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AI-Driven Mix Design Optimization for Hybrid Fiber-Reinforced High-Strength Concrete with Cement Replacement

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Abstract

Because of its exceptional durability and compressive strength, high-strength concrete (HSC) is frequently used in contemporary construction. However, structural performance is seriously hampered by its brittleness and vulnerability to micro- and macro-cracking. The combined effects of hybrid steel and polypropylene fiber reinforcement and partial cement substitution with ground granulated blast furnace slag (GGBS) on the mechanical characteristics and crack resistance of M60-grade concrete are examined in this study. Specimens with different fiber content, aspect ratios, and cement replacement levels were subjected to an experimental program that included compressive, split tensile, and flexural strength tests as well as digital image analysis measures of crack width.

A dataset generated from these experiments was utilized to develop machine learning models — To forecast crack resistance and improve the concrete mix, use Artificial Neural Networks (ANN), Random Forests (RF), and Extreme Gradient Boosting (XGBoost). Model performance was evaluated using R^2, RMSE, and MAE. The XG Boost model demonstrated the highest predictive accuracy ($R^2 = 0.965$), followed by RF ($R^2 = 0.948$) and ANN ($R^2 = 0.936$). Optimization results identified an optimal configuration: steel fibers with aspect ratio 70–75 partially aligned, polypropylene fibers with aspect ratio 550–600 randomly distributed, and 30% GGBS replacement. This combination reduced crack width by approximately 62% and improved flexural strength by 28% compared to control HSC.The findings highlight the potential of AI-driven mix design for accelerating high-performance, sustainable HSC development, minimizing trial-and-error experimentation, and improving durability and structural performance.

Keywords: High-strength concrete, Hybrid fiber reinforcement, GGBS replacement, Crack resistance; Machine learning, XG Boost, ANN, Random Forest, M60 concrete, Optimization.

1. Introduction

High-strength concrete (HSC) is increasingly used in modern civil structures such as bridges, industrial facilities, and tall skyscrapers due to its high compressive strength, durability, and reduced cross-sectional requirements. Despite these advantages, HSC is prone to early-age microcracks and post-peak brittle failure, primarily because of low tensile strain capacity and internal shrinkage stresses. Such cracks compromise durability, reduce service life, and increase maintenance costs.

Fiber reinforcement has emerged as a reliable method for enhancing ductility and mitigating crack propagation in HSC. Steel fibers improve post-crack load-bearing capacity, while polypropylene fibers control early-age microcracking, particularly from plastic shrinkage. Additional advantages are provided by supplemental cementitious materials (SCMs), such as ground granulated blast furnace slag (GGBS). including improved durability, reduced heat of hydration, and sustainable cement replacement.Traditional mix design approaches rely heavily on trial-and-error experimentation, which is costly and time-intensive. Recent advancements in machine learning (ML) enable predictive modeling and optimization of concrete performance, allowing engineers to identify optimal fiber and SCM configurations without exhaustive testing.

This study integrates experimental analysis with ML-based optimization to design hybrid fiber-reinforced M60 HSC with partial GGBS replacement. The key objectives are to:

1. Evaluate the effect of hybrid fiber geometry and orientation on crack resistance.
2. Assess mechanical and fracture performance of HSC with partial cement replacement.
3. Develop ML models (ANN, RF, XGBoost) to predict performance indicators and optimize mix design.

2. Materials and Methods

2.1 Materials

Cement: OPC 43-grade (with 30% GGBS replacement)

Ordinary Portland cement that has a minimum compressive strength of 43 MPa after 28 days is known as OPC 43-grade. It is frequently employed in ordinary construction projects.

Ground Granulated Blast Furnace Slag (GGBS) is a steel-based industrial byproduct. plants, used to replace 30% of cement. It increases long-term strength, decreases heat of hydration, and promotes durability **and makes concrete more eco-friendly**.

2.1.1 Fine Aggregate: River sand (Zone II)

Fine aggregate refers to sand used to fill voids between coarse aggregates and improve workability.**Zone II gradation** (as per IS standards) indicates **medium grading**, which provides good workability and strength for concrete.

