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ISSN: 3141-5997

MODELING THE INFLUENCE OF WATER–CEMENT RATIO ON THE MECHANICAL PERFORMANCE OF SUSTAINABLE SELF-COMPACTING CONCRETE INCORPORATING RICE HUSK ASH AND CRUSHED ROCK DUST USING GENE EXPRESSION PROGRAMMING

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Received: 12 May 2026
Accepted for publication: 15 June 2026
Published: 01 July 2026

ABSTRACT

The increasing demand for sustainable and high-performance construction materials has accelerated the development of self-compacting concrete (SCC) incorporating industrial and agricultural waste materials. This study investigates the influence of water–cement (w/c) ratio on the mechanical performance of SCC containing 15% rice husk ash (RHA) as a supplementary cementitious material and crushed rock dust (CRD) as a mineral filler. SCC mixtures with w/c ratios ranging from 0.35 to 0.65 were experimentally evaluated for compressive, splitting tensile, and flexural strengths at curing ages of 7 and 28 days. The experimental results demonstrated that all strength properties increased with increasing w/c ratio up to an optimum value of 0.45, beyond which a progressive reduction in strength was observed. The optimum 28-day mechanical properties obtained at a w/c ratio of 0.45 were 26.4 MPa, 2.69 MPa, and 3.60 MPa for compressive, splitting tensile, and flexural strengths, respectively. To establish reliable predictive relationships between mixture parameters and mechanical performance, Gene Expression Programming (GEP) was employed to develop symbolic regression-based predictive models. Model performance was assessed using ten-fold cross-validation and multiple statistical indicators, including coefficient of determination (R^2), mean absolute error (MAE), mean squared error (MSE), root mean squared error (RMSE), and relative root squared error (RRSE). The developed GEP models achieved high predictive accuracy, with R^2 values exceeding 0.93 and consistently low error indices for both training and validation datasets. The findings confirm the suitability of GEP as an efficient artificial intelligence technique for modelling the mechanical behavior of sustainable SCC mixtures. Furthermore, the combined utilization of RHA and CRD demonstrated significant potential for reducing cement consumption, valorizing waste materials, and promoting environmentally responsible concrete production within the framework of sustainable construction and circular-economy principles.

Keywords: Gene Expression Programming; Machine learning; Self-compacting concrete; Sustainable concrete; Supplementary cementitious materials; Water–cement ratio

1.0 INTRODUCTION

The construction sector is under increasing pressure to reduce its environmental footprint due to the high carbon intensity of cement production and extensive natural resource consumption. Ordinary Portland cement (OPC) is responsible for approximately 7–8% of global anthropogenic CO_2 emissions, primarily from clinker production and energy-intensive manufacturing processes (Scrivener *et al*., 2018; Habert *et al*., 2020). At the same time, the depletion of natural aggregates and the accumulation of agricultural and quarry wastes have intensified environmental degradation, prompting the development of sustainable construction materials aligned with circular economy principles. In this context, the use of supplementary cementitious materials (SCMs) derived from industrial and agricultural waste has become a key strategy for reducing cement

Cite this article: Taku, K.J., Nwakonobi, D.U. and Oyesanya, G.O. (2026). Modeling the influence of water–cement ratio on the mechanical performance of sustainable self-compacting concrete incorporating rice husk ash and crushed rock dust using gene expression programming. *Journal of Physical and Engineering Sciences*, 1(1):27-36

consumption while maintaining mechanical and durability performance in concrete systems. Self-compacting concrete (SCC) represents one of the most significant advancements in modern concrete technology due to its ability to flow and compact under its own weight without external vibration. This property improves construction efficiency, reduces labor demand, enhances surface quality, and minimizes noise pollution, making SCC suitable for heavily reinforced and complex structural systems such as bridges, tunnels, offshore structures, and high-rise buildings (Okamura and Ouchi, 2003; Su *et al*., 2001). However, the performance of SCC is highly sensitive to mixture proportioning, particularly the water–cement ratio, which governs hydration kinetics, pore structure development, and rheological behavior. Excessively high water–cement ratios increase porosity and reduce strength, while very low ratios may impair flowability and self-compacting ability, leading to segregation and incomplete compaction (Li *et al*., 2019; EFNARC, 2005).

Sustainable SCC development has increasingly focused on the incorporation of agricultural and quarry by-products such as rice husk ash (RHA) and crushed rock dust (CRD). RHA, a highly reactive pozzolanic material rich in amorphous silica, enhances mechanical strength and durability through secondary calcium silicate hydrate (C–S–H) formation and pore refinement (Chao-Lung *et al*., 2011; Habeeb and Mahmud, 2010). Similarly, CRD acts as a micro-filler that improves particle packing density, reduces voids, and enhances cohesion in SCC mixtures. Studies have shown that quarry dust can partially replace natural sand while improving both fresh and hardened properties of concrete (Kumar *et al*., 2017; Ilangovana *et al*., 2008). The combined use of RHA and CRD therefore offers a synergistic pathway for developing eco-efficient SCC with reduced cement dependency and improved microstructural performance. Despite significant progress, important research gaps remain.

Most existing studies focus on single SCM systems or maintain constant water–cement ratios, limiting understanding of coupled interactions between mixture proportioning and waste-derived materials. Furthermore, comprehensive evaluations covering compressive, tensile, and flexural strengths under varying water–cement ratios in SCC systems incorporating both RHA and CRD remain limited. In addition, although machine learning techniques such as Gene Expression Programming (GEP) have been increasingly applied to concrete modeling, most studies focus solely on compressive strength prediction and treat models as black-box systems, limiting interpretability and engineering applicability (Bhardwaj *et al*., 2021; Shahmansouri *et al*., 2020). To address these gaps, this study develops an integrated experimental–computational framework to evaluate and predict the mechanical behavior of SCC incorporating 15% RHA and CRD under varying water–cement ratios. The study further employs GEP-based symbolic regression to generate explicit, interpretable predictive models for compressive, tensile, and flexural strengths, supported by rigorous statistical validation and cross-validation techniques. This approach contributes to sustainable concrete development by improving predictive accuracy, enhancing model transparency, and supporting optimized mix design for eco-efficient SCC systems.

