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A Data-Driven Approach for Estimation and Multi-Objective Optimization of Concrete Mix Design

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The study focuses on establishing the optimum concrete mix of ratios through a comprehensive analysis of experimental results. For this purpose, a total of sixty concrete mixtures were prepared by varying the proportions of key constituents, including cement, water, fine aggregate, and coarse aggregate. Using experimental data, Genetic Expression Programming (GEP) has been used to develop predictive equations for compressive strength and slump with cement, water, and coarse aggregates and fine aggregates as inputs. These equations are useful to estimate compressive strength and workability of concrete for particular ingredients. Moreover, mathematical multi objective optimization has been conducted by Genetic Algorithm (GA) using these equations as basis functions and optimum content of cement, water, fine aggregate and coarse aggregate have been determined for obtaining maximum compressive strength, maximum slump at lowest cost. Further, multi objective optimizations of different grades of concrete with slump and cost separately have also been carried out to determine these ingredients. Thus, by implementing the present results a more accurate number of mixed proportions with desired compressive strength, and slump can be obtained at minimum cost.

1 Introduction

After water, concrete is the most widely used material. It holds a vital position in the construction industry. However, conventional concrete mix designs depend on codal guidelines and trial mixes in both laboratory and field conditions to meet the required standards for strength, workability, and durability [1–3]. Different codal provisions [4] meet the needs for concrete mixture design in India and its neighbouring country. Different costly admixture enhances the performance of concrete but simultaneously cost of concrete increases substantially. Thus, it is very difficult to design mixture proportion for getting maximum performance at low cost. Therefore, it is necessary to optimize the concrete mix proportions to obtain

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the maximum performance of concrete without using the admixtures, after establishing the multidimensional nonlinear relationship between the raw material and desired performance.

Several researchers have employed various machine learning techniques to predict concrete properties. Early studies used Artificial Neural Networks (ANN) for mix proportioning and compressive strength prediction [2–3]. Chen et al. developed the Compos system combining multiple linear regression and ANN to analyze material-performance relationships [4]. Mustapha and Mohamed proposed a Weighted SVM model for high-performance concrete, while Taffese and Sistonen reviewed ML methods for durability forecasting [5–6]. Later works applied ANN, ANFIS, and hybrid models for strength estimation [7–9], with ANFIS often showing the best accuracy. Marani et al. used GANs, and other studies adopted SVM, AdaBoost, and regression-based approaches [10–13]. In 2021, various models including ANN, ANFIS, SVM, XGBoost, and hybrid networks were applied for predicting compressive and shear strength of different concrete types [14–20]. More recent work by Mohammed and Ismail showed MARS outperforming other models for reinforced beam shear strength [21]. Earlier comparisons also found that combining ANN and SVM improved accuracy [22–23]. Overall, ANN, ANFIS, and hybrid ML models have consistently delivered the most reliable predictions for concrete properties.

Over the years, many studies have focused on optimizing concrete mix design through experimental, analytical, and computational techniques. Early research emphasized achieving desired workability and strength using experimental or analytical methods [24–28], while later works introduced advanced algorithms such as the Densified Mixture Design Algorithm (DMDA) and robust design techniques for improved performance and cost-efficiency [29–31]. With the rise of artificial intelligence, methods like Artificial Neural Networks (ANN), Genetic Algorithms (GA), and hybrid models were applied to optimize mix proportions and minimize costs [32–36]. Further advancements included Particle Swarm Optimization (PSO) and other heuristic algorithms that provided faster and more accurate optimization results compared to GA [29, 37–39].

