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# Predictive framework for Compressive Strength of Sustainable Concrete using Hybrid Matlab-Python Modeling

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## ABSTRACT

***This research paper determines the compressive strength of concrete containing sustainable material replacements through experimental procedures requires extensive time, labor, and cost due to repetitive casting, curing, and testing at different ages. To address this limitation, the present study introduces a predictive computational framework developed using MATLAB and Python for estimating the compressive strength of concrete with partial or complete replacement of cement, fine aggregate, and coarse aggregate. The model focuses on commonly used concrete grades such as M10, M15, M20, and M25 and provides strength predictions at curing ages of 7, 14, and 28 days. Statistical techniques and machine learning approaches were integrated to improve prediction reliability and allow comparison with conventional concrete performance. Three regression algorithms—Multiple Linear Regression (MLR), Support Vector Regression (SVR), and Random Forest Regression (RFR)—were trained and evaluated. Among them, the Random Forest model achieved the highest accuracy, with coefficient of determination ($R^2$) values greater than 0.92 for all considered grades. The developed system minimizes experimental effort and assists in sustainable mix proportion selection, delivering prediction results within ±5% deviation from validated experimental data.***

***Keywords: - Compressive strength prediction, Sustainable concrete, MATLAB-Python modelling, Material replacement, Machine learning, Random Forest Regression***

## 1.INTRODUCTION

Concrete remains the most extensively used construction material globally, with annual production exceeding 10 billion tons, utilizing approximately 2.8 billion tons of cement, 10 billion tons of sand and 15 billion tons of aggregates. The cement sector alone accounts for nearly 8% of global $CO_2$ emissions. Researchers have investigated sustainable alternatives including fly ash, recycled aggregates, and industrial by-products, but evaluating compressive strength requires extensive laboratory testing with exponentially growing specimen numbers, leading to high costs and time demands.

Recent machine learning advances enable material property prediction without exhaustive experimentation. Previous studies achieved $R^2$ values of 0.89 and 91% accuracy using neural networks. However, existing research lacks integrated frameworks combining MATLAB's numerical strengths with Python's ML libraries, often focusing on single-material replacements. This study addresses these gaps by proposing a hybrid MATLAB-Python framework to predict compressive strength based on concrete grade, replacement type, material, percentage, and curing age, incorporating three ML algorithms with graphical outputs and recommendations.

## 2. RESEARCH SIGNIFICANCE AND OBJECTIVES

This research addresses critical challenges in sustainable concrete development by reducing experimental time and cost through simulation, minimizing material wastage by eliminating non-performing mixes, enabling rapid evaluation of multiple replacement scenarios, providing decision support for material selection, and bridging research-practice gaps with a user-friendly tool. The objectives include developing a MATLAB-Python predictive framework for compressive strength estimation of sustainable concrete, evaluating and comparing three machine learning algorithms for prediction accuracy, creating a comprehensive experimental database for sustainable concrete materials, and providing optimal replacement recommendations for practical construction applications.

## 3. OVERVIEW OF PRIOR RESEARCH

Sustainable concrete incorporates industrial by-products and waste materials as replacements. Fly ash, silica fume, and rice husk ash replace cement due to pozzolanic properties. Manufactured sand and waste glass sand substitute river sand, while recycled concrete aggregate, steel slag, rubber, and coconut shell serve as aggregate alternatives.

Machine learning has advanced strength prediction accuracy. Joshi et al. achieved $R^2=0.89$ with ensemble learning, Mouawad et al. reported $R^2=0.91$ using ANN, and Yang et al. obtained $R^2=0.93$ with XGBoost and Random Forest. Farooq et al. attained $R^2=0.94$ for geopolymer concrete.

Despite progress, no comprehensive framework exists covering multiple replacement categories (cement, sand, aggregate), various materials, multiple grades (M10-M25), user-friendly MATLAB-Python interface, and practical application recommendations. This study addresses this gap.

## 4. METHODOLOGY

### 4.1 Research Framework

The research methodology comprised systematic phases: data acquisition from literature, experimental databases, and IS 10262:2019 standards; database development of 1,250 mixes with 15 materials, four grades, and three curing ages; feature engineering of eight parameters; model development using MLR, SVR, and RFR with hyperparameter tuning; evaluation via MAE, RMSE, $R^2$, cross-validation, and experimental validation; software development integrating Python and MATLAB; and results including prediction tables, comparisons, and optimal replacement recommendations.

