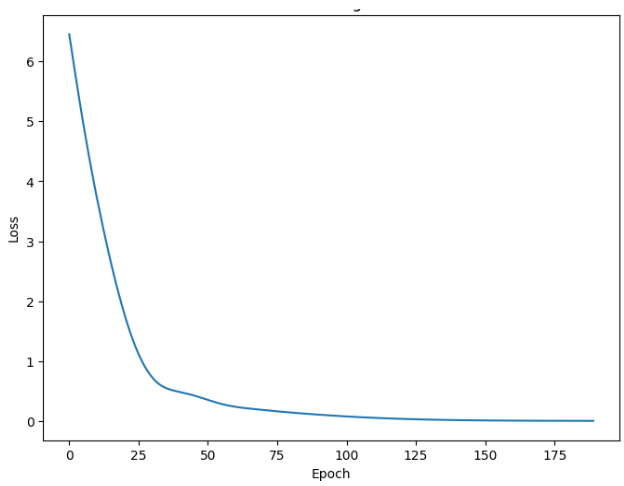


**Figure 13**: ANN training loss

### 3.12 Comparative Analysis of Predictive Results with Previous Studies

Comparing the three models as expressed in Figure 14 and Table 7 reveal that the ANN outperforms both the linear and polynomial regressions, evidenced by its highest $R^2$ and lowest error metrics (RMSE, MAE, SI). While the polynomial regression model offers a significant improvement over the linear model by capturing non-linear relationships, the ANN provides the best overall fit, making it the most accurate predictor of compressive strength among the tested approaches.


https://dx.doi.org/10.4314/njt.v44i4.1

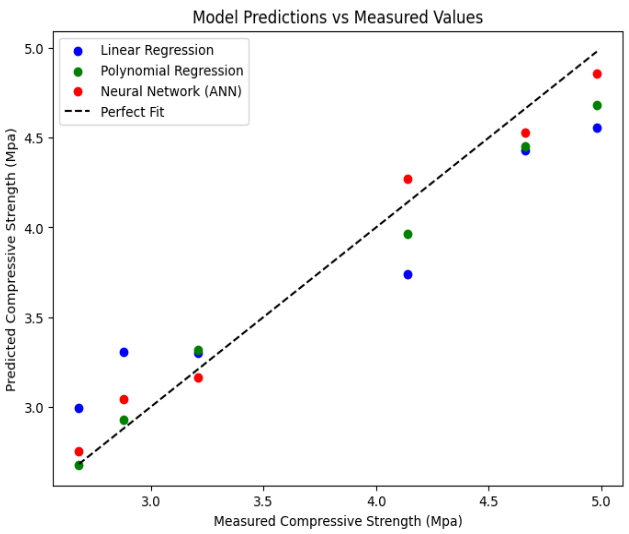


**Figure 14**: Parity plot comparing three models

**Table 7:** Model comparison

| Model | $R^2$ | RMSE | MAE | SI | Correlation |
|---|---|---|---|---|---|
| Linear Regression | 0.854 | 0.337 | 0.314 | 0.090 | 0.976 |
| Polynomial Regression | 0.962 | 0.171 | 0.139 | 0.046 | 0.997 |
| Neural Network | 0.982 | 0.118 | 0.112 | 0.031 | 0.994 |

Table 8 shows that the current study's finding are consistent with findings from previous studies, many of which highlight the superior capability of non-linear and machine learning approaches over conventional statistical models in capturing complex interactions among material constituents.