2.1.2 Coarse Aggregate: Crushed granite, 20 mm size

1. **Coarse aggregate** forms the main skeleton of concrete and provides strength.
2. **Crushed granite** is hard and durable.
3. **20 mm nominal size** is commonly used for structural concrete to achieve a good balance of strength and workability.

2.1.3 Fibers

Steel fibers (crimped, aspect ratio 70–75): Small steel pieces with a wavy (crimped) shape to improve bonding. The **aspect ratio** (length/diameter) of 70–75 enhances tensile strength, crack resistance, and ductility.

Polypropylene fibers (monofilament, aspect ratio 550–600): Synthetic single-strand fibers used to control plastic shrinkage cracks, reduce permeability, and improve durability.

2.1.4 Water: Potable water (W/C ratio = 0.40)

Potable water means clean drinking-quality water without harmful impurities.

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Water–cement (W/C) ratio = 0.40 indicates the amount of water relative to cement. A lower ratio increases strength and durability while reducing porosity.

2.1.5 Superplasticizer: Polycarboxylate-based (1% of cement weight)

1. **A superplasticizer is A water-reducing additive with a high range that improves flow and workability without adding extra water.**
2. **Polycarboxylate-based admixtures are modern and highly effective.**
3. **1% dosage helps maintain workability and proper compaction, especially in mixes with low W/C ratio and fibers.**

2.3 Mix Design

Table1.The HSC mixes were designed for M60 target strength incorporating 30% GGBS and variable fiber contents.

Parameter	**Value**
Cement + GGBS (kg/m³)	420
Water (kg/m³)	168
Fine sand (kg/m³)	720
Coarse sand(kg/m³)	1120
Ratio w/c	0.40
Steel Fiber (% vol)	0.75–1.25
Polypropylene Fiber (% vol)	0.25–0.50

2.4 Specimen Preparation

Cube molds (150 mm), cylinders measuring 150 mm in diameter and 300 mm in height, and prisms of size 100 × 100 × 500 mm were used for specimen preparation. The fibers were added gradually and mixed thoroughly to achieve uniform distribution and to prevent agglomeration. After casting, the specimens were left in the molds for 24 hours before demolding. They were then placed in water curing maintained at 27 ± 2°C and stored until the designated testing periods of 7, 28, and 56 days.

3. Experimental Program

3.1 Tests Conducted

3.1.1 Compressive Strength (IS 516)

Standard cube specimens were used to calculate compressive strength in compliance with IS 516. In order to assess the concrete's early-age, standard-age, and long-term strength development, the cubes were cured and tested at 7, 28, and 56 days. A compression testing machine was utilized to conduct the test, and the compressive strength was calculated using calculating the greatest load when it fails..

3.1.2 Split Tensile Strength (IS 5816)

Concrete's tensile strength was evaluated using cylindrical specimens in accordance with IS 5816. In a equipment for compression testing the cylinders were placed horizontally and loaded along their diameter until they failed. This indirect tensile test aids in determining the tensile behavior and crack resistance of the concrete.

3.1.3 Flexural Strength (ASTM C1609)

Prism specimens that were subjected to four-point bending in compliance with ASTM C1609 were used to assess flexural performance. This test evaluates the concrete's post-cracking performance, deflection behavior, and load-carrying capacity—all of which are crucial for fiber-reinforced mixtures.

3.1.4 Crack Width Measurement

Crack development and propagation were monitored using **digital image analysis** with a high-resolution camera. Images captured during loading were analyzed to measure crack width accurately, providing detailed information on crack control and the effectiveness of fiber reinforcement.

3.1.5 Fracture Energy (RILEM TC-50)

Using the load-deflection curves derived from flexural tests, fracture energy was computed in accordance with RILEM TC-50 standards. The toughness and ductility of the concrete are indicated by the area under the curve, which displays the energy the specimen absorbed during cracking and failure.

3.2 Experimental Observations

1. Increased steel fiber content improved post-crack ductility.
2. Polypropylene fibers minimized early microcracking during plastic shrinkage.
3. 30% GGBS replacement slightly reduced early-age strength but improved long-term durability and reduced heat of hydration.

