Construction Focus, Vol 16, No 1(2023), 13 - 27

PREDICTION OF ABRASION RESISTANCE OF LBPA CONCRETE USING ANN

YA'U Jamilu[1], GAMBO Sanusi[2], ALIYU Ibrahim[3], SHETTIMA Lawan[1], ALI Ibrahim[1], ADAMU Zubairu Waziri[1]

[1]Department of Building Technology, Abubakar Tafawa Balewa University Bauchi, Nigeria
[2]Department of Building, Ahamadu Bello University Zaria, Nigeria
[3]Department of Civil Engineering, Ahamadu Bello University Zaria, Nigeria.

Correspondence: yaumsc3748@gmail.com

ABSTRACT

The construction industry relies heavily on Portland cement (PC), a critical component of concrete. However, Portland cement is costly and has significant environmental drawbacks. Cement production is the third-largest contributor to global CO_2 emissions, following fossil fuel combustion and deforestation. This study aimed to investigate the effects of partially replacing cement with Locust Bean Pod Ash (LBPA) on the properties of concrete containing 0%, 5%, 10%, and 15% LBPA. The Department of Environment (DoE) method of mix design was adopted to produce 72 specimens. Concrete properties such as workability, compressive strength, and abrasion resistance were examined. A Conditional Tabular Generative Adversarial Network (CTGAN) was utilized to expand the dataset to 500 samples for Artificial Neural Network (ANN) model prediction of LBPA concrete properties. The recorded slump values were 50 mm for 0% replacement, 45 mm for 5%, 42 mm for 10%, and 38 mm for 15%, respectively. Compressive strength tests showed a reduction in strength with increasing LBPA replacement levels. The average 28-day compressive strength values for 0%, 5%, 10%, and 15% LBPA replacements were 23.13 N/mm², 21.14 N/mm², 18.53 N/mm², and 14.62 N/mm², respectively. The control specimen had an average 28-day abrasion resistance of 0.101%, while samples with 5%, 10%, and 15% LBPA replacements exhibited values of 0.073%, 0.100%, and 0.130%, respectively. ANN models were employed to predict the abrasion resistance of LBPA concrete. The models demonstrated high accuracy, with R^2 values ranging from 0.82 to 0.97, and minimal errors, confirming their reliability. It is recommended that Limestone-based Cement (LBC) be replaced with Locust Bean Pod Ash (LBPA) at levels of up to 10%. The abrasion resistance of LBPA concrete falls within the BS 8204-2:2003 standards, indicating adequate wear resistance even at higher LBPA replacement levels. The successful application of ANN models in predicting the abrasion resistance of LBPA concrete highlights its potential as a sustainable cement alternative, supporting its use in concrete production.

KEYWORDS: *Abrasion Resistance, Artificial Neural Network (ANN), Compressive Strength, Locust Bean Pod Ash, Workability.*

INTRODUCTION

Background to the Study

The rapid pace of global infrastructure development has significantly increased the demand for concrete, reaffirming its status as the most widely used construction material worldwide. Concrete is a man-made composite primarily composed of cement and natural aggregates such as gravel, sand, or crushed stone. In some cases, artificial aggregates such as blast furnace slag, expanded clay, or broken brick can be used as alternatives (Ali et al., 2019). Standard concrete consists of limestone-based cement, aggregates, water, and occasionally, chemical admixtures (Nwaobakata & Eme, 2018).

The construction industry relies heavily on Portland cement (PC), a critical component of concrete (Ibedu, Akinola, & Omole, 2023). However, PC is costly and has significant environmental drawbacks. Cement production is the third-largest contributor to global CO_2 emissions, following fossil fuel combustion and deforestation (Salawu, 2018). It is estimated that cement manufacturing emits between 0.8 and 1.3 tons of CO_2 per ton of cement produced, accounting for approximately 8–10% of global emissions (Wilson, 2015). As a result, reducing cement usage is essential for minimizing greenhouse gas emissions (Olubajo, Adebayo, & Aluko, 2020).

The drive for sustainable and environmentally responsible construction practices has led to increased research into the use of agricultural and industrial by-products as supplementary cementitious materials (SCMs). One promising candidate is locust bean pod ash (LBPA), valued for both its availability and beneficial properties. Locust bean pod husks are an agricultural waste product derived from processing the African locust bean fruit, commonly found in northern Nigeria during harvest seasons. Globally, ongoing research focuses on recycling such wastes to support environmental sustainability (Ali et al., 2019).

Studies have shown that replacing up to 20% of cement with LBPA can maintain or even enhance the compressive strength of concrete, while higher replacement levels may reduce strength but improve sustainability (Shubbar et al., 2018; Smith, 2017; Patel & Nguyen, 2020). The pozzolanic activity of LBPA contributes to these effects by refining the concrete's microstructure and improving pore distribution, which influences both early- and long-term strength characteristics (Garcia, Martinez, & Fernandez, 2017). However, further research is needed to optimize the use of LBPA, particularly in determining the ideal replacement ratios that balance mechanical performance with environmental benefits (Smith, 2018; Lee & Davis, 2018).

Utilizing LBPA as a partial cement replacement offers considerable sustainability advantages. It helps reduce the carbon footprint associated with cement production by lowering reliance on PC (Olutoge et al., 2015). Additionally, repurposing locust bean pod waste mitigates environmental pollution by converting agricultural residues into valuable construction materials (Adewuyi & Olaoye, 2018). This approach promotes sustainable construction, improves resource efficiency, and supports the circular economy by reintegrating waste into the production cycle (Olawale & Ayodele, 2020).

