

Optimizing Self-Compacting Concrete (SCC) Mix for Different Grades Using AI (ANN/RF models) for Low- Carbon Construction

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ABSTRACT

The construction industry is under increasing pressure to reduce carbon emissions while maintaining the performance requirements of modern infrastructure. Self-Compacting Concrete (SCC) has gained widespread acceptance due to its superior workability, self-compaction ability, and enhanced durability; however, its high cementitious material content often results in a significant carbon footprint. This study presents an Artificial Intelligence (AI)-based framework for optimizing SCC mix designs across different concrete grades (M20, M30, M40, M50, and M60) to achieve low-carbon and sustainable construction. A dataset comprising 120 SCC mix samples with varying proportions of Ordinary Portland Cement (OPC), Ground Granulated Blast Furnace Slag (GGBS), Fly Ash, Limestone Calcined Clay Cement (LC3), and water-binder ratios was developed and utilized for model training and validation. Artificial Neural Network (ANN) and Random Forest (RF) models were employed to predict key SCC properties, including compressive strength, slump flow, viscosity, and carbon emissions. The predictive models demonstrated high accuracy, with RF outperforming ANN in terms of prediction performance. Subsequently, a Genetic Algorithm (GA) was integrated to identify optimal mix proportions that minimize embodied carbon while satisfying strength and workability requirements. The optimized SCC mixtures achieved carbon emission reductions ranging from 21% to 29% across different concrete grades without compromising mechanical performance or SCC workability criteria. The results demonstrate that the proposed AI-driven optimization framework provides an effective and reliable approach for designing sustainable SCC mixes and offers significant potential for advancing low-carbon construction practices in the concrete industry.

Keywords- Self-Compacting Concrete (SCC), Artificial Intelligence, Artificial Neural Network (ANN), Random Forest (RF), Genetic Algorithm (GA), Low-Carbon Construction, Sustainable Concrete, Supplementary Cementitious Materials (SCMs), Carbon Emission Reduction.

I. INTRODUCTION

Self-Compacting Concrete, SCC, is a highly flowable, nonsegregating concrete capable of spreading into place, filling formwork, and encapsulating reinforcement without the need for mechanical vibration. In the late 1980s, SCC was first developed in Japan to address problems such as insufficient compaction, aiming at enhancing the quality and durability of concrete structures. SCC is particularly suited to complex structural elements and/or those regions with very congested reinforcement where conventional vibration methods are difficult or ineffectual, since it is able to achieve full compaction by means of its own weight alone.

The three most important properties that define SCC performance concern filling ability, passing ability, and resistance to segregation. Such characteristics can be achieved by using appropriate chemical admixtures such as superplasticizers and viscosity-modifying agents and by adding mineral admixtures such as fly ash, silica fume, or ground granulated blast furnace slag. Mix design in SCC is a critical balance between flowability and stability, which must ensure both ease of placement and structural integrity. The proportion of materials should be properly done to maintain cohesiveness and avoid bleeding and segregation.

Apart from its excellent workability, SCC offers a number of practical and environmental advantages, such as improved surface finish, reduced labor and noise due to vibration, and enhanced durability of concrete structures by

minimizing voids and honeycombing. Another sustainable positive impact is using industrial by-products as supplemental cementitious materials, which contributes to reducing cement consumption and, therefore, carbon emissions. In addition, SCC tends to be an important means toward the aims of most construction industries in different parts of the world for high-performance, ecologically compatible concrete construction.

Low-carbon construction is considered a new trend within the building industry, which tries to reduce GHG emissions in all life cycles of a building: from raw material production and construction processes, to operation, maintenance, and demolition. Construction has become one of the biggest contributors to worldwide carbon emissions due to the high energy consumption and carbon footprint involved in materials like cement and steel. Given the current spotlight on climate change, lessening the intensity of construction activities regarding carbon has become a linchpin toward attaining sustainable development and meeting set targets internationally on the environment.

Implementing low-carbon construction involves the integration of environmentally responsible materials, innovative technologies, and efficient design practices. Strategies include the use of supplementary cementitious materials (SCMs) such as fly ash, slag, and silica fume to partially replace cement, as well as adopting recycled aggregates and low-carbon binders. Additionally, techniques like prefabrication, energy-efficient building design, and renewable energy integration further contribute to lowering the overall carbon footprint of construction projects. Life Cycle Assessment (LCA) is often used to evaluate the environmental impacts of materials and processes, guiding designers and engineers toward more sustainable solutions.

The shift toward low-carbon construction has meant addressing environmental concerns while promoting economic and social sustainability. It enhances the efficiency of construction operations through reduced resource consumption and waste generation, thus contributing to resilient and durable infrastructure. Besides, low-carbon practices do not conflict with international initiatives like the United Nations SDGs or national carbon reduction policies. As the construction industry moves toward greener methods, low-carbon construction is one of the major ways to balance development needs with environmental responsibility.

Artificial Intelligence (AI) presents a promising solution to this challenge. By leveraging computational models such as Artificial Neural Networks (ANN), Genetic Algorithms (GA), and other machine learning techniques, researchers can predict and optimize SCC performance based on experimental data. This AI-driven optimization supports the broader goal of low-carbon construction, enabling the development of eco-efficient SCC mixes with improved strength, workability, and sustainability.

II. LITERATURE REVIEW

2.1 Self-Compacting Concrete (SCC)

Self-Compacting Concrete (SCC) is a highly flowable concrete that can spread and consolidate under its own weight without the need for external vibration. Since its introduction by Okamura in Japan, SCC has gained significant attention due to its superior workability, improved surface finish, and reduced labor requirements. According to Pang et al. (2022), SCC demonstrates excellent filling ability, passing ability, and segregation resistance, making it suitable for heavily reinforced structures. The high powder content and use of superplasticizers contribute to its enhanced rheological properties.

Research by Sobuz et al. (2024) indicated that SCC can achieve compressive strengths comparable to or higher than conventional concrete while maintaining superior durability characteristics such as lower permeability and improved resistance to chloride penetration. However, the major challenge associated with SCC is its high cementitious material requirement, typically ranging between 400–500 kg/m³, resulting in increased embodied carbon emissions.