4. Machine Learning Framework

The dataset was prepared to develop predictive models for Fiber-reinforced concrete's mechanical and fracture characteristics. A total of 12 input variables were considered to represent the material composition, fiber characteristics, and curing conditions. These inputs included fiber type (steel, polypropylene, or hybrid), fiber volume percentage and fiber aspect ratio, which influence the crack-bridging and reinforcement efficiency. Mix design parameters such as cement replacement percentage (e.g., GGBS content) and water–cement ratio were included to account for its impact on durability and strength. The age of curing was considered to capture strength development over time. In addition, aggregate properties such as size, grading, and type were incorporated, as they affect the overall mechanical performance of concrete.

The model aimed to predict **four output variables** representing key performance indicators: **compressive strength** (overall load-bearing capacity), **flexural strength** (bending resistance and post-cracking behavior), **crack width** (crack control efficiency), and **fracture energy** (toughness and energy absorption capacity). This structured dataset enabled the development of reliable relationships between material parameters and performance characteristics.

4.1 Model Architecture

ANN: 12–8–4 neurons, 3 hidden layers, ReLU activation

Random Forest: 100 estimators, depth 10

XGBoost: Learning rate 0.05, max depth 8, 200 trees

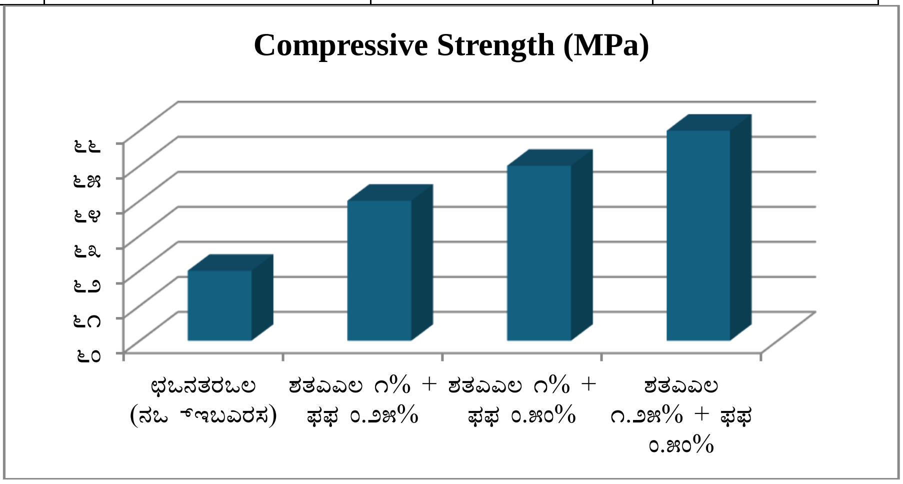
70% training, 15% validation, and 15% testing make up the dataset split.