Given the variability in LBPA's chemical composition, the application of machine learning techniques such as Artificial Neural Networks (ANNs) is becoming increasingly valuable. ANNs are capable of modeling complex, nonlinear relationships between input variables and concrete properties, making them effective in predicting the compressive strength and durability of concrete containing various SCMs (Zhao et al., 2019; Li et al., 2017). This study aims to investigate the influence of LBPA on concrete performance and to develop an ANN model to predict its properties, addressing critical research gaps and supporting the development of optimized, sustainable concrete mixtures.

LITERATURE REVIEW

Neural Networks (ANN - Artificial Neural Network)

An Artificial Neural Network (ANN) is a concept in the field of artificial intelligence that attempts to mimic the network of neurons that make up the human brain, enabling computers to understand information and make decisions in a human-like manner (Thakur & Konde, 2021). In recent years, Artificial Neural Networks (ANNs) have been widely used across various application domains. Most applications employ feedforward ANNs along with the backpropagation (BP) learning algorithm. Several variations of the traditional BP algorithm and alternative ANN training methods have also been developed (Qamar & Zardari, 2023).

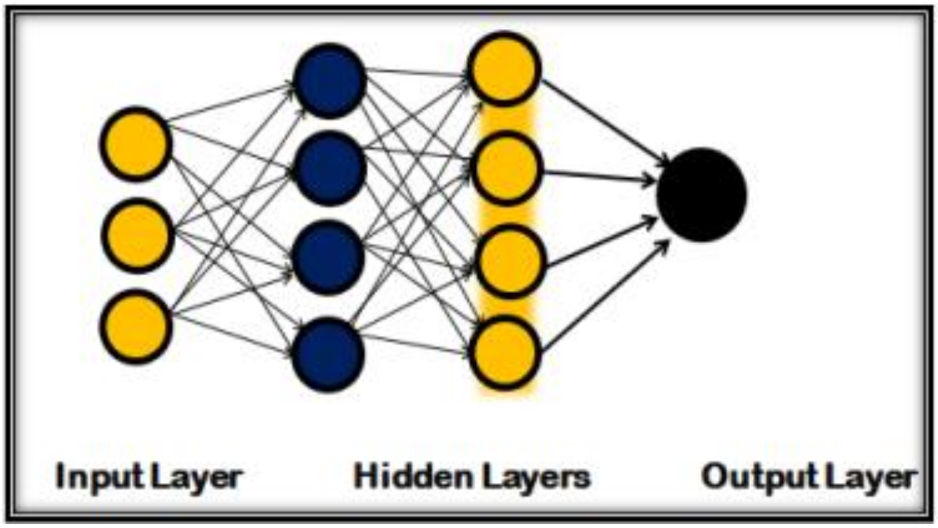

Figure 1: The architecture of an artificial neural network
Source: Qamar & Zardari (2023).

i. **Input Layer:** As the name suggests, it accepts inputs in several different formats provided by the programmer.
ii. **Hidden Layer:** The hidden layer presents in-between input and output layers. It performs all the calculations to find hidden features and patterns.
iii. **Output Layer:** The input goes through a series of transformations using the hidden layer, which finally results in output that is conveyed using this layer.

Application of ANNs in prediction of concrete containing supplementary cementitious material

Researchers have increasingly focused on incorporating various SCMs, including fly ash, slag, and silica fume, into concrete mixes to enhance performance and reduce environmental impact. For instance, Özcan et al. (2019) compared the accuracy of predicting the compressive strength of silica fume concrete using Artificial Neural Networks (ANNs) and Fuzzy Logic (FL). The study utilized 48 different samples with four water-to-cement ratios, three cement dosages, and three partial silica fume replacement ratios, achieving better predictive accuracy with ANNs than with FL. Nevertheless, it was concluded that both ANN and FL could serve as alternative methods for predicting compressive strength, although the relatively small sample size and limited number of input parameters might have affected the outcomes.

Similarly, Gupta et al. (2013) used ANNs to predict the compressive strength of concrete containing nano-silica. The authors developed a model to estimate the 28-day compressive strength of concrete partially replacing cement with nano-silica, using data sourced from existing literature. They concluded that compressive strength values of concrete can be effectively predicted using ANN models within a short period and without conducting physical experiments, though with some margin of error.

ANN in Concrete Modelling and Sustainability Implications in Concrete Technology

Predictive modelling has become an essential tool in concrete technology, allowing researchers and engineers to forecast the properties of concrete based on its composition and curing conditions.

a. Applications of ANNs in Concrete Modelling

i. Compressive Strength Prediction: Artificial Neural Networks (ANNs) can predict the compressive strength of concrete based on mix proportions, curing conditions, and other influencing factors.

ii. Slump Flow Prediction: ANNs can model the slump flow of concrete, helping to ensure the desired workability and flow characteristics.

iii. Durability Prediction: ANNs can predict the durability of concrete structures, including resistance to sulfate attack, chloride penetration, and other forms of degradation (Jahangir & Moustafa, 2020).

b. Applications of ANNs in Sustainability of Concrete Technology

i. Reduced Material Waste through Optimized Mix Design: ANNs can help reduce material waste by optimizing concrete mix proportions, thereby minimizing the environmental impact of concrete production.

ii. Improved Energy Efficiency: ANNs can assist in designing more energy-efficient concrete structures, reducing both energy consumption and greenhouse gas emissions associated with cement production.

iii. Increased Use of Supplementary Cementitious Materials (SCMs): ANNs can help identify optimal replacement levels for SCMs such as fly ash, slag, or locust bean pod ash, thereby reducing the environmental footprint of concrete production.