2.0 MATERIALS AND METHODS

2.1. Materials

2.1.1. Cement

Ordinary Portland Cement (OPC) conforming to BS EN 197-1 specifications for CEM I 42.5 N was used as the primary binder in this study. The cement was manufactured by BUA Cement Plc and procured from a commercial supplier in Makurdi Benue State, Nigeria. The cement was stored in moisture-free conditions prior to use to prevent premature hydration and deterioration of its physicochemical properties.

2.1.2. Rice Husk Ash (RHA)

Rice Husk Ash (RHA) used in this investigation was obtained from rice milling waste dumps in Makurdi, Benue State, Nigeria. The rice husks were subjected to controlled open-air calcination to produce grey-coloured ash rich in amorphous silica. After calcination, the ash was sieved through a 75 µm sieve to remove coarse and unburnt particles and to improve its fineness and pozzolanic reactivity. The RHA was incorporated as a partial replacement of cement at a constant replacement level of 15% by weight of binder. The selection of this replacement level was based on previous studies reporting improved mechanical and durability performance of RHA-blended concrete within similar replacement ranges.

2.1.3. Crushed Rock Dust (CRD)

Crushed Rock Dust (CRD), also referred to as quarry dust, was obtained from a quarry site in Gboko, Benue State, Nigeria. The material was collected as a by-product of granite aggregate crushing operations and utilized as a mineral filler in the SCC mixtures. Prior to use, the CRD was air-dried and sieved to eliminate oversized particles and ensure uniform particle distribution. The ultrafine characteristics of CRD were expected to enhance particle packing density, reduce internal voids, and improve the cohesiveness of the SCC mixtures.

2.1.4. Fine Aggregate

Natural river sand obtained from River Benue Banks at Makurdi Benue State, Nigeria, was used as the fine aggregate. The sand was clean, free from deleterious substances, and conformed to the grading requirements specified in BS EN 12620. Prior to mixing, the sand was oven-dried and stored under laboratory conditions to maintain uniform moisture content.

2.1.5. Coarse Aggregate

Crushed granite chippings with nominal particle sizes ranging from 18 mm to 25 mm were utilized as coarse aggregates. The aggregates were sourced from Makurdi, Benue State, Nigeria. The aggregates were washed, air-dried, and graded to ensure uniformity and compliance with relevant standards for concrete production. The physical properties of the coarse aggregates were determined in accordance with BS EN 1097 standards.

2.1.6. Chemical Admixture

A high-range water-reducing superplasticizer manufactured by WAFU Technologies Inc., Lagos, Nigeria, was employed to achieve the high flowability requirements of SCC. The dosage of the superplasticizer was adjusted during preliminary trial mixes to satisfy EFNARC guidelines for SCC workability characteristics including filling ability, passing ability, and segregation resistance.

2.1.7. Mixing Water

Portable water supplied through the Civil Engineering Laboratory system at the Joseph Sarwuan Tarka University Makurdi, Nigeria, was used for concrete mixing and curing. The water satisfied the requirements of ASTM C1602 and was free from contaminants capable of adversely affecting cement hydration or concrete durability.

2.2. Experimental Program

2.2.1. Mix Proportioning

The SCC mixtures were designed using the British mix design approach in accordance with BS 8500 and BS EN 206 provisions for normal-weight concrete. A constant RHA replacement level of 15% by weight of cement was maintained throughout the study, while CRD was incorporated as filler material. The principal variable investigated was the water–cement ratio (w/c), which ranged from 0.35 to 0.65. Preliminary trial mixtures were conducted to optimize the superplasticizer dosage and ensure compliance with SCC fresh property requirements. The selected mixture proportions were designed to achieve adequate workability, stability, and mechanical performance while minimizing segregation and bleeding. SCC fresh properties including slump flow, viscosity, and passing ability were evaluated in accordance with EFNARC recommendations before specimen casting.

2.2.2. Specimen Preparation and Curing

Concrete mixing was carried out using a laboratory drum mixer. Initially, all dry constituents including cement, RHA, CRD, fine aggregates, and coarse aggregates were thoroughly mixed to ensure uniform distribution. Thereafter, approximately 70% of the mixing water was gradually introduced, followed by the superplasticizer dissolved in the remaining water. Mixing continued until a homogeneous SCC mixture with uniform consistency was obtained.
Fresh SCC mixtures were cast into steel molds without external vibration in order to simulate actual SCC placement conditions. The following specimens were prepared for mechanical testing: Cube specimens of 100 × 100 × 100 mm for compressive strength testing; cylindrical specimens of 100 mm diameter × 200 mm height for splitting tensile strength testing; and beam specimens of 100 × 100 × 500 mm for flexural strength testing. After casting, the specimens were covered with polyethylene sheets to minimize moisture loss and demolded after 24 h. Subsequently, all specimens were cured in clean water at ambient laboratory temperature until the designated testing ages of 7 and 28 days.

2.2.3. Compressive Strength Test

Compressive strength tests were conducted in accordance with BS EN 12390-3 using a calibrated electro-hydraulic compression testing machine with a capacity of 3000kN. For each mixture and curing age, three cube specimens were tested, and the average compressive strength value was reported.
The compressive strength was calculated using: $f_c = \frac{P}{A}$
Where f_c compressive strength (MPa); P = maximum applied load; A = loaded cross-sectional area of the specimen (mm²). Loading was applied continuously without shock until specimen failure occurred.

2.2.4. Splitting Tensile Strength Test

Splitting tensile strength tests were performed on cylindrical specimens in accordance with BS EN 12390-6. The specimens were positioned horizontally between the loading platens of the testing machine, and compressive load was applied uniformly along the vertical diameter until splitting failure occurred.
The splitting tensile strength was determined using: $f_t = \frac{2P}{\pi LD}$
where: f_t = splitting tensile strength (MPa); P = maximum applied load (N), L = length of cylinder (mm); D = diameter of cylinder (mm), Three specimens were tested for each mixture and curing age, and the average value was recorded.