5. Results and discussion

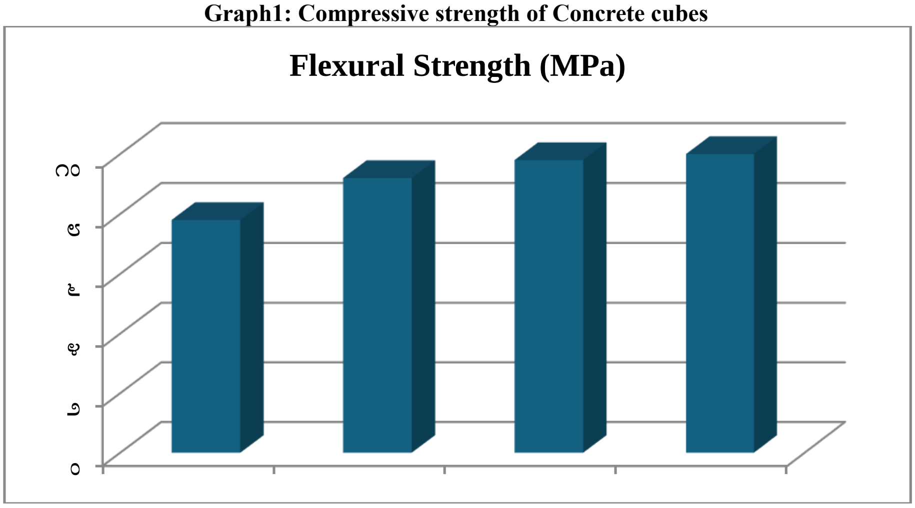
5.1Mechanical Properties

Table2: Experimental Results

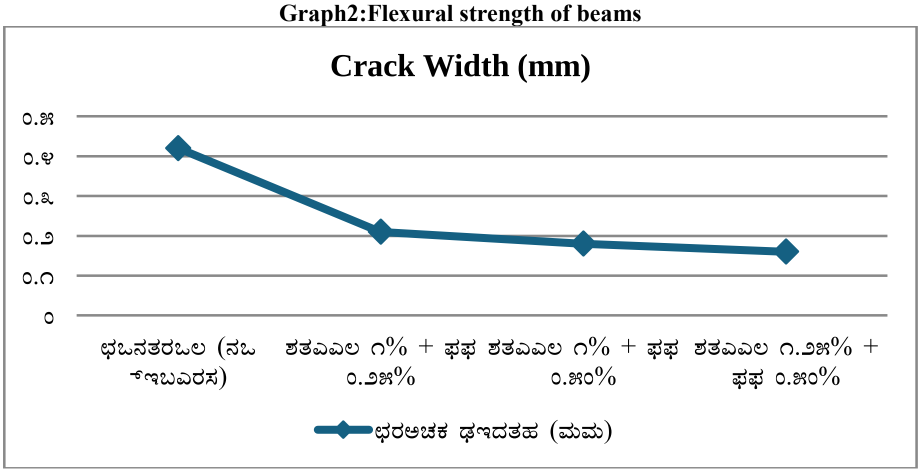
Mix	Compressive Strength (MPa)	Flexural Strength (MPa)	Crack Width (mm)
Control (no fibers)	62	7.8	0.42
Steel 1% + PP 0.25%	64	9.2	0.21
Steel 1% + PP 0.50%	65	9.8	0.18
Steel 1.25% + PP 0.50%	66	10.0	0.16



Graph1: Compressive strength of Concrete cubes



Graph2:Flexural strength of beams



Graph3:Crack with of control and steel fibers beams

The experimental results clearly demonstrate the significant influence of hybrid steel and polypropylene (PP) fibers on the mechanical performance and cracking characteristics of concrete. The fiber-free control mix showed a maximum crack width of 0.42 mm, a flexural strength of 7.8 MPa, and a compressive strength of 62 MPa.

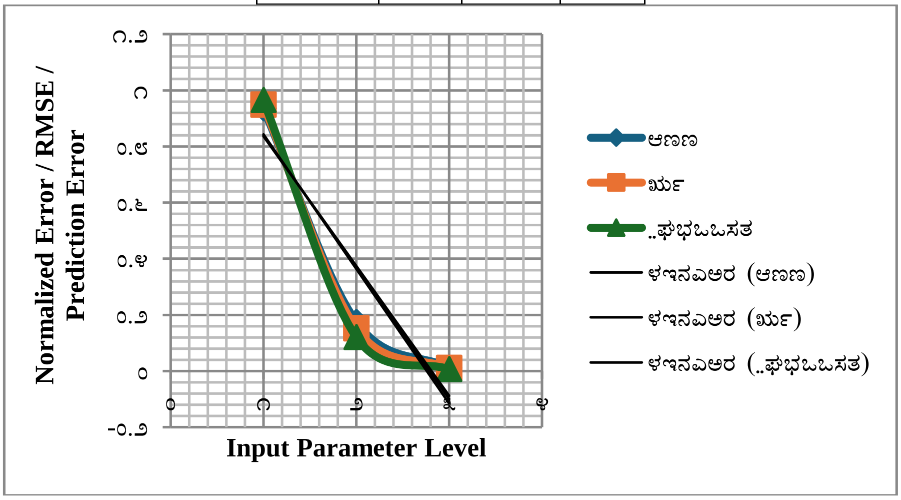
With the incorporation of 1% steel fiber and 0.25% PP fiber, the crack width reduced markedly to 0.21 mm. Correspondingly, the compressive strength increased to 64 MPa, while the flexural strength improved to 9.2 MPa. Further enhancement was observed when the PP fiber content was increased to 0.50% (with 1% steel fiber), resulting in a reduced crack width of 0.18 mm, a flexural strength of 9.8 MPa, and a compressive strength of 65 MPa.