Over the years, numerous studies have been conducted to optimize concrete mixture design using various methodologies. Abbasi et al. (1987) [27] carried out experimental research to optimize concrete mix based on specific workability and compressive strength requirements. Shilstone (1990) [28] introduced a quantitative technique for optimizing aggregate proportions and allowed for adjustments during construction. Kasperkiewicz (1994) [33] applied analytical methods using locally available materials to develop cost-effective concrete mixes. Chang et al. (2001) [32] proposed the Densified Mixture Design Algorithm (DMDA) to produce high-performance concrete with enhanced workability and durability. Soudki et al. [34] utilized full factorial experimental design to statistically optimize mix proportions suitable for hot climates. Nunes et al. (2006) [40] applied a robust mix design approach for self-compacting concrete. Ahmad (2007) [37] introduced a laboratory trial procedure aimed at minimizing the cost of concrete mix design. Yeh (2007) [35] employed various analytical tools such as Artificial Neural Networks (ANN), Nonlinear Programming, and Genetic Algorithms (GA) to optimize concrete mixtures for both performance and cost-effectiveness. Lee et al. (2009) [36] integrated GA, ANN, and the convex hull method to determine cost-effective concrete mixtures under specific strength criteria. Yeh (2009) [29] further refined mix optimization using a flattened simplex-centroid design combined with ANN. Akalin et al. (2010) [31] used a D-optimal design approach to optimize self-consolidating high-strength concrete. Xiaoyong and Wendi (2011) [38] developed a mix design method based on experimental data and orthogonal analysis to identify key factors influencing compressive strength. Jayaram et al. (2010) [39] highlighted the effectiveness of elitism-based Particle Swarm Optimization (PSO) for designing high-performance concrete with fly ash, reducing the number of trial mixes required. Ghiamat et al. (2019) [41] demonstrated that optimizing genetic operators can lead to a 13% reduction in construction costs and bridge superstructure weight by minimizing the use of pre-stressing tendons. Naseri (2019) [42] found that PSO outperforms GA in achieving better concrete mix solutions. According to Sobhani's study, PSO yields faster and more accurate results than GA. Finally, Feng et al. (2021) [43] employed ANFIS combined with PSO, ACO, and DEO to estimate the superplasticizer demand in self-consolidating concrete.

Traditionally, concrete mix design has relied on codal provisions, trial-and-error laboratory tests, and the use of costly admixtures to achieve desired performance. While recent studies have explored various machine learning and heuristic optimization techniques—such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), Adaptive Neuro-Fuzzy Inference Systems (ANFIS), Genetic Algorithms (GA), and others—to predict or optimize concrete properties, a significant limitation remains: these models generally do not yield explicit predictive equations. Most function as black-box systems, offering little interpretability or transferability for practitioners seeking to design mixes under different conditions. Consequently, despite their predictive accuracy, such models are difficult to adapt in real-world scenarios without access to original training data or computational resources. Moreover, many existing studies either focus solely on property prediction or attempt optimization without an integrated, multi-objective framework that simultaneously considers compressive strength, workability (slump), and cost—an essential trade-off in practical construction settings.

To address these gaps, the present study introduces a novel approach that combines Genetic Expression Programming (GEP) with Genetic Algorithm (GA) to derive interpretable, explicit equations for predicting compressive strength and slump based on the weights of cement, fine aggregate, coarse aggregate, and water. These equations serve as basis functions in a multi-objective optimization procedure that minimizes cost while maximizing performance indicators. The methodology has been validated using experimental data generated from locally available materials, ensuring regional applicability. Optimized mix proportions have been presented for various strength and slump requirements, including separate solutions for high, medium, and low workability levels, as well as cost-effective designs across different concrete grades. Unlike existing black-box approaches, the proposed model offers transparent, adaptable, and practically useful outcomes, thereby representing a significant advancement in the field of performance-based and cost-effective concrete mix design.

2 Optimization Methodology

The effectiveness of any optimal design primarily relies its design variables and parameters [44, 45]. During optimization, design variables are adjusted to improve the design, while design parameters remain fixed and cannot be changed. The primary goal of optimization is to find the best values for the design variables to achieve the desired design. Design objectives are commonly represented by performance functions. These are accompanied by both equality and inequality constraints [45–49]. Mathematically, the optimization process can be represented as follows:

Minimize $\boldsymbol{f_n}(\mathbf{y})$

Subjected to $\boldsymbol{g_j}(\mathbf{y}) \leq \mathbf{0} \quad \forall_j \boldsymbol{\epsilon} \boldsymbol{J}$

$$\boldsymbol{x_i^L} \leq \boldsymbol{x_i} \leq \boldsymbol{x_i^U} \quad \forall_i \boldsymbol{\epsilon} \boldsymbol{K}$$

Where, $\boldsymbol{f_n}(\mathbf{y})$ is the objective function, $g_j(y)$ represents jth constraint, $\mathbf{y} = [\mathbf{x}, \mathbf{z}]$ is an n-dimensional vector that includes both the design variable vector ($\mathbf{x} = [x_1, x_1, \dots, x_K]^T$) and design parameter vectors ($z = [z_1, z_1, \dots, z_K]^T$), x_i^L and x_i^U represent the lower and upper bounds respectively of ith design variable. In single-objective optimization, only one objective function is considered. However, in multi-objective optimization, multiple objective functions can be used under the same set of constraints.