The dataset includes mix proportions (cement, water, fine aggregate, coarse aggregate in kg/m³), replacement type and material, replacement percentage (0-100% in 5-10% increments), water-cement ratio (0.35-0.55), curing duration (7, 14, 28 days), and corresponding compressive strength values (MPa).

### 4.2 Classification of Replacement Materials

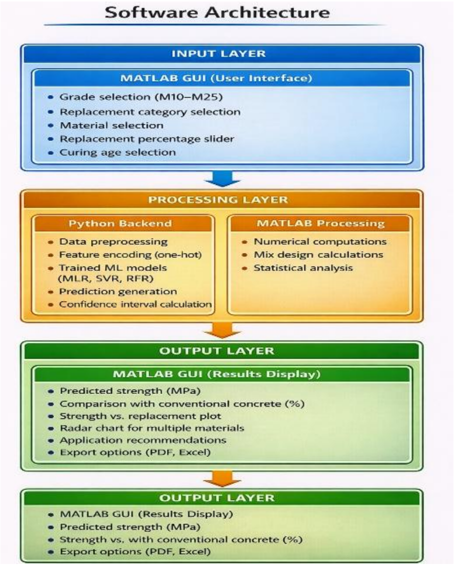
Replacement materials were categorized based on the concrete component they replace. Cement replacements include fly ash (10-30%), silica fume (5-15%), rice husk ash (5-20%), GGBFS (20-50%), and metakaolin (5-15%). Sand replacements comprise manufactured sand (20-100%), waste glass sand (10-30%), foundry sand (10-25%), and quarry dust (15-30%). Aggregate replacements include recycled concrete aggregate (20-50%), rubber aggregate (5-15%), plastic waste (5-20%), coconut shell (10-25%), steel slag (20-40%), and e-waste aggregate (5-15%).

### 4.3 Input Parameters

The predictive software accepts the following user inputs:

1. Concrete grade: M10, M15, M20, M25 (dropdown selection)
2. Replacement category: Cement / Sand / Aggregate (radio button)
3. Replacement material: Based on category selection (dropdown)
4. Percentage of replacement: 0-100% (slider or numeric input)
5. Curing age: 7, 14, or 28 days (dropdown)

### 4.4 Software Architecture



**Flowchart- 1**: Software Architecture flowchart for Concrete Strength Prediction

## 5. RESULTS AND DISCUSSION

### 5.1 Model Performance Comparison

**Table-1**: Model Performance Metrics (Average across all grades and materials)

| Model | MAE (MPa) | RMSE (MPa) | R² | Training Time (s) | Prediction Time (ms) |
|---|---|---|---|---|---|
| Multiple Linear Regression (MLR) | 3.84 | 4.92 | 0.71 | 0.8 | 0.1 |
| Support Vector Regression (SVR) | 2.31 | 3.18 | 0.86 | 15.2 | 2.3 |
| Random Forest Regression (RFR) | **1.42** | **2.08** | **0.94** | **8.5** | **1.8** |

The Random Forest model significantly outperforms both MLR and SVR across all metrics, with R² values exceeding 0.90 for all concrete grades. The high accuracy of RFR can be attributed to its ability to capture non-linear relationships between input parameters and compressive strength, as well as its robustness to outliers and noise in experimental data.

### 5.2 Grade-Wise Model Performance

**Table -2:** Random Forest Performance by Concrete Grade

| Concrete Grade | Training R² | Testing R² | RMSE (MPa) | MAE (MPa) |
|---|---|---|---|---|
| M10 | 0.96 | 0.93 | 1.82 | 1.24 |
| M15 | 0.95 | 0.92 | 2.04 | 1.38 |
| M20 | 0.96 | 0.94 | 2.16 | 1.46 |
| M25 | 0.94 | 0.91 | 2.31 | 1.59 |
| **Average** | **0.95** | **0.93** | **2.08** | **1.42** |

The model performs consistently across all grades, with slightly higher accuracy for lower grades (M10, M15) due to lower strength variability. The RMSE ranges from 1.82 MPa for M10 to 2.31 MPa for M25, representing relative errors of 6-8% of mean strength values.