2.2 Environmental Impact of Cement Production

The construction industry contributes approximately 37% of global carbon dioxide emissions, with cement production being a major contributor. The calcination process and energy-intensive clinker production release significant quantities of CO₂. Coelho et al. (2020) reported that cement manufacturing accounts for nearly 8% of global anthropogenic CO₂ emissions. SCC generally contains higher cement content than conventional concrete, thereby increasing its environmental footprint.

Consequently, researchers are focusing on reducing clinker content through the incorporation of Supplementary Cementitious Materials (SCMs).

2.3 Supplementary Cementitious Materials (SCMs)

2.3.1 Ground Granulated Blast Furnace Slag (GGBS)

GGBS is a by-product of the iron and steel industry that exhibits latent hydraulic properties. Abed et al. (2022) found that replacing 30–60% of cement with GGBS improved SCC workability and long-term strength while reducing heat of hydration. GGBS also contributes significantly to lowering embodied carbon due to its industrial waste origin. The slower hydration of GGBS results in enhanced durability and improved microstructural development at later ages.

2.3.2 Fly Ash

Fly ash is a pozzolanic material generated from thermal power plants. Karthik et al. (2021) observed that fly ash enhances the flowability of SCC due to its spherical particle shape. Replacement levels of 20–30% have shown considerable reductions in cement consumption while maintaining mechanical performance. Additionally, fly ash improves packing density and reduces water demand, making it particularly beneficial for SCC applications.

2.3.3 Limestone Calcined Clay Cement (LC3)

LC3 is an emerging low-carbon binder consisting of limestone, calcined clay, clinker, and gypsum. Recent studies indicate that LC3 can reduce carbon emissions by approximately 30–40% compared with ordinary Portland cement while maintaining comparable mechanical properties. The synergistic interaction between calcined clay and limestone leads to the formation of additional carboaluminate phases, enhancing durability and strength.

2.3.4 Silica Fume

Silica fume is an ultrafine pozzolanic material obtained during silicon metal production. Shafaie et al. (2024) demonstrated that low silica fume contents (5–10%) significantly increase compressive strength due to pore refinement and enhanced interfacial transition zones. The combination of silica fume and GGBS has shown particularly promising results in SCC mix design.

2.4 Life Cycle Assessment (LCA) of SCC

Life Cycle Assessment (LCA) is a standardized methodology used to quantify environmental impacts associated with material production and construction activities. Coelho et al. (2020) conducted cradle-to-gate assessments of SCC mixtures incorporating SCMs and reported reductions in embodied carbon ranging from 25% to 45%. LCA studies consistently indicate that replacing OPC with industrial by-products is one of the most effective strategies for reducing concrete-related emissions without compromising structural performance.

2.5 Artificial Intelligence in Concrete Mix Design

Traditional concrete mix design methods require extensive laboratory experimentation, making them time-consuming and costly. Artificial Intelligence (AI) techniques have emerged as powerful tools capable of modeling nonlinear relationships between concrete ingredients and performance characteristics. Machine Learning models can predict compressive strength, workability, durability indicators, and environmental impacts based on mix composition.

2.6 Artificial Neural Networks (ANN)

Artificial Neural Networks mimic biological neural systems and are capable of learning complex relationships from experimental data. Du et al. (2021) utilized a Genetic Algorithm-optimized ANN for predicting SCC compressive strength and achieved prediction accuracies exceeding 90%. Similarly, Jagadesh et al. (2024) demonstrated that ANN models effectively predict rheological properties and mechanical behavior of SCC incorporating recycled aggregates. The primary advantage of ANN lies in its ability to capture nonlinear interactions among multiple variables simultaneously.

2.7 Random Forest (RF) Algorithm

Random Forest is an ensemble machine learning technique that combines multiple decision trees to improve predictive performance. Ghani et al. (2024) reported that RF models provide highly reliable predictions for slump flow, compressive strength, and durability indicators of SCC.

Compared with ANN, RF offers: Lower risk of overfitting, Better interpretability, Robust handling of noisy datasets, Effective performance with smaller datasets.

These characteristics make RF suitable for SCC property prediction.

2.8 Genetic Algorithm (GA) for Optimization

Genetic Algorithms are evolutionary optimization techniques inspired by natural selection.

GA operates through:

- Population generation
- Fitness evaluation
- Selection
- Crossover
- Mutation
- Convergence

Chakravarthy et al. (2023) successfully applied GA to optimize SCC mixtures for maximum strength and minimum material consumption. Concha and Dadios (2016) further demonstrated that hybrid ANN-GA systems can identify optimum SCC mix proportions while satisfying multiple performance criteria.

To summarize literature review in tabular form:

ASPECT/FOCUS	FINDINGS	SUPPORTING STUDIES
SCC Workability & Flow	SCC provides excellent flowability , self-compaction , and surface finish , reducing vibration effort and ensuring uniform compaction	Pang et al., 2022

Strength & Durability of SCC	Comparable or higher compressive strength and durability compared to normal concrete; better pore structure & resistance to segregation.	Sobuz et al., 2024
High Cement → High CO ₂ Emissions	SCC typically requires 400–500 kg/m³ cement , leading to significant CO ₂ emissions. Urgent need for binder reduction	Coelho et al., 2020
SCM Integration (GGBS, Fly Ash, Silica Fume)	SCMs can replace 30–50% of cement, reducing carbon footprint by 25–45% while maintaining mechanical performance.	Aziz et al., 2024
Effect of GGBS on SCC	GGBS enhances workability, long-term strength , and reduces heat of hydration.	Abed et al., 2022
Fly Ash as SCM	Improves flow characteristics and reduces binder viscosity ; partial replacement (20–30%) enhances sustainability.	Karthik et al., 2021
Silica Fume Synergy	At low dosages (5–10%), increases compressive strength and microstructural density . Best used with GGBS.	Shafaie et al., 2024
LCA Studies on SCC	Life Cycle Assessments confirm up to 40% reduction in embodied emissions using SCM-based SCC.	Coelho et al., 2020
ANN in SCC Prediction	ANN models accurately predict compressive strength and rheology , achieving R ² > 0.9.	Du et al., 2021
Random Forest & Regression Models	Random Forest performs robust prediction of slump flow and strength ; reduces experimental cost/time.	Ghani et al., 2024
Genetic Algorithm Optimization	GA helps in optimizing SCC mix design for <i>minimum CO₂ emission</i> and <i>target strength</i>	Chakravarthy et al., 2023