This objective function can be determined successfully by GEP using software GeneXproTools. The process begins with the random generation of chromosomes for the initial population using the software. Next, these chromosomes are evaluated, and the fitness of each individual is measured. Based on their fitness levels, individuals are selected for reproduction, during which mutations may occur, producing offspring with new traits. This cycle—comprising genome representation, selective pressure, and reproduction with mutation—repeats for each new generation. The process continues either for a set number of generations or until a desired solution is found. The detailed workflow is illustrated in Fig. 1.

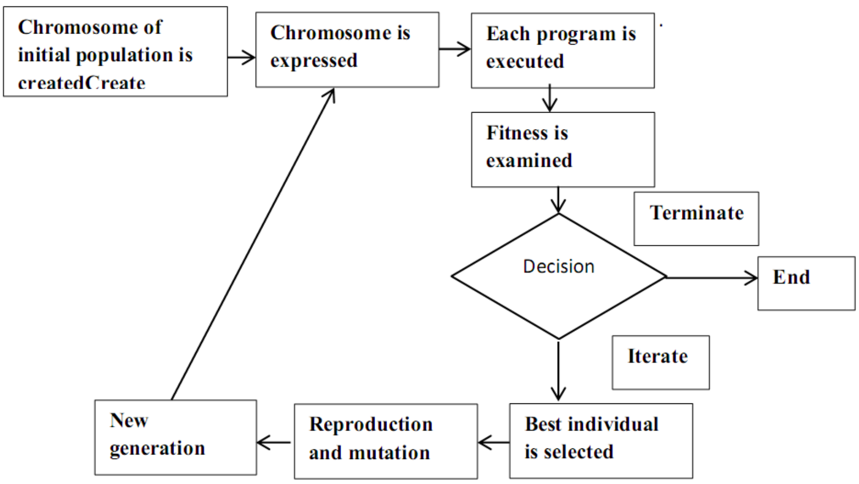


Fig.1 - The detailed procedure for GEP

3 Experimental Program

For developing the optimization procedure of concrete mixture design, extensive experimental program has been conducted. Arbitrarily chosen 62 concrete trial mixes have been carried out in this programme. The experimental work employed Portland Pozzolana Cement (PPC) in accordance with IS 1489 (Part 1):1991 [44]. Crushed stone from a nearby hill served as the coarse aggregate, while river sand sourced locally was used as the fine aggregate—both conforming to IS 383:1970 [45]. All mixes were prepared using potable water. No chemical admixtures were added during the course of the experiments. Total 62×3=186 number of cubes of dimension 150×150×150 mm were cast to determine the compressive strength of concrete. After 24 hours, the cubes have been demoulded and placed in a curing tank for 28 days under ambient temperature conditions. Subsequently, their compressive strength has been determined using a standard compression testing machine. The average strength of three cubes cast from the same concrete mix has been recorded as the representative compressive strength for that particular mix. The average 28-day compressive strength results for all 62 concrete mixtures, along with the corresponding mix proportions per 100 kg of each mixture, are presented in Table 1. It is to be mentioned that, a total of 62 concrete mixes were selected arbitrarily to ensure a reasonable spread of mix proportions within practical limits. Although the selection was not based on a systematic design of experiments, the chosen mixes collectively represent a diverse range of water–cement ratios, aggregate contents, and binder proportions commonly encountered in conventional concrete practice.

