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EXPERIMENTAL AND SOFT COMPUTING – BASED PERFORMANCE ANALYSIS OF CONCRETE WITH BRICK WASTES AND FLY ASH: A SUSTAINABLE APPROACH FOR WASTE MANAGEMENT

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Abstract

The concrete industry has experienced substantial growth in recent decades, driving increased consumption of natural resources, particularly aggregates and cement. In pursuit of sustainable and cost-effective alternatives, overburnt brick aggregates have emerged as a viable substitute. This is particularly relevant in southern India, where extensive brick manufacturing generates not only large volumes of usable bricks but also significant quantities of overburnt brick waste. Typically discarded in landfills, this waste poses environmental challenges; however, recycling it into coarse aggregates—referred to as overburnt brick aggregates (OBB)—offers a sustainable pathway for resource conservation and waste management. This study explores the partial replacement of natural coarse aggregates with OBB in concrete production, in combination with Class C fly ash as a supplementary cementitious material to further enhance sustainability. A series of concrete mixes incorporating varying proportions of OBB and fly ash were prepared and evaluated for mechanical performance. Results indicated that up to 40–50% replacement of natural coarse aggregate with OBB can be achieved without compromising strength, and in some cases, it enhanced both strength and durability. In addition to the experimental program, statistical modeling was conducted to examine the relationships between primary mix design parameters and the compressive strength (CS) of cementitious composites containing cement (C), fly ash (F), fine aggregate (FA), OBB, coarse aggregate (CA), water content (W), and chemical admixtures (A). Pearson's correlation analysis and Ordinary Least Squares (OLS) regression were applied to quantify parameter interactions and their influence on CS. The correlation heatmap revealed strong multicollinearity among several mix constituents, while regression analysis identified cement, fly ash, and admixture dosage as key predictors of CS. Variance Inflation Factor (VIF) analysis confirmed significant collinearity in FA, C, and OBB, potentially affecting coefficient stability. Residual diagnostics indicated overall model adequacy, with limited influential outliers. These findings provide both experimental and statistical insights to optimize sustainable mix designs incorporating non-conventional aggregates such as OBB.

Keywords: Concrete Mix Design, Pearson Correlation, Regression Analysis, VIF, Compressive Strength.

1. INTRODUCTION

Concrete remains one of the most extensively used construction materials worldwide, with its production consuming substantial quantities of natural resources. Coarse

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aggregates constitute approximately 70% of the total concrete volume, yet they are becoming increasingly scarce and costly. A key attribute of concrete is its ability to perform reliably under harsh environmental conditions, provided that its constituents are proportioned appropriately. An optimal concrete mix must ensure not only durability and strength but also adequate workability, ease of transport, placement, and finishing.

In response to environmental concerns, a growing body of research has investigated the use of overburnt brick waste (OBBW) and industrial by-products as replacements for natural aggregates, thereby enhancing the environmental sustainability of concrete [4]. The utilization of construction and demolition (C&D) waste in producing sustainable building materials—such as bricks—can divert significant waste volumes from landfills and contribute to land conservation [1][3].

Recent studies have demonstrated that OBBW can serve as a partial substitute for conventional coarse aggregates in concrete [11]. OBBW maintains the structural performance of concrete while reducing its overall density [3], making it particularly suitable for lightly loaded or non-structural applications. Under moderate loading conditions, overheated brick aggregates have also been shown to perform effectively in both reinforced and plain concrete structures. However, due to their porous microstructure, overburnt bricks exhibit high water absorption, which can adversely affect cement hydration, setting, and durability. To mitigate this, pre-saturation of these aggregates is recommended prior to mixing.

Compared with brick-based aggregates, crushed stone aggregates generally provide superior fire resistance and sound absorption [2]. Additionally, durability studies involving materials such as metakaolin have reported that replacement levels of up to 50% can yield satisfactory performance outcomes [5].

Modern cementitious composite design increasingly prioritizes sustainability, resource efficiency, and cost-effectiveness. Supplementary cementitious materials (SCMs), such as fly ash, and alternative aggregates, such as overburnt brick aggregate (OBB), have been studied for their potential to reduce clinker consumption without compromising mechanical properties [14].

While several investigations have examined the effects of SCMs and unconventional aggregates on compressive strength, limited research has applied a comprehensive statistical framework that integrates correlation analysis, regression modeling, and multicollinearity diagnostics for such material systems.

The present study addresses this gap by employing an integrated statistical approach on experimentally derived mix design data, enabling the quantification of each constituent's relative influence on compressive strength.

2. MATERIALS AND METHODS

Mix composition data were obtained from laboratory trials conducted in accordance with IS and ASTM standards for material characterization and strength testing. The

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investigated parameters included cement (C), fly ash (F), fine aggregate (FA), overburnt brick aggregate (OBB), coarse aggregate (CA), water content (W), and admixture dosage (A). Pearson's correlation coefficients were calculated to assess linear associations among variables, while an Ordinary Least Squares (OLS) regression model was formulated with compressive strength (CS) as the response variable. Variance Inflation Factor (VIF) analysis was employed to evaluate multicollinearity, and residual diagnostics—were used to verify model adequacy.

2.1 Aggregates

The coarse aggregates used in this study comprised crushed stone sourced from a local quarry, selected to meet the specified graduation requirements. The fine aggregates consisted of clean river sand, free from deleterious organic and inorganic impurities. Their physical properties were determined in accordance with standard testing procedures, and the results are shown in Table 1.

Table 1: Properties of Fine Aggregate

Sl. No.	Characteristics Values
Specific gravity	3.12
Water absorption	2.10 %
Fineness modulus	3.01
Zone	II

2.2 Over-Burnt Brick Waste (OBBW)

Over-burnt brick waste was sourced from a nearby brick manufacturing unit. These bricks, characterized by their blackened appearance, are generally discarded as waste [7]. The collected material was crushed and sieved to obtain aggregates of 20 mm downsize. The physical properties were tested as per IS standards, and the results are provided in Table 2.