METHODOLOGY

Concrete mix design

The Department of Environment (DoE) method of mix design was adopted for this study to design a 25 N/mm² concrete grade in accordance with BS EN 1008:2002 for mixing water for concrete.

a. Selection of Targeted mean strength of Concrete

Based on the definition of characteristic strength of concrete a margin “M” is adopted which will add to the specific strength ($f$cu) and is called target strength ($f$cm); thus,

$$f_{cm} = f_{cu} + M \text{ --------------- } (1)$$

Where;

$M = K x S$ and

K = Is a value appropriate to the percentage defective permitted below the characteristic strength.

S = Is the standard deviation.

M = Strength margin.

b. Determination of Free-Water Cement Ratio of Concrete

The total water in a concrete mix consists of water absorbed by the aggregate to bring it to a saturated surface-dry condition, and the free-water available for the hydration of the cement and for the workability of the fresh concrete.

c. Determination of Water Content of Concrete

Determination of water content was obtained from the maximum sizes of aggregate and the desired or specified slump.

d. Determination of Cement Content of Concrete Containing Locust Bean Pod Ash

This was carried out using the semi-analytical approach stated as,

$$\textbf{Cement content} = \frac{\textit{Free water content}}{\textit{Free water cement ratio}} \quad \text{-- (2)}$$

e. Determination of Total Aggregate Content of Concrete

using the values of free-water content and the specific gravity of the combined aggregates.

$$\textbf{Total aggregate content} = \rho_c - (W_c + C_c) \text{ -- (3)}$$

Where;

ρ_c is the wet density concrete (kg/m^3).

C_c is the cement content (kg/m^3)

W_c is the free-water content (kg/m^3)

f. Determination of Fine and Coarse Aggregate Content of Concrete

The preparation of the fine and coarse aggregates is computed for recommended ranges for the proportion of fine aggregates depending on the maximum size of coarse aggregate, the required slump, the grading zone of the aggregates used and the free-water cement ratio.

Experimental Design

The casting of the cubes were carried out immediately after the workability test. The mould was lubricated with an engine oil to allow for easy removal of the concrete, the concrete will be casted in 100mm moulds, the moulds was filled and compact in three layers and tampered 25 times at each layer, and after casting the cubes will be left for 24hours before de-molding. A total number of 50 cubes were cast as presented in Table 1

Table 1: Concrete samples for different percentages of Locust Bean Pod Ash (LBPA)

Replaced % of Cement by LBPA (by volume)	0%	5%	10%	15%	Total
Compressive strength test at 7, 14, and 28 days (concrete cubes of size 100x100x100mm).	9	9	9	9	36
Density at 28 days (concrete cubes of size 100x100x100mm).	3	3	3	3	12
Abrasion test at 28 days (concrete cubes of size 100x100x100mm).	3	3	3	3	12
Total number of samples = 50					

Slump Test

The slump test is an empirical test that measures the workability of fresh concrete and was done in accordance with BS EN 12350-2:2019.

Density Test

The test of hardened concrete was carried out according to BS EN 12390-7:2019. EN12390-7:2019/AC: 2020

$$D = \frac{M}{V} \text{ ---------------------------------- (4)}$$

Where D is the density of the concrete specimen in kg/m³, M is the mass of the specimen and V its volume.

Compressive Strength of Concrete Containing Locust Bean Pod Ash

The compressive strength of the cubes were determine by crushing in accordance with BS EN 12390-3: 2019.

Abrasion Resistance

The mass of the cubes before brushing was recorded and named W_1 and after brushing the mass was recorded and named W_2. The mass of the detached matter i.e. w_1 -w_2 was recorded and the percentage weight loss of all the specimens were recorded and carried out in accordance to ASTM C944/C944M-2012.

$$\text{Abrasion resistance test} = \frac{W1 - W2}{W2} \times 100 \text{ --- } (5)$$

Artificial Neural Networks (ANN) Model Development

To develop a machine learning model for predicting the properties of Locust Bean Pod Ash (LBPA) concrete, Python 3.11 and an Artificial Neural Network (ANN) algorithm were used. The prediction focused on concrete samples in which LBPA replaced cement at levels of 0%, 5%, 10%, and 15%.

To enhance the dataset, which is crucial for improving machine learning accuracy, additional data were generated using CTGAN as synthetic data generation tool. The ANN was chosen for its high predictive accuracy, adaptability, and robustness. CTGAN was employed as a data augmentation technique to address the problem of limited or imbalanced experimental datasets.

Developing an ANN model requires a large dataset; however, generating over 500 samples in the laboratory is often uneconomical and time-consuming. Therefore, CTGAN was used to generate additional synthetic data. The final dataset was divided into two sets: 70% (350 samples) for training the model and 30% (150 samples) for testing its accuracy. Cross-validation was applied to fine-tune the model parameters.

The steps used in developing the ANN model are outlined below:

Data Collection:

A dataset of concrete samples with known strength properties was gathered. This dataset included input features (quantities of cement, LBPA, fine aggregate, coarse aggregate, curing time, and water) and the corresponding concrete strength values (compressive strength and water abrasion resistance of LBPA concrete).

ii. Data Pre-processing:

The data were cleaned and pre-processed. This involved normalizing input features, handling missing values, and splitting the dataset into training and testing sets.

iii. Designing the Neural Network:

In Python, the Neural Network Toolbox was used to design the ANN. The network architecture was defined, including the number of layers and neurons per layer, as well as the input, output, and hidden layers.

iv. Training the ANN:

The training data were used to train the neural network. Python provides functions for ANN training, such as *trainlm* for Levenberg–Marquardt backpropagation. A validation dataset was set aside to monitor network performance and prevent overfitting.

v. Validation and Hyper parameter Tuning:

The model was continuously validated during training, and hyper parameters such as learning rate, number of neurons, and number of epochs were adjusted to optimize performance.

vi. Testing:

The trained ANN was evaluated using the testing dataset to assess its generalization and predictive accuracy.

vii. Performance Assessment:

The model's performance was analyzed using metrics such as the coefficient of determination (R^2) to measure how well it predicted the concrete properties.

viii. Visualization:

Predictions of concrete properties were visualized using linear regression plots.

ix. Deployment:

Once the model's performance was satisfactory, it was deployed for concrete property prediction, involving integration into a larger software system.