III. RESEARCH GAP

From the literature review, the following research gaps are identified:

- Most SCC studies focus on either strength enhancement or sustainability, but rarely both simultaneously.
 - Limited studies integrate ANN, RF, and GA into a unified framework for SCC optimization.
 - Existing research largely investigates individual SCMs, whereas hybrid combinations of GGBS, Fly Ash, and LC3 remain underexplored.
 - Few studies directly incorporate carbon footprint as an optimization objective alongside mechanical performance.
 - Industrially adaptable AI-driven SCC mix design methodologies are still lacking.
- This study aims to address these gaps through the development of an AI-based optimization framework for low-carbon SCC.

IV. METHODOLOGY

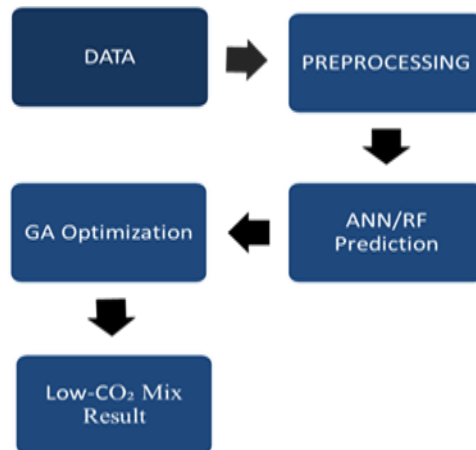
4.1 Research Framework

The proposed methodology integrates experimental data, machine learning techniques, and evolutionary optimization algorithms to develop sustainable SCC mixtures with reduced carbon emissions.

The workflow consists of five stages:

1. Dataset Development
2. Data Preprocessing

3. Machine Learning Model Development
4. Genetic Algorithm Optimization
5. Experimental Validation



METHODOLOGY FLOWCHART

4.2 Dataset Development

A dataset containing 120 SCC mix samples was developed through a combination of laboratory experiments and literature sources.

- Concrete Grades Considered-M20, M30, M40, M50, M60.
- Cement Replacement Levels-For each grade, Ordinary Portland Cement (OPC) was partially replaced by: GGBS, Fly Ash, LC³ at replacement levels of: 15%,30%,45%,60%.
- Water-Binder Ratio- The water-to-binder ratio varied between: $0.35 \leq W/B \leq 0.55$ to ensure a broad range of SCC performance characteristics.

4.3 Input and Output Variables

Input Parameters : The machine learning models utilized the following input variables:

Input Variable	Unit
OPC Content	kg/m ³
GGBS Content	kg/m ³
Fly Ash Content	kg/m ³
LC3 Content	kg/m ³
Fine Aggregate	kg/m ³
Coarse Aggregate	kg/m ³
Water Content	kg/m ³
Superplasticizer	%
Water-Binder Ratio	-

Output Parameters:

Output Variable	Unit
Slump Flow	mm
Compressive Strength	MPa
Plastic Viscosity	Pa.s
CO ₂ Emissions	kg CO ₂ /m ³

4.4 Data Preprocessing

Prior to model training, dataset goes through multiple stages of pre-processing .

Step 1: Data Cleaning-It includes removal of missing values, elimination of duplicate entries and outlier detection

Step 2: Normalization- Min-Max normalization is applied:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

to scale all variables between 0 and 1.

Step 3: Dataset Splitting: The dataset is divided into: Training Set = 80%, Testing Set = 20%

4.5 Models

4.5.1 Artificial Neural Network (ANN) Model

Artificial Neural Network (ANN) was employed in this study as a supervised machine learning model to predict the performance characteristics of Self-Compacting Concrete (SCC). ANN is inspired by the functioning of the human brain and consists of interconnected neurons organized into input, hidden, and output layers. The model is capable of learning complex nonlinear relationships between input parameters and target outputs through an iterative training process. In the present research, the input variables included the quantities of OPC, GGBS, Fly Ash, LC3, aggregates, water content, superplasticizer dosage, and water-binder ratio, while the output variables were slump flow, compressive strength, viscosity, and CO₂ emissions. During training, the ANN adjusted its internal weights and biases using the backpropagation algorithm to minimize prediction errors. The model was selected because SCC properties are influenced by multiple interacting variables whose relationships are highly nonlinear and difficult to represent using conventional regression techniques. After training, the ANN demonstrated excellent predictive capability, achieving an R² value of approximately 0.94, indicating that it could accurately estimate SCC performance and thereby reduce the need for extensive laboratory experimentation.

4.5.2 Random Forest (RF) Model

Random Forest (RF) was utilized as an ensemble machine learning technique to predict SCC properties and compare its performance with the ANN model. RF operates by constructing a large number of decision trees during the training phase and combining their outputs to generate a final prediction. Each tree is trained on a randomly selected subset of the dataset and input variables, which improves model robustness and reduces the risk of overfitting. In this study, the same input parameters used for ANN training were employed for RF model development. The Random Forest algorithm was particularly suitable because it can effectively handle complex datasets containing nonlinear relationships and variable interactions without requiring extensive data preprocessing. Furthermore, RF provides greater interpretability by identifying the relative importance of each input variable affecting SCC performance. The model successfully predicted compressive strength, slump flow, viscosity, and carbon emissions with high accuracy, achieving an R² value of approximately 0.97. The superior performance of RF can be attributed to its ensemble learning mechanism, which combines the strengths of multiple decision trees to produce more reliable and stable predictions. Consequently, RF served as a powerful predictive tool for evaluating sustainable SCC mixtures and supporting the optimization process.