Table 1 Summary of measured compressive strength and corresponding the mixture proportions

Serial number	Cement (kg)	Sand (kg)	CA (kg)	Water (kg)	Slump (mm)	Strength (MPa)
1	18.06	21.96	52.22	7.76	0.00	38.67
2	21.04	20.85	48.64	9.47	155.00	43.70
3	18.85	21.80	50.87	8.48	40.00	47.01
4	17.18	23.01	51.21	8.60	135.00	45.59
5	17.63	21.85	53.48	7.04	0.00	57.38
6	18.70	19.86	52.84	8.60	20.00	46.70
7	14.66	21.92	56.09	7.33	10.00	29.90
8	14.65	23.46	54.56	7.33	20.00	29.15
9	18.07	21.55	52.06	8.31	40.00	33.69
10	20.58	20.49	49.46	9.47	20.00	35.72
11	16.56	22.80	53.20	7.45	20.00	20.00
12	18.78	22.15	51.69	7.38	30.00	38.33
13	20.87	21.48	50.13	7.53	40.00	32.00
14	15.70	23.17	54.06	7.07	0.00	30.45
15	18.06	21.96	52.22	7.76	0.00	36.15
16	19.55	21.37	50.83	8.25	20.00	50.00
17	13.93	24.52	54.58	6.97	15.00	25.33
18	15.43	23.61	53.55	7.41	8.00	26.67
19	16.73	23.02	52.22	8.02	30.00	28.00
20	15.12	21.17	56.90	6.80	5.00	28.77
21	17.38	20.08	55.06	7.47	10.00	36.29
22	19.43	19.12	53.49	7.96	28.00	36.68
23	13.63	22.36	57.21	6.81	10.00	28.00
24	15.42	21.39	55.80	7.40	0.00	33.72
25	16.46	20.96	54.69	7.90	75.00	29.87
26	14.09	23.71	55.16	7.04	29.00	31.33
27	15.42	23.11	53.75	7.71	9.00	30.07
28	17.40	22.32	51.58	8.70	36.00	28.86