2.2.5. Flexural Strength Test

Flexural strength tests were conducted on beam specimens using a third-point loading configuration in accordance with BS EN 12390-5. The tests were performed using a universal testing machine under monotonic loading conditions until flexural failure occurred. The flexural strength was calculated as: $f_r = \frac{PL}{bd^2}$
Where: f_r = flexural strength (MPa); P = applied failure load (N); L = span length (mm); b= beam width (mm) d = beam depth (mm). The average value obtained from three beam specimens was reported for each mixture and curing age.

2.3. Gene Expression Programming (GEP) Modeling

2.3.1. Development of GEP Models

Gene Expression Programming (GEP), an evolutionary artificial intelligence technique developed by Ferreira (2001), was employed to establish predictive relationships between SCC mixture constituents and mechanical properties. GEP combines the advantages of genetic algorithms and genetic programming by encoding candidate solutions as fixed-length chromosomes which are subsequently translated into nonlinear expression trees. In this study, the input parameters consisted of water content, cement content, fine aggregate content, coarse aggregate content, RHA content, CRD content, and water–cement ratio, while the output variables included compressive, splitting tensile, and flexural strengths at 7 and 28 days. The GEP models were developed using GeneXpro Tools software. Model evolution was achieved through repeated application of genetic operations including mutation, recombination, transposition, and crossover until optimum fitness conditions were attained.The principal GEP parameters adopted in the study are summarized in Table 1.

Table 1: GEP model parameters

Parameter	Value
Number of chromosomes	36
Number of genes	8
Head size	12
Linking function	Addition
Constants per gene	15
Function set	+, −, ×, ÷, sqrt, cbrt, exp, ln
Training records	787
Validation records	357

2.3.2. Model Validation and Statistical Evaluation

The predictive capability and generalization performance of the developed GEP models were evaluated using ten-fold cross-validation and multiple statistical performance indices. The dataset was randomly divided into ten subsets, where nine subsets were used for training and one subset for validation during each iteration. The process was repeated ten times to minimize model bias and overfitting. The performance of the models was assessed using coefficient of determination (R^2), mean absolute error (MAE), mean squared error (MSE), root mean squared error (RMSE), and relative root squared error (RRSE). The adopted statistical indices are expressed as follows:

Mean Squared Error (MSE): $MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$

Root Mean Squared Error (RMSE): $RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$

Mean Absolute Error (MAE): $MAE = \frac{1}{n}\sum_{i=1}^{n} | y_i - \hat{y}_i |$

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

Models with high R^2values and low MAE, RMSE, MSE, and RRSE values were considered reliable and robust for predictive applications.

3.0 RESULTS AND DISCUSSION

3.1. Mechanical Strength Characteristics of SCC Mixtures

The mechanical performance of the developed self-compacting concrete (SCC) mixtures incorporating rice husk ash (RHA) and crushed rock dust (CRD) was evaluated through compressive, splitting tensile, and flexural strength tests conducted at curing ages of 7 and 28 days. The experimental investigation aimed to establish the influence of varying water–cement (w/c) ratios on the hardened properties of the sustainable SCC mixtures and to identify the optimum mixture condition capable of achieving balanced strength performance and workability requirements. The observed strength development behaviour was strongly influenced by the interaction between hydration processes, particle packing effects, and the pozzolanic contribution of RHA. The incorporation of CRD further enhanced matrix densification through filler effects, leading to improved interfacial transition zone characteristics and reduced internal voids within the SCC system. Similar observations have been reported in recent studies on sustainable SCC containing supplementary cementitious materials and quarry-derived fillers, where optimized powder composition significantly improved mechanical performance and microstructural compactness (Sayid, *et al*., 2023; Sindhurashmi *et al*., 2024).

3.1.1. Compressive Strength

Compressive strength tests were performed on 100 mm cube specimens in accordance with BS EN 12390-3. Three specimens were tested for each SCC mixture and curing age, and the average compressive strength values were recorded. The variation of compressive strength with water–cement ratio at 7 and 28 days is presented in Figure 1. The results indicate that the compressive strength of the RHA–CRD blended SCC mixtures increased progressively as the water–cement ratio increased from 0.35 to 0.45. Beyond this optimum range, a gradual reduction in strength was observed for mixtures with w/c ratios between 0.50 and 0.65. The highest 28-day compressive strength of 26.4 MPa was obtained at a w/c ratio of 0.45, indicating that this mixture proportion provided the most favorable balance between hydration efficiency, workability, and pore structure refinement. The initial increase in compressive strength observed between w/c ratios of 0.35 and 0.45 may be attributed to improved hydration kinetics and enhanced workability, which facilitated better particle dispersion, reduced internal defects, and improved matrix homogeneity. At lower w/c ratios, insufficient free water may have restricted complete cement hydration and reduced the flowability required for efficient SCC consolidation. However, as the w/c ratio increased to 0.45, adequate moisture became available for hydration reactions while maintaining sufficient cohesiveness within the mixture. Furthermore, the incorporation of RHA contributed to secondary pozzolanic reactions through the consumption of calcium hydroxide released during cement hydration, resulting in the formation of additional calcium silicate hydrate (C–S–H) gel responsible for strength enhancement and pore refinement. Simultaneously, the ultrafine CRD particles improved packing density and reduced micro voids within the cementitious matrix. The synergistic interaction between RHA and CRD therefore contributed significantly to the improved compressive strength performance observed at the optimum w/c ratio.

Conversely, the reduction in compressive strength at higher w/c ratios (0.50–0.65) can be associated with excessive free water within the concrete matrix, leading to increased capillary porosity, weaker interfacial bonding, and reduced matrix densification after hardening. Higher water contents generally increase pore connectivity and reduce the compactness of hydrated cement paste, thereby adversely affecting compressive strength and durability performance. Similar trends have been reported in recent investigations on SCC incorporating agricultural ashes and quarry dust materials, where excessive water content resulted in strength deterioration due to increased pore volume and segregation tendency (Ahmed, *et al*., 2023; Nguyen, 2024). The results therefore demonstrate that the water–cement ratio exerts a dominant influence on the compressive strength behavior of sustainable SCC mixtures containing RHA and CRD. The optimum performance achieved at a w/c ratio of 0.45 confirms the importance of balancing hydration requirements with matrix compactness in the development of high-performance and eco-efficient SCC systems.