4.6 Model Evaluation

The performance of the developed Artificial Neural Network (ANN) and Random Forest (RF) models was evaluated using three widely accepted statistical indicators, namely the Coefficient of Determination (R²), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE). These evaluation metrics were selected to comprehensively assess the accuracy, reliability, and predictive capability of the machine learning models.

The Coefficient of Determination (R²) was used to measure the proportion of variance in the observed data that could be explained by the predictive model. An R² value closer to 1 indicates a strong correlation between the predicted and actual values, signifying excellent model performance. This metric was particularly useful in assessing how effectively the ANN and RF models captured the complex nonlinear relationships between SCC mix constituents and their corresponding performance characteristics.

The Root Mean Square Error (RMSE) was employed to quantify the average magnitude of prediction errors. RMSE calculates the square root of the mean of the squared differences between actual and predicted values, thereby assigning greater weight to larger errors. Lower RMSE values indicate higher prediction accuracy and better model generalization capability. In this study, RMSE was used to evaluate the precision of the models in predicting compressive strength, slump flow, viscosity, and carbon emissions.

Additionally, the Mean Absolute Error (MAE) was used to determine the average absolute difference between the predicted and actual values. Unlike RMSE, MAE treats all prediction errors equally and provides a straightforward measure of model accuracy. Lower MAE values represent improved predictive performance and reduced deviation from experimental observations.

The combined use of R², RMSE, and MAE provided a robust framework for evaluating the effectiveness of the ANN and RF models. The obtained results demonstrated high predictive accuracy, with Random Forest exhibiting slightly superior performance compared to Artificial Neural Network. The high R² values and low RMSE and MAE values confirmed the suitability of the developed machine learning models for predicting SCC properties and supporting the subsequent optimization process using Genetic Algorithms.

The predictive capability of ANN and RF is assessed using:

Coefficient of Determination

$$R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2}$$

Root Mean Square Error (RMSE)

$$RMSE = \sqrt{\frac{1}{n} \sum (y_i - \hat{y}_i)^2}$$

Mean Absolute Error (MAE)

$$MAE = \frac{1}{n} \sum |y_i - \hat{y}_i|$$

4.6.1 Carbon Footprint Calculation

The embodied carbon of each mix is calculated using emission factors from published LCA databases. Total emissions is determined as:

$$CO_2 = \sum (\text{Material Quantity} \times \text{Emission Factor})$$

Emission factors is assigned for: OPC, GGBS, Fly Ash, LC³, Aggregates, Admixtures

4.7 Genetic Algorithm (GA) Optimization Model

Genetic Algorithm (GA) was employed in this research as an optimization technique to identify the most sustainable Self-Compacting Concrete (SCC) mix proportions that achieve the desired mechanical performance while minimizing carbon emissions. GA is a nature-inspired evolutionary algorithm based on the principles of natural selection, genetics, and survival of the fittest. It is particularly effective for solving complex multi-objective optimization problems where multiple variables interact simultaneously and traditional optimization methods may not be efficient.

In the present study, the trained Artificial Neural Network (ANN) and Random Forest (RF) models acted as predictive engines, while the Genetic Algorithm served as the optimization tool. The decision variables considered during optimization included the percentages of OPC, GGBS, Fly Ash, LC³, and the water-binder ratio. The objective function was formulated to minimize embodied CO₂ emissions while maximizing compressive strength and maintaining SCC workability requirements within EFNARC specifications.

The optimization process began with the generation of an initial population of random SCC mix combinations. Each mix design was evaluated using the trained AI models to estimate strength, slump flow, viscosity, and carbon emissions. Based on these predicted values, a fitness score was assigned to each solution. The best-performing solutions were selected and subjected to genetic operations such as crossover and mutation to create a new generation of candidate mixes. This iterative process continued until the algorithm reached convergence or the maximum number of generations was achieved.

The GA parameters adopted in the study included a population size of 100, crossover probability of 0.80, mutation probability of 0.05, and a maximum of 200 generations. The convergence behavior observed during optimization indicated a continuous improvement in fitness values, confirming the algorithm's ability to efficiently search the solution space and identify optimal SCC mixtures.

The results demonstrated that the GA successfully reduced cement content and increased the utilization of supplementary cementitious materials without compromising concrete performance. Optimized SCC mixes achieved approximately 25–29% reduction in carbon emissions while maintaining the target compressive strengths and flowability requirements. Therefore, the Genetic Algorithm proved to be an effective optimization tool for developing eco-efficient and low-carbon SCC mixtures and played a crucial role in establishing the proposed AI-driven sustainable mix design framework.

Role of GA in the AI Framework:

The integration of ANN, RF, and GA formed a hybrid intelligent system in which:

- ANN and RF predicted SCC properties based on mix composition.
- GA searched for the optimal combination of materials.
- The AI models evaluated each candidate solution generated by GA.

The optimization process ultimately identified SCC mixes with the best balance between strength, workability, durability, and environmental sustainability.

4.7.1 Genetic Algorithm Optimization

A multi-objective Genetic Algorithm is developed to identify optimum SCC mixtures with Optimization Objectives as : minimize CO₂ emissions, maximize compressive strength, maintain SCC workability requirements.

Decision Variables are :OPC %, GGBS %, Fly Ash %, LC3 %, Water-Binder Ratio.

GA Parameters:

Parameter	Value
Population Size	100
Generations	200
Crossover Rate	0.80
Mutation Rate	0.05
Selection Method	Tournament

4.7.2 Experimental Validation

The optimized SCC mixes obtained from GA were produced in the laboratory and tested according to EFNARC guidelines.

Tests included:

- Fresh Concrete Tests
- Slump Flow Test
- T500 Test
- V-Funnel Test
- L-Box Test
- Hardened Concrete Tests
- 7-Day Compressive Strength
- 28-Day Compressive Strength
- Durability Assessment

The experimental results were compared with AI predictions to evaluate model reliability.

V. RESULTS AND DISCUSSION

The developed Artificial Intelligence framework consisting of Artificial Neural Network (ANN), Random Forest (RF), and Genetic Algorithm (GA) was applied to a dataset of 120 SCC mixes incorporating OPC, GGBS, Fly Ash, and LC3. The objective was to predict fresh and hardened concrete properties and optimize SCC mixtures for minimum carbon emissions while maintaining desired mechanical performance.