Table 2: Comparison between Coarse Aggregate and Over Burnt Clay Bricks

Characteristics Values	Coarse aggregates	Over burnt brick wastes
Specific gravity	2.62	2.41
Impact Value (%)	13.21	18.40
Crushing value (%)	15.24	19.32
Water absorption (%)	1.25	4.23

2.3 Cement

Ordinary Portland Cement (OPC) of 53 grade, conforming to IS 12269:2013, was used throughout the investigation. The detailed specifications are given Table 3.

Table 3: Properties of cement

Sl. No.	Characteristics Values
Normal consistency	31 %
Initial Setting Time	52 min.
Final Setting Time	540 min
Specific gravity	3.12

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2.4 Water

Potable water, suitable for drinking, was used in the preparation and curing of all concrete mixes. The quality of water plays a vital role in influencing both the workability and strength development of concrete, and only clean water meeting IS standards was used in this research.

2.5 Fly Ash

Fly ash, an industrial by-product, was utilized as a partial replacement for cement in the concrete mixes. The fly ash used in this study was obtained from a paper mill located in Bhadravathi, Shimoga District. This material was incorporated as a mineral admixture to enhance the sustainability and performance characteristics of the concrete.

3. MIX PROPORTIONS OF MATERIALS

The concrete mix design recommendation for IS – 10262:2009 [10] was followed in the preparation of the concrete mix. A mix proportioning ratio of 1:1:2 was utilized and the (w/c) ratio was 0.40 in each instance. For the proper workability factor, water reducing plasticizer is used.[9]. Proportion of materials is given in Table 4. by varying percentages of over burnt brick waste materials with 28 days compressive strength.

3.1 Compressive strength

For each mix design, compressive strength test was carried out in accordance with IS codal provisions at 7-, 14- and 28-days curing. Table 4 presents the results of compressible strength of concrete with varying percentages of over burnt brick waste with fly ash for 28 days and shown graphically in Figure 1.

Table 4: Mix proportions and Compressive strength results

Mix Designation	Materials	Compressive strength, N/mm^2		
		7 days	14 days	28 days
M1	NM	17.1	25.416	28.24
M2	NM + OBBW (5%) + FA (10%)	17.22	25.56	28.4
M3	NM+ OBBW (10%) + FA (10%)	17.31	25.68	28.56
M4	NM + OBBW (15%) + FA (10%)	17.52	25.61	29.1
M5	NM + OBBW (20%) + FA (10%)	18.25	26.87	30.98
M6	NM + OBBW (25%) + FA (10%)	18.55	27.21	31.25
M7	NM + OBBW (30%) + FA (10%)	19.25	28.66	32.41
M8	NM + OBBW (35%) + FA (10%)	19.4	29.18	32.5
M9	NM + OBBW (40%) + FA (10%)	19.6	29.62	32.65
M10	NM + OBBW (45%) + FA (10%)	21.71	30.28	34.65
M11	NM + OBBW (50%) + FA (10%)	20.55	31.25	34.15
M12	NM + OBBW (55%) + FA (10%)	20.88	31.22	33.82

NM – Nominal Mix, OBBW – Over burnt brick waste, FA – Fly ash

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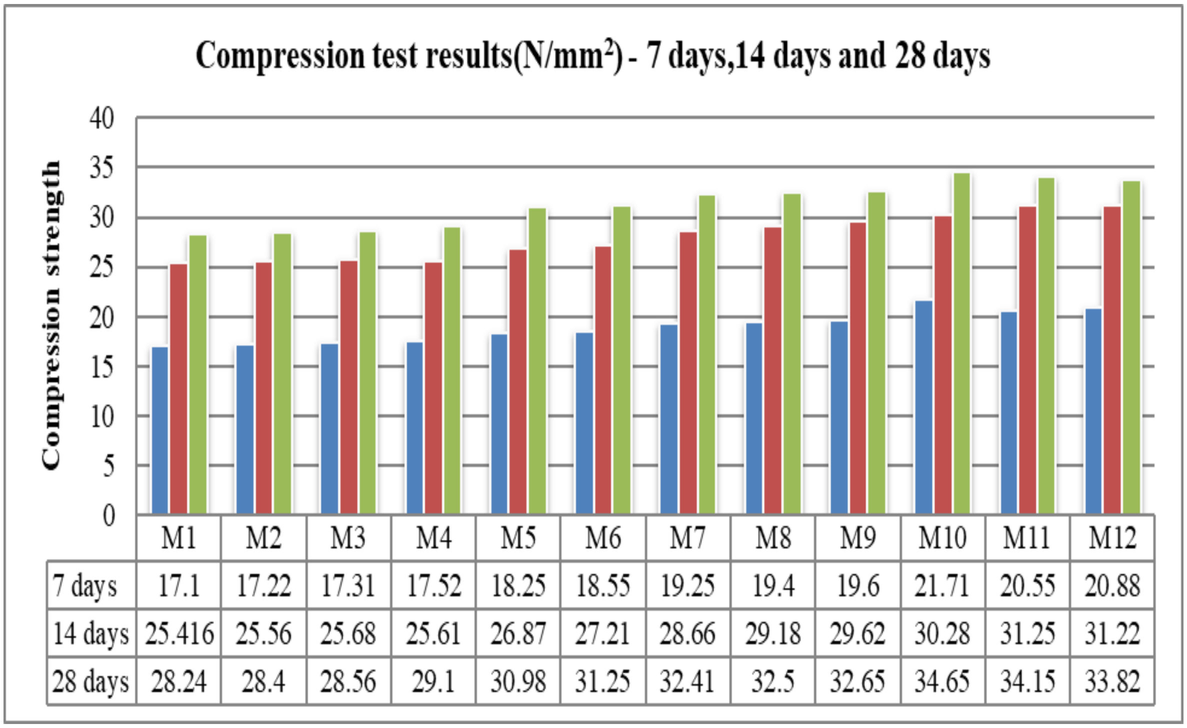

Figure1: Graphical representation of Compressive strength results

3.2 Split Tensile strength

The split tensile strength was carried out in a cylinder of dimensions diameter 150 mm x 300 mm according to IS codal provisions after 7 and 28 days of curing. Table 5 gives the results of split tensile strength with varying percentages of over burnt brick waste and fly ash. The results are shown in the form of graph Figure 2.