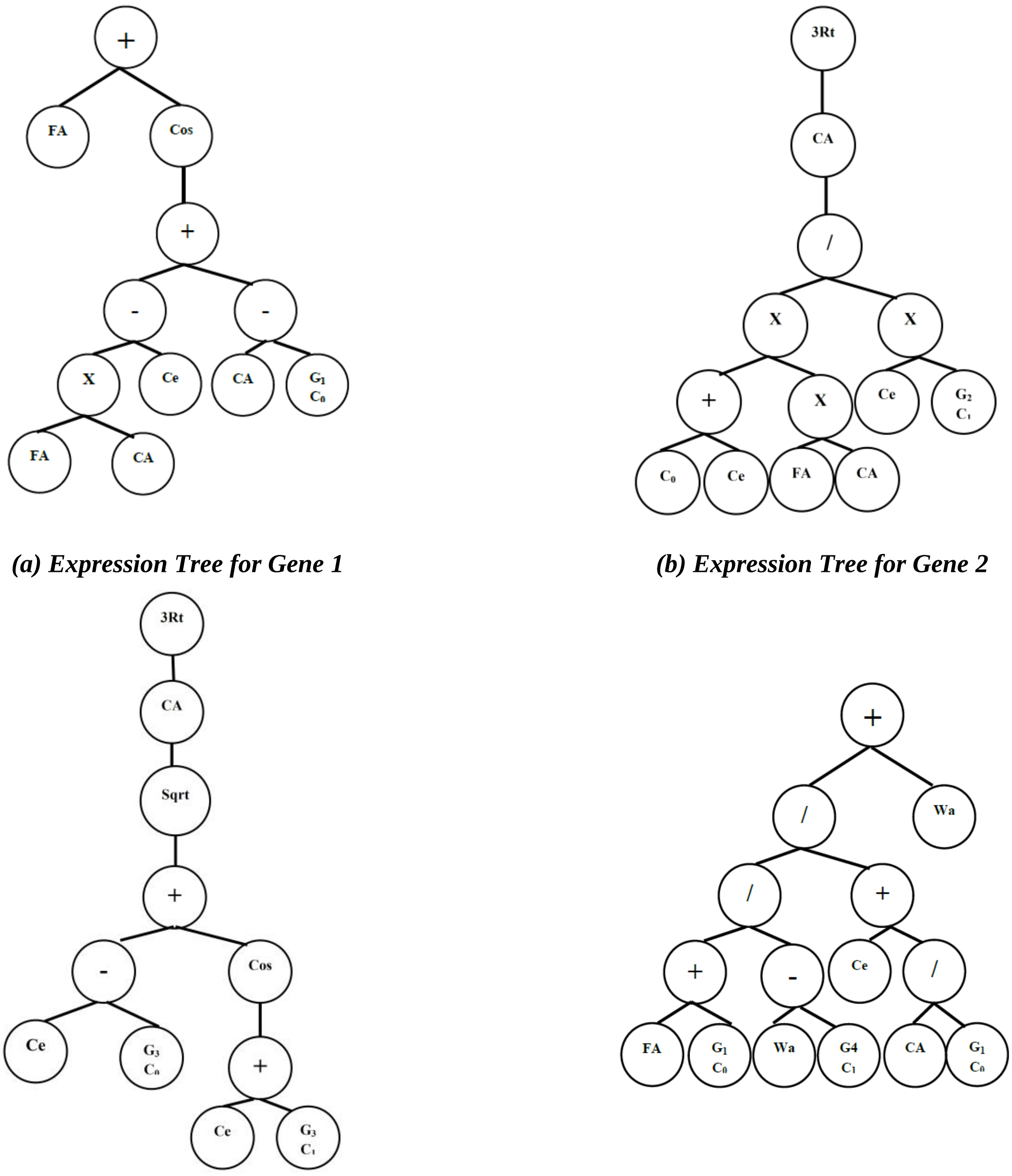
Serial number	Cement (kg)	Sand (kg)	CA (kg)	Water (kg)	Slump (mm)	Strength (MPa)
29	15.12	21.17	56.90	6.80	5.00	28.77
30	17.38	20.08	55.06	7.47	10.00	36.29
31	19.43	19.12	53.49	7.96	28.00	36.68
32	12.41	23.49	57.28	6.82	0.00	17.42
33	14.17	22.47	55.85	7.51	8.00	25.88
34	18.34	27.86	45.54	8.27	30.00	37.33
35	20.23	26.82	43.85	9.10	20.00	34.00
36	22.56	25.44	42.30	9.70	40.00	25.63
37	23.08	25.13	42.10	9.69	95.00	34.93
38	13.54	25.30	56.20	4.96	0.00	24.91
39	16.25	23.15	52.36	8.24	9.00	27.12
40	17.16	22.60	51.13	9.10	30.00	21.88
41	15.34	28.03	49.72	6.90	50.00	30.00
42	15.97	27.72	48.97	7.34	70.00	33.33
43	15.66	27.71	48.95	7.68	70.00	27.33
44	16.52	21.14	54.09	8.26	10.00	35.75
45	13.63	22.36	57.21	6.81	10.00	31.76
46	15.42	21.39	55.82	7.36	0.00	33.72
47	16.49	21.00	54.80	7.71	75.00	29.87
48	15.97	27.72	48.97	7.34	70.00	33.00
49	17.67	26.14	48.77	7.42	70.00	38.67
50	17.72	26.06	48.61	7.62	70.00	43.11
51	16.40	27.41	48.98	7.22	60.00	30.66
52	16.42	27.48	48.54	7.55	60.00	33.33
53	15.66	27.71	48.95	7.68	70.00	27.33
54	15.97	27.72	48.97	7.34	70.00	33.00
55	17.67	26.14	48.77	7.42	30.00	38.67
56	18.08	25.62	48.70	7.60	20.00	40.01
57	14.94	29.04	49.45	6.57	85.00	34.22
58	16.31	28.08	48.60	7.01	105.00	33.00
59	17.07	26.27	49.15	7.51	70.00	31.83
60	17.62	26.12	48.86	7.40	70.00	38.67
61	15.02	27.09	50.68	7.21	60.00	26.97
62	15.83	27.13	49.60	7.44	60.00	33.00

4 Optimization of Concrete mix design

The data presented in Table 1 have been utilized to generate basis functions using GEP, aimed at evaluating the influence of mixture proportions and subsequently deriving equations for compressive strength and slump as functions of cement, sand, coarse aggregate, and water. An arbitrarily selected 80% of the data was used for training, while the remaining 20% was used for testing. In this study, k-fold cross-validation was not employed due to the limited number of samples, although it is generally considered a more robust approach for preventing over-fitting.