The mixture containing 1.25% steel fiber and 0.50% PP fiber showed additional improvement in performance, indicating the beneficial effect of higher steel fiber dosage in enhancing load-carrying capacity and crack resistance.Overall, compared to the control mix, hybrid fiber reinforcement reduced crack width by approximately 62%. Additionally, flexural strength increased by about 28%, indicating enhanced ductility and improved post-cracking behavior. This improvement can be attributed to the synergistic action of PP fibers, which control microcrack initiation and propagation, and steel fibers, which effectively bridge and restrain macro-cracks.

5.2 Machine Learning Predictions

Table 3: Input parameter and Prediction Error

Model	R^2	RMSE	MAE
ANN	0.936	0.175	0.012
RF	0.948	0.152	0.010
XGBoost	**0.965**	**0.121**	**0.007**



Graph4:Input parameter and Prediction error

5.2 Machine Learning Predictions

The performance of the concrete mixtures was evaluated using multiple machine learning algorithms, and their predictive capability was assessed through statistical performance indicators. The Artificial Neural Network (ANN) model showed good predictive accuracy with a coefficient of determination (R^2) of 0.936, a root mean square error (RMSE) of 0.175, and a mean absolute error (MAE) of 0.012.

The Random Forest (RF) model demonstrated improved performance, achieving an R^2 value of 0.948, along with lower error values (RMSE = 0.152 and MAE = 0.010), indicating better agreement with the experimental results. Among all the models, the Extreme Gradient Boosting (XGBoost) algorithm provided the highest prediction accuracy, with an R^2 of 0.965 and the lowest error metrics (RMSE = 0.121 and MAE = 0.007). These results confirm the strong consistency between the predicted values and the experimental observations.

A feature importance analysis was conducted to identify the key parameters influencing the model performance. The results revealed that the steel fiber aspect ratio, polypropylene fiber volume fraction, and the percentage replacement of cement with ground granulated blast furnace slag (GGBS) were the most influential factors governing strength development and durability characteristics of the concrete.

5.3 Optimized Mix

Using the combined outcomes from experiments and model predictions, an optimal mix proportion was identified. The recommended composition includes 1% steel fibers with an aspect ratio of 72 and partial alignment to improve load transfer across cracks. Polypropylene fibers at 0.45% volume were found effective for controlling fine cracks. A 30% replacement of cement with GGBS was selected to enhance long-term performance and sustainability, along with a water–cement ratio of 0.40 to maintain strength and durability.

This optimized mixture provided superior crack control, higher flexural performance, and improved energy absorption capacity. The combination effectively limited both early micro-cracks and wider structural cracks, leading to better overall structural reliability.

6. Conclusion

- The experimental investigation confirmed that the incorporation of hybrid steel and polypropylene (PP) fibers significantly improves the mechanical and cracking performance of M60 high-strength concrete. The optimum hybrid combination (1.25% steel + 0.50% PP) achieved the maximum flexural strength of 10.0 MPa and compressive strength of 66 MPa.
- Hybrid fiber reinforcement effectively controlled crack propagation. Compared with the control mix, the crack width was reduced from 0.42 mm to 0.16 mm, representing an approximate **62% reduction**, demonstrating the synergistic action of steel fibers to prevent large cracks and PP fibers in arresting micro-cracks.
- **The application of 30% GGBS** as **a portion cement substitution** contributed to improved sustainability and long-term performance, while maintaining the required strength level **has a 0.40 water-to-cement ratio.**
- Machine learning models successfully predicted concrete recital with a high degree of accuracy. Among the models, XG Boost showed the best concert (R^2 = 0.965, RMSE = 0.121, MAE = 0.007), indicating strong agreement between experimental and predicted results and highlighting its suitability for mix optimization.
- The integrated experimental–ML approach identified an optimized mix consisting of **1% steel fibers (aspect ratio 72), 0.45–0.50% PP fibers, and 30% GGBS**, which provided enhanced crack resistance, improved flexural behavior, and better structural reliability.
- The study demonstrates that combining hybrid fiber technology with data-driven prediction tools can reduce extensive laboratory trials and support efficient, performance-based concrete mix design.
- Future research may focus on multi-objective optimization considering strength, durability, and cost, as well as advanced analysis
- of fiber orientation and distribution to further enhance the structural performance of hybrid fiber-reinforced concrete.

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