Table 4: Mix proportions and Split strength results

Mix Designation	Materials	Split tensile strength N/mm^2		
		7 days	14 days	28 days
M1	NM	1.42	2.01	2.45
M2	NM + OBBW (5%) + FA (10%)	1.45	2.10	2.51
M3	NM+ OBBW (10%) + FA (10%)	1.51	2.15	2.54
M4	NM + OBBW (15%) + FA (10%)	1.50	2.14	2.55
M5	NM + OBBW (20%) + FA (10%)	1.55	2.12	2.62
M6	NM + OBBW (25%) + FA (10%)	1.54	2.16	2.64
M7	NM + OBBW (30%) + FA (10%)	1.60	2.19	2.65
M8	NM + OBBW (35%) + FA (10%)	1.62	3.10	2.68
M9	NM + OBBW (40%) + FA (10%)	1.61	3.12	2.64
M10	NM + OBBW (45%) + FA (10%)	1.63	3.14	2.69
M11	NM + OBBW (50%) + FA (10%)	1.64	3.11	2.62
M12	NM + OBBW (55%) + FA (10%)	1.58	2.98	2.52

NM – Nominal Mix, OBBW – Over burnt brick waste, FA – Fly ash

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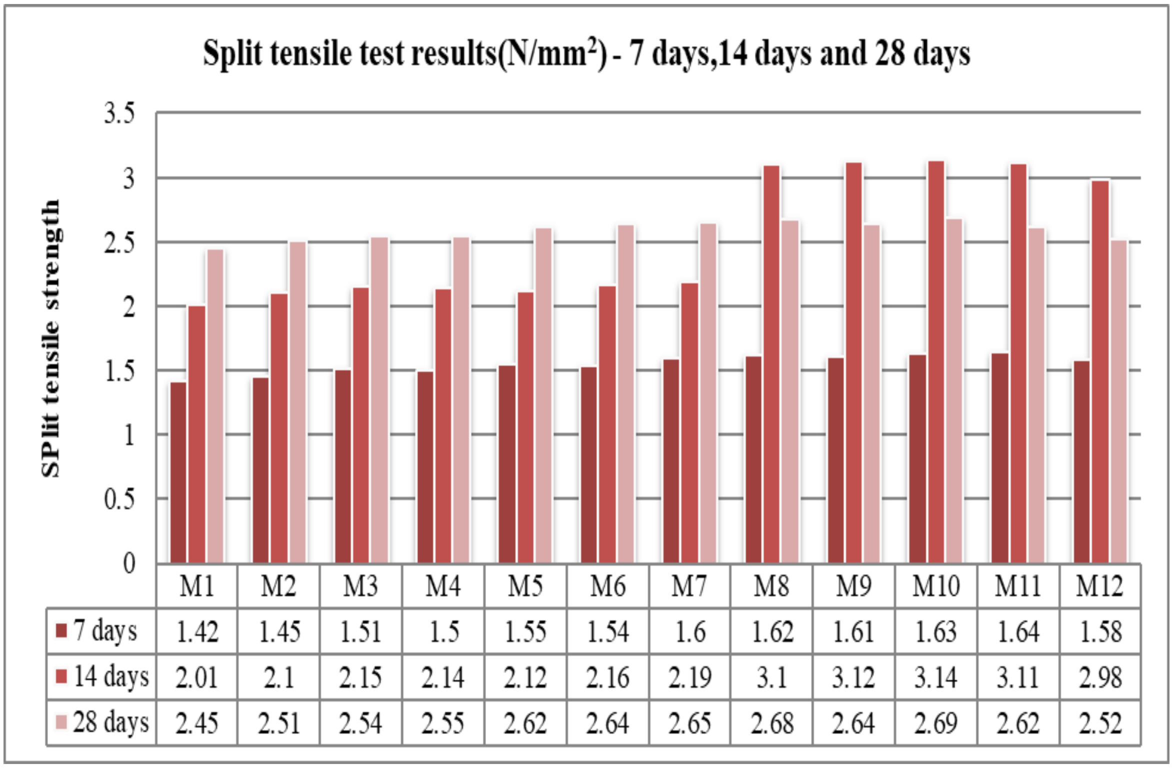

Figure 2: Graphical representation of Split tensile strength results

3.3 Flexural strength

The test was done after 28 days of curing. The flexural test was carried out in 100×100×500 mm beams according to IS codal provisions. Table 5 gives the results of flexural strength with various percentages of micro-silica. The results are shown in a Figure 3.

Table 5: Mix proportions and Flexural strength results

Mix Designation	Materials	Flexural strength, N/mm^2		
		7 days	14 days	28 days
M1	NM	1.64	2.65	3.40
M2	NM + OBBW (5%) + FA (10%)	1.66	2.42	3.42
M3	NM+ OBBW (10%) + FA (10%)	1.65	2.52	3.48
M4	NM + OBBW (15%) + FA (10%)	1.71	2.62	3.46
M5	NM + OBBW (20%) + FA (10%)	1.72	2.58	3.51
M6	NM + OBBW (25%) + FA (10%)	1.74	2.69	3.52
M7	NM + OBBW (30%) + FA (10%)	1.69	2.66	3.54
M8	NM + OBBW (35%) + FA (10%)	1.75	2.71	3.50
M9	NM + OBBW (40%) + FA (10%)	1.77	2.74	3.55
M10	NM + OBBW (45%) + FA (10%)	1.81	2.76	3.56
M11	NM + OBBW (50%) + FA (10%)	1.80	2.75	3.52
M12	NM + OBBW (55%) + FA (10%)	1.77	2.72	3.49