In other studies the performance of the Gene Expression Programming (GEP) model [45–51] was compared with existing models such as Artificial Neural Network (ANN), Support Vector Machine (SVM), and Particle Swarm Optimization (PSO) etc. he GEP model exhibited satisfactory prediction results, comparable to those obtained from conventional machine learning techniques. Its major advantage lies in its ability to generate explicit mathematical equations, which can be easily utilized by other users without requiring retraining. Furthermore, the derived equations from GEP can serve as basis functions for optimization tasks, thereby enhancing its practical applicability and interpretability compared to the black-box nature of ANN, SVM, and PSO models.

This study used GeneXpro Tools 4.0 (www.genexprotools.soft112.com/) [52–54] to develop an objective function. The function predicts compressive strength based on Cement (Ce), Fine Aggregate (FA), Coarse Aggregate (CA), and Water (Wa). In this study, 50 chromosomes with four genes each have been utilized, using multiplication as the linking function. The optimum was reached at the 105411th generation. An R^2 value of 0.78 has been obtained. The model produced an R^2 of 0.78. The evolved genetic tree is illustrated in Fig. 2, with the resulting equation presented in Equation 1. This equation is very useful to predict compressive strength for a given amount of cement, fine aggregate, coarse aggregate and water. The actual vs. predicted value of 28 days compressive strength is presented in Fig. 3.



(a) Expression Tree for Gene 1

(b) Expression Tree for Gene 2

(c) Expression Tree for Gene 3

(d) Expression Tree for Gene 4

Fig. 2: Generated four genetic expression tree (after GeneXpro (www.genexprotools.soft112.com)/) combined with multiplication for the development of basis function of strength.

$$\left(\frac{1}{strength}\right)=\left(cos\left(\left(\left(Ce-\left(FA\times CA\right)\right)+\left(CA-G1C0\right)\right)\right)+FA\right)\times\left(\frac{CA^{\frac{1.0}{3.0}}}{\left(\left(Ce\times G2C1\right)-\left(G2C0+Ce\right)\right)\times\left(FA\times CA\right)}\right)\times$$
$$\times\left(\frac{CA^{\frac{1.0}{3.0}}}{sqrt\left(\left(cos\left(\left(G3C1+Ce\right)\right)+\left(Ce-G3C0\right)\right)\right)}\right)\times\left(\frac{\frac{\left(FA+G4C0\right)}{\left(Wa-G4C1\right)}}{\left(\frac{CA}{G4C0}\right)+Ce}+Wa\right) \tag{1}$$

Where:

G1C0 = -0.417908, G2C0 = -1.931427, G3C0 = -2.006286, G3C1 = -6.755158, G4C0 = -4.951355, G4C1 = 0.797516

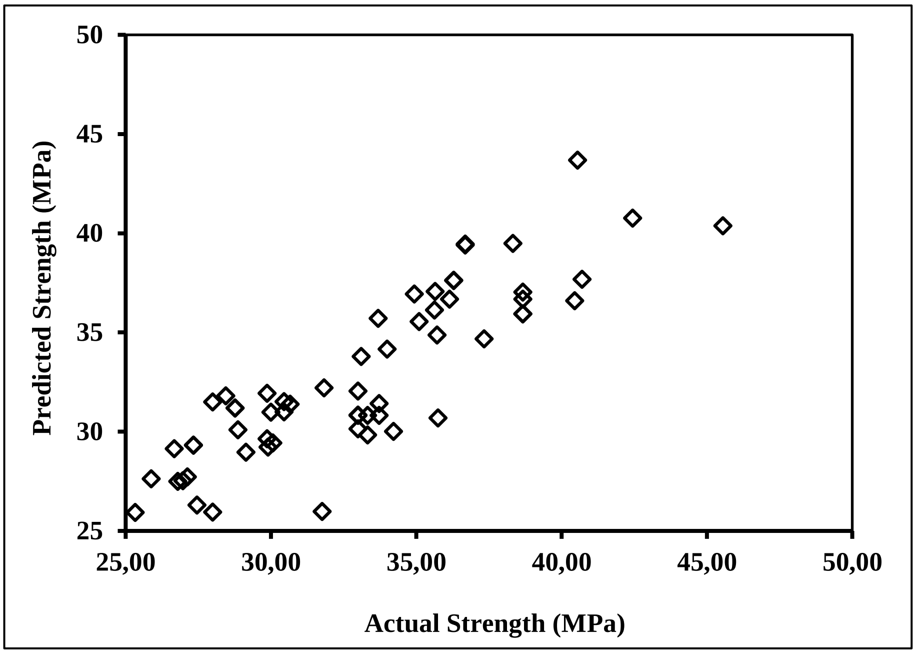


Fig. 3 - Actual vs. predicted 28 days compressive strength.