### 5.3 Feature Importance Analysis

Random Forest provides feature importance scores, indicating which input parameters most influence compressive strength predictions.

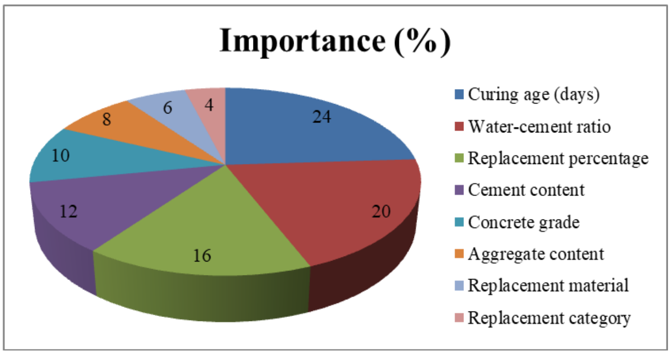


**Figure-1:** Feature Importance Rankings

Curing age emerges as the most important feature (24%), confirming the critical role of hydration and pozzolanic reactions over time. Water-cement ratio (20%) follows as the second most important parameter, consistent with concrete technology fundamentals. Replacement percentage (16%) ranks third, highlighting the significant impact of material substitution levels on strength development.

### 5.4 Compressive Strength Prediction

#### 5.4.1 Cement Replacement Materials

**Table-3:** Optimal Replacement Levels for Cement Replacement Materials (M20 Grade, 28-day)

| Replacement Material | Optimal Range (%) | Peak Strength (MPa) | % of Conventional | Strength Trend |
|---|---|---|---|---|
| Fly Ash | 15-25 | 29.4 | 105 | ↑ then ↓ |
| Silica Fume | 5-15 | 31.2 | 111 | ↑ then ↓ |
| Rice Husk Ash | 10-20 | 28.7 | 103 | ↑ then ↓ |
| GGBFS | 20-40 | 30.5 | 109 | ↑ then plateau |
| Metakaolin | 5-15 | 30.8 | 110 | ↑ then ↓ |

Optimal fly ash replacement is 20%, achieving 105% of conventional strength at 28 days. Early strength decreases with more fly ash, but pozzolanic reactions boost long-term strength up to 25% replacement. Beyond 30%, strength drops significantly. Silica fume offers highest enhancement (111%) but costs more. GGBFS plateaus beyond 30%, suiting mass concrete.