NM – Nominal Mix, OBBW – Over burnt brick waste, FA – Fly ash

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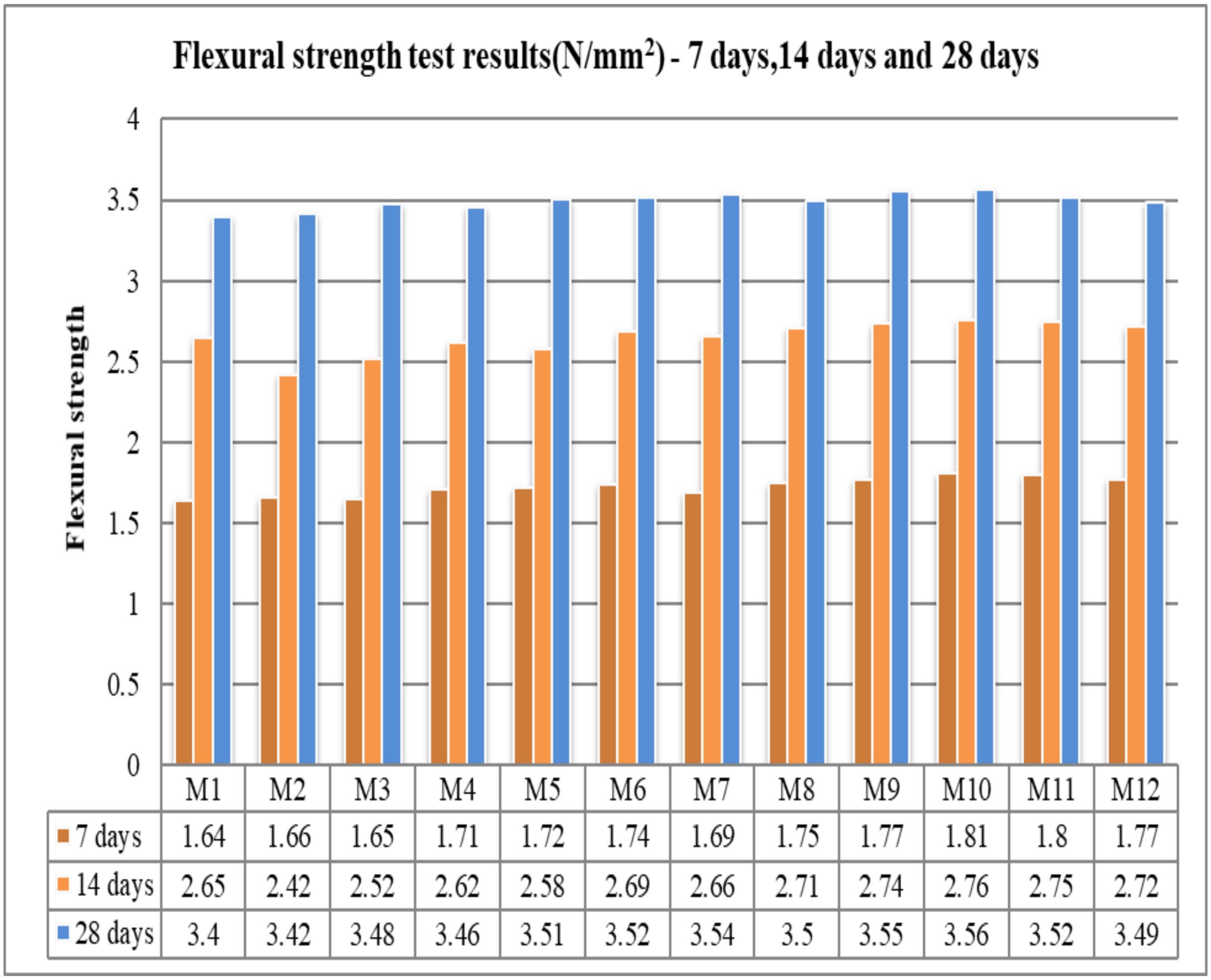


Figure 3: Graphical representation of Split tensile strength results

4. MICRO STRUCTURAL ANALYSIS

This EDS (Energy Dispersive X-ray Spectroscopy) spectrum, obtained through SEM (Scanning Electron Microscopy), identifies the chemical elements present in the analyzed region of the sample and shows their relative concentrations.

X-axis represents the energy of the emitted X-rays in kiloelectronvolts (keV). Since each element has characteristic X-ray emission energies, its peaks appear at specific positions along this axis.

And **Y-axis r**epresents the intensity (counts), i.e., the number of X-rays detected at each energy level. Taller peaks indicate a higher relative abundance of that element in the scanned area.

