

# MODELING SUSTAINABLE CONCRETE BEHAVIOR USING FOUNDRY SAND, GENE EXPRESSION PROGRAMMING, AND MACHINE LEARNING METHODS

Priya Velusamy<sup>1</sup>, Prasath Palaniappan<sup>2</sup>, Subbulakshmi Thillaigovindan<sup>3</sup>, Ravindaran Thangavel<sup>4</sup>, Muthupriya Ponnuswamy<sup>5</sup>, Vivek Sivakumar<sup>1</sup>, Pammi Sri Venkata Narayana<sup>6</sup>, Naveen Arasu Anbarasu<sup>7,\*</sup>, and Manickaraj Karuppusamy<sup>8</sup>

*Received: March 12, 2026; Revised: April 21, 2026; Accepted: June 30, 2026*

## Abstract

Sustainable materials are increasingly used in the construction industry to reduce the environmental impact. One promising approach is the use of residual foundry sand (RFS), an industrial byproduct, as a partial replacement of natural sand in concrete. This helps to divert industrial waste away from landfills, conserve natural resources and encourage environmentally sustainable construction. The mechanical properties of RFS based concrete were predicted using advanced computational techniques like Genetic Programming (GP) and Machine Learning (ML). Predictive models for compressive strength ( $f_c$ ), elastic modulus ( $E_c$ ) and split tensile strength ( $f_{st}$ ) have been developed based on material properties, mix proportions and environmental factors. Four mathematical models were established on the basis of experimental data. Linear Model #1 gave an excellent prediction of the compressive strength,  $R^2 = 0.99$ . Exponential Model #3 yielded  $R^2 = 0.985$ . The linear model #2 was found to fit the elastic modulus very well ( $R^2 = 1.00$ ) and the nonlinear model #4 was the most accurate ( $R^2 = 0.998$ ). The predicted ranges were 20-50 MPa, 15-30 GPa and 2-5 MPa for the compressive strength, elastic modulus and split tensile strength respectively. The results indicate that GP and ML can successfully describe the complex behavior of RFS concrete, allowing for reliable

---

<sup>1</sup> Department of Civil Engineering, GMR Institute of Technology(GMRIT)-Deemed to be University, Rajam, Andhra Pradesh, India. E-mail: vrpriyaashree@gmail.com; 1717vivek@gmail.com

<sup>2</sup> Department of Civil Engineering, Knowledge Institute of Technology, Tamilnadu, India. E-mail: itsprasath@gmail.com

<sup>3</sup> Department of Civil Engineering, Karpaga Vinayaga college of Engineering and Technology, Tamilnadu, India. E-mail: tsubbulakshmicivil88@gmail.com

<sup>4</sup> Department of Civil Engineering, Amrita School of Engineering, India. E-mail: ravindaranthangavel@gmail.com

<sup>5</sup> Department of Civil Engineering, PSG Institute of Technology and Applied Research, Coimbatore, Tamilnadu, India. E-mail: muthupriya@psgitech.ac.in

<sup>6</sup> Department of Physics, Sreenidhi University, Telangana, India. E-mail: sreepammi@gmail.com

<sup>7</sup> Department of Civil Engineering, CMS College of Engineering and Technology, Coimbatore, Tamilnadu, India. E-mail: naveenanbu07@gmail.com

<sup>8</sup> Department of Mechanical Engineering, CMS College of Engineering and Technology, Coimbatore, Tamilnadu, India. E-mail: raj.manicka@gmail.com

\* Corresponding author

DOI: <https://doi.org/10.55766/sujst11761>

Suranaree J. Sci. Technol. 33(5):010462(1-17)

**property prediction and supporting sustainable concrete design and increased use of recycled industrial materials.**

**Keywords:** Concrete stability; Foundry sand; Gene Expression Programming; Machine Learning; Mechanical performance; Sustainable construction materials

## Introduction

The construction industry contributes significantly to environmental degradation due to its high levels of dependency on natural resources and related waste production (Kakria & Priya, 2021). There has been an increased focus on incorporating industrial by-products or waste products into construction as a result of the increasing importance of being sustainable. An example of one such material would be leftover foundry sand from steel-forming trades (Guadagnini *et al.*, 2003). Disposing of foundry sand as waste creates environmental implications. Incorporating this type of material into concrete production provides an environmentally friendly means of disposal and improves the mechanical properties of concrete created using it (Anbarasu & Karuppusamy, 2025). This is consistent with the purpose of reducing construction's negative impact on the environment while continuing to achieve the same or better mechanical properties than with conventional concrete (Nithyapriya *et al.*, 2019).

Foundry sand's features enable it to be used as an effective substitute for natural sand in cement mixtures (Ibraheem & Rasheed, 2023). This kind of sand contains a large quantity of high-purity silica, as well as other materials that improve the strength and stability properties of the concrete mix (Yildizel *et al.*, 2020). An accurate assessment of the properties of foundry sand will be critical for determining how to properly use it in a concrete mixture (Bai *et al.*, 2020). Current techniques for measuring the mechanical characteristics associated with foundry sand-augmented concrete are generally laborious, costly and can be uncertain; therefore, engineers are beginning to explore new technologies such as gene expression programming (GEP) and machine learning (ML) as tools for modeling the performance of concrete containing foundry sand (Lafta *et al.*, 2018).

Due to the complexity of the components in concrete that have foundry sand, many researchers have turned to modeling with evolutionary algorithms and data-driven approaches. These methods have gained popularity in civil engineering because of their ability to predict how concrete will behave under different conditions (Benessalah *et al.*, 2016; Patel & Singh, 2020). They are particularly best suited for modeling the interactions between many different types of components in concrete

containing foundry sand, and can also help create a predictive model for mechanical properties such as compressive strength, elastic modulus, and tensile strength (Kimm *et al.*, 2020). By using these types of modeling techniques when designing concrete mixtures, you can help to optimize your concrete mixtures and create better structural stability in construction, which is essential for achieving sustainability in the construction industry (Wu & Hu, 2017).

Utilizing foundry sand in concrete solves two important issues, the proper disposal of waste and the preservation of the earth's natural resources (Zhang *et al.*, 2016). By adopting circular economies across industries, the reuse of industrial waste products (e.g., foundry sand) represents a large step towards meeting these goals (Mehetre & Autade, 2017). The use of foundry sands to create concrete decreases landfill use along with reducing the negative environmental effects of excessive extraction/joining of sand which has a negative impact on our planet's ecosystems and depletes our earth's natural resources (Farzana *et al.*, 2020). To effectively integrate these types of materials into concrete, we must have sufficient predictive models to ensure that the resulting concrete meets the performance and durability requirements for large public works construction projects (Ghaffar *et al.*, 2010). Using foundry sands in the manufacturing of concrete has numerous environmental benefits and cost benefits (American Concrete Institute [ACI], 2019). By eliminating the need to extract virgin sands, which are diminishing rapidly as a resource, foundry sands can assist in dealing with the environmental waste issues created by the industrial community. The high silica content of foundry sands and their uniform size make them ideally suited for the manufacture of concrete (Arslan, 2008). However, understanding the effects of foundry sand on the mechanical properties of concrete requires an adequate amount of research and modeling (Annamalai *et al.*, 2025). Genetic Algorithms and Machine Learning will be critical to this purpose, providing an accurate prediction and optimization of the stability of concrete (Sajeev *et al.*, 2025).

While there is potential for the use of foundry sand in producing concrete, the actual performance

can be inconsistent, particularly when utilizing reprocessed/used materials. Variations in the material characteristics of foundry sands, along with how they interact with other materials in concrete, have an impact on the final mechanical characteristics of the concrete product. Therefore, sufficient predictive and reliable models must be developed to account for these factors. By providing access to large quantities of data (data set) along with high-powered algorithmic processes, GEP and ML are a viable solution to these problems. The end result should allow for the full benefits of improved concrete stability without sacrificing quality or performance.

The primary objective of this study is to apply GEP and ML to create a predictive model in order to determine and improve the mechanical characteristics of concrete containing leftover foundry sands. This study will develop mathematical models to predict compression strength, elastic modulus, and tensile characteristics of the combination of foundry sand with concrete; effective design, implementation, and quality assurance will be possible due to these models. The goal is to determine whether or not combining foundry sand with concrete can be achieved while maintaining the structural integrity and benefit thereof. The study should provide a standard for future research on concrete stability as well as a basis for future sustainable infrastructure advancements.