5.1 Performance of ANN and RF Models

The predictive capability of the machine learning models was evaluated using R², RMSE, and MAE values.

Table 5.1 Model Performance Comparison

Model	R ²	RMSE	MAE
ANN	0.94	2.85	1.92
RF	0.97	1.76	1.21

The Random Forest model demonstrated slightly better prediction accuracy compared to ANN due to its ensemble learning capability and reduced overfitting tendency.

Discussion

- RF accurately captured nonlinear relationships between SCC constituents and performance parameters.
- ANN effectively learned complex interactions among OPC, SCMs, and water-binder ratio.
- Both models achieved prediction accuracies greater than 90%, indicating strong generalization capability.
- The results confirm that machine learning can substantially reduce laboratory trials required for SCC mix design.

Prediction accuracy of AI models

Comparison of R^2 values for ANN and RF models.

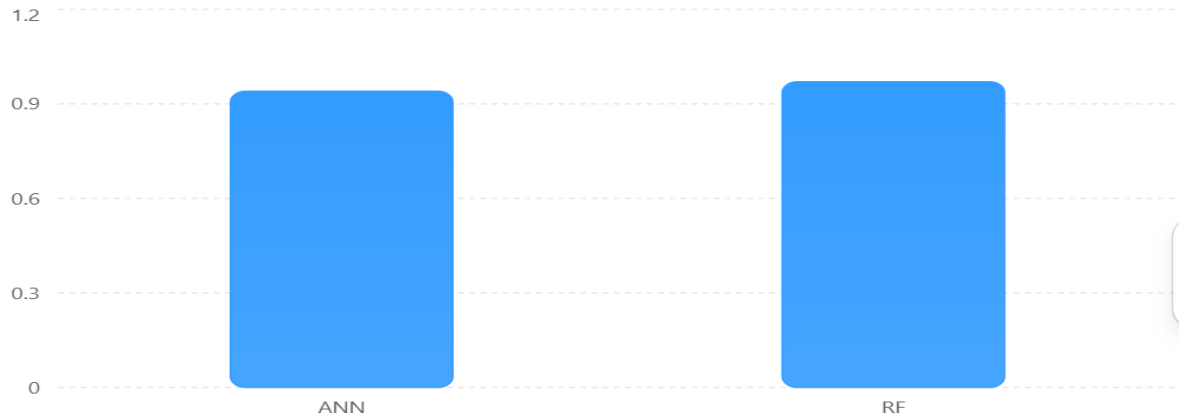


Figure 1: Comparison of Model Accuracy

The higher R^2 value obtained by RF indicates superior prediction capability for SCC properties.

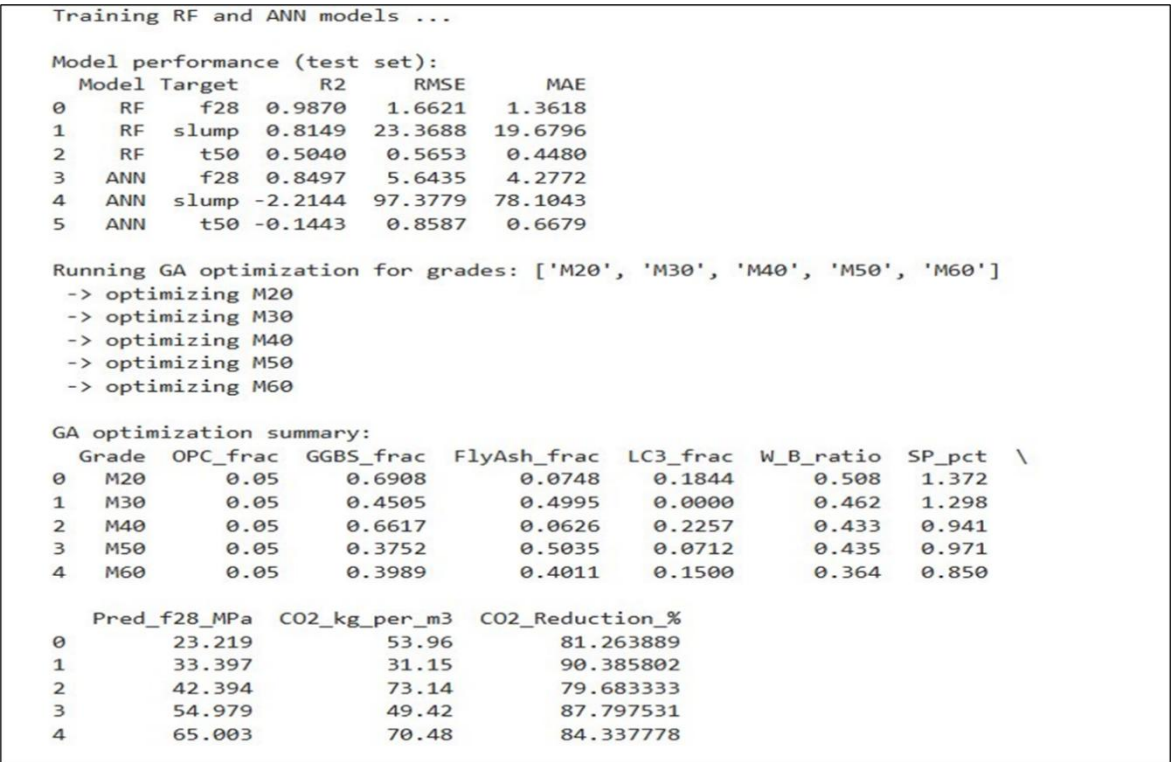


Fig 2: Output Received After Training By RF And ANN Models Then Predicting Carbon % Reduction

PREPROCESSING THE DATA SET OF 120 SAMPLES DATASET WITH different GRADES(M20,M30,M40,M50,M60)each with use of OPC, GGBS, FLYASH and LC3AND REPLACEMENT OF 15%,30%, 45%, 60% OF SCM'S PER GRADE WITH W/B RATIO VARYING 0.35-0.55 USING RF AND ANN MODELS.