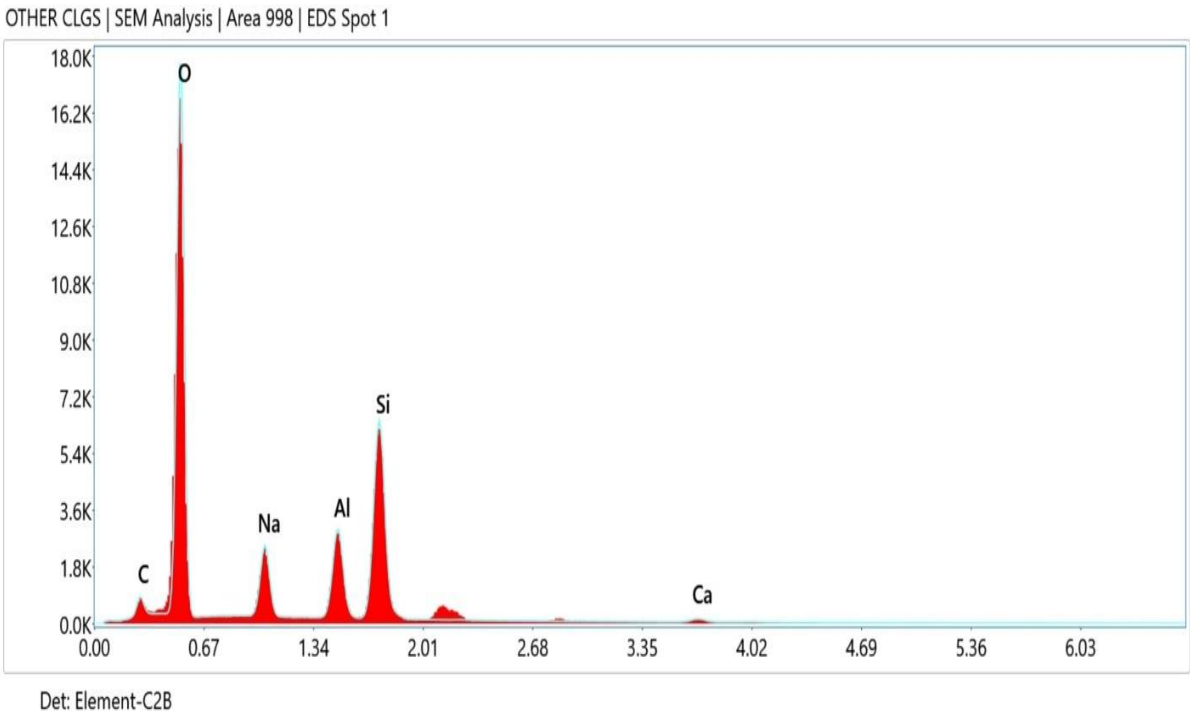
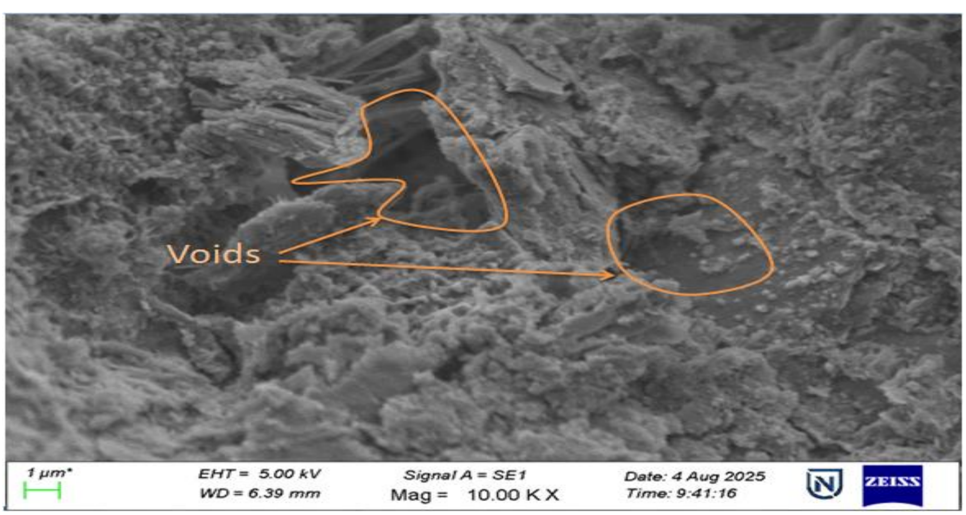


Figure 4: EDS analysis of concrete mix (M10)

The EDS spectrum Figure 4 shows an extremely high oxygen peak (~17k counts), confirming that the sample is largely composed of oxides. Carbon is present, possibly due to carbonation, organic matter, or the conductive coating applied during SEM analysis. Sodium, which was not observed in earlier spectra, appears here and associated with the fly ash. Aluminum is attributed to aluminosilicate phases, while silicon exhibits a strong peak, likely originating from quartz or other silicate minerals. Calcium, on the other hand, appears as a minor peak, much lower than in previous spectra, indicating a reduced presence of cementitious or lime-bearing phases.



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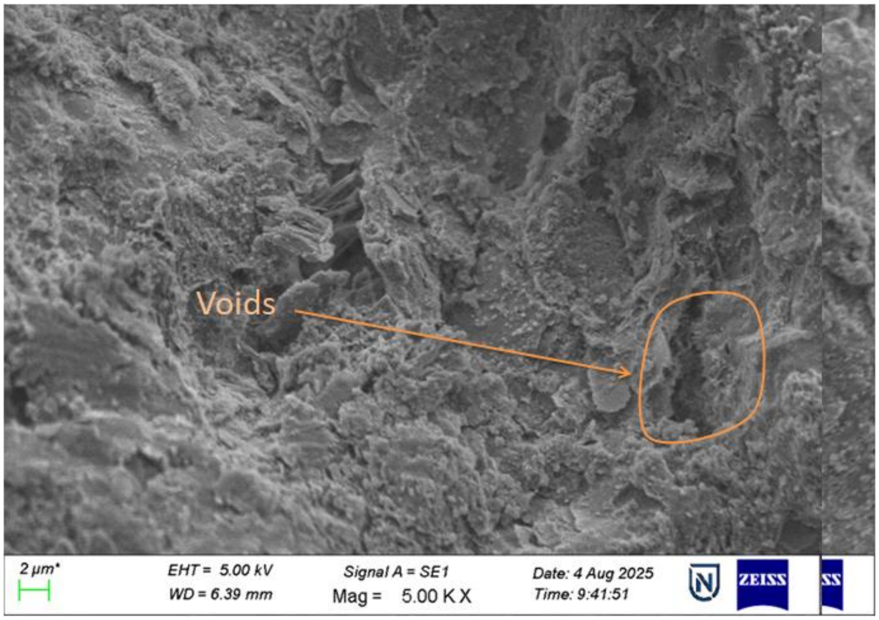

Figure 5: SEM analysis of concrete mix (M10)

The SEM morphology Figure 5 shows that fly ash particles are predominantly spherical (cenospheres or pleurospheres), whereas ceramic or masonry particles appear as angular grains. Elemental indicators such as potassium and iron can provide further distinction—fly ash contains both K and some Fe, while ceramics may also exhibit them but with different patterns. In elemental maps or surrounding regions, if the matrix is rich in calcium (paste) and a particle stands out as Na–Al–Si, it is likely a fly ash inclusion. Conversely, the presence of several Na–Al–Si angular grains suggests feldspathic masonry fragments in brick waste. Overall, this spectrum represents fly ash and the observed particles are angular, they are probably feldspar-rich masonry fractions from brick wastes. SEM images representing irregular shaped voids and void characteristic of brick waste materials. Voids are formed due to the drying shrinkage process, which creates void's structure. The surface is rough, providing excellent interlocking potential when used brick waste as aggregate in concrete. Smaller fine grains within and around the pores shows the presence of fine ash. The high porosity of these materials reduces its bulk density, making it a promising aggregate for the concrete.