Performance Evaluation of Predictive Models

To evaluate predictive models, the coefficient of determination (R^2) was used.

i. Coefficient of Determination (R^2):

R^2 measures the proportion of the variance in the dependent variable predictable from the independent variables, with values ranging from 0 to 1, where 1 indicates perfect prediction. It is given by the equation:

$R^2 = 1 - \frac{SS_{res}}{SS_{tot}}$ ------- (6)

Where; SS_{res} is the sum of squares of the residuals, $\sum(yi - \hat{y}i)^2$

SStot is the total sum of squares, $\sum(yi - \bar{y})^2$

y_i are the actual values

$\hat{y}_i$ are the predicted values

$\bar{y}$ is the mean of the actual values.

High R^2 coupled with a low error rate demonstrates that the model provides an accurate and dependable representation of the data, while a low R^2 and high error rate indicate poor model performance.

RESULTS AND DISCUSSIONS

Effects of LBPA on Fresh Properties of Concrete

Slump Test Results

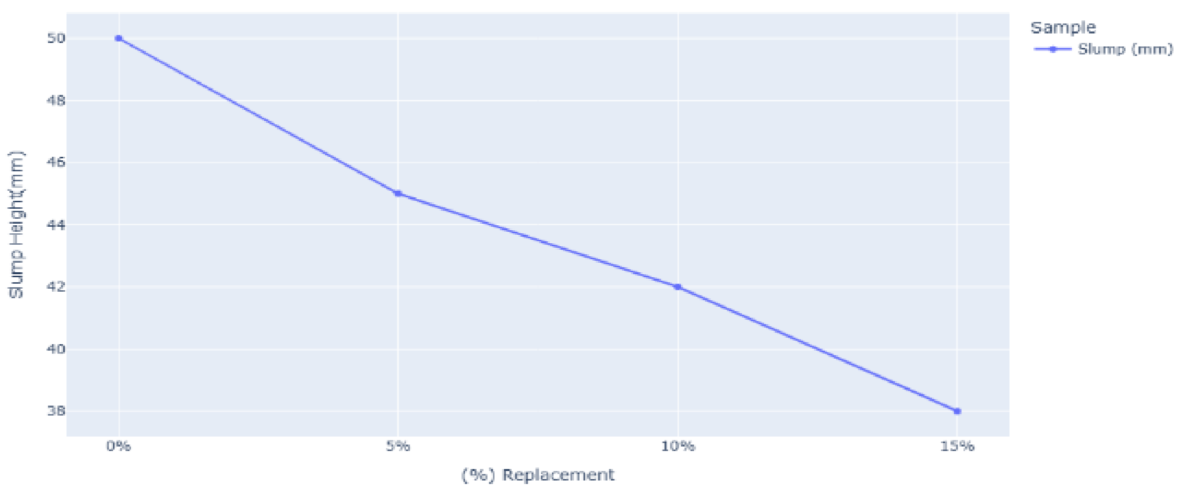

Figure 1: Slump Test results of concrete containing LBPA

Interpretation of Results

The slump values for concrete mixes incorporating LBPA as a partial replacement for Portland Cement (PC) decrease as the replacement percentage increases. The recorded slump values were 50 mm for 0% replacement, 45 mm for 5%, 42 mm for 10%, and 38 mm for 15%. Figure 1 further illustrates that as the LBPA content increases the workability of the mixes decreases with the control mix.

Discussion

This observation is supported by the findings of Ali (2019) *et al.* and Akpenpuun *et al.* (2019), who reported similar trends in reduced workability with higher LBPA content.