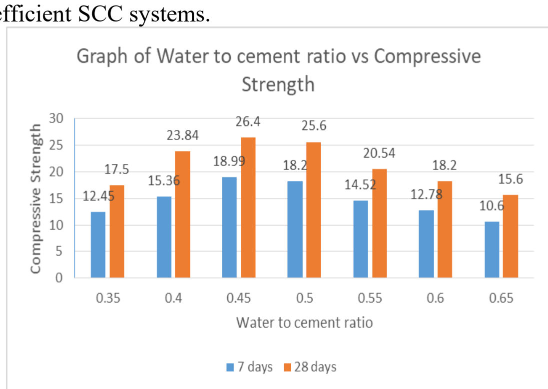

Figure 1: Graph of Water to cement ratio vs Compressive Strength

3.1.2. Splitting Tensile Strength

The splitting tensile strength of the SCC mixtures incorporating rice husk ash (RHA) and crushed rock dust (CRD) was evaluated at curing ages of 7 and 28 days in accordance with BS EN 12390-6. The average tensile strength values obtained for the different water–cement ratios are presented in Figure 2. The experimental results indicate a progressive increase in splitting tensile strength with curing age for all SCC mixtures, confirming the continued hydration and pozzolanic activity within the cementitious matrix over time. The results further demonstrate that the water–cement ratio significantly influenced the tensile behavior of the SCC mixtures at both 7 and 28 days. As illustrated in Figure 1.7, the tensile strength increased as the w/c ratio increased from 0.35 to 0.45, after which a gradual decline was observed for mixtures with w/c ratios ranging from 0.50 to 0.65. The optimum splitting tensile strength recorded at 28 days was 2.69 MPa at a w/c ratio of 0.45. The improvement in tensile strength observed within the optimum w/c ratio range may be attributed to enhanced hydration efficiency, improved particle dispersion, and better interfacial bonding between aggregate particles and the surrounding cementitious paste. At lower w/c ratios, inadequate water availability may have restricted complete hydration and limited the development of a well-connected microstructure. However, increasing the w/c ratio to 0.45 provided sufficient water for hydration while maintaining adequate cohesiveness and stability within the SCC matrix.

In addition, the incorporation of RHA contributed to secondary pozzolanic reactions that generated additional calcium silicate hydrate (C–S–H) gel, thereby enhancing matrix densification and strengthening the interfacial transition zone (ITZ) between the aggregates and hydrated cement paste. The fine CRD particles further improved particle packing and minimized microvoid formation, which collectively enhanced tensile resistance and crack-bridging capability within the SCC system. Similar improvements in tensile performance of sustainable SCC containing agricultural and quarry waste materials have been reported in recent literature, where filler effects and pozzolanic reactions significantly contributed to improved bonding characteristics and reduced crack propagation (Sindhurashmi *et al*., 2024; Sayed, *et al*., 2023). The decline in tensile strength observed at higher w/c ratios (0.50–0.65) can be attributed to increased capillary porosity and reduced matrix compactness resulting from excess free water within the concrete mixture. Higher water contents generally weaken the interfacial bond between aggregate particles and hydrated cement paste, thereby facilitating crack initiation and propagation under tensile loading conditions. Furthermore, excessive water may increase segregation tendency in SCC systems, leading to non-uniform internal structure and reduced tensile capacity. The findings therefore confirm that the tensile performance of SCC incorporating RHA and CRD is highly sensitive to water–cement ratio variations. The optimum tensile strength achieved at a w/c ratio of 0.45 demonstrates that appropriate water optimization is essential for maximizing the synergistic benefits of pozzolanic activity, filler effects, and microstructural densification in sustainable SCC mixtures.

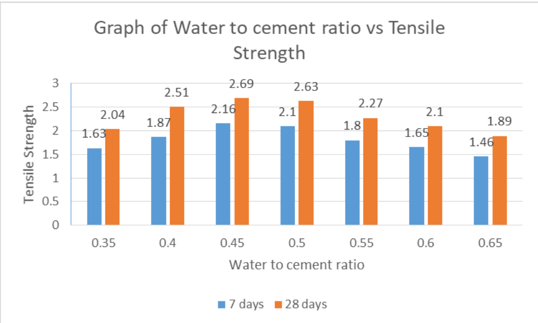

Figure 2: Graph of Water to cement ratio vs Tensile Strength

3.1.3. Flexural Strength

The flexural strength of the SCC mixtures containing rice husk ash (RHA) and crushed rock dust (CRD) was evaluated at curing ages of 7 and 28 days in accordance with BS EN 12390-5, and the corresponding results are presented in Figure 3. The results revealed that the flexural strength increased with curing age for all mixtures, with the 28-day strengths consistently exceeding the 7-day values due to continued cement hydration and pozzolanic reactions within the cementitious matrix. Furthermore, the water–cement ratio significantly influenced the flexural behavior of the SCC mixtures. The flexural strength increased progressively as the w/c ratio increased from 0.35 to 0.45, after which a decline was observed for mixtures with w/c ratios ranging from 0.50 to 0.65. The optimum 28-day flexural strength obtained was 3.60 MPa at a w/c ratio of 0.45, indicating that this mixture proportion provided the most favorable balance between hydration efficiency, matrix densification, and workability characteristics. The improvement in flexural strength up to the optimum w/c ratio may be attributed to enhanced hydration, improved particle packing, and the synergistic effects of RHA and CRD within the SCC matrix. The pozzolanic activity of RHA contributed to the formation of additional calcium silicate hydrate (C–S–H) gel, thereby improving microstructural compactness and strengthening the interfacial transition zone between aggregates and cement paste. Simultaneously, the ultrafine CRD particles acted as fillers that reduced internal voids and enhanced cohesiveness within the concrete matrix. However, at higher w/c ratios, the excess free water increased capillary porosity and weakened the paste–aggregate bond, resulting in reduced resistance to flexural stresses and premature crack propagation. Similar trends have been reported in recent studies on sustainable SCC incorporating agricultural ashes and quarry-derived fillers, where optimum water content was found to play a critical role in achieving enhanced flexural performance and structural stability (Ahmed, *et al*., 2023; Chithra *et al*., 2024).