**Table 8**: Comparative summary of predictive modelling performance

| Study & Material System | Modelling Methods | Best Model & Performance Indicators | Key Observations |
|---|---|---|---|
| Current Study (2025) – Laterite replacement (0–30%) in cement blocks | Linear Regression, Polynomial Regression, ANN | ANN: $R^2$ = 0.982, RMSE = 0.118, MAE = 0.112 | ANN outperformed linear and polynomial regression; 0–20% laterite remained structurally acceptable. |
| Sinkhonde [20] – Laterite blocks with metakaolin geopolymer & molasses | GBR, MLP, AdaBoost, k-means | GBR: Training $R^2 > 0.93$; Testing $R^2 < 0.68$ | Models showed strong learning performance, though testing accuracy indicated overfitting. Age identified as most influential variable. |
| Anand [21] – AAC blocks with CDW, FA, and additives | Linear Regression, ANN, GPR | GPR provided highest accuracy | Machine learning models successfully predicted compressive and flexural strength; GPR performed best. |
| Awolusi et al. [22] – Laterized paving blocks with waste glass | Mathematical model for strength prediction | $R^2 \approx 0.90$; Adequate Precision ≈ 10.7 | Waste glass enhanced compressive strength and model showed strong predictive capability. |
| Adetona [23] – Laterite-sand cement mortar | CCD and predictive mixture models | Models satisfied NIS standards with strong prediction accuracy ($R^2$ generally > 0.95) | Optimization enabled strength improvement with lower cement content. |
| Khalid [24]– Laterized concrete with calcium carbide waste | RSM/CCD predictive models | High predictive accuracy across responses ($R^2 > 0.95$) | Combined LS and CCW enhanced strength; optimal mix achieved 81.3% desirability. |
| Naik [25] – Paver blocks with waste glass aggregate | RSM modelling | $R^2$ values: 0.951–0.998 depending on property | Replacement up to 30% improved strength and durability; models highly accurate. |


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**Table 8**: Comparative summary of predictive modelling performance

| Study & Material System | Modelling Methods | Best Model & Performance Indicators | Key Observations |
|---|---|---|---|
| Patil [26] – Self-compacting concrete with laterite & polypropylene fiber | RSM/CCD | Models validated with <5% error margin | Laterite additives improved strength and durability; optimized designs presented. |
| Oguine & Ndububa [27] – Laterite concrete | Multivariate regression | $R^2$ = 0.98, RMSE = 0.33 | Strong fit; 25% replacement produced maximum compressive strength (33.56 MPa). |
| Kiran [28] – Ceramic waste in paver blocks | RSM models | Models showed strong optimization potential, improvements up to 30% CW | Demonstrated waste utilization benefits and strong predictive performance. |

## 4.0 CONCLUSIONS

The following conclusions have been drawn from the findings made in this study:

**1. Grading characteristics**: Laterite exhibited a higher Coefficient of Uniformity (CU = 15.40) than sand (CU = 9.47), indicating a wider range of particle sizes and better grading.

**2. Water absorption**: Water absorption increased with laterite replacement, reaching 2.95% at 30%, compared to 1.88% for the control mix, suggesting higher porosity and potential durability concerns.

**3. Bulk density**: Bulk density decreased linearly with laterite replacement, from 2448 kg/m³ (0%) to 2180 kg/m³ (30%), confirming increased porosity.

**4. Compressive strength**: Compressive strength decreased with higher laterite content, with a significant reduction observed beyond 25%, limiting structural applications.

**5. Statistical significance:** ANOVA confirmed significant differences in compressive strength between replacement levels ($p = 0.000157$), with Scheffé post-hoc analysis showing strength reductions at 25% and 30% replacement.

**6. Predictive modeling**: ANN achieved the highest accuracy ($R^2 = 0.982$, RMSE = 0.118), outperforming polynomial ($R^2 = 0.962$) and linear regression ($R^2 = 0.854$) in predicting compressive strength.

## RECOMMENDATION

Based on the compressive strength and bulk density results, laterite can be used only as a partial replacement for sharp sand. It is recommended that the laterite substitution level be limited to a maximum of 20%, as higher replacement levels lead to significant reductions in strength and increases in porosity, which may compromise the structural integrity of the blocks. Thus, laterite cannot serve as a complete substitute for sharp sand in load-bearing applications. Further research may explore the use of waterproofing agents and chemical admixtures to improve the performance of lateritic sandcrete blocks at higher replacement levels.

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