Effects of LBPA on the Hardened Properties of Portland cement Concrete

Density of LBPA Portland cement Concrete

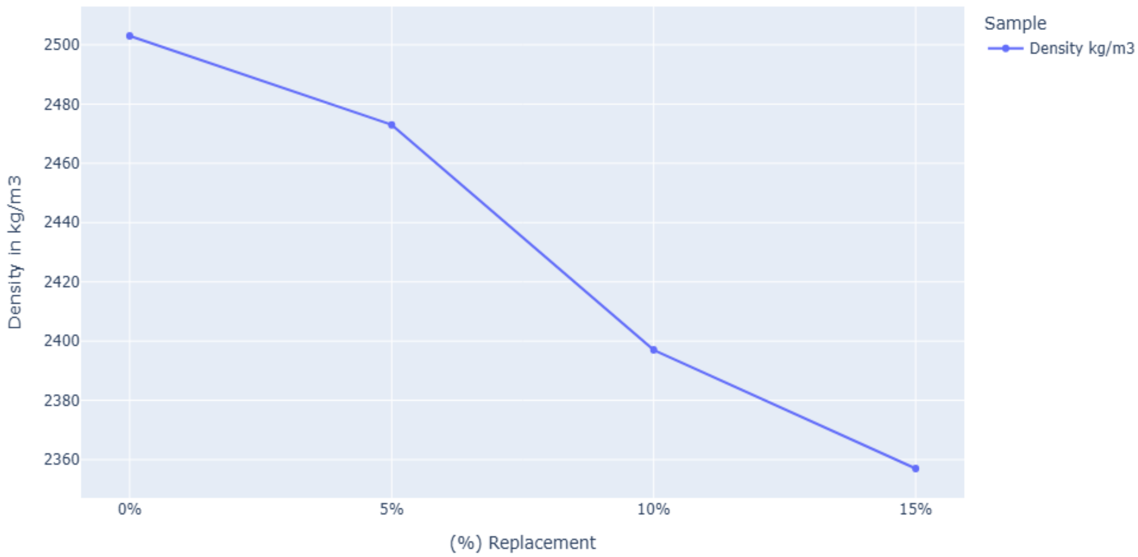

Figure 2: 28 days Density of LBPA Concrete

Interpretation of Results

Figure 2 show that the density of concrete samples incorporating both Portland Cement (PC) and LBPA increased with longer curing periods, ranging from 2357 kg/m³ to 2503 kg/m³. At 28 days, the densities of concrete specimens cured in water with 5%, 10%, and 15% LBPA replacements were recorded at 2473 kg/m³, 2397 kg/m³, and 2357 kg/m³, respectively, compared to 2503 kg/m³ for the control (0% replacement). This represents a density reduction of 1.20%, 4.23%, and 5.83% for 5%, 10%, and 15% LBPA replacements, respectively, when compared to the control as presented in Figure 2.

Discussion

These findings are consistent with the results reported by Ali (2019) *et al.* and Ndububa &Uloko (2018), who observed similar trends of decreasing density with higher LBPA content.

Compressive Strength of LBPA Portland cement Concrete

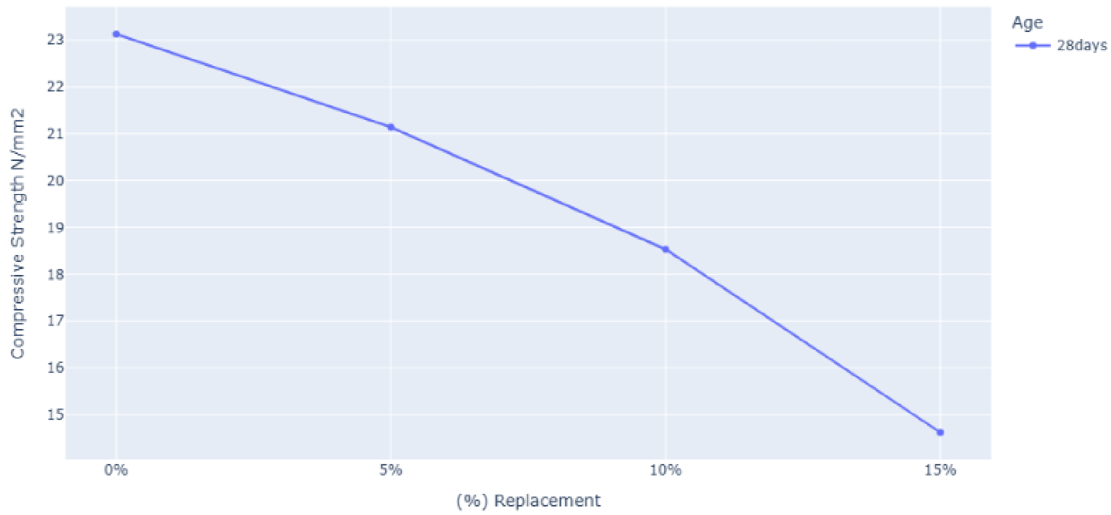

Figure 3: Average 28 days Compressive Strength of LBPA concrete

Interpretation of Results

In Figure 3, the compressive strengths of Portland cement with LBPA concrete were tested at 7, 14, and 28 days. At 28 days, concrete samples with 5%, 10%, and 15% LBPA replacements achieved compressive strengths of 21.14 N/mm², 18.53 N/mm², and 14.62 N/mm², respectively, compared to 23.13 N/mm² for the control (0% replacement). This corresponds to compressive strength reductions of 8.60%, 19.87%, and 36.79% for 5%, 10%, and 15% LBPA replacements, respectively, when compared to the control sample. These results indicate that increasing the LBPA content decreases the compressive strength of the concrete, though the strength increases with longer curing periods as presented in Figure 3.

Discussion

These findings are consistent with the results of Nkapheeyan *et al.* (2023); Ali *et al.* (2019) and Akpenpuun *et al.* (2019), who also observed a reduction in strength with higher LBPA content but noted strength gains over extended curing durations.

Abrasion Resistance Test on LBPA Portland cement Concrete

Figure 4: 28 days Density of LBPA Concrete

Interpretation of Results

Figure 5 presents the average abrasion resistance of LBPA concrete samples cured in water for 28 days. The abrasion resistance values ranged from 0.073% to 0.130%. The control specimen had an average 28-day abrasion resistance of 0.101%, while the samples with 5%, 10%, and 15% LBPA replacements exhibited values of 0.073%, 0.100%, and 0.130%, respectively.

Discussion

Despite minor variations, all concrete samples demonstrated abrasion resistance well within the acceptable range specified by BS 8204-2:2003, which limits weight loss due to abrasion between 0.05% and 0.40% as indicated in Figure 4. This indicates that even with LBPA as a partial replacement for cement, the concrete maintains sufficient resistance to wear.