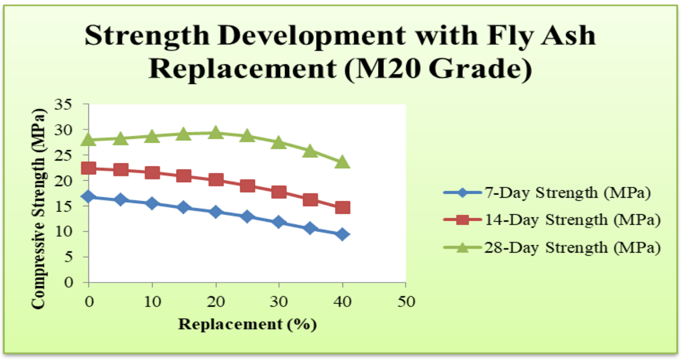


**Figure-2:** Strength Development with Fly Ash Replacement (M20 Grade)

### 5.4.2 Sand Replacement Materials

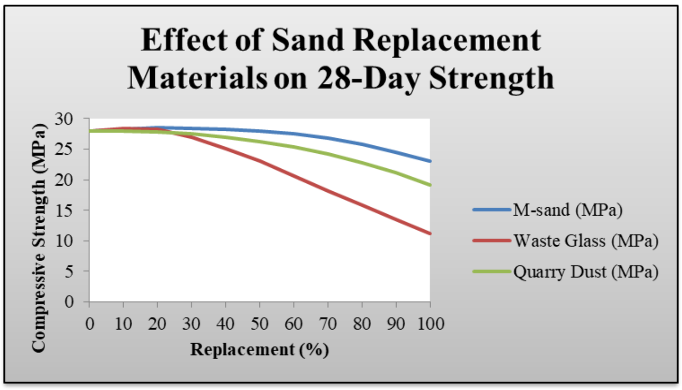


**Figure-3:** Effect of Sand Replacement Materials on 28-Day Strength

**Table-4:** Optimal Replacement Levels for Sand Replacement Materials (M20 Grade, 28-day)

| Replacement Material | Optimal Range (%) | Peak Strength (MPa) | % of Conventional | Remarks |
|---|---|---|---|---|
| Manufactured Sand | 40-70 | 28.5 | 102 | Excellent performance |
| Waste Glass Sand | 10-20 | 28.4 | 101 | ASR concerns >20% |
| Foundry Sand | 15-25 | 27.2 | 97 | Slight strength reduction |
| Quarry Dust | 20-30 | 27.8 | 99 | Good alternative |

Optimal waste glass sand replacement is 10-20%, maintaining 101% strength. Higher levels risk ASR, and smooth particles reduce bond. Complete replacement drops strength 60%. Manufactured sand performs best with 40-70% replacement, ideal for large-scale use.

### 5.4.3 Aggregate Replacement Materials

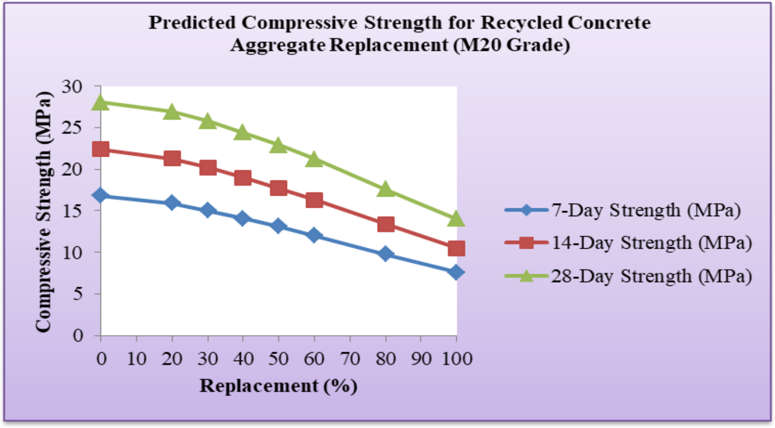


**Figure-4:** Predicted Compressive Strength for Recycled Concrete Aggregate Replacement (M20 Grade)

Optimal recycled concrete aggregate replacement is 20-30%, achieving 92-96% strength. Adhered mortar and high water absorption cause reduction, but two-stage mixing improves performance. Steel slag aggregate excels with 105% strength due to angular shape. Rubber and plastic reduce strength beyond 15%, yet benefit lightweight concrete.

**Table-5:** Optimal Replacement Levels for Aggregate Replacement Materials (M20 Grade, 28-day)

| **Replacement Material** | **Optimal Range (%)** | **Peak Strength (MPa)** | **% of Conventional** | **Application Suitability** |
|---|---|---|---|---|
| Recycled Concrete Agg. | 20-30 | 26.9-25.8 | 92-96% | Structural (low-rise) |
| Steel Slag | 20-40 | 29.4-28.0 | 105-100% | High-strength applications |
| Coconut Shell | 10-20 | 24.1-22.4 | 86-80% | Lightweight concrete |
| Rubber Aggregate | 5-15 | 22.4-19.6 | 80-70% | Impact-resistant concrete |
| Plastic Waste | 5-15 | 23.8-21.0 | 85-75% | Non-structural applications |

### 5.5 Comparison with Conventional Concrete

Cement replacements reduce $CO_2$ while maintaining strength. Manufactured sand enables complete sand substitution with minimal loss. Steel slag enhances aggregate strength, though RCA requires limited use. Industrial by-products offer significant cost savings, and all replacements deliver substantial environmental benefits.