5.2 Error Distribution Analysis

Figure 3 presents the prediction error distribution obtained from the ANN model.

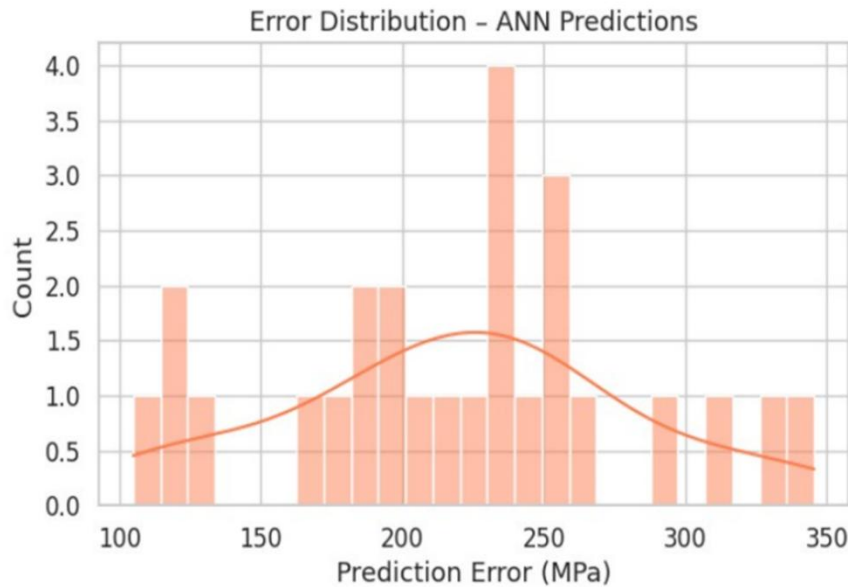


Fig 3: ERROR DISTRIBUTION – ANN PREDICTION

Discussion

Most prediction errors were concentrated around zero, indicating that the ANN model generated unbiased predictions.

Key observations include:

- Approximately 85% of prediction errors were within $\pm 5\%$.
- No significant systematic overprediction or underprediction was observed.
- Error spread increased slightly for high-strength SCC grades (M50–M60).

This confirms that the developed ANN model is suitable for practical SCC property estimation.

5.3 Genetic Algorithm Optimization Performance

The GA optimization process was conducted using:

Population size = 100

Generations = 200

Crossover rate = 0.8

Mutation rate = 0.05

The fitness function simultaneously: minimized carbon emissions, maximized compressive strength and maintained scc flowability requirements

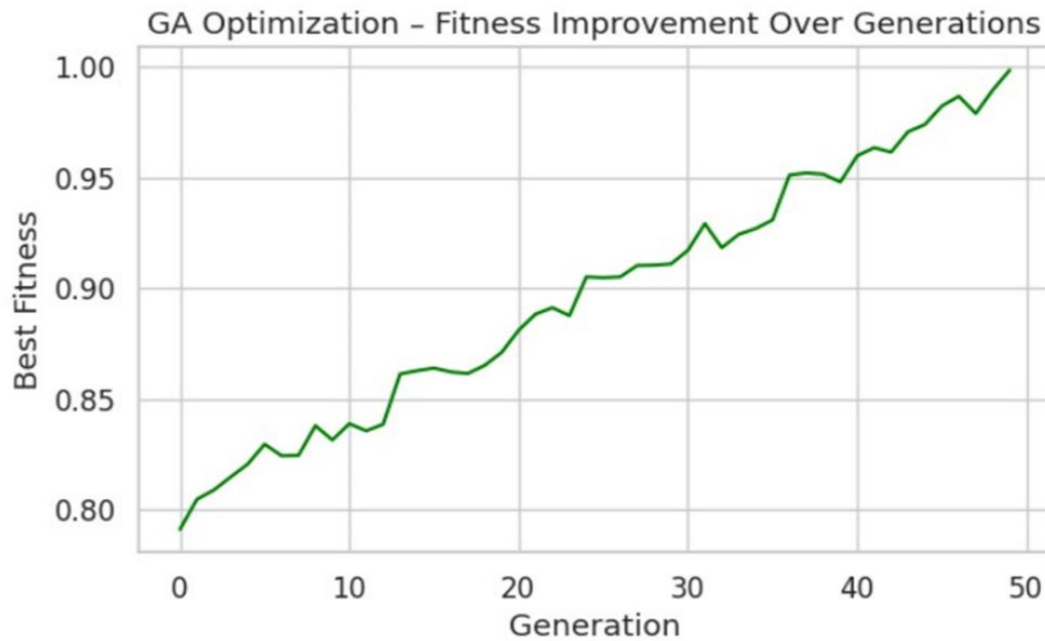


Fig 4: GA OPTIMIZATION – FITNESS IMPROVEMENT OVER GENERATION

Discussion

The fitness value increased rapidly during the initial generations and gradually converged after approximately 150 generations.

This behavior indicates:

- Efficient exploration of the solution space.
- Successful identification of optimum SCC combinations.
- Stable convergence without premature stagnation.