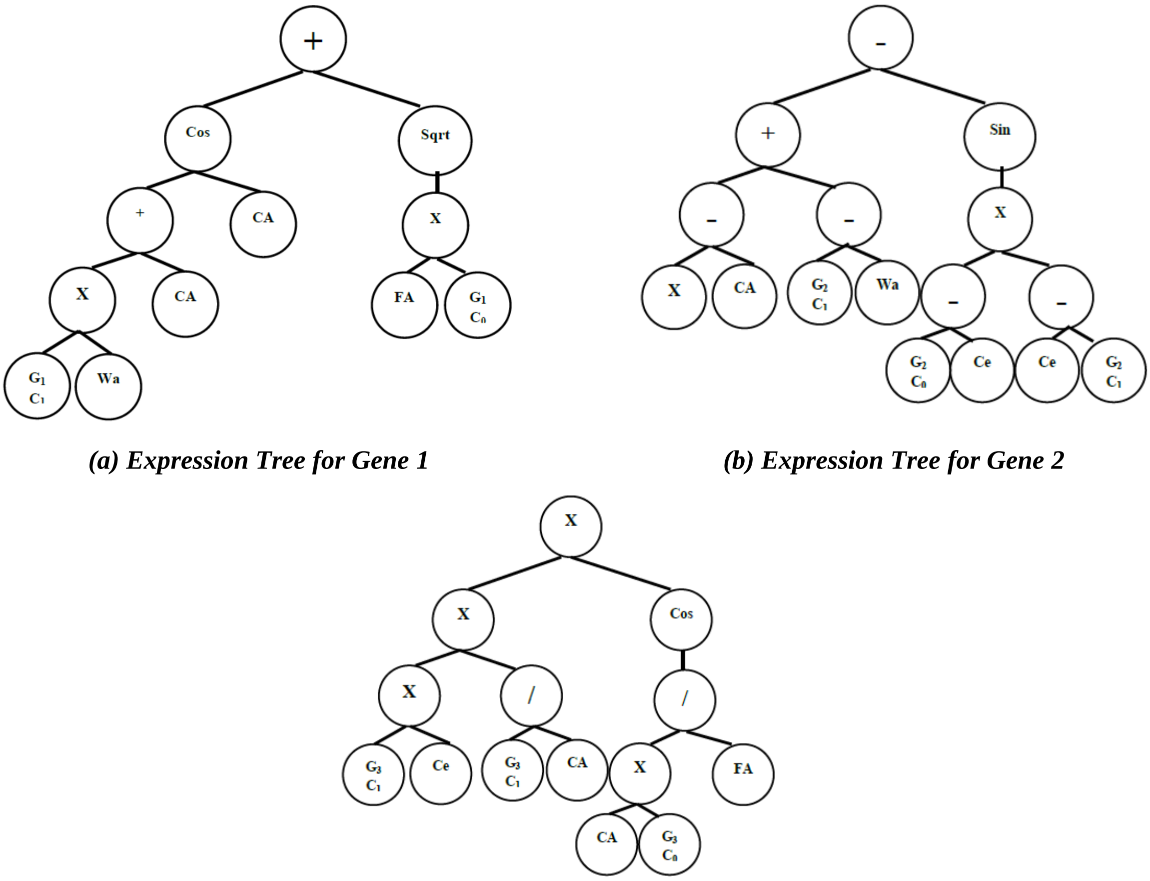
For obtaining another objective function, which estimates slump as a function of Ce, FA, CA and Wa the same software package has been used. Here the numbers of chromosomes are fifty numbers. Each of the chromosomes comprise three number genes. In the present procedure, linking function has been used as “Addition”. Equation 2 shows the developed equations. The optimum has been reached at 605411th generation. The genetic expression tree is expressed as Fig. 4. R^2 value obtained is 0.68. The actual vs. predicted slump is shown in Fig. 5.