5 MACHINE LEARNING

5.1. Data Preparation

The dataset for machine learning analysis was compiled from 150 peer-reviewed publications, consolidated into a single table. The dataset includes parameters such as compressive strength, cement content, fine aggregate, coarse aggregate, water content, Over Burnt Brick waste (OBB), and fly ash (F). After preprocessing, a total of 590 samples were obtained for analyzing the compressive strength of concrete incorporating fly ash and over burnt brick waste.

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5.2. Material Description

Cement, the primary binder in concrete, plays a decisive role in determining both early-age and long-term compressive strength. The water-to-cement ratio is a critical parameter, as excessive water generally reduces strength, while the type and quality of water also influence hydration and strength development. The inclusion of supplementary and alternative materials—such as fly ash and demolition waste—affects the overall performance of concrete. Fly ash effectiveness depends on concrete type, mix proportions, desired workability, and curing conditions. Strength typically increases with fly ash content up to an optimum dosage, beyond which it declines due to reduced early hydration rates. Similarly, over burnt brick waste contributes to strength enhancement within specific replacement thresholds, but excessive dosages can reduce performance.

5.3. Data Splitting

To develop and evaluate predictive models, the dataset was partitioned into training and testing subsets. The training set was used to fit the models, while the testing set evaluated predictive performance on unseen data, ensuring objective assessment. After evaluating multiple train–test split ratios, a 70:30 split was identified as optimal and applied consistently across all models in this study.

5.4. Performance Indices

Several machine learning models were developed to predict compressive strength. Their performance was assessed using four widely adopted evaluation metrics: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Squared Error (MSE), and the Coefficient of Determination (R^2). The mathematical formulations of these metrics are provided in Table 6.

- **Root Mean Square Error (RMSE):** Measures the standard deviation of prediction errors by computing the square root of the average squared differences between predicted and actual values. It is sensitive to large errors, making it useful for detecting outliers. Lower RMSE values indicate better performance.
- **Mean Absolute Error (MAE):** Represents the average magnitude of errors without considering their direction, expressed in the same units as the target variable. It is less sensitive to outliers and offers an intuitive measure of accuracy.
- **Mean Squared Error (MSE):** Calculates the mean of squared prediction errors, penalizing larger errors more heavily. While effective for model comparison, its squared units make interpretation less direct.
- **Coefficient of Determination (R^2):** Indicates the proportion of variance in the dependent variable explained by the model, ranging from 0 (no explanatory power) to 1 (perfect prediction).

Collectively, RMSE and MSE provide sensitivity to large deviations, MAE offers a straightforward measure of average error magnitude, and R^2 evaluates explanatory power

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relative to a baseline. Using all four metrics ensures a comprehensive and balanced evaluation of each model's predictive capability for concrete compressive strength.

Table 6: Equations of different performance indices

Sl. No.	Performance Indices	Equation
1.	Root Mean square error	$RSME = \sqrt{\left(\sum_{i=1}^{n} (y-\hat{y})^2/n\right)}$
2.	Mean absolute error	$MAE = \sum_{i=1}^{n} \lvert (y-\hat{y})/n \rvert$
3.	Median absolute error	$MedAE = median\{ \bigcup_{i=1}^{n} \lvert y_i-\hat{y}_i \rvert \}$
4.	R^2 Score	$R^2 = 1 - \left(\sum_{i=1}^{n} (y-\hat{y})^2\right) / \left(\sum_{i=1}^{n} (y-\bar{y})^2\right)$

6. MACHINE LEARNING MODELS

6.1 Linear Regression

Linear Regression is a fundamental predictive modeling technique used to estimate continuous outcomes from a set of input features. The model learns by adjusting its coefficients (weights) and intercept (bias) to minimize the **Mean Squared Error (MSE)** between predicted and actual values. Parameter optimization is typically achieved via **gradient descent**, resulting in the best-fit linear equation. The mathematical formulation is provided in **Table 7**.

6.2 Lasso Regression

Lasso Regression extends the basic linear regression model by incorporating **L1 regularization** into the loss function. This penalty term drives some coefficients toward zero, effectively performing **feature selection** and reducing model complexity. While its training process parallels that of linear regression, optimization techniques such as **coordinate descent** are commonly employed to efficiently manage the L1 penalty. The corresponding equation is presented in **Table 7.**

6.3 Decision Tree Regression

Decision Tree Regression predicts continuous values by **recursively partitioning** the feature space into subsets based on optimal split points that minimize the **Mean Squared Error (MSE)** within each node. Unlike gradient-based methods, decision trees use **greedy algorithms** to determine splits. While they offer high interpretability, they are prone to overfitting and may require **pruning** or other regularization strategies. The mathematical representation is given in **Table 7**.