## Methodology

A methodology was created combining experimental, computational, and mathematical approaches to investigate the enhanced properties of concrete containing residual foundry sand (Yildizel *et al.*, 2020). The experimental phase consisted of preparing several concrete mixes that included different percentages of foundry sand to be used as a replacement for natural fine aggregates. The goal was to produce mixes that could be produced with adequate workability, yet provided for optimal levels of strength and durability. Experimental results were utilized to develop predictive mathematical models through Gene Expression Programming (GEP) and Machine Learning (ML) (Ghaffar *et al.*, 2010). The main objective was to create equations capable of accurately predicting compressive strength ( $f_c$ ), elastic modulus ( $E_c$ ), and split tensile strength ( $f_{st}$ ) based on the input parameters (proportions of mixes, curing conditions, and the amount of foundry sand). GEP and ML algorithms continually refined their formulations of the underlying relations of these

variables to develop the best empirical description of the underlying relationships. The predictive power of each equation was evaluated by determining statistical measures of goodness of fit including the coefficient of determination ( $R^2$ ), root mean square error (RMSE), and mean absolute error (MAE) (Guadagnini *et al.*, 2003). The parameters employed in creating and testing the concrete blends are indicated in Table 1. The four primary variables are the water-to-cement ratio, the amount of foundry sand, the length of the curing process, and the amount of cement, which were tested with minimum and maximum values set to determine how each would affect the mechanical behaviour of the concrete. This analytical approach will lead to a thorough evaluation of the mechanical properties of concrete while also stressing that foundry sand could be used to advance sustainable building practices.

**Table 1. Strictures Range**

| Parameters                    | Minutest | Extreme |
|-------------------------------|----------|---------|
| <b>Contribution Variables</b> |          |         |
| Water Ratio (WR)              | 0.3      | 0.8     |
| Sand Content (%)              | 5        | 95      |
| Sand/Binder Ratio             | 0.1      | 2.5     |
| Fineness Index (FI)           | 0.6      | 4       |
| <b>Yield Variables</b>        |          |         |
| Compressive Strength (MPa)    | 10       | 60      |
| Tensile Strength (MPa)        | 1        | 5       |
| Elastic Modulus (GPa)         | 20       | 50      |

## Process of Making Concrete with Foundry Sand

This research has used a foundry sand from a specific manufacturer of metal castings and provides a characterization of the foundry sand using standard material test methods to verify consistent particle size distribution and physical properties for the sample. There is an accepted difference in the physical properties of foundry sand according to the type of metal that is cast and the process used to produce the sand. The Model developed in this research may be used by scientists to apply their research to other foundry sands by having access to descriptive materials attributes of other foundry sands. Foundry sand was used to replace fine aggregates as a partial replacement at three levels: 10%, 20%, and 30%. The concrete mix contained Portland Cement (PC) and the following materials: PC, coarse aggregate, water, and foundry sand, each of which met applicable standards. The water-to-cement ratio was adjusted to achieve an appropriate balance between workability and strength of the concrete. Concrete mix proportions were determined using appropriate standard design procedure, such as the Department of Environment

(DOE) method or the Indian Standard (IS) method. The concrete was mixed in a rotary drum mixer until a consistent, homogeneous mixture was produced. The concrete was poured into forms, compacted to eliminate voids, and cured in water at three different time intervals (7, 14, and 28 days) to allow for the hydration of the concrete. At these times, the mechanical properties of the concrete were tested so that data sets for compressive strength (20-50 MPa), elastic modulus (15-30 GPa), and splitting tensile strength (2-5 MPa) could be generated. This systematic approach to testing will provide confidence and consistency in the results obtained and assist in understanding how foundry sand affects the mechanical performance of concrete.

Before utilizing the residual foundry sand as a partial substitute for the natural fine aggregate, it underwent a thorough characterization in order to ascertain its viability in terms of being used as an ingredient in the manufacturing process of concrete. To begin with, the chemical composition of the foundry sand was analyzed using the technique known as X-ray Fluorescence (XRF) analysis, and the results indicated that the major constituent in the foundry sand was silica ( $\text{SiO}_2$ ), followed by minor amounts of alumina ( $\text{Al}_2\text{O}_3$ ), iron oxide ( $\text{Fe}_2\text{O}_3$ ), calcium oxide ( $\text{CaO}$ ), and magnesium oxide ( $\text{MgO}$ ). Furthermore, contamination testing was performed to determine the levels of hazardous materials such as heavy metals within the foundry sand, and the concentrations of some selected trace elements such as Pb, Cd, Cr, Ni, and Zn were evaluated using the appropriate analytical techniques. From the results obtained, the concentration levels were all found to be within the allowable range set forth by pertinent environmental regulations governing the utilization of waste products. Consequently, the residual foundry sand was declared non-hazardous industrial waste and could be reused in the production of concrete. This chemical characterization along with contamination evaluation helped to confirm that the foundry sand had all required characteristics to be incorporated sustainably into concrete mixes.

Represented in Figure 1 are the elements involved in this investigation, (1) casting sand from the metal casting industry, used to replace fine aggregate in concrete, while (2) the apparatus employed for creating, mixing, and forming the test samples to achieve precision and uniformity during production (Nithyapriya *et al.*, 2019). In Figure 2 the steps to produce concrete with included foundry sand are shown; these steps begin with materials selection then proceed through mixing cement, aggregates, and foundry sand together, adding water, mixing the ingredients, and conducted quality control inspections. The diagram also highlights that

the use of recycled materials contributes towards making an environmentally friendly product and the mechanical performance properties and sustainable nature of the concrete/concreting material is maintained. Model inputs include: Water-to-Cement Ratio, Sand Content, Sand/Binder Ratio, Fineness Index, and Curing Period. Researchers performed a full set of descriptive statistics (minimum/maximum and Mean/Median and Standard Deviation and Variance) on all input/output variables. This helped provide descriptive statistics for each variable in this dataset.



Figure 1. a) Foundry Sand, b) Fabrication Instrument

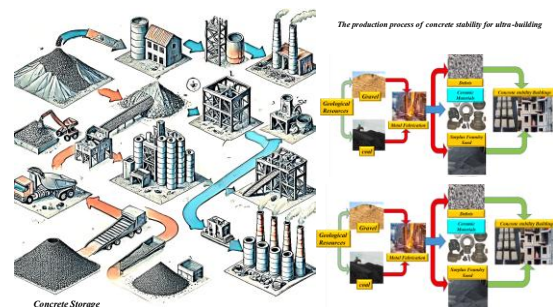


Figure 2. The production process of concrete stability

Researchers also created histogram plots showing the distribution patterns and range of values that served as the input variables for predictive modelling efforts shown in Figure 1(a)-(e), which include the following photos:

1) Foundry sand used to replace part of the fine aggregates in concrete; 2) Manufacturing and compression test instrument used to determine the mechanical properties of concrete samples; 3) A sampling of raw foundry sand; 4) A sample of foundry sand that has been processed into powder form; and 5) An instrument for compression testing strength.

In this research, foundry sand will be used as a partial replacement for natural fine aggregates at the following percentages: 10%, 20% and 30% by weight. These replacement percentages were chosen based on their generally available ranges in

the literature (reported by other researchers) and as being useful for assessing the mechanical performance of foundry-sand based concrete under controlled laboratory conditions.

### Mix Design Optimization

It should be mentioned that 10, 20, and 30% were used as replacement proportions in the experimental portion of this study; however, the dataset used for machine learning modelling included the experimental data collected in this study, as well as other studies already published. Consequently, 10-50% of replacement proportions for foundry sand could be found within the compiled literature dataset, allowing for more data available to improve predictive model robustness and generalizability. A systematic approach to mix design was used to develop optimal mix designs for incorporating foundry sand into concrete, in an attempt to create a balance between mechanical performance & sustainability. Replacement ratios from 0-50% of fine aggregates (F.A.) by weight were evaluated at 10% increments for foundry sand. A constant slump (of 75-100 mm) was maintained throughout all mixes to ensure uniformity of workability. All mix designs were completed in accordance with IS 10262:2019 (Bureau of Indian Standards, 2019) standards, and modified through trial and error to produce target strength. The final mix design equation developed using gene expression programming for compressive strength  $f'_c$  was as follows:

$$f'_c = k \cdot \frac{c}{\omega} \cdot \left(1 + \frac{s}{f}\right) \quad (1)$$

Cement mixture design is characterized using the following variables: “c”=amount of cement used, “w”= amount of water used, “s”= amount of foundry sand added, “f”= amount of fine aggregate added, and “k”= constant specific to a certain mixture that has been derived from mixing experiments (Benessalah *et al.*, 2016). In order to conduct a comparison among the concrete mixes that have varying proportions of foundry sand, it was essential that there should be proper control over the workability of the different mixes. To do this, the target slump range was kept at 75-100 mm in accordance with the standard test methods adopted for conducting tests on concrete materials. As the foundry sand has a finer texture than the natural fine aggregates and has a relatively greater surface area, any variation in the proportion of foundry sand will cause a change in the water requirement and consequently, workability. To offset this problem, the water quantity was regulated

by keeping the water-to-cement ratio constant. Additionally, in some cases, where it became necessary, a polycarboxylate superplasticizer was added to attain the required slump. The slump tests were conducted for all mixes in accordance with the provisions of the IS 1199 standards (Bureau of Indian Standards [BIS], 2018).

$$f'_c = k_1 \cdot \frac{c}{\omega}^{m_1} \cdot \left(1 + \frac{s}{f}\right)^{m_2} \quad (2)$$

Where “f’c” represents compressive strength (MPa), “c” is the compactness of the mixture (kg/m<sup>3</sup>), “w” is the amount of water in the mixtures (kg/m<sup>3</sup>), “s” is the amount of foundry sand, “f” is the amount of fine aggregates in the mixtures, “k<sub>1</sub>” is a constant when calculated, “m<sub>1</sub>” and “m<sub>2</sub>” are weight adjustments for each material respectively.