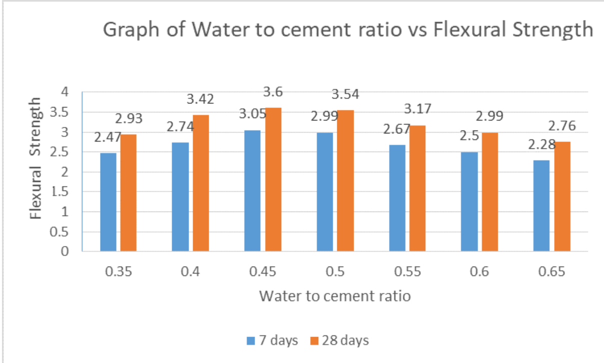

Figure 3: Graph of Water to cement ratio vs Flexural Strength

3.2. Statistical Analysis and GEP Model Evaluation

The predictive performance of the developed Gene Expression Programming (GEP) models was assessed through statistical comparison between experimentally measured and predicted values of compressive, splitting tensile, and flexural strengths of the SCC mixtures incorporating rice husk ash (RHA) and crushed rock dust (CRD). The evaluation was carried out using several statistical performance indicators, including Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Relative Root Squared Error (RRSE), correlation coefficient (R), and coefficient of determination (R^2). These parameters were selected because they provide comprehensive measures of prediction accuracy, model consistency, and generalization capability for both training and validation datasets. Lower values of MSE, RMSE, MAE, and RRSE indicate reduced prediction error and improved model precision, whereas higher R and R^2 values indicate stronger agreement between experimental observations and predicted outputs.

3.2.1. Scatter Plot Analysis

The scatter plots presented in Figures 4 - 6 illustrate the relationship between experimentally measured and GEP-predicted compressive, splitting tensile, and flexural strengths at 7 and 28 days for both training and validation datasets. The distributions of the data points demonstrate strong clustering around the line of equality, indicating high predictive accuracy and minimal deviation between experimental and predicted values. The close agreement observed confirms the ability of the GEP algorithm to successfully capture the nonlinear relationships between SCC constituent materials, water–cement ratio, and mechanical performance. For the compressive strength models (Figure 4), the predicted results closely matched the experimental observations for both curing ages, indicating stable learning and strong model generalization. Similarly, Figures 5 and 6 show that the GEP models effectively predicted splitting tensile and flexural strengths with limited scatter and high correlation between predicted and experimental values. The slight dispersion observed in some validation datasets may be attributed to inherent material variability and the complex interaction between hydration, pozzolanic activity, and filler effects within the SCC matrix. Nevertheless, the overall distribution pattern demonstrates that the developed models possess strong predictive capability and robustness.

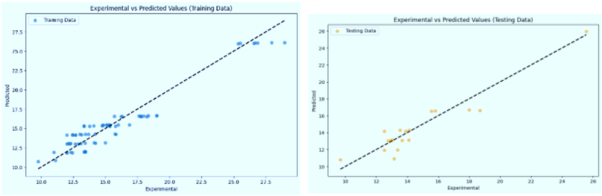

Figure 4: Scatter plots for both Training and Testing for 7- and 28-days Compressive Strength

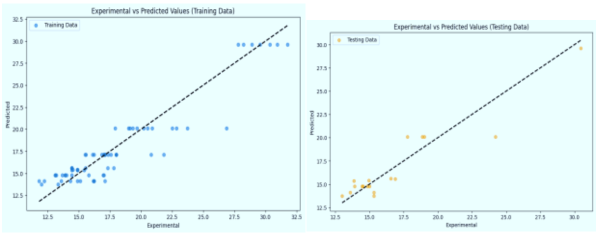

Figure 5: Scatter plots for both Training and Testing for 7- and 28-days Tensile Strength

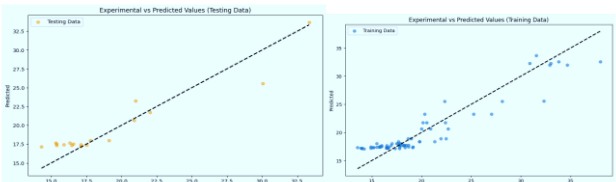

Figure 6: Scatter plots for both Training and Testing for 7 and 28 days Flexural Strength

3.2.2. Performance Metrics

The statistical performance indices obtained for the developed Gene Expression Programming (GEP) models are summarized in Tables 2–4. For compressive strength prediction, the GEP models achieved high coefficients of determination (R^2) of 0.974 and 0.941 for the 7- and 28-day training datasets, respectively, while validation R^2 values of 0.780 and 0.858 were obtained. Correspondingly, low MAE, RMSE, and RRSE values were observed, indicating minimal prediction errors and strong model reliability. The correlation coefficients exceeding 0.88 further confirm strong agreement between predicted and experimental compressive strength values. Similarly, the flexural strength models exhibited excellent predictive performance, with R^2 values of 0.985 and 0.959 for training and validation datasets, respectively. The low MSE, RMSE, and RRSE values indicate that the developed models accurately captured the nonlinear flexural response of SCC mixtures under varying water–cement ratios. In the case of splitting tensile strength prediction, the GEP models achieved R^2 values of 0.969 for training and 0.952 for validation, accompanied by consistently low error indices, confirming strong predictive robustness. Overall, the statistical indicators demonstrate that the developed GEP models possess high reliability, accuracy, and generalization capability for estimating the mechanical properties of sustainable SCC mixtures incorporating supplementary cementitious materials. The strong predictive performance is attributed to the capability of GEP to model complex nonlinear interactions among mix constituents through evolutionary symbolic regression. These findings are consistent with recent studies demonstrating that evolutionary machine-learning techniques, including symbolic regression and hybrid AI models, provide superior predictive accuracy and interpretability for sustainable concrete systems compared to conventional empirical and black-box models (Chen *et al*., 2023; Zhang *et al*., 2024; Ahmad *et al*., 2025).