Table 7: Equation of different models

Sl. No	Model Name	Equation
1.	Linear regression	$\hat{y} = \theta_0 + \theta_1 x_1 + \theta_2 x_2 \dots\dots\dots + \theta_m x_m$ $J(\theta) = \left(\sum_{i=1}^{n} (y-\hat{y})^2\right)/2n$
2.	Lasso regression	$J(\theta) = \left(\sum_{i=1}^{n} (y-\hat{y})^2\right)/2n + \alpha \sum_{i=1}^{n} \lvert \theta_i \rvert$
3.	Decision tree regression	$J(\theta) = \left(\sum_{i=1}^{n} (y-\hat{y})^2\right)/2n + \alpha \sum_{i=1}^{n} \lvert \theta_i \rvert$

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Table 8 summarizes the predictive performance of different regression models using evaluation metrics including Root Mean Squared Error (RMSE), Mean Squared Error (MSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2). The **Decision Tree Regressor** demonstrates superior performance, achieving an RMSE of **3.50** and an R^2 of **0.98**, indicating an excellent fit and strong predictive capability. In comparison, traditional linear models such as **Linear Regression** and **Lasso Regression** exhibit moderate performance, with RMSE values in the range of **4.20–4.50** and R^2 values between **0.57** and **0.65**, reflecting a weaker alignment between predicted and observed values. This disparity suggests that linear models are less effective in capturing the complex, nonlinear relationships inherent in the dataset. Overall, the results confirm that **tree-based approaches** provide higher accuracy and robustness for strength prediction in concrete mixes incorporating fly ash and overburnt brick waste. Figure 4 represents Actual vs predicted of various regression models

Table 8: Performance metrics of various regression models

Models	RMSE	MSE	MAE	R^2
Linear Regression	4.20	17.62	3.90	0.65
Lasso Regression	4.50	20.25	4.10	0.57
Decision Tree Regressor	3.50	12.25	2.90	0.98

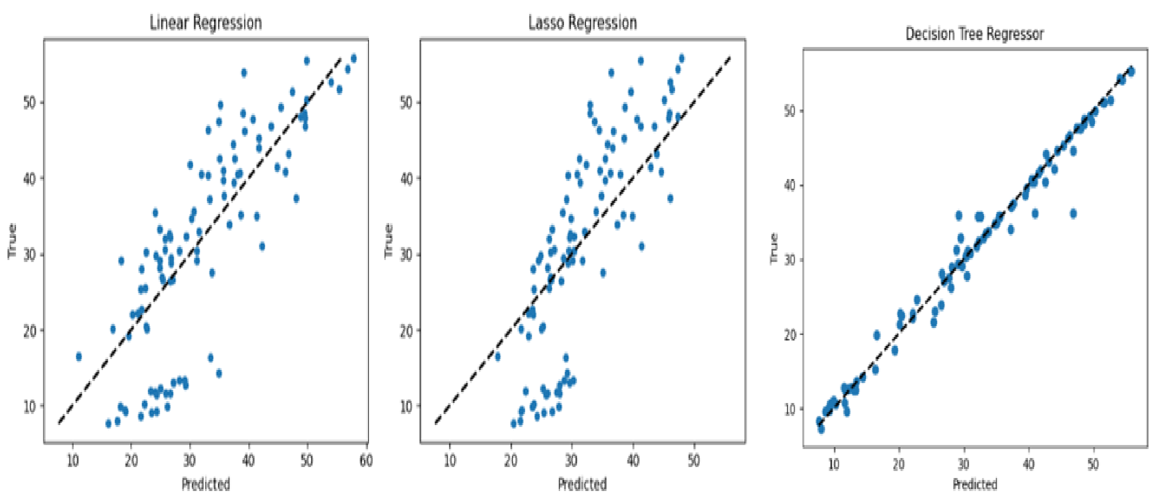

Figure 6: Actual vs predicted of various regression models

5.4 Exploratory Data analysis

The correlation heatmap in **Figure 7** provides a detailed overview of the linear associations among the variables in the dataset. Correlation coefficients range from –1 to +1, where values approaching +1 indicate a strong positive relationship, values near –1 denote a strong negative relationship, and values close to 0 suggest negligible correlation. A perfect correlation (**+1.00**) was observed between cement (C) and variable G, indicating complete redundancy or a direct dependency between these two parameters.

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Cement (C) demonstrated a strong positive correlation with compressive strength (CS) (**+0.77**), confirming its dominant role in strength development. A moderate negative correlation with fly ash (F) (**–0.48**), suggesting a mix design trade-off where higher cement content is generally paired with reduced fly ash. A moderate positive correlation with admixture dosage (A) (**+0.31**), implying that mixes with higher cement often include slightly higher admixture levels.

Admixture (A) exhibited a moderate positive correlation with CS (**+0.30**), indicating a beneficial but less pronounced effect on strength compared to cement.

Compressive Strength (CS) showed the strongest positive correlation with C (**+0.77**), confirming cement as the primary strength contributor.

A moderate positive correlation with fine aggregate (FA) (**+0.48**), indicating potential improvement in packing density and particle interlock. A moderate negative correlation with F (**–0.38**), consistent with reduced early-age strength in fly ash–rich mixes. Additionally, a high correlation between FA and overburnt brick aggregate (OBB) (**+0.78**) was noted, indicating potential multicollinearity.

Fly ash (F) maintained a negative association with both C (**–0.48**) and CS (**–0.38**). These correlations highlight cement content as the most influential parameter for CS, while also revealing variable interdependencies that could introduce redundancy in regression modeling.