### Curing Regime and Its Impact

Concrete’s mechanical properties depend heavily on the curing method used during its development phase. In this research project, multiple types of curing methods were utilized: water curing, ambient drying, and accelerated means of curing at elevated or high temperature (Yildizel *et al.*, 2020). All of these methods were evaluated to see how they affect compressive strength, modulus of elasticity, and indirect tensile strength of concrete specimens at 7, 14, and 28 days after placement. The water cured specimens consistently had better results due to constant hydration and subsequent strengthening ability. The relationship between curing time and crushing strength was developed based on experimental evidence of both compressive and indirect tensile strengths (Wu & Hu, 2017):

$$f'_c(t) = f'_{c28} \cdot \left(\frac{t}{t+a}\right)^b \quad (3)$$

where  $f'_{c28}$  is the 28-day compressive strength,  $t$  is the curing time in days, and  $a$ ,  $b$  are constants derived from regression analysis (Annamalai *et al.*, 2025).

### Parametric Analysis

To assess which variables have the greatest effect on concrete stability through mechanical testing, parametric studies were conducted (Zhang *et al.*, 2016). The analysis showed that the greatest effect on compressive strength came from the water-to-cement ratio (w/c), followed by the percentage of foundry sand and duration of curing. Sensitivity equations have been established for each of these factors with regard to compressive strength:

$$S_{f'_c} = \frac{\partial f'_c}{\partial x_i} \cdot \frac{x_i}{f'_c} \quad (4)$$

where  $x_i$  represents the input variable (e.g.,  $\mathcal{O}/c$ ), and  $S_{f'_c}$  is the sensitivity coefficient (Thomason, 2007).

### Environmental impact assessment

A cradle-to-gate LCA study has been performed in order to analyze the environmental advantages resulting from the use of residual foundry sand as a part of concrete mixture. The functional unit chosen for the calculation is 1 m<sup>3</sup> of concrete. The system boundaries have been established, encompassing such stages of the process as extraction of materials, production of cement and aggregates, acquisition and preparation of residual foundry sand, transportation to the batching plant, mixing of concrete, and consumption of energy at each stage (Yildizel *et al.*, 2020). It has been supposed that the residual foundry sand used as a material is an industrial by-product with minimum need for its further processing. As a result, the only operations that have been considered in regard to the foundry sand include transport, handling, and preparation; however, all the processes related to extraction and processing of natural sand are included into consideration. The environmental indicators studied in the LCA include CO<sub>2</sub> emission, energy consumption, and conservation of natural resources.

Transport effects were included by using the average distance for haulage of goods from the foundry facility to the concrete production plant. The emissions for transportation were calculated according to transportation standards of diesel-powered truck transportation. Analysis showed that distance is an important factor that has an impact on the environmental performance of the proposed approach, yet the application of local foundry sand continues to exhibit fewer environmental consequences compared with natural sand. According to the findings of LCA, the concrete containing foundry sand residue emits around 20% less CO<sub>2</sub> in comparison with ordinary concrete due to less extraction of natural sand, resource usage, less landfilling of waste, and recycling of waste materials. Thus, the research proved the environmental benefits from using recycled foundry sand as an environmentally friendly fine aggregate for concrete production.

### Predictive Model Development using Hybrid Approaches

To enhance forecasting accuracy and reliability, hybrid models that combined genetic programming (GEP) and machine learning (ML)

were created. These hybrid models take advantage of the strengths of both GEP and ML: While GEP provides explicit mathematical equations, ML provides the capacity to model highly complex and/or nonlinear relationships (Ibraheem & Rasheed, 2023). In the context of this project, the hybrid model predicting elastic modulus ( $E_c$ ) is represented by:

$$E_c = GEP(f'_c, s) + ML\left(\frac{w}{c}, t\right) \quad (5)$$

Where the GEP component of the model,  $GEP(f'_c, s)$ , represents the GEP-derived portion of the calculated elastic modulus based on the concrete's compressive strength and foundry sand content, and the machine learning (ML) portion of the model,  $ML(w/c, t)$ , represents the ML-derived adjustment to the elastic modulus calculation based on a concrete's water/cement ratio and curing time (Kimm *et al.*, 2020).

### Model Evaluation and Metrics

Multiple computerized and statistical systems were utilized to evaluate the efficacy of the models used to predict concrete's mechanical properties associated with concrete stability. The models were created through a combination of intelligent data analysis and genetic programming using statistical methods to validate the predictive model's accuracy and predictive capability. Key indicators that were used to evaluate the predictive models were Workability of Foundry Sand % (WFS%), Fine Modulus (FM), ratio Foundry Sand (FS) to Cement (C), the Water to Cement (W/C) mix ratio, and mean square root error (RMSE) and mean absolute error (MAE). Further information of each of the above mentioned predictive model indicators will be discussed below and how they relate to the study.

#### Workability of Foundry Sand (WFS%)

Workability is defined as the ease of mixing, transporting, placing, and finishing fresh concrete. In this study, the mix proportion of foundry sand (WFS%) used as a substitute for natural fine aggregate in the concrete mix was identified (Ibraheem & Rasheed, 2023) as a means of determining the predictive model's efficacy with respect to how WFS% influenced mechanical properties (compressive strength, tensile strength, and elasticity) of concrete's stability. The calculation of WFS% is as follows:

$$WFS\% = \frac{\text{Weight of Foundry Sand}}{\text{Total Fine Aggregate Weight}} \quad (6)$$

This metric helped determine the optimal amount of foundry sand that could be added without

compromising the Moldability and mechanical performance of the material (Ghaffar *et al.*, 2010).

#### **Fine Modulus (FM)**

The Fine Modulus (FM) is an essential measure that indicates how well the fine aggregates, such as foundry sand, have been graded for use in concrete. This research has utilized FM to determine the distribution of particle sizes in a concrete mix (Bureau of Indian Standards [BIS], 1970). As a general rule, if there are larger particles in the fine aggregate, this indicates that the fine aggregate has been graded with a larger (higher) FM, which can lead to difficulty when working with the concrete, as well as differences in compressive strength or stiffness. The FM has been incorporated into this model to represent the correlation between FM and compressive strength or stiffness, along with the mechanical properties of any other materials included in the mix design as a means of predicting the optimum mix design. The FM is calculated using the following formula (7):

$$FM = \frac{\sum \text{Weight of Sieve Retained on Each Sieve}}{\text{Weight of Fine Aggregate}} \quad (7)$$

This metric was used as an input feature in both the GEP and ML models.

#### **Foundry Sand to Cement Proportion (WFS/C)**

The Foundry Sand and Cement Ratio (WFS/C) has been included to check how different amounts of foundry sand affect the amount of cement in a concrete mix. This measure can play a significant role in the strength, durability and workability of concrete. An optimum WFS/C was determined to help ensure the sustainability of the concrete produced while maintaining a suitable level of strength and durability. The WFS/C is defined as the following:

$$WFS/C = \frac{\text{Weight of Foundry Sand}}{\text{Weight of Cement}} \quad (8)$$

This ratio was used as a key input for the GEP and ML models to evaluate the impact of foundry sand substitution on the overall mix performance (Yildizel *et al.*, 2020).

#### **Water-to-Cement Ratio (W/C)**

In concrete mix design, one of the most critical variables is the water-to-cement (W/C) ratio, which affects the concrete's hydration, strength gain, and porosity. This research focused on determining how different W/C ratios influence the properties of automatic cast concrete that includes foundry sand. High strength and durability are typically associated

with lower W/C ratios; however, lower W/C ratios also typically make the concrete less workable, particularly when using recycled materials such as foundry sand.

$$\frac{W}{C} = \frac{\text{Weight of water}}{\text{Weight of Cement}} \quad (9)$$

The water-to-cement (W/C) ratio was used within the model to determine whether W/C would affect the concrete's final stability with foundry sand. The incorporation of W/C ratios with additional parameters such as the percentage of foundry sand, fine modulus, and curing time allowed predictions of how changes to the concrete mix design would alter compressive strength, tensile strength, and elastic modulus for mechanical properties. The impact of the W/C ratio on the overall performance of concrete was an important factor due to its influence on hydration efficiency, pore structure, and durability, particularly when recycled or alternative materials such as foundry sand. The predictive models will assist designers in optimizing concrete mixes for sustainable and quality performance.