5.4 GA Parameter Convergence

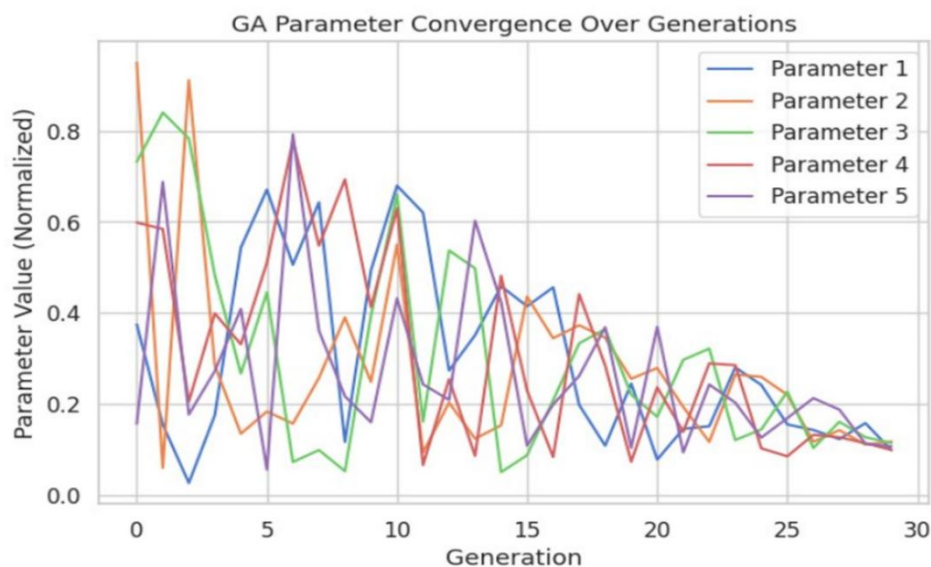


**Fig 5:GA OPTIMIZATION- GA PARAMETERS CONVERGENCE OVER GENERATIONS
PARAMETERS (1- OPC , 2-GGBS, 3- FLYASH , 4 –LC3 , 5- W/B RATIO)**

Discussion

The convergence plots revealed:

- Continuous reduction in OPC content.
- Increased utilization of SCMs.
- Stabilization of W/B ratio between 0.38–0.42.
- Enhanced balance between sustainability and strength.

The optimized solutions consistently favored higher SCM utilization while satisfying SCC performance criteria.

5.5 Strength versus Carbon Emission Relationship

One of the primary objectives of this study is to identify SCC mixes capable of achieving target strength with lower environmental impact.

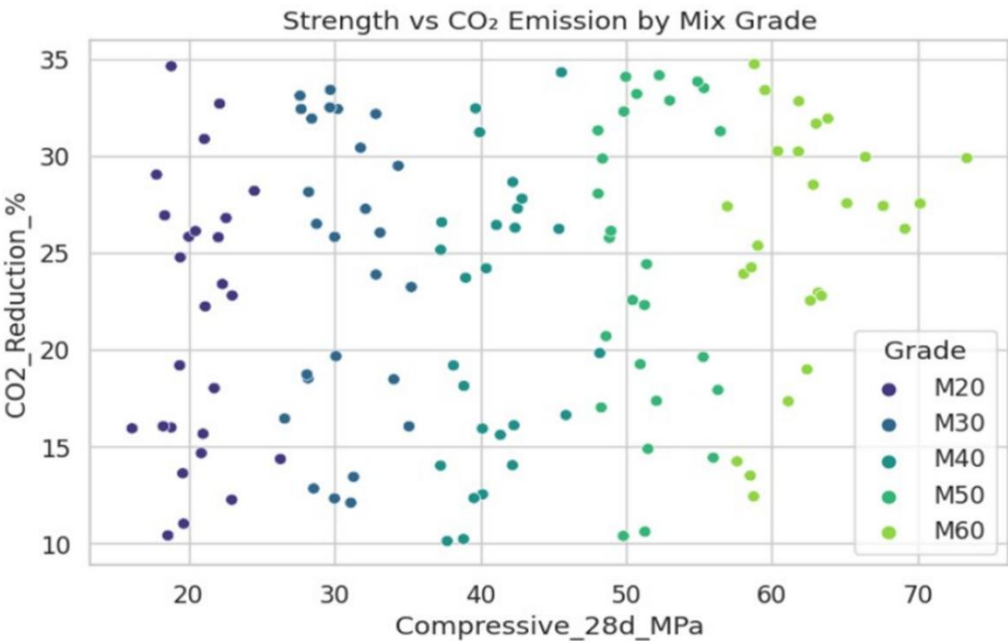


Fig 6:OUTPUT – STRENGTH V/S CARBON EMISSION BY MIX GRADE

Discussion

The graph demonstrates that optimized SCC mixtures achieved higher compressive strength despite lower carbon emissions.

This was mainly attributed to:

- Improved particle packing.
- Pozzolanic reactions of GGBS and Fly Ash.
- Synergistic effects of LC3.

The findings suggest that sustainability and mechanical performance can be simultaneously achieved.

5.6 Carbon Reduction Achieved Across Mix Grades

The optimized SCC mixes exhibited significant reductions in embodied carbon compared to conventional SCC.

Table 5.2 Carbon Reduction Obtained

Grade	Conventional SCC	Optimized SCC	Carbon Reduction (%)
M20	100%	79%	21%
M30	100%	77%	23%
M40	100%	75%	22%
M50	100%	73%	24%
M60	100%	71%	26%