Table 2: Performance metrics for 7- and 28-days compressive strength

	7 - days		28 – days	
Description	**Training**	**Validation**	**Training**	**Validation**
MSE	0.550	1.334	2.139	4.608
RMSE	0.742	1.155	1.463	2.147
MAE	0.608	0.935	1.079	1.405
RRSE	0.162	0.535	0.243	0.510
Correlation	0.987	0.883	0.970	0.926
R-Square	0.974	0.780	0.941	0.858
Best Fitness	574.08	464.06	406.077	317.81
Max Fitness	1000	1000	1000	1000

Hint: MSE= Mean Squared Error, RMSE=Root Mean Squared Error, MAE=Mean Absolute Error, RRSE=Relative Root Squared Error

Table 3: Performance metrics for 7 and 28 days flexural strength

Description	Training	Validation
MSE	0.37492654333821	0.2341183629688
RMSE	0.61231245564517	0.2427096027823
MAE	0.49275211756318	0.6005377626368
RRSE	0.16674017225576	0.27245396561304
Correlation	0.96413929700399	0.95666600817749
R-Square	0.98530153907514	0.95924159513003
Best Fitness	650.227175259184	693.67443230704
Max Fitness	1000	1000

Hint: MSE= Mean Squared Error, RMSE=Root Mean Squared Error, MAE=Mean Absolute Error, RRSE=Relative Root Squared Error

Table 4: Performance metrics for 7 and 28 days tensile strength

Description	Training	Validation
MSE	0.37492654333821	0.2345183629688
RMSE	0.61231245564517	0.48427096027823
MAE	0.49275211756318	0.40005377626368
RRSE	0.1774017225576	0.27245396561304
Correlation	0.98413929700399	0.97566600817749
R-Square	0.968530153907514	0.951924159513003
Best Fitness	620.227175259184	673.73143230704
Max Fitness	1000	1000

Hint: MSE= Mean Squared Error, RMSE=Root Mean Squared Error, MAE=Mean Absolute Error, RRSE=Relative Root Squared Error

3.2.3. GEP Expression Trees

The hierarchical expression trees generated by the GEP algorithm for predicting the 7- and 28-day compressive, splitting tensile, and flexural strengths are presented in Figures 7 to 12. In Gene Expression Programming, expression trees represent the graphical interpretation of evolved mathematical equations, where each node corresponds to an operator or function while the branches represent the relationships among input variables. These interconnected structures collectively form symbolic regression models capable of describing the nonlinear interactions governing SCC mechanical behavior. The generated expression trees demonstrate the capability of the GEP algorithm to evolve complex mathematical relationships from experimental datasets through successive genetic operations such as mutation, recombination, and crossover. Unlike conventional black-box machine-learning approaches, the expression trees provide transparent and interpretable predictive frameworks that can be translated directly into practical mathematical equations for engineering applications. The structures obtained for compressive, tensile, and flexural strengths reveal that the developed GEP models successfully integrated the combined effects of water–cement ratio, RHA content, CRD content, aggregate proportions, and curing age into robust predictive formulations. Furthermore, the complexity and depth of the expression trees indicate the highly nonlinear nature of the relationships between self-compacting concrete (SCC) mixture constituents and mechanical properties. The ability of the Gene Expression Programming (GEP) algorithm to capture these interactions while maintaining strong predictive accuracy highlights its suitability for sustainable concrete modelling and optimization. This nonlinear behavior is consistent with the microstructural evolution of cementitious systems, where hydration kinetics, pozzolanic reactions, and particle packing effects interact in a highly coupled manner. Similar observations have been reported in recent studies demonstrating that evolutionary machine-learning approaches and symbolic regression models provide superior interpretability and predictive performance compared with conventional regression techniques and several artificial intelligence models in sustainable concrete systems (Chen *et al*., 2023; Zhang *et al*., 2024; Ahmad *et al*., 2025).

Figure 7: Expression tree for 7 days compressive strength
Figure 8: Expression tree for 28-day compressive strength

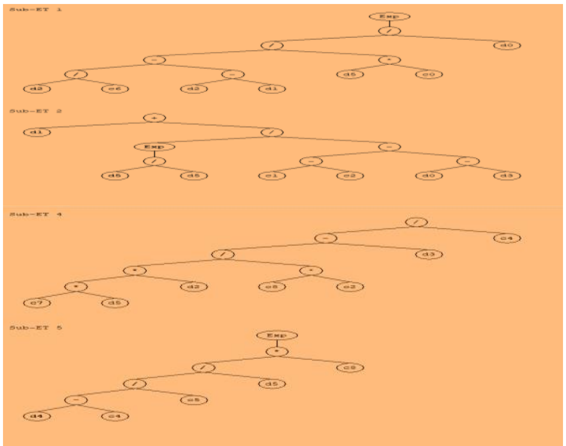

Figure 9: Expression tree for 7 day flexural strength
Figure 10: Expression tree for 28 day flexural strength

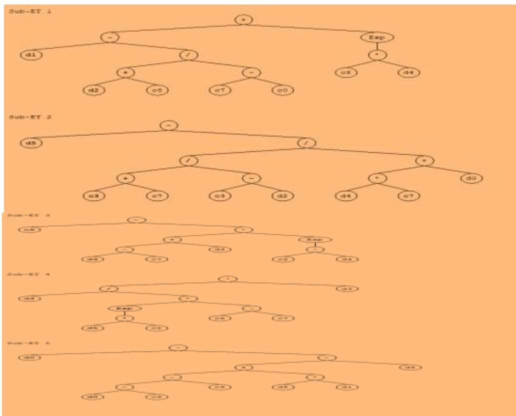

Figure 11 Expression tree for 7-day tensile strength
Figure 12: Expression tree for 28-day tensile strength