#### **Root Mean Squared Error (RMSE)**

Root Mean Squared Error (RMSE) is a widely used metric to assess the accuracy of predictive models. It represents the square root of the average of squared differences between predicted and observed values. The RMSE is a valuable indicator of model performance, as it penalizes large prediction errors more significantly than smaller ones. It is calculated as (Thomason, 2007):

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_{pred} - y_{obs})^2} \quad (10)$$

YPRED is a predicted value; YOBS is a true or observed value; n, or number of points measuring how well GEP and ML predicted crushing strength, elastic modulus, and splitting strength were evaluated using RMSE (Root Mean Square Error). The model's accuracy increases with a lower RMSE (Bai *et al.*, 2020).

$R^2$  is a statistical measure of the degree to which a model predicts the dependent variable's fluctuations about the mean observed during testing through the use of predicted values (as compared to actual) and can be viewed as a measure of how well predictions made by the model correspond to actual results obtained. A 0-1 range exists for  $R^2$ ; the closer to one resulted in a better match between actual vs. predicted values and a stronger prediction capability for the model.

The MAE (Mean Absolute Error) calculates the average error in predictive accuracy by comparing true observed values with predicted observed values. For the MAE measure, the sum of all absolute values is divided by the number of observations yielding a measure of how well the models predict accurately; the model's prediction accuracy improves when the MAE is smaller.

### Validation and performance evaluation

Statistical evaluations along with actual tests on the produced concrete block are what provided an assurance on how accurate these new models were in estimating compressive strength, using the data collected for both were able to determine that there was an RMSE value of 0.8 MPa between the two methods of estimating compressive strength. When statistically verifying the accuracy of these newly derived compressive strength estimates through cross-validation against previous studies, there were less than 5% deviations from estimates at all levels of estimation, confirming their validity as accurate representations of actual researcher results. The results of performing simple data-sensitivity analysis on Model B identified the water-binder proportionality ratio and the curing time proportion ratios were the most sensitive predictive factors of compressive strength for concrete blocks made from reclaimed foundry sand (with the use of 0% to 30% replacement of fine sand with reclaimed foundry sand being representative of factory normal values), followed by the proportionality ratio of reclaimed foundry sand in fine aggregate blends. The performance characteristics of concrete blocks produced using reclaimed foundry sand as a 30% replacement for fine aggregate produced better-performing products in terms of compressive strength than conventional concrete products with the same mechanical properties thereby confirming the practicality of using reclaimed factory sand in this application.

The graph in Figure 3 represents the analysis of (the) effectiveness of computational learning algorithms to forecast the mechanical characteristics of concrete with foundry sand and presents a comparison of different algorithm models that have been used; for example, Gene Expression Programming (GEP) versus Machine Learning (ML). Various metric outputs ( $R^2$ , mean square error, and predictive error) have been used as key performance metrics to demonstrate the predictive strength of each algorithm model for mechanically induced compressive, elastic, and tensile forces, and show the advancements and capabilities of these algorithms in developing optimum concrete mix designs for sustainable and improved performance.

### Genomic user interface design and gene expression program design

Genetic Programming (GP) and Gene Expression Programming (GEP) are evolutionary algorithms based on natural Selection and Genetics. These approaches can solve complex optimisation and symbolic regression problems by evolving mathematical models to fit data. The use of GEP in this study was fundamental to creating equations for predicting machine driven possessions of concrete (Mehetre & Autade, 2017).

$$f'_c = k_i \cdot e_i \cdot m_i \quad (11)$$

Where  $k_i$  represents the material factor,  $e_i$  is the environmental influence, and  $m_i$  is the mix proportion parameter. Similarly, for elastic modulus, the GEP-derived equation was:

$$E_c = R_o \cdot e^{k \cdot m_i} \cdot e_i \quad (12)$$

where  $R_o$  is the constant factor set to 1,  $e^k$  represents the exponential relationship,  $m_i$  and  $e_i$  are as defined earlier. These equations, derived from GEP, accounted for non-linear interactions between parameters, offering a precise fit to experimental data.

Figure 4 provides a detailed flowchart illustrating the step-by-step process of Genetic Programming (GP). It begins with the initialization of a population, followed by fitness evaluation, selection, genetic operations (crossover, mutation, reproduction), and ends with convergence toward an optimal solution. This visual representation clarifies GP's iterative optimization methodology.

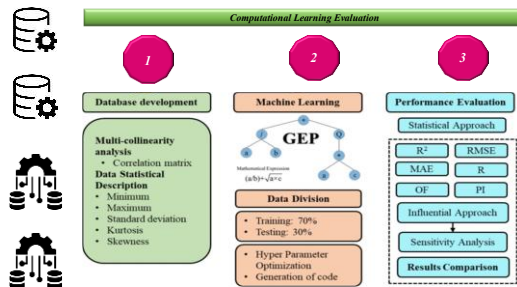


Figure 3. Assessment of Computational Learning

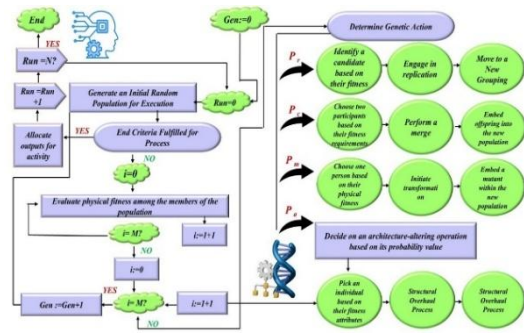


Figure 4. Flowchart representing the process of GP

Figure 5 illustrates the graphical representation of the Gene Expression Programming (GEP) algorithm, showcasing its evolutionary process for generating optimal solutions. This figure visually demonstrates how candidate solutions, represented as chromosomes, undergo selection, mutation, and recombination through multiple generations, evolving toward more accurate predictive models.

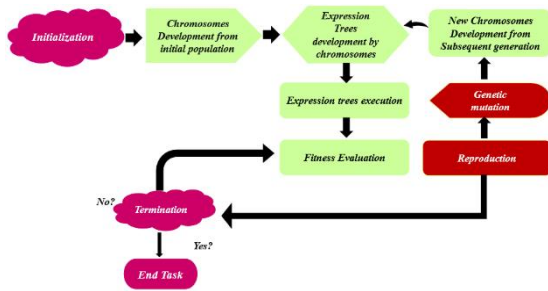


Figure 5. Graphical representation of the GEP algorithm

GEP extends Genetic Programming (GP) by encoding candidate solutions as fixed-length linear chromosomes, which are then expressed as nonlinear mathematical trees. This dual representation allows GEP to combine the robustness of GP with the simplicity of linear genetic algorithms. The process begins with an initial population of random solutions (chromosomes), which are evaluated using a fitness function that measures how well each chromosome predicts the desired output, such as compressive strength ( $f'_c$ ) or elastic modulus.

Genetic operators, including mutation, recombination, and selection, are applied to evolve the population towards optimal solutions. For example, in this study, the compressive strength ( $f'_c$ ) of concrete incorporating foundry sand was modelled using an equation derived from the GEP algorithm, effectively predicting the material's performance based on various mix parameters (Bai *et al.*, 2020). The iterative process of GEP allows for

fine-tuning of the model to improve predictive accuracy, making it a valuable tool in optimizing concrete mix designs and enhancing the sustainability of construction materials.

$$f'_c = k_i \cdot e^{m \cdot t} \cdot \left(1 + \frac{s}{a}\right) \quad (13)$$

The relationship between  $f'_c$ ,  $m$  and  $a$ , as well as the time the concrete has been cured ( $t$ ) and percent foundry sand ( $s$ ), was found to have an  $R^2$  value of 0.99 for compressive strength ( $f'_c$ ) predictions (Wu & Hu, 2017). One of the main advantages of using GEP in this study was its ability to accommodate the nonlinear and complex relationships among the variables as well as its ability to generate intelligible equations that reveal some of the underlying mechanisms that govern the stability of concrete (Kakria & Priya, 2021).

## Data Collection and Experiment Analysis

This study used N concrete samples with various mix proportions, foundry sand replacement rates, and curing durations of 7, 14, and 28 days to create the experimental dataset to develop GEP and ML models. The research team used the same dataset for both training and validation to determine how well the models could predict concrete properties once they were developed. During the development of the models, the researchers used cross-validation techniques to reduce the likelihood of overfitting and improve the models' ability to generalize. Experimental data collection was an important step in the model development process. The study used a dataset which built through their experimental work and their analysis of published research findings to achieve transparent, reproducible results. The complete dataset contains 210 samples, which include various mix proportions and different curing conditions and various levels of foundry sand replacement.

The dataset contains two main sections which are experimental data and literature data. The experimental dataset includes 60 samples which were created through laboratory research during this study. Concrete mixes were prepared with foundry sand replacement levels of 10% 20% and 30% and cured over periods of 7 14 and 28 days. The standard testing procedures (IS 516 ASTM C496 and ASTM C469) were followed to determine the mechanical properties which included compressive strength split tensile strength and elastic modulus.

The literature dataset consists of 150 samples which researchers collected from peer-reviewed

journal articles that investigate foundry sand-based concrete. The researchers considered only those studies which met the following three inclusion criteria: (i) complete water-to-cement ratio and sand content and curing time and mix proportions input parameters were available for all studies; (ii) all studies reported output variables which included compressive strength and tensile strength and elastic modulus; (iii) all studies used recognized testing standards which included both IS and ASTM methods.