Artificial Neural Network Model Dataset Simulation, Validation, and Preprocessing

To assess the property of LBPA concrete, this study generated 500 datasets from experimental results, which were then expanded using synthetic data via the CTGAN library in Python on Jupyter Notebook. The study involved eleven (11) variables: water (W), cement (C), Locust Bean Pond Ash (LBPA), crushed stones (C.A), river sand (F.A), compressive strength (CS), density (D), and age of the LBPA concrete. The dependent variables is the abrasion resistance (AR) of the LBPA concrete as presented in Table 2.

Table 2: Statistical Analysis of Variables for modelling the properties of LBPA Concrete

Variables	Count	Mean	Standard deviation	Minimum	Maximum
Water	500	210.000	0.000	210.00	210.000
Cement	500	272.520	41.810	176.00	415.000
LBPA	500	25.500	41.790	0.00	126.2600
Fine	500	851.000	0.000	851.00	851.00
Coarse	500	999.000	0.000	999.00	999.000
D	500	2478.280	112.600	2197.00	2707.000
CS	500	12.700	3.800	6.390	26.460
Age	500	28.000	0.000	28.00	28.000
AR	500	0.150	0.120	0.000	0.410

Table 3: Outlier Analysis for Variables Used in LBPA Concrete

	Abrasion Resistance Model								
Variables	W	C	LBPA	F.A	C.A	D	CS	Age	AR
Outliers	0	0	0	0	0	2	1	0	0

Validation of the Artificial Neural Network Model for Predicting the Abrasion Resistance of LBPA Portland cement Concrete

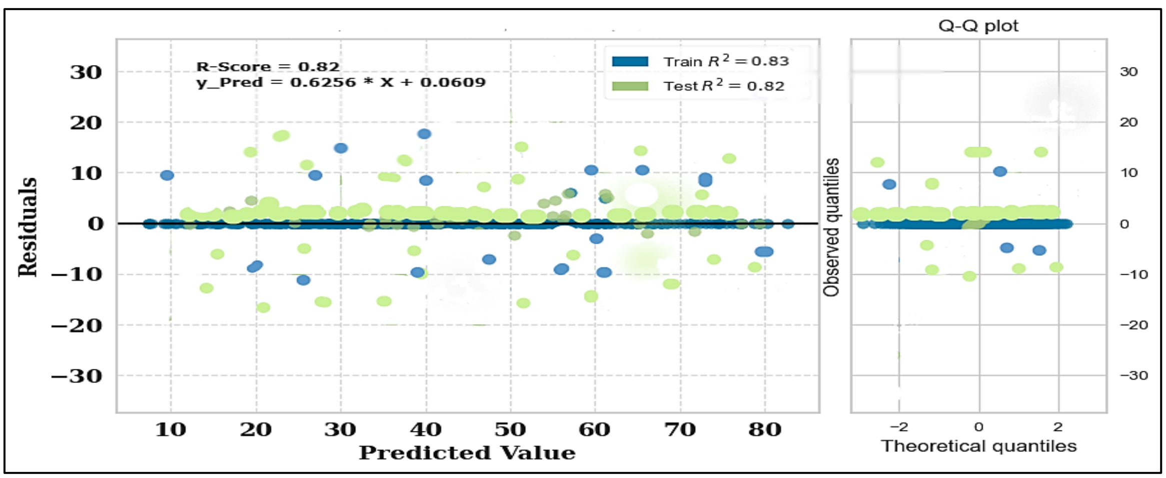

Figure 5: Residual plot of the train and test R^2 score of abrasion resistance for LBPA Concrete

Interpretation of Results

Figure 5 indicates that the model's errors are randomly distributed, suggesting that the model captures the main pattern of the data. The training and testing show that the model performs very well on the training data and moderately on unseen data, which suggests some overfitting, but still acceptable generalization. The Q–Q (quantile–quantile) plot compares the distribution of residuals with a normal distribution and observed that most points lie close to the diagonal line, implying that the residuals approximate a normal distribution, which validates the model's assumptions about error behavior.

DISCUSSION

The ANN model for predicting the abrasion resistance of LBPA concrete shows strong performance. Figure 5 displays a training R^2 value of 0.83, indicating that the model explains about 83% of the variance in the training data, thus effectively capturing the dataset's relationships. The testing R^2 value of 0.82 confirms robust generalization to new data, suggesting the model performs well overall in predicting abrasion resistance (Lee *et al.*, 2020; Smith & Kumar, 2021). It is emphasise that the R^2 value closed to unity (1) means perfect prediction. These results suggest that LBPA can be used to produce concrete with up to 10% LBPA replacement.