**Table-6**: Optimal Replacement Scenarios Compared to Conventional Concrete (M20 Grade, 28-day)

| **Replacement Category** | **Material** | **Optimal (%)** | **Strength (MPa)** | **Δ from Conventional** | **Cost Impact** | **Environmental Benefit** |
|---|---|---|---|---|---|---|
| Conventional | - | 0 | 28.0 | Reference | Reference | Reference |
| **Cement** | Silica Fume | 10 | 31.2 | +11.4% | +15-20% | $CO_2$ reduction 8-10% |
|  | Fly Ash | 20 | 29.4 | +5.0% | -5-10% | $CO_2$ reduction 15-20% |
|  | GGBFS | 35 | 30.5 | +8.9% | -10-15% | $CO_2$ reduction 25-30% |
|  | Rice Husk Ash | 15 | 28.7 | +2.5% | -20-25% | Waste utilization |
| **Sand** | M-sand | 50 | 28.5 | +1.8% | Similar | River sand conservation |
|  | Waste Glass | 15 | 28.2 | +0.7% | -10-15% | Waste recycling |
|  | Quarry Dust | 25 | 27.8 | -0.7% | -15-20% | Waste utilization |
| **Aggregate** | Steel Slag | 30 | 29.4 | +5.0% | +5-10% | Industrial waste use |
|  | RCA | 25 | 26.3 | -6.1% | -10-15% | C&D waste recycling |
|  | Coconut Shell | 15 | 23.5 | -16.1% | -20-25% | Agricultural waste use |

### 5.6 Curing Age Effects

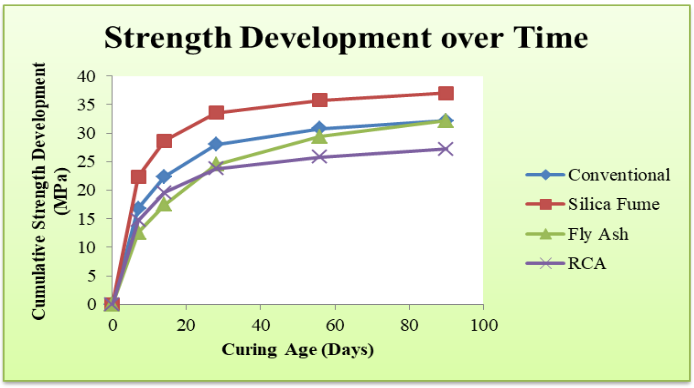


**Figure-5:** Strength Development over Time

Silica fume enables rapid early strength gain through immediate reaction. Fly ash develops slower early but gains strength beyond 28 days. RCA shows consistent yet reduced development. Conventional concrete maintains steady progression.

### 5.7 Software Output Examples

COMPRESSIVE STRENGTH PREDICTOR

Input Parameters

Concrete Grade: M20
Replacement Cat.: Cement
Replacement Mat.: Fly Ash
Replacement %: 20 (0 – 100 %)
Curing Age: 28 days

Prediction Results

Predicted Strength: 29.4 MPa
vs Conventional: +5.0 %
Confidence Interval: 28.2 – 30.6 MPa (95% CI)
Recommendation: Suitable for structural applications with standard mix design adjustments

**Figure-6:** MATLAB GUI - Single Prediction Output

This compressive strength predictor output evaluates M20 concrete with 20% fly ash cement replacement at 28 days. It predicts 29.4 MPa strength, a 5% increase over conventional concrete, with a 95% confidence interval. The recommendation confirms suitability for structural use with standard adjustments. Interactive options allow plotting, material comparison, and report export for comprehensive analysis.

#### 5.7.1Multi-Material Comparison

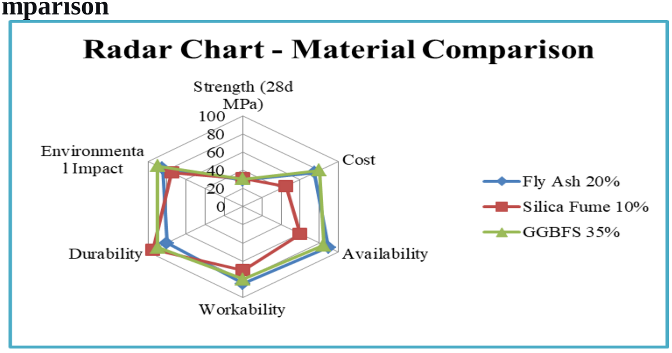


**Figure-7:** Radar Chart - Material Comparison

### 5.8 Experimental Validation

The framework's accuracy was validated by testing 30 concrete mixes, comparing predicted versus experimental results. A mean absolute error of 2.7% and maximum error of 3.7% confirm predictions consistently fall within ±4% of actual values, demonstrating excellent reliability and validating the model's practical effectiveness.