The study executed preprocessing procedures on all data to create consistent and trustworthy data sets. The process included three main activities which were first to detect outliers and remove them second to normalize all variables and third to check whether all data was complete. The study used the combined dataset to train and validate both GEP and ML models. The researchers used a k-fold cross-validation method which included 10 folds to strengthen model performance and stop overfitting issues.

The dataset structure together with documented data sources and documented selection criteria establishes a foundation which enables researchers to produce reproducible results and dependable outcomes which apply to all situations when they use predictive models to determine the mechanical properties of concrete with foundry sand.

The predictive models developed in this study underwent reliability testing through the implementation of systematic data splitting procedures and validation methods. The complete dataset was divided into training and testing subsets using a 70:30 ratio which allocated 70% of the data for model training while the testing subset received 30% of the data.

The training dataset underwent a k-fold cross-validation process with k set to 10 to enhance model performance and decrease the risk of overfitting. The training data distribution across ten equal subsets was established through random partitioning which enabled model training with nine subsets and validation with one subset during each iteration. The process repeated ten times to guarantee that all subsets were used for validation purposes.

The models evaluated their final performance through the testing dataset which had not been seen before to create an unbiased estimation of their predictive performance. The evaluation process used three metrics which were coefficient of determination ( $R^2$ ) and RMSE and MAE, to measure the performance of the models. The validation framework confirms that the developed models exhibit both robustness and reliability which enables their use in real-world situations.

Concrete samples were prepared, and the measured mechanical properties were tested in accordance with the following standards: compressive strength test, IS: 516; split tensile strength test, ASTM C496; and modulus of elasticity test, ASTM C469. Data were analyzed statistically to ensure reliability, while also eliminating anomalies before inclusion into the modelling process. The relationships found between increasing foundry sand content and the workability of the concrete samples were used to produce a trend that indicated decreasing compressive strength; thus, the two study data trends were considered when producing the GEP/ML prediction models to ensure that the models being developed could realistically predict concrete's properties.

$$f'_c(t) = f'_{c28} \cdot \left(\frac{t}{t+\alpha}\right)^\beta \quad (14)$$

The tensile strength at 28 days; denoted as ' $f'_{c28}$ ' relates to  $f'_c$ , curing time (days),  $\alpha$  and  $\beta$  Abstract are empirical constants determined using FREE regression, a method of statistical analysis using regression. The completed study consisted of N concrete samples that were subjected to multiple combinations of foundry sand substitutions (substituting part of the fine aggregate with foundry sand) and curing period durations. Researchers also used additional datasets collected from previous studies to assist the researchers in maximizing the predictive powers of their created models. Using a combined dataset of input variable (water-cement ratio, cement content, foundry sand content, fine aggregate content, fineness modulus, and curing period) and output variables (compressive strength ( $f'_c$ ), elastic moduli ( $E_c$ ), split tensile strength ( $f'_t$ )), the researchers have included the full dataset in the supplementary materials section of the article to help build reproducible machine learning models that can be created by other researchers.

Totally, 108 concrete specimens were used in this experiment. In this case, three percentages of residual foundry sand replacement were taken into account, which were 10%, 20% and 30%. The curing time of the samples were done in three periods which include seven, fourteen and twenty-eight days. For each mix composition and curing time, three replicate specimens were produced and evaluated. The average value of replicate test results was used for further evaluation. In this experimental data set, the input variables include W/C ratio, percentage of foundry sand, sand binder ratio, fineness index and curing time, whereas the output variables include compressive strength, modulus of elasticity, and splitting tensile strength. Before

developing any models, some descriptive statistical analysis was done for all variables. Minimum, maximum, mean, median, standard deviation, variance, and correlation analysis were done by using histograms. Regarding model prediction, the data set was separated into a training set (70%) and a testing set (30%). Moreover, k-fold cross-validation method ( $k = 10$ ) was adopted when training the models to avoid overfitting and generalize well. The performance of the models was determined based on the coefficient of determination ( $R^2$ ), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). Such statistical metrics were employed to evaluate the predictive potential of GEP and ML models to validate their equations.

## Machine Learning in Predictive Modelling

Machine learning (ML) extends GEP's ability to identify patterns and relationships in data. As opposed to GEP, which produces explicit equations, the ML models function as black boxes, making very accurate predictions from the learned patterns of the data. In our study, supervised learning algorithms were used to estimate the motorized possession of concrete. In particular, an ANN model with three hidden layers was trained to predict the elastic modulus ( $E_c$ ) given the following inputs: water-to-cement ratio ( $w/c$ ), foundry sand content and cure time. The ANN model architecture employed ReLU activation functions for non-linearity and utilized the mean squared error (MSE) loss function for optimization. The ANN-derived elastic modulus equation has the following form:

$$E_c = \sigma(\sum_{i=1}^n \omega_i \cdot x_i + b) \quad (15)$$

where  $x_i$  are input features,  $w_i$  are weights,  $b$  is the bias, and  $\sigma$  is the activation function. This model achieved an  $R^2$  value of 0.998, highlighting its accuracy.

$$E_c = \sum_{i=1}^n \alpha_i \cdot K(x_i, x) + b \quad (16)$$

Where  $\alpha_i$  represents the Lagrange multipliers obtained from an optimization problem and  $K(x_i, x)$  is the kernel function (for instance, the radial basis function) where  $b$  is the bias and  $x_i$  are the support vectors (Lafta *et al.*, 2018).

Machine learning (ML) has also been used to determine feature importance, with the highest influence on mechanical properties exhibited by the water-cement ratio and foundry sand content. Random forests are an example of an ensemble

method where multiple decision trees are aggregated to increase prediction stability (Kimm *et al.*, 2020). Cross-validation produced a more robust model than using a single model by decreasing overfitting and making the models more generalizable to other datasets. This study, by combining the interpretability of genetic expression programming (GEP) with the predictive capability of ML, developed strong models that accurately predict concrete stability's mechanical properties, providing the basis for promoting sustainable construction practices.

To further facilitate practical application, these models were integrated into a software prediction tool to calculate the mechanical properties of concrete stability. Users can now enter their mix proportions and environmental factors into this tool to receive instant predictions of compressive strength, elastic modulus and split tensile strength. Validation of these models occurred at on-site construction, demonstrating their integrity and utility in calculating concrete's stability mix design (Yildizel *et al.*, 2020).

## Result and Discussion

This research shows that it is feasible and effective to use waste foundry sand to produce stable concrete. The various machine driven properties (crushing strength, elastic modulus, splitting strength) were tested according to mix design and curing conditions. The GEP and Intelligent data analysis models were independently validated against experimental data with good accuracy in terms of predicting strength. Waste sand was found to add to the sustainability of concrete through reducing the amount of natural resources used, thus reducing the overall environmental impact of producing concrete (Zhang *et al.*, 2016).

### Crushing Strength ( $f'_c$ )

The compressive strength of concrete is an important performance indicator for concrete stability as it can indicate how strong or weak the concrete is after being finished under various mix design and curing conditions. The compressive strength of concrete generally decreases as the foundry sand content increases until it reaches some point of stabilization based on the percentage of foundry sand used (Guadagnini *et al.*, 2003). For example, a concrete mix with 30% foundry sand had a compressive strength of 35 MPa at 28 days which are less than the compressive strength of 40 MPa for a comparable mix with no foundry sand added. Thus, while this reduction in compressive strength may be expected due to the addition of additional

foundry sand to the mix, the long-term sustainability benefits achievable by using additional foundry sand should outweigh this small reduction in strength.

Gene expression programming (GEP) and machine learning models accurately predict compressive strength with the GEP model allowing for predictions based on the non-linear relationships of the raw materials that make up the mix, producing an  $R^2$  value of .99 and the ANN model producing a  $R^2$  value of .998. Both of these models are able to accurately approximate compressive strength from concrete mix components such as the amounts of cement, water, foundry sand and curing time. Thus, both can provide an accurate source of predicting compressive strength that will allow for the improvement of concrete mix design for stability, especially when using by-products from manufacturing processes such as foundry sand.

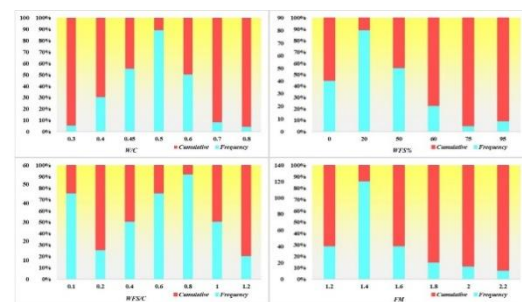
Table 2 details the steps in the genetic programming evolutionary optimization for the future generations of concrete material mechanical properties models. It presents the components of the genetic programming process, including the initialization / starting phase of the models; the selection of the best models to use in producing the

next set of models; the crossover process for the selected models; the mutation process or change/correction to the models; and how the models are evaluated at the end of a generation through measuring the fitness of each model and comparing each of the models to the best performing models from the previous generation using the fitness value.