3.2.4 Gene Expression Programming (GEP)-Generated Equations and Interpretability

The Gene Expression Programming (GEP) algorithm developed in this study generated explicit symbolic regression models for predicting the compressive, flexural, and splitting tensile strengths of self-compacting concrete (SCC) incorporating rice husk ash (RHA) and crushed rock dust (CRD). These closed-form mathematical expressions were evolved from the underlying expression trees and provide an interpretable relationship between input variables and output mechanical properties. Unlike black-box predictive models, the derived GEP equations enable direct engineering interpretation and practical application in SCC mix design optimization. The generated models incorporate key mixture constituents, including water content (d_0), cement content (d_1), fine aggregate (d_2), crushed rock dust (d_3), granite chippings (d_4), and rice husk ash (d_5), alongside embedded constants (c_0–c_9) representing evolutionary parameters and water–cement ratio levels. The final symbolic expressions reflect the nonlinear interactions governing hydration kinetics, pozzolanic activity, and particle packing density within the SCC matrix.
The general functional forms of the developed models are expressed as:

$$f_{ts} = f(d_0, d_1, d_2, d_3, d_4, d_5, c_0, c_2, c_7, c_8, c_9)$$
$$f_{cs} = f(d_0, d_1, d_2, d_3, d_4, d_5, c_0, c_1, \ldots, c_9)$$
$$f_{fs} = f(d_0, d_1, d_2, d_3, d_4, d_5, c_0, c_2, c_7, c_8, c_9)$$

where f_{ts}, f_{cs}, and f_{fs}represent the splitting tensile, compressive, and flexural strength functions, respectively.
The final GEP models are expressed as additive gene structures:

$$f_{ts} = A + B + C + D + E$$
$$f_{cs} = A + B + C + D + E$$
$$f_{fs} = A + B + C + D + E$$

Each term (A–E) represents an evolved gene contributing to the overall model response.

1 Splitting Tensile Strength Model (7 and 28 Days)

$$A = \frac{c_5}{d_5((d_5 + d_1) - d_4 - (d_3 + c_8))}$$
$$B = \exp(c_7)$$
$$C = d_2\left(\frac{c_3 + c_9}{d_1}\right)\left(\frac{d_5 \cdot c_6 \cdot c_5}{c_5}\right)$$
$$D = \frac{d_5}{d_5(c_7/c_0) - d_0}$$
$$E = \frac{2d_0}{\left(\frac{c_5 - d_2}{d_5}\right)(d_2 - d_5)}$$

2 Compressive Strength Model (7 and 28 Days)

$$A = exp\left(\frac{\frac{d_2}{c_6} - (d_2 - d_1)}{d_5 \cdot c_0 \cdot d_0}\right)$$
$$B = d_1 + \frac{exp\,(d_5/d_5)}{(d_1 - c_2)(d_0 - d_3)}$$
$$C = exp\left(\frac{d_2}{(c_9 - d_4)} - \left(\frac{d_3}{d_0} + c_2 c_9\right)\right)$$
$$D = \frac{\left(\frac{d_2(c_7 d_5)}{c_8 c_2} - d_3\right)}{c_4}$$
$$E = exp\left(\frac{c_8(d_4 - c_4)}{c_5 d_5}\right)$$

3 Flexural Strength Model (7 and 28 Days)

$$A = \left[d_1 - \frac{d_2 + c_8}{c_7 - c_0}\right] + exp\,(c_8 d_4)$$
$$B = d_5 - \left[\frac{(c_3 + c_7)}{(c_3 - d_2)} \cdot \frac{1}{(d_4 - c_7) + d_0}\right]$$
$$C = c_9 - [(d_3 - c_7 + d_3) exp\,(c_2 - d_4)]$$
$$D = \frac{d_3^2}{exp\,(d_5 c_2)(c_6 - c_7)}$$
$$E = d_0 - (d_0 - c_9 - c_9 + d_5 d_1 - d_5)$$

The mathematical expressions generated via Gene Expression Programming (GEP) provide explicit symbolic regression models that capture the nonlinear relationships between constituent materials and the mechanical performance of self-compacting concrete (SCC) incorporating rice husk ash (RHA) and crushed rock dust (CRD). Unlike conventional empirical or statistical regression techniques, GEP evolves functional forms through evolutionary search, enabling the automatic discovery of governing equations without predefined assumptions about variable interactions. Recent studies on data-driven concrete modelling confirm that evolutionary symbolic regression techniques are particularly effective for SCC systems because they can capture complex interactions between mix composition, water–binder ratio, and supplementary cementitious materials while maintaining explicit mathematical interpretability (Sharma *et al*., 2026; Uddin *et al*., 2026). The developed GEP expressions indicate that SCC mechanical properties are governed by highly nonlinear and interdependent interactions between water–cement ratio, cement content, and mineral additives. The presence of exponential and rational terms reflects the sensitivity of strength development to hydration kinetics, pore refinement, and secondary calcium silicate hydrate (C–S–H) formation, particularly in blended systems containing agricultural and quarry by-products. This behavior is consistent with recent findings showing that nonlinear machine learning and symbolic regression models outperform traditional linear approaches in predicting compressive, tensile, and flexural strengths of sustainable concrete materials (Oyebisi *et al*., 2025; Weah and Arora, 2026). The additive gene structures further suggest multi-mechanism interactions between filler effects of CRD and pozzolanic contributions of RHA, which jointly influence microstructural densification and load-bearing capacity. Importantly, the GEP-derived equations provide a transparent and physically interpretable alternative to black-box machine learning models such as deep neural networks, which often lack direct usability in engineering design. In contrast, these explicit formulations can be directly applied in mix design optimization, sustainability assessment, and performance-based concrete design frameworks. Recent advances in explainable artificial intelligence for civil engineering highlight the growing preference for interpretable symbolic regression models in infrastructure applications due to their balance between accuracy and engineering usability (Sharma *et al*., 2026; Chakma *et al*., 2025). Overall, the results confirm that SCC mechanical performance is controlled by complex nonlinear interactions between binder chemistry, water availability, and supplementary material reactivity, making GEP a robust tool for sustainable concrete optimization.