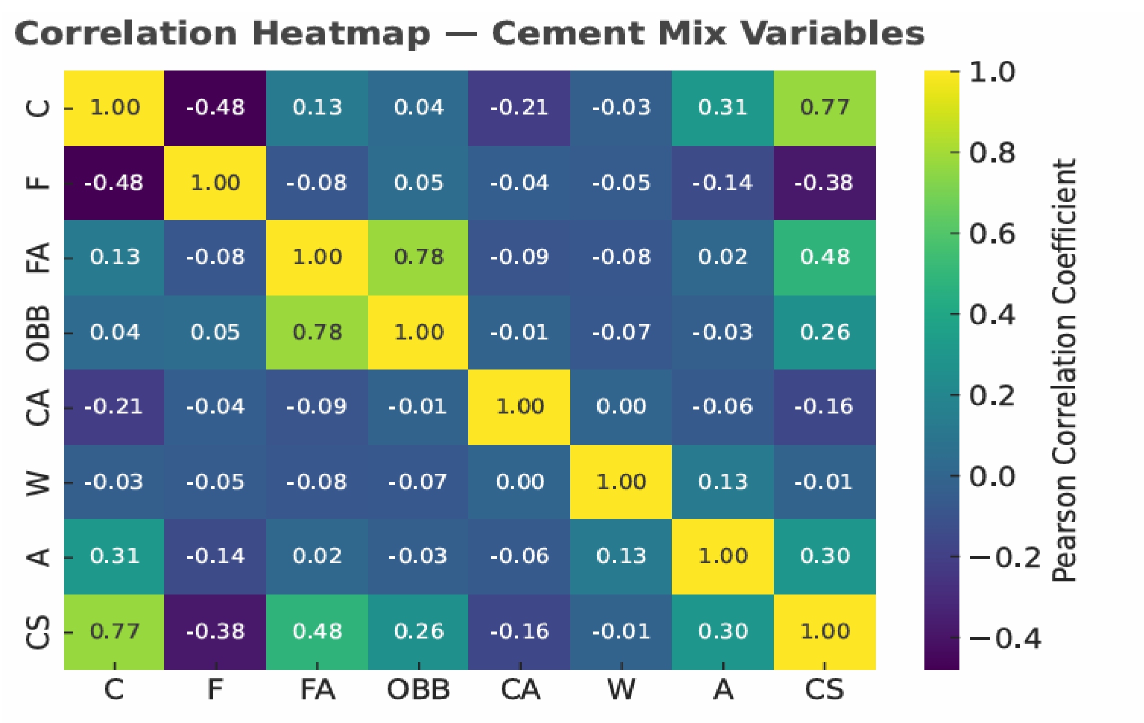

Figure 7: Correlation between different attributes

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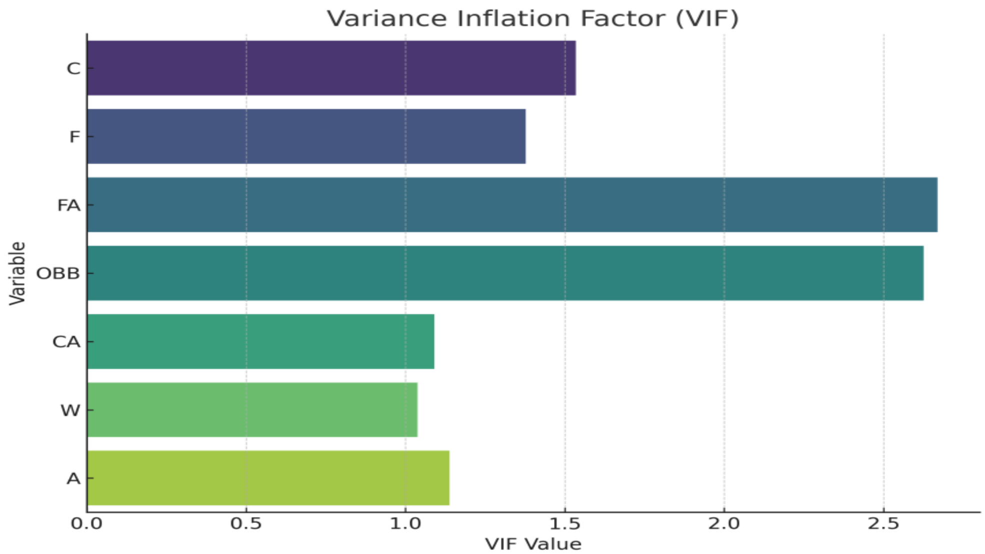

Figure 8: Variance Inflation Factor analysis

Variance Inflation Factor (VIF) analysis further quantified multicollinearity levels. All variables exhibited VIF values below the critical threshold of 5, indicating no severe multicollinearity. However, FA (~2.65) and OBB (~2.60) recorded the highest VIF values, suggesting moderate interdependence—likely due to aggregate proportioning effects. Cement (C), fly ash (F), coarse aggregate (CA), water (W), and admixture (A) all recorded VIF values close to 1.0–1.5, reflecting negligible correlation with other predictors. While the current model remains statistically stable, future mix optimization should monitor FA and OBB proportions to prevent inflation of standard errors. If additional correlated variables are introduced, techniques such as ridge regression or principal component analysis (PCA) may be employed to address multicollinearity. Figure 8 illustrates Variance Inflation Factor analysis.

6. CONCLUSIONS

This study investigates the feasibility of using overburnt brick waste (OBBW) as a partial replacement for natural coarse aggregates in concrete, with replacement levels ranging from 5% to 55%. A constant 10% Class C fly ash dosage was maintained as a supplementary cementitious material (SCM) across all mixes. The objective was to evaluate the mechanical performance and structural suitability of OBBW-based mixes while promoting sustainability in concrete production.

Experimental results showed that replacing up to 50% of natural coarse aggregates with OBBW significantly enhanced compressive, split tensile, and flexural strengths compared to the control mix. Peak performance was achieved at 45–50% replacement, beyond which strength gradually declined due to OBBW's higher porosity and water absorption, which impair matrix bonding. Optimal OBBW content produced structural-grade concrete

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with high strength and reduced self-weight, making it advantageous for lightweight structural applications.

Correlation analysis revealed strong positive relationships between cement content and compressive strength (CS), and between admixture dosage and CS, alongside a moderate negative correlation between fly ash dosage and CS at 28 days. High inter-correlation was observed among fine aggregate (FA), cement (C), and OBBW. The Ordinary Least Squares (OLS) regression model demonstrated strong predictive capability, while Variance Inflation Factor (VIF) analysis confirmed severe multicollinearity among FA, C, and OBBW.

Based on the findings, OBBW replacement should be limited to ≤50% for structural applications. Cement content should be balanced for cost efficiency and sustainability, with partial replacement by fly ash considered to enhance durability. Admixtures can provide additional performance gains. Long-term curing tests are recommended to capture the delayed benefits of fly ash. Predictive modeling—using regression or machine learning—should be applied for mix optimization, with careful monitoring and mitigation of multicollinearity.

The combined use of experimental testing, correlation mapping, regression analysis, and multicollinearity diagnostics offers a robust approach to sustainable concrete mix design. When optimally proportioned, OBBW and fly ash enable cost-effective, high-performance, and environmentally responsible concrete production, supporting circular economy goals and sustainable construction practices.

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