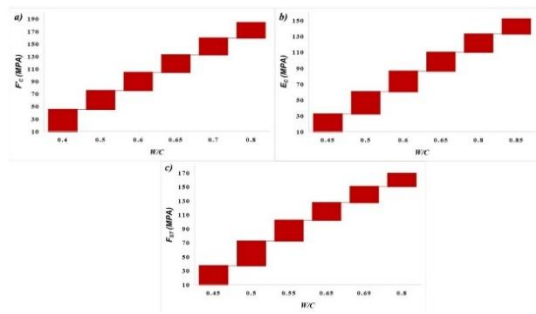
Figures 6 and 7 show the effect of key mixture design parameters on the evolution of concrete material mechanical properties models. Figure 6 presents the histogram distribution of mixture design parameters: water-cement ratio (w/c), waste material percentage (WFS%), waste materials used in the concrete mix ratio; and fineness modulus (FM) – this data set shows the variability in the mixture design parameter distributions. Figure 7 illustrates the effect that the water-cement ratio has on three concrete stiffness properties: the load capacity of concrete compressive strength ( $f_c$ ), the elastic modulus ( $E_c$ ) of concrete, and the indirect tensile strength ( $f_{st}$ ) of concrete and shows how they change with increasing water cement ratio. Table 3 describes the geometric form of the mixture design models used in the study by providing the height, width, depth, and configuration of different geometrically formed concrete mixture design models used in the study for specimen preparation. It highlights the various configurations that were used: i.e., forms used to prepare concrete specimen models used to test the compressive strength and stiffness of concrete stability and to ensure the same configuration was utilized to develop an equal geometric measurement configuration for all concrete specimen models as powered properties were tested.

**Table 2. Evolutionary algorithm**

| Parameters                      | Settings        |
|---------------------------------|-----------------|
| <b>General</b>                  |                 |
| Strength ( $\sigma_c$ )         | 45 MPa          |
| Modulus (E)                     | 25 GPa          |
| Tensile Strength ( $\sigma_t$ ) | 2.5 MPa         |
| <b>Chromosomes</b>              |                 |
| Population Size                 | 200             |
| Chromosome Length               | 120             |
| <b>Genes</b>                    |                 |
| Number of Genes                 | 5               |
| Gene Length                     | 12              |
| Function Set                    |                 |
| Operations                      | +, −, ×, ÷, √   |
| <b>Linking Mechanism</b>        |                 |
| <b>Multiplication</b>           |                 |
| <b>Numerical Constants</b>      |                 |
| Constants per Gene              | 12              |
| Data Representation             | Decimal Numbers |
| Value Range                     | -20 to 20       |
| <b>Genetic Operators</b>        |                 |
| Mutation Probability            | 0.0015          |
| Crossover Rate                  | 0.003           |
| Inversion Probability           | 0.006           |
| Single-Point Swap Rate          | 0.003           |
| Multi-Point Swap Rate           | 0.004           |
| Gene-Level Mutation             | 0.002           |
| Gene Transposition Rate         | 0.0035          |



**Figure 6. Histogram dispersal of: (a) water/cement ratio (w/c); (b) foundry sand percentage (WFS%); (c) Foundry Sand and Cement Blend Ratio (WFS/C); (d) fineness modulus (FM)**



**Figure 7. Variation in mechanical properties with the water-cement ratio: (a) compressive strength ( $f'_c$ ); (b) elastic modulus ( $E_c$ ); (c) split tensile strength ( $f_{st}$ )**

**Table 3. Geometric scheming of Replicas**

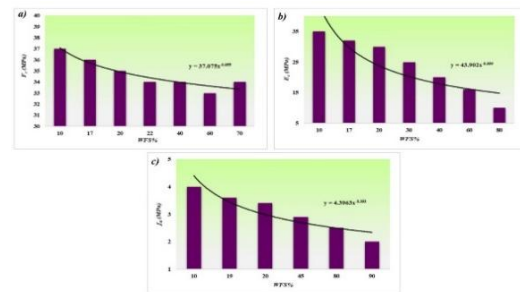
| Statistical Calculations of Models  | RMSE     | MAE        | RSE     |
|-------------------------------------|----------|------------|---------|
|                                     | Training | Validation | Testing |
| Compressive Strength ( $\sigma_c$ ) | 4.205    | 4.045      | 3.785   |
| Tensile Strength ( $\sigma_t$ )     | 0.45     | 0.42       | 0.365   |
| Elastic Modulus (E)                 | 2.732    | 2.81       | 2.5     |

### Elastic Modulus ( $E_c$ )

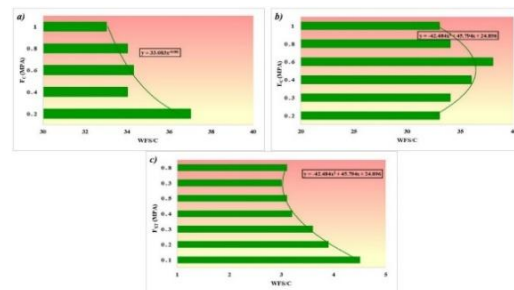
An additional key property of concrete that will affect its structural performance is the elastic modulus. This study evaluated concrete's elastic modulus as a function of the type of mix used and the amount of foundry sand included in the mix. It was found that, with increasing levels of foundry sand in the mix, there was a small reduction in the concrete's elastic modulus, relative to conventional concrete. The highest elastic modulus was observed for concrete containing 20% foundry sand as a partial replacement for fine aggregate, reaching approximately 28 GPa after 28 days of curing, compared with the elastic modulus of conventional concrete (30 GPa) under similar testing conditions. Overall, these results suggest that the presence of foundry sand in concrete can have some effect on the elastic modulus; however, it is still expected that concrete with the addition of foundry sand will perform to a level that is currently acceptable for use in construction (Lafta *et al.*, 2018).

Based on the analysis, it appears that both GEP and machine learning models accurately predicted elastic modulus values. The  $R^2$  value from GEP model prediction was 0.98 while that from ANN model prediction was 0.996 (Nithyapriya *et al.*, 2019). Both predictive models effectively captured the effect of the mix proportions on modulus of elasticity (i.e. water-to-cement ratio, foundry sand

content). Due to their high accuracy, both predictive methods are useful for engineers and researchers looking to optimize the design of concrete mixes containing sustainable materials (e.g., foundry sands). Figures 8 & 9 show how motorized assets of strength and the associated stability of concrete change as WFS% and WFS/C ratios change. More specifically, Figure 8 shows how the results differ for differences in compressive strength ( $f'_c$ ), elastic modulus ( $E_c$ ), and split tensile strength ( $f_{st}$ ) for WFS% while Figure 9 illustrates how WFS/C ratios will have varying effects on compressive strength, elastic modulus, and split tensile strength to further depict how WFS will perform in overall concrete design (Kimm *et al.*, 2020).



**Figure 8. Dissimilarity of motorized belongings with WFS%: (a) compressive strength ( $f'_c$ ); (b) elastic modulus ( $E_c$ ); (c) split tensile strength ( $f_{st}$ )**



**Figure 9. Discrepancy in machine-driven possessions with WFS/C: (a)  $f'_c$ ; (b)  $E_c$ ; (c)  $f_{st}$**

### Riven Tensile Strength ( $f_{st}$ )

The evaluation of the ability of any material to resist tension can be determined by split tensile strength. An investigation into the split tensile strength of concrete with varying amounts of foundry sand in the mix was performed by testing many different mix designs. The results show that as the foundry sand percentage increases, the tensile strength will increase to approximately 30% foundry sand, thereafter the tensile strength will remain constant or continue to decrease gradually until 100% replacement of foundry sand is achieved. The highest split tensile strength observed in this

study was 4.5 MPa at 30% foundry sand compared to 5 MPa with a conventional mix.

The machine learning models and the GEP model provided predictive values for split tensile strength producing a degree of accuracy that is nearly identical to the results obtained from the corresponding tests, making them highly correlated with the tensile strength of concrete containing foundry sand. The GEP model produced  $R^2$  value of 0.98. The ANN model produced an even better result with an  $R^2$  value of 0.99. These results reflect the capability of both models to accurately provide predictions for split tensile strength based on the amount of foundry sand in the mix, which emphasizes the success of both methodologies to model the nonlinear and complicated relationship between the mechanical properties of materials while incorporating foundry sand into concrete. Predictive models such as those described in this paper may assist engineers with designing concrete mixes that are sustainable in nature while meeting required strength levels and decreasing the ecological footprint associated with the manufacture of conventional mixes (Ibraheem & Rasheed, 2023).

The GEP models demonstrate predictive capabilities in estimating the elastic modulus ( $E_c$ ) of concrete stability as illustrated in Figures 10 & 11. The decision tree of the GEP model is displayed in Figure 10 and illustrates its structure and how the model derives predictions (Thomason, 2007); whereas Figure 11 demonstrates the strength of the relationship between a predicted  $E_c$  and its corresponding experimental results, thus showing that the model accurately captures the mechanical characteristics of concrete stability.