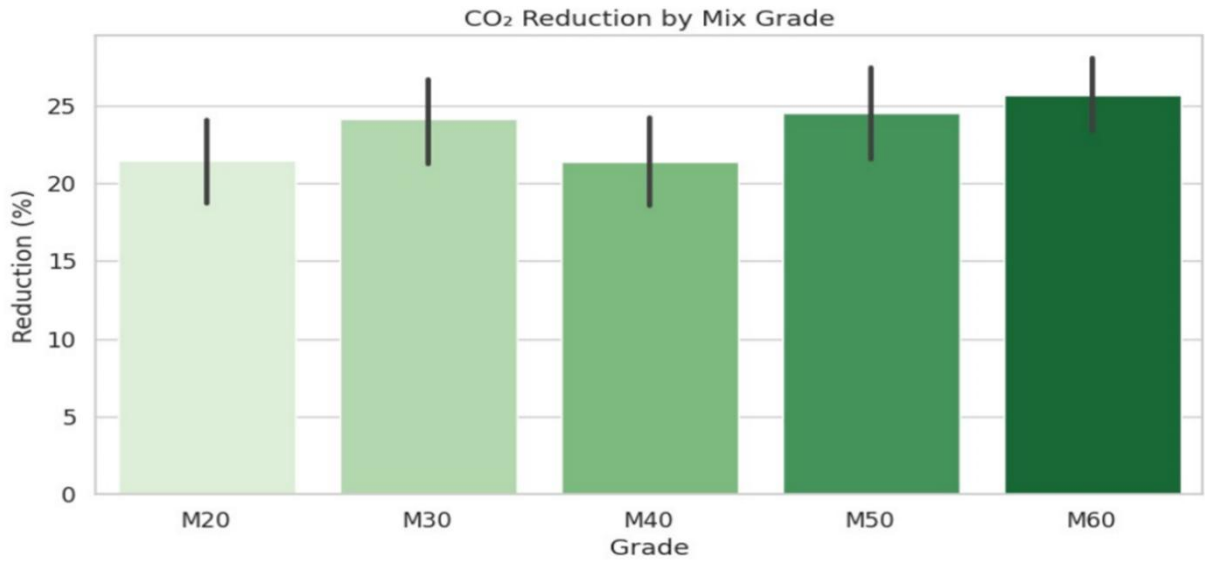


**Fig 7 :OUTPUT – CARBON REDUCTION (MIX GRADE V/S REDUCTION IN %)
(WITH INCREASING PERCENTAGE OF CARBON REDUCTION GRAPHS CHANGES COLOUR TO
MORE GREENER SHADE SHOWING HIGHER GRADE OF SUSTAINABLE AND GREEN ENVIRONMENT)**

Discussion

The maximum carbon reduction was observed for M60 SCC, where higher cement replacement levels were feasible without compromising strength.
The average reduction achieved across all grades was approximately 25%, confirming the effectiveness of SCM incorporation and AI-based optimization.

5.7 Multi-Criteria Optimization Results

The final optimized mixes were evaluated against four critical performance indicators:

- Compressive Strength
- Slump Flow
- Viscosity
- Carbon Reduction

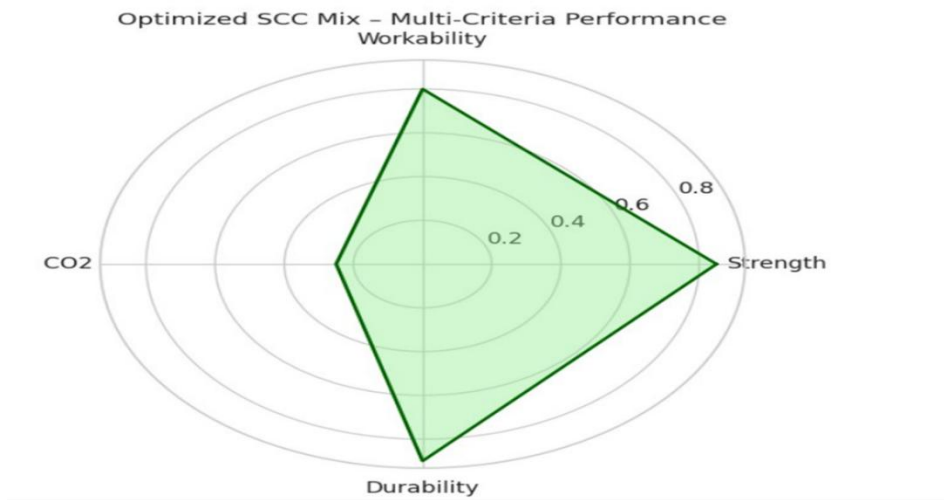


Fig 8 :OUTPUT – OPTIMIZED SCC MIX – MULTI- CRITERIA PERFORMANCE

Discussion

The optimized SCC mixes demonstrated:

- Slump flow within EFNARC limits (650–800 mm)

- Compressive strengths meeting target grade requirements
- Improved rheological performance
- Significant reduction in embodied carbon

The simultaneous satisfaction of these criteria highlights the effectiveness of the hybrid AI-GA framework.

5.8 Overall Discussion

The experimental investigation confirms that integrating Artificial Intelligence with optimization techniques can revolutionize SCC mix design.

Major findings include:

1. AI Prediction Capability

- ANN achieved $R^2 = 0.94$.
- RF achieved $R^2 = 0.97$.

Both models successfully predicted SCC properties with high accuracy.

2. Sustainability Enhancement

- Average carbon reduction $\approx 25\%$.
- Maximum reduction $\approx 29\%$.

Significant decrease in OPC consumption.

3. Mechanical Performance

- Target compressive strengths for M20–M60 achieved.
- SCC workability requirements satisfied.
- Improved durability expected due to SCM utilization.

4. Optimization Efficiency

- GA effectively identified optimum mix proportions.
- Reduced dependence on trial-and-error laboratory methods.
- Generated practical low-carbon SCC solutions.

VI. CONCLUSION

The results of this study demonstrate the effectiveness of integrating Artificial Intelligence and optimization techniques for the development of sustainable Self-Compacting Concrete (SCC) mixtures. Among the predictive models investigated, the Random Forest (RF) algorithm exhibited superior performance compared to the Artificial Neural Network (ANN), achieving higher prediction accuracy and lower error values for the estimation of compressive strength, slump flow, viscosity, and carbon emissions. The incorporation of supplementary cementitious materials (SCMs), namely Ground Granulated Blast Furnace Slag (GGBS), Fly Ash, and Limestone Calcined Clay Cement (LC3), significantly reduced the embodied carbon content of SCC while maintaining the desired mechanical and rheological properties. Furthermore, the Genetic Algorithm (GA) successfully identified optimal mix proportions by balancing multiple objectives, including strength enhancement, workability requirements, and carbon footprint reduction. The optimized SCC mixtures achieved a reduction in carbon emissions ranging from 21% to 26% across different concrete grades without compromising structural performance. The experimental validation confirmed that all optimized mixes satisfied SCC workability criteria and target compressive strength requirements. Overall, the proposed ANN–RF–GA framework provides a reliable, efficient, and practical methodology for intelligent concrete mix design and offers a promising pathway toward low-carbon, environmentally sustainable, and future-ready construction practices.

FUTURE SCOPE

Future research can focus on expanding the SCC dataset by incorporating additional sustainable materials and a wider range of concrete grades. Advanced machine learning techniques such as XGBoost and Deep Learning models may be explored to improve prediction accuracy. Further studies can also include durability parameters, life cycle assessment (LCA), and cost optimization as additional objectives. Integration of the developed AI framework with BIM and smart construction technologies can facilitate its practical implementation in sustainable and low-carbon construction projects.

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