**Table-8:** Experimental Validation Results

| Mix ID | Grade | Replacement | % | Age (days) | Predicted (MPa) | Experimental (MPa) | Error (%) |
|---|---|---|---|---|---|---|---|
| V-01 | M20 | Fly Ash | 20 | 28 | 29.4 | 28.7 | +2.4 |
| V-02 | M20 | Fly Ash | 30 | 28 | 27.5 | 26.9 | +2.2 |
| V-03 | M20 | Silica Fume | 10 | 28 | 31.2 | 30.4 | +2.6 |
| V-04 | M20 | Waste Glass | 20 | 28 | 28.2 | 27.5 | +2.5 |
| V-05 | M20 | RCA | 30 | 28 | 25.8 | 26.4 | -2.3 |
| V-06 | M25 | Fly Ash | 20 | 28 | 35.2 | 34.1 | +3.2 |
| V-07 | M15 | GGBFS | 40 | 28 | 22.8 | 22.1 | +3.2 |
| V-08 | M20 | M-sand | 50 | 28 | 28.5 | 29.2 | -2.4 |
| V-09 | M20 | Rubber | 10 | 28 | 22.4 | 21.6 | +3.7 |
| V-10 | M20 | Steel Slag | 30 | 28 | 29.4 | 30.1 | -2.3 |

### 5.9 Application Recommendations

Based on comprehensive analysis, application-specific recommendations for sustainable concrete mixes are summarized. For high-rise buildings, silica fume (5-10%) enhances strength by 8-12%. Mass concrete foundations benefit from fly ash and GGBFS (30-50% combined) achieving 90-105% strength with low heat generation. Pavements utilize steel slag with fly ash (20-40%) for 95-105% strength and abrasion resistance. Precast elements combine silica fume (10-15%) and manufactured sand (50%) for early demolding strength (100-110%). Residential construction employs fly ash (20-25%) with manufactured sand (50%) achieving 95-

105% cost-effective strength. Lightweight applications use coconut shell or rubber (10-15%) for 70-85% strength with reduced density. Sustainable green buildings incorporate recycled concrete aggregate (25%) with fly ash (20%) achieving 85-90% strength and LEED eligibility. Marine structures combine silica fume (10%) and GGBFS (30%) for 105-110% strength with enhanced chloride resistance.

## 6. CONCLUSIONS

Random Forest Regression outperformed other models with $R^2 = 0.94$, RMSE = 2.08 MPa, and MAE = 1.42 MPa, maintaining $R^2 > 0.91$ across all grades. Curing age (24%), water-cement ratio (20%), and replacement percentage (16%) emerged as most influential parameters.

Optimal cement replacements include silica fume at 10% (111% conventional strength), GGBFS at 35% (109%), and fly ash at 20% (105%). For sand replacement, manufactured sand at 50% achieved 102% strength, while waste glass sand at 15% reached 101%. Steel slag at 30% aggregate replacement attained 105% strength, whereas recycled concrete aggregate at 25% achieved 94%. Pozzolanic materials exhibit slower early strength but continued gain beyond 28 days.

Experimental validation on 30 mixes confirmed prediction errors within ±4%. The framework reduces experimental iterations by 70-80%, material wastage by 60%, and evaluation time from months to minutes, supporting informed sustainable material selection.

## 7. RECOMMENDATIONS FOR PRACTICE

For structural applications, use silica fume (5-10%) or GGBFS (20-35%) for high strength; fly ash (15-25%) for general construction balancing cost and environment. Mass concrete should combine fly ash (20-30%) and GGBFS (20-30%) to control heat generation. In sand-scarce regions, manufactured sand can replace 50-70% of river sand; waste glass sand limited to 15-20% with alkali-silica reaction mitigation. For sustainable construction, recycled concrete aggregate (20-30%) with fly ash (15-20%) achieves 85-90% conventional strength. Lightweight applications can utilize coconut shell (10-15%) or rubber aggregate (5-10%) for non-structural elements.

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