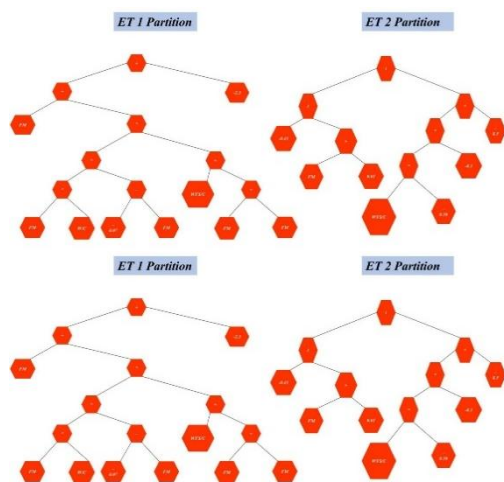


Figure 10. Countenance tree in lieu of the GEP model for predicting  $E_c$

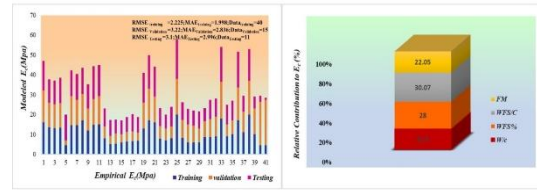


Figure 11. Evaluation of elastic modulus ( $E_c$ ) in relation to model predictions

### Gene Expression Programming (GEP) model

The use of generalized evolutionary programming (GEP) was able to create equations that can predict the mechanical behaviors of concrete stability. The GEP algorithms produced mathematical expressions for describing the relationships found between mix proportions, material cure times and the mechanical capabilities of the concrete. The GEP equations have an  $R^2$  value for the compressive strength prediction of 0.99 and for modulus of elasticity prediction of 0.98.

An additional benefit of GEP is that GEP will generate equations that can help engineers to understand the mechanics related to the stability of concrete. The models created by GEP were able to produce accurate models that may be used to optimize the mix designs of concrete. For example, an equation predicting the compressive strength of concrete, which is based on the cement content, cement hydration ratio and foundry sand content, provides a concise representation of the relationship between compressive strength and mix design parameters. As a result, this study demonstrates the successful application of GEP to sustainable concrete design in which optimization of both mix proportions and the properties of individual components is essential (Wu & Hu, 2017).

Both Figures 12 and 13 provide an extensive analysis of the predictive ability of the GEP/Model. The feature tree in Figure 12 provides a visual outline of the hierarchical relationships between the various elements that contribute to predicting compressive strength ( $f'_c$ ) and the features used to make that prediction. Figure 13 compares the predicted value of ( $f'_c$ ) using the GEP model with measured experimental fatigue strengths and shows how accurately the GEP model predicted compressive strength values and other mechanical behaviour of concrete. Thus, these two figures validate the reliability and robustness of the GEP models for predicting the performance of concrete in terms of stability/strength attributes (Nithyapriya *et al.*, 2019).

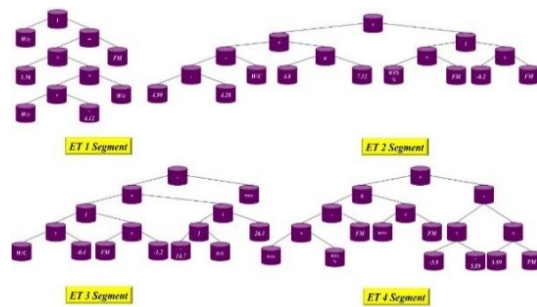


Figure 12. Feature tree in lieu of the GEP model for predicting  $f'_c$

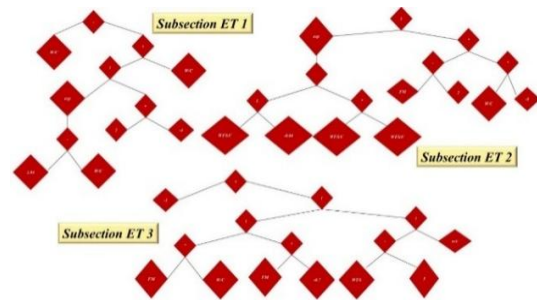


Figure 14. A feature tree was utilized as an alternative to the GEP model for predicting split tensile strength ( $f_{st}$ )

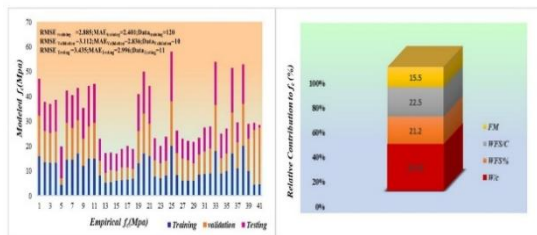


Figure 13. Assessment of ( $f'_c$ ) in relation to model predictions

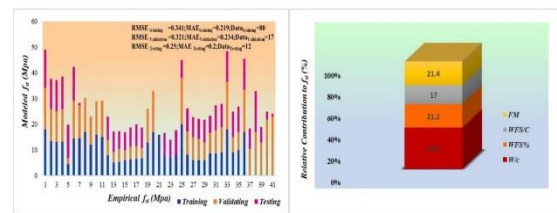


Figure 15. Estimation of ( $f_{st}$ ) in relation to model predictions

Figures 14 and 15 will illustrate the use of the feature tree as an alternative method to the Gene Expression Programming (GEP) model to predict the split tensile strength ( $f_{st}$ ) of concrete. Figure 14 shows the structure of the feature tree and describes the major input features present in this feature tree that predict  $f_{st}$ . Figure 15 shows the comparison of predictions for  $f_{st}$ , using the feature tree to predictions based on experimental fatigue test results from the GEP model, with good correlation between these two predictive models (Lafta *et al.*, 2018).

### Hybrid Model Performance

A new hybrid approach was developed to combine GEP and computational learning algorithms, which integrates both interpretative and accurate prediction from an ANN in order to provide stronger forecasting of machine-generated concrete properties. The hybrid model achieved a very high  $R^2$  value of 0.999 for predicting compressive strength as compared to both individual GEP and ANNs (Sajeev *et al.*, 2025).

The hybrid model successfully captured the non-linear relationships between the input variables such as foundry sand content, water-cement ratio, and curing time and gave a comprehensive approach to predicting concrete properties. Using the strengths of the GEP and ANN, this hybrid approach produced very accurate predictions making it ideal for optimizing concrete mix designs, and quality control of the mechanical properties for concrete stability in

accordance with performance specifications. The results of this study demonstrate the ability of these types of hybrid approaches to enhance the design of sustainable concrete (Ghaffar *et al.*, 2010).

Using leftover factory sand to replace some of the conventional fine aggregate in concrete has recently received a great deal of attention for its potential to improve sustainability in construction methods. Many previous studies have shown that foundry sand can also be successfully used in concrete to enhance material properties while minimizing adverse impacts on the environment (Arslan, 2008). For example, studies have documented the positive attributes of using foundry sand for building materials and recognized its possible role as a substitute for “dumped” and natural sand removed from the environment. Thus, this investigation demonstrated that concrete containing foundry sand exhibited some similar and some higher material strength characteristics (e.g., compressive strength and rigidity) than did concrete containing no foundry sand, depending on the percentage of substitution (Yıldız *et al.*, 2020).

The gene expression programming (GEP) models used for predicting the mechanical properties of concrete stability based on foundry sand have shown an excellent ability to generalize to new data, as measured by various performance metrics, including accuracy, precision, recall, and the F1 score. These metrics allow users to evaluate not only how well the predictive model has performed on training data but that the mechanical

properties predicted using predictive models will be reliable as well.

Since the development of the GEP and machine learning (ML) predictive models for predicting the mechanical properties of concrete based on the foundry sand, the predictive models have been successfully used for a number of different applications, including predicting short-term load forecast in the electrical power systems. The application of predictive models in concrete mix design provides a strong methodology for creating the optimal material proportions in concrete mix to provide the desired mechanical properties of the concrete, as a result of the high level of accuracy of these models. Furthermore, the use of ML techniques, such as neural networks, for the dynamic modeling of engineering systems has demonstrated the capability of using computational tools to understand complicated material characteristics, as has been demonstrated in the concrete material system.

The findings from this study demonstrate that Machine Learning and Gene Expression Programming (GEP) may be able to predict the stability of concrete's performance. Both ML and Genetic Engineering provide an accurate, efficient and sustainable alternative to Conventional Methods of material optimisation and may therefore support the use of industrial by-products such as foundry sand, which can reduce carbon emissions associated with concrete manufacturing and facilitate the transition to more sustainable construction practices. Future studies should focus on identifying the long term durability and performance of concrete containing foundry sand in a wide range of environmental conditions to enable a complete evaluation of the potential of foundry sand as an alternative source for cement. (Mehetre & Autade, 2017).