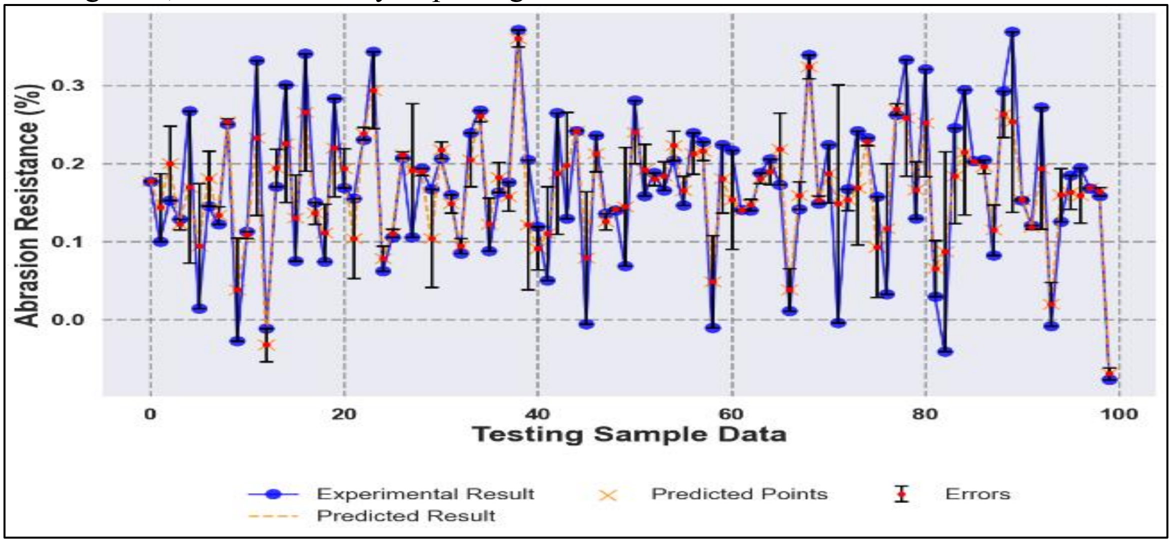

Figure 6: Representation of Experimental, Predicted, and Error Values

Interpretation of Results

Figure 6 demonstrates the model's ability to accurately predict and measured abrasion resistance values. This figure compares experimental results (blue dots) with predicted results (orange line and yellow X markers) for 100 testing samples. The close alignment of the experimental and predicted points indicates the model's strong predictive capability.

Discussion

The small vertical error bars show that the prediction errors are relatively low, confirming the model's accuracy and stability. A few deviations at higher and lower ends indicate minor outliers or variability in material properties, which is normal in concrete experiments. The ANN model demonstrates good agreement between predicted and experimental abrasion resistance, with small and randomly distributed errors showing that the model reliably captures the relationship between input parameters and abrasion resistance.

SUMMARY, CONCLUSION AND RECOMMENDATIONS

Summary of Findings

In terms of workability, a decrease in slump values was observed, ranging from 50 mm for 0% replacement to 38 mm for 15%, indicating reduced workability with increasing LBPA content.

The 28-day compressive strength tests recorded a strength of 21.14 N/mm² for 5% replacement, compared with the control value of 23.13 N/mm²**,** reflecting a decrease in strength at higher LBPA contents.

Abrasion resistance tests showed values ranging from 0.073% to 0.130%**,** with all samples falling within the acceptable range

specified by BS 8204-2:2003 (0.05%–0.40%). This demonstrates that even with LBPA incorporation, the concrete maintained sufficient wear resistance.
The Artificial Neural Network (ANN) models effectively predicted abrasion resistance, displaying high accuracy with R^2 values ranging from 0.82 to 0.83. The datasets were well-distributed, and residual plots showed minimal, randomly distributed errors, confirming the reliability and robustness of the models.

CONCLUSION

A 5% replacement of Locust Bean Pod Ash (LBPA) produced the best overall results in terms of workability, compressive strength, and abrasion resistance.
The Artificial Neural Network (ANN) model proved effective in predicting the abrasion resistance properties of LBPA concrete with high accuracy.
The findings support the use of LBPA as a sustainable and eco-friendly alternative to cement in concrete production, contributing to the advancement of green construction materials.

Recommendation

Based on the results of this study, the study recommends that Portland cement (PC) can be replaced with Locust Bean Pod Ash (LBPA) at levels of up to 5% in concrete mixes to achieve optimal performance.

REFERENCES

Ali, H., Babatunde, R. I., Ibrahim, A., & B.O, A. (2019). Investigation of Locus Beans Waste Ash as Partial Replacement for Cement in Concrete Structures. *International Journal of Advances in Scientific Research and Engineering*, 5(4), 149–153. https://doi.org/10.31695/IJASRE.2019.33133

ASTM International. (2012). *ASTM C944/C944M–12 – Standard test method for abrasion resistance of concrete or mortar surfaces by the rotating-cutter method.* ASTM International.

Akpenpuun, T. D., Akinyemi, B. A., Olawale, O., Aladegboye, O. J., and Adesina, O. I. (2019). Physical, Mechanical properties and Internal Structure Characteristics of Cement-Locust Bean Pod Waste Ash Mortars. Nig. J. Pure & Appl. Sci. Vol. 32. https://doi.org/10.7910/DVN/VA04VU

Adewuyi, A. P., &Olaoye, R. A. (2018). The use of locust bean pod ash as a supplementary cementitious material in concrete production. *Journal of Sustainable Development*, 11(2), 52-63.

British Standards Institution. (2002). *BS EN 1008:2002 – Mixing water for concrete – Specification for sampling, testing and assessing the suitability of water, including water recovered from processes in the concrete industry, as mixing water for concrete.* BSI Standards Publication.

British Standards Institution. (2003). *BS 8204-2:2003 – Screeds, bases and in-situ floorings – Part 2: Concrete wearing surfaces – Code of practice.* BSI Standards Publication.

British Standards Institution. (2019). *BS EN 12350-2:2019 – Testing fresh concrete – Part 2: Slump test.* BSI Standards Publication.

British Standards Institution. (2019). *BS EN 12390-3:2019 – Testing hardened concrete – Part 3: Compressive strength of test specimens.* BSI Standards Publication.

British Standards Institution. (2019). *BS EN 12390-7:2019 – Testing hardened concrete – Part 7: Density of hardened concrete.* BSI Standards Publication.

British Standards Institution. (2020). *EN 12390-7:2019/AC:2020 – Testing hardened concrete – Part 7: Density of hardened concrete (Amendment).* BSI Standards Publication.