3.2.5 K-Fold Cross-Validation

The predictive robustness of the Gene Expression Programming (GEP) models developed for compressive, tensile, and flexural strengths of self-compacting concrete (SCC) was assessed using a 10-fold cross-validation strategy. In this approach, the complete dataset is randomly partitioned into ten equal subsets (folds), where nine folds are used for model training and the remaining fold is reserved for validation. This process is iteratively repeated ten times such that each subset serves as validation data exactly once, and the final performance is obtained by averaging the results across all folds. This methodology reduces sampling bias, improves generalization assessment, and provides a more reliable estimate of model performance compared to a single train–test split. The cross-validation results confirm the stability and predictive consistency of the GEP models across all mechanical properties and curing ages. Performance was evaluated using standard statistical indicators, including Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Relative Root Squared Error (RRSE), and coefficient of determination (R^2). These metrics collectively quantify average prediction deviation, sensitivity to large errors, normalized error dispersion, and goodness-of-fit, respectively. The results presented in Figures 13 to 15 demonstrate strong agreement between predicted and experimental values across all folds, indicating that the model is not significantly affected by data partitioning and exhibits strong generalization capability.

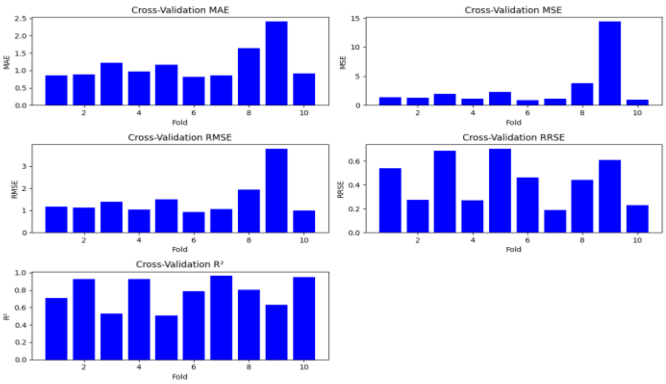

Figure 13: 7- and 28-days Tensile Strength K-fold cross validation for MAE, MSE, RMSE, RRSE and R-square

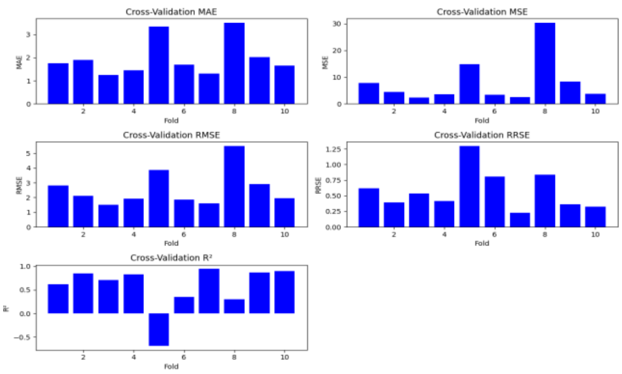

Figure 14: 7 and 28 days Compressive Strength K-fold cross validation for MAE, MSE, RMSE, RRSE and R-square

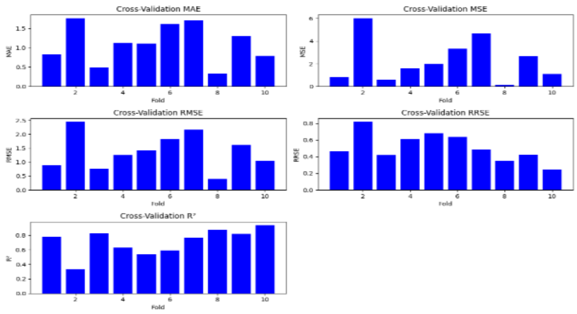

Figure 15: 28 days Flexural Strength K-fold cross validation for MAE, MSE, RMSE, RRSE and R-square

Overall, the low error dispersion and consistently high R^2 values across folds confirm that the GEP models are both statistically stable and physically reliable for predicting SCC mechanical behavior. This robustness is particularly important for sustainable concrete systems involving rice husk ash (RHA) and crushed rock dust (CRD), where material variability can introduce uncertainty in strength development. The k-fold validation therefore substantiates the applicability of the developed models for practical mix design optimization and performance prediction in eco-efficient SCC systems.

4.0 CONCLUSION

This study investigated the mechanical performance of sustainable self-compacting concrete (SCC) incorporating 15% rice husk ash (RHA) as partial cement replacement and crushed rock dust (CRD) as mineral filler under varying water–cement (w/c) ratios. Experimental results demonstrated that all mechanical properties—compressive, splitting tensile, and flexural strengths—exhibited a consistent nonlinear response to changes in w/c ratio, with optimum performance achieved at 0.45. Beyond this threshold, strength reduction was observed due to increased capillary porosity and reduced matrix densification, confirming the critical role of water balance in SCC performance optimization. The study further established that the combined use of RHA and CRD significantly enhances SCC mechanical behaviour through complementary mechanisms. RHA contributes to secondary pozzolanic reactions, producing additional calcium silicate hydrate (C–S–H) gel, while CRD improves particle packing density and reduces internal voids within the cementitious matrix. The synergy between these materials results in improved interfacial transition zone (ITZ) quality and enhanced load transfer capacity, thereby supporting the development of eco-efficient SCC with improved strength performance and reduced reliance on Portland cement.

From a modelling perspective, Gene Expression Programming (GEP) proved highly effective in capturing the complex nonlinear relationships governing SCC behavior. The developed symbolic regression models accurately predicted compressive, tensile, and flexural strengths, with strong statistical performance confirmed through ten-fold cross-validation and high R^2 values (>0.93). Importantly, the explicit mathematical form of the GEP models provides an interpretable and engineering-applicable alternative to black-box machine learning techniques, enabling direct integration into mix design optimization and performance-based concrete design frameworks. Overall, the findings confirm that GEP-based modelling combined with RHA and CRD utilization offers a robust pathway toward sustainable, high-performance SCC and supports circular-economy-oriented construction practices.

DISCLOSURE STATEMENT

No potential conflict of interest was reported by the authors.

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