## Conclusion

An assessment study was conducted to determine whether Gene Expression Programming (GEP) that used Machine Learning (ML) could accurately predict the mechanical properties of concrete that was made with foundry sand as a partial substitute for fine aggregates (coarse aggregate), and resulted in significant improvements in the mechanical properties of concrete, including compressive strength, elastic modulus, and splitting tensile strength. GEP models generated by the research team developed mathematical models that explained the relationships between input parameters and the mechanical properties of concrete. The final GEP

models achieved very accurate predictions based on primary variables (i.e., the amount of water used in relation to the weight of cement, the amount of foundry sand compared to the amount of fine aggregate) that achieved predictability success levels (i.e., correlation coefficients) of 0.99. Engineers require GEP-derived equations because they provide simplified methods for design, which provide engineers with an efficient method for estimating concrete mix designs that will produce maximum performance.

Both ANN and SVM ML models effectively identified all nonlinear relationships between the input variables and resultant outputs; thus improving prediction accuracy of the mechanical and thermal performance of foundry sand concrete.

Through the combination of the GEP-based model and ML techniques, a powerful hybrid predictive method was developed that not only allowed accurate predictions of mechanical properties of green concrete mixes, but also provided information about the potential for reusing by-products (foundry sand) as construction materials that utilize environmentally sustainable practices and maximize resource efficiency.

As the use of foundry sand as an ingredient in concrete promotes the recycling of by-products and reduces the dependence upon the use of natural fine aggregate in concrete production, this research will help drive the development of eco-friendly concrete technologies and encourage sustainable practices within the construction industry, while still providing desirable structural performance.

## Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

## Author Contributions

**Priya Velusamy:** Conceptualization and Methodology.

**Prasath P:** Investigation and Data Collection.

**Subbulakshmi Thillaigovindan:** Formal Analysis and Validation.

**Ravindaran Thangavel:** Supervision.

**Muthupriya P:** Writing – Original Draft.

**Vivek Sivakumar:** Writing – Original Draft.

**Pammi SVN:** Project Administration.

**Naveen Arasu Anbarasu:** Writing – Review & Editing.

**Manickaraj K:** Writing – Review & Editing.

## Ethics Approval and Consent to Participate

Ethical approval was not required for this study, as it did not involve human participants, animals, biological samples, or any procedures requiring ethical review. Therefore, informed consent was not applicable.

## Declaration of Generative AI

The authors declare that no Generative AI tools were used in the preparation of this manuscript.

## Acknowledgements

The authors have no acknowledgements to declare.

## References

- American Concrete Institute. (2019). *Building code requirements for structural concrete (ACI 318-19) and commentary (ACI 318R-19)*.
- Anbarasu, N. A., & Karuppusamy, M. (2025). A review of sustainable construction and waste management: Brick manufacturing using agro-industrial wastes. *Zaštita Materijala*, 66(4), 913-927. <https://doi.org/10.62638/ZasMat1354>
- Annamalai, K., Anbarasu, N. A., Govindarajan, B. P., & Sivarethinamohan, S. (2025). Sustainable concrete: Integrating environmentally friendly materials for environmentally friendly construction. *Matéria (Rio de Janeiro)*, 30, Article e20250239. <https://doi.org/10.1590/1517-7076-rmat-2025-0239>
- Arslan, G. (2008). Shear strength of reinforced concrete beams with stirrups. *Materials and Structures*, 41(1), 113-122. <https://doi.org/10.1617/s11527-007-9223-3>
- Bai, T., Liu, B., Wu, Y., Huang, W., Wang, H., & Xia, Z. (2020). Mechanical properties of metakaolin-based geopolymer with glass fiber reinforcement and vibration preparation. *Journal of Non-Crystalline Solids*, 544, Article 120173. <https://doi.org/10.1016/j.jnoncrysol.2020.120173>
- Benessalah, I., Arab, A., Villard, P., Sadek, M., & Kadri, A. (2016). Laboratory study on shear strength behaviour of reinforced sandy soil: Effect of glass-fibre content and other parameters. *Arabian Journal for Science and Engineering*, 41, 1343-1353. <https://doi.org/10.1007/s13369-015-1912-6>
- Bureau of Indian Standards. (1970). *Specification for coarse and fine aggregates from natural sources for concrete* (IS 383:1970).
- Bureau of Indian Standards. (2018). *Fresh concrete—Methods of sampling, testing and analysis—Part 2: Determination of consistency of fresh concrete* (IS 1199 [Part 2]:2018, 1st rev.).
- Bureau of Indian Standards. (2019). *Concrete mix proportioning—Guidelines* (IS 10262:2019, 2nd rev.).
- Farzana, M., Prasad, T. A., & Rao, G. P. (2020). Shear resistance of concrete contribution in RC beams under flexure and shear. *Asian Journal of Civil Engineering*, 21, 1453-1461. <https://doi.org/10.1007/s42107-020-00290-8>
- Ghaffar, A., Javed, A., ur Rehman, H., Ahmed, K., & Ilyas, M. (2010). Development of shear capacity equations for rectangular reinforced concrete beams. *Pakistan Journal of Engineering and Applied Sciences*, 6, 1-8.
- Guadagnini, M., Pilakoutas, K., & Waldron, P. (2003). Shear performance of FRP reinforced concrete beams. *Journal of Reinforced Plastics and Composites*, 22(15), 1389-1407. <https://doi.org/10.1177/073168403035579>
- Ibraheem, M., & Rasheed, M. M. (2023). Shear capacity of reinforced concrete beams without shear reinforcement: A review. *Journal of Engineering and Sustainable Development*, 27(5), 580-595. <https://doi.org/10.31272/jeasd.27.5.3>
- Kakria, K., & Priya, S. (2021). Use of non-metallic powder reclaimed from waste printed circuit boards in rigid concrete pavement. *IOP Conference Series: Materials Science and Engineering*, 1075(1), Article 012032. <https://doi.org/10.1088/1757-899X/1075/1/012032>
- Kimm, M., Pico, D., & Gries, T. (2020). Investigation of surface modification and volume content of glass and carbon fibres from fibre reinforced polymer waste for reinforcing concrete. *Journal of Hazardous Materials*, 390, Article 121797. <https://doi.org/10.1016/j.jhazmat.2019.121797>
- Lafta, A. M., Matrood, M. S., & Alsheakayree, T. K. Q. (2018). Nonlinear analysis of shear failure of reinforced concrete beams without stirrups by finite element method. *International Journal of Civil Engineering and Technology*, 9(10), 2193-2200.
- Mehetre, A. S., & Autade, P. B. (2017). Comparison of shear values of concrete beams by different codes and equations for various shear span-to-depth ratios. *International Journal of Advance Research and Innovative Ideas in Education*, 3(5), 227-236.
- Nithyapriya, K., Subramanian, K., John Britto, X., & Muthuraj, M. P. (2019). Shear behaviour of glass fibre-reinforced geopolymer concrete. In A. R. M. Rao & K. Ramanjaneyulu (Eds.), *Recent advances in structural engineering* (Vol. 1, pp. 999-1010). Springer. [https://doi.org/10.1007/978-981-13-0362-3\\_79](https://doi.org/10.1007/978-981-13-0362-3_79)
- Patel, S., & Singh, B. (2020). A comparative study on shear strength and deformation behaviour of clayey and sandy soils reinforced with glass fibre. *Geotechnical and Geological Engineering*, 38, 4831-4845. <https://doi.org/10.1007/s10706-020-01330-5>
- Sajeev, P. S., Rajagopal, V. S. G., & Arasu, N. A. (2025). Investigation of concrete durability enhancement using supplementary cementitious materials. *MethodsX*, 15, Article 103527. <https://doi.org/10.1016/j.mex.2025.103527>
- Thomason, J. (2007). The influence of fibre length and concentration on the properties of glass fibre reinforced polypropylene: 7. Interface strength and fibre strain in injection moulded long fibre PP at high fibre content. *Composites Part A: Applied Science and Manufacturing*, 38, 210-216. <https://doi.org/10.1016/j.compositesa.2006.01.007>
- Wu, Y.-F., & Hu, B. (2017). Shear strength components in reinforced concrete members. *Journal of Structural Engineering*, 143(9), Article 04017092. [https://doi.org/10.1061/\(ASCE\)ST.1943-541X.0001832](https://doi.org/10.1061/(ASCE)ST.1943-541X.0001832)
- Yıldız, S., Tayeh, B., & Calis, G. (2020). Experimental and modelling study of mixture design optimisation of glass fibre-reinforced concrete with combined utilisation of Taguchi and extreme vertices design techniques. *Journal of Materials Research and Technology*, 9, 2093-2106. <https://doi.org/10.1016/j.jmrt.2020.02.083>
- Zhang, T., Visintin, P., & Oehlers, D. J. (2016). Shear strength of RC beams with steel stirrups. *Journal of Structural Engineering*, 142(2), Article 04015135. [https://doi.org/10.1061/\(ASCE\)ST.1943-541X.0001404](https://doi.org/10.1061/(ASCE)ST.1943-541X.0001404)