British Standards Institution. (1992). *BS 882:1992. Specification for aggregates from natural sources for concrete*. London: BSI.

British Standards Institution. (2016). *BS EN 196-3:2016. Methods of testing cement – Part 3: Determination of setting times and soundness*. London: BSI.

British Standards Institution. (2002). *BS EN 1008:2002*. Mixing Water for Concrete - *Specification for Sampling, Testing and Assessing the Suitability of Water, Including Water Recovered from Processes in the Concrete Industry, as Mixing Water for Concrete.* British Standards Institution (BSI).

British Standards Institution. (2009). *BS EN 12350-2:2009. Testing Fresh Concrete - Part 2: Slump Test*. British Standards Institution (BSI).

British Standards Institution. (2002). *BS EN 12390-3:2002. Testing Hardened Concrete - Part 3: Compressive Strength of Test Specimens.* British Standards Institution (BSI).

British Standards Institution. (2019). *BS EN 12390-7:2019. Testing Hardened Concrete - Part 7: Density of Hardened Concrete.* British Standards Institution (BSI).

Garcia, S., Martinez, C., & Fernandez, R. (2017). Impact of pozzolanic reaction of locust bean pod ash on concrete microstructure and strength characteristics. *Construction and Building Materials, 145*, 423–431.

Gupta, S. (2013). Using artificial neural network to predict the compressive strength of concrete containing nano-silica. *Civil Engineering and Architecture, 1*(3), 96–102.

Ibedu, M. U., Akinola, S. R., & Omole, D. O. (2023). The influence of ordinary Portland cement on the mechanical properties of concrete: A review. *International Journal of Structural Engineering, 29*(1), 45–60.

Jahangir, M. H., & Moustafa, M. (2020). Artificial neural network-based prediction of compressive strength of concrete. *Journal of Building Engineering*, 32, 101758.

Lee, J., Kim, J., & Kim, K. (2020). Prediction of concrete durability using artificial neural networks with supplementary cementitious materials. *Construction and Building Materials, 240*, 117931. https://doi.org/10.1016/j.conbuildmat.2019.117931

Lee, K., & Davis, M. (2018). Mechanical properties of concrete with agricultural waste materials as supplementary cementitious materials. *Construction and Building Materials, 176*, 340–355.

Li, Q., Guo, R., Jin, Z., & Wang, Y. (2017). Predicting the compressive strength of concrete using artificial neural network and support vector machine. *Construction and Building Materials, 140*, 91–98.

Mungle, N. P., Mate, D. M., Mankar, S. H., Tale, V. T., Vairagade, V. S., & Shelare, S. D. (2024). Applications of computational intelligence for predictive modeling of properties of blended cement sustainable concrete incorporating various industrial byproducts towards sustainable construction. *Asian Journal of Civil Engineering, 25*(8), 5939–5954.

Ndububa, E. E., & Uloko, J. O. (2018). Locust bean pod ash (LBPA) as a pozzolanic material in concrete. *International Journal of Environmental Science, Management and Engineering Research, 1*(2), 57–67.

Nkapheeyan, F. I., Megat, M. J., Iorwuese, A., Julius, L. A., Solomon, M. S., & Hassan, C. S. (2023). Performance of high strength concrete containing locust bean pod ash as cement replacement. *Journal of Engineering Structures and Materials, 50*, 104170. https://doi.org/10.1016/j.jobe.2022.104170

Olubajo, O. A., Adebayo, T. I., & Aluko, B. T. (2020). Reducing greenhouse gas emissions through the use of alternative cementitious materials. *Journal of Cleaner Production, 247*, 119130.

Olawale, F. A., & Ayodele, A. S. (2020). Environmental sustainability through the use of locust bean pod ash in construction. *Environmental Management and Sustainable Development, 9*(1), 78–91.

Olutoge, F. A., Olaniyan, O. S., & Adeniyi, O. A. (2015). Investigating the pozzolanic potential of locust bean pod ash in concrete. *International Journal of Engineering Research & Technology, 4*(6), 517–523.

Özcan, F., Atiş, C. D., Karahan, O., Uncuoğlu, E., & Tanyildizi, H. (2009). Comparison of artificial neural network and fuzzy logic models for prediction of long-term compressive strength of silica fume concrete. *Advances in Engineering Software, 40*(9), 856–863.

Qamar, R., & Zardari, B. A. (2023). Artificial neural networks: An overview. *Mesopotamian Journal of Computer Science, 2023*, 124–133.

Salawu, R. A. (2018). Environmental impact of cement production and the need for sustainable solutions. *Environmental Science and Pollution Research, 25*(13), 12345–12358.

Shubbar, A. A., Jafer, H., Al-Shadeedi, A., Dulaimi, A., & Hashim, K. (2018). The development of a new low carbon binder for construction as an alternative to cement. *Journal of Cleaner Production, 193*, 94–102.

Smith, A., & Kumar, P. (2021). Application of machine learning algorithms for predicting concrete properties: A review. *Materials Today: Proceedings, 47*, 5211–5217. https://doi.org/10.1016/j.matpr.2021.04.356

Thakur, A., & Konde, A. (2021). Fundamentals of neural networks. *International Journal for Research in Applied Science and Engineering Technology, 9*(8), 407–426.

Wilson, A. (2015). Carbon dioxide emissions from cement production: A comprehensive review. *Journal of Environmental Management, 157*, 183–197.

Zhao, Z., Feng, P., Zhang, Y., & Su, T. (2019). Application of artificial neural network on performance prediction of sustainable concrete. *Journal of Cleaner Production, 231*, 1238–1249.