$$\left(-slump\right)=\left(\begin{array}{l}\cos\left(\left(\left(G1C1\times Wa\right)+CA\right)^{3}\right)-\\ exp\left(sqrt\left(FA\times G1C0\right)\right)\end{array}\right)+\left(\begin{array}{l}\left(sin\left(G2C0-Ce\right)\times\left(Ce-G2C1\right)\right)-\\ \left(\left(Ce-CA\right)+\left(Ce-FA\right)\right)\end{array}\right)+$$
$$\left(cos\left(\left(CA\times G3C0\right)-FA\right)\times\left(\left(G3C1\times Ce\right)\times\left(\frac{G3C1}{CA}\right)\right)\right) \tag{2}$$

Where:

G1C0 = 0.769226, G1C1 = 8.956025, G2C0 = -3.461945, G3C0 = 1.017578, G3C1 = -7.566498

It is to be mentioned that the GEP-derived equations, although explicit, are inherently complex. In these expressions, G1, G2, and G3 represent the gene numbers, while C0, C1, etc., denote the constants associated with each respective gene (Fig. 2 and Fig. 3). For example, G2C1 refers to the constant C1 corresponding to the second gene.



(a) Expression Tree for Gene 1 *(b) Expression Tree for Gene 2*

(c) Expression Tree for Gene 3

Fig. 4 - Generated genetic algorithm tree (after GeneXpro (www.genexprotools.soft112.com)/) combined with addition for the development of basis function of slump.

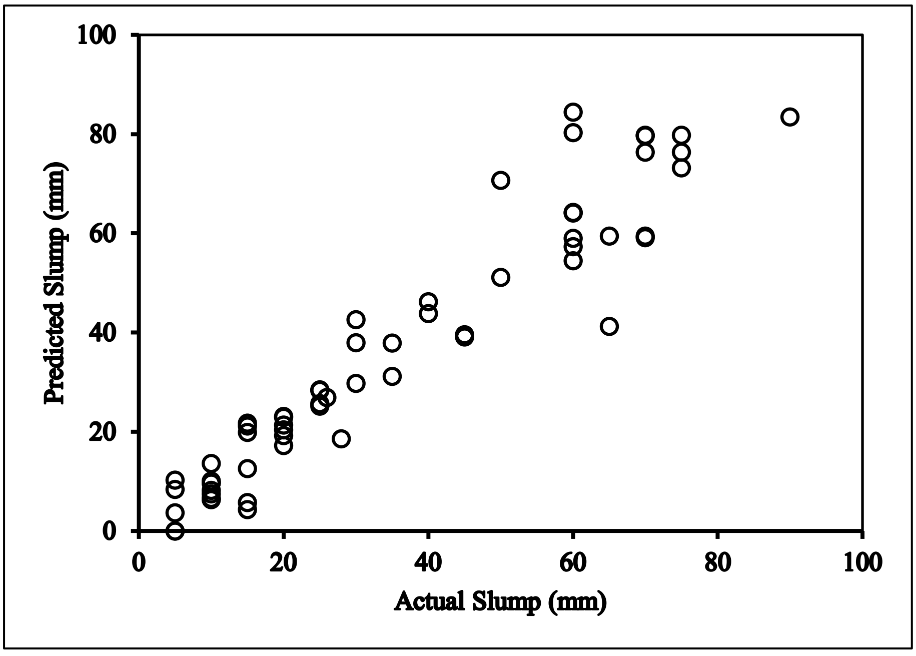


Fig. 5 - Actual vs. predicted slump.

Further, it is to be noted that, the modest R^2 values indicate that the developed models may not fully capture the variability present in the experimental data. This can be attributed to several factors, including the relatively small dataset size, inherent randomness in concrete mix preparation, and experimental uncertainties during material batching, mixing, and testing. Variations in aggregate moisture content, compaction quality, and curing conditions can also introduce noise into the data, thereby limiting the model's ability to achieve higher predictive accuracy.

An additional objective function, designed to estimate the mixture cost using material costs from the Indian market, has been developed and is shown in Equation 3. The unit costs per kilogram for cement, sand, coarse aggregate, and water have been taken as Rs 7, 0.415, 0.563, and 0.001, respectively.

$$cost = 7 * Ce + 0.415 * FA + 0.563 * CA + 0.001 * Wa \quad (3)$$

In the present study, to maximize concrete strength and slump while minimizing cost (i.e. to minimize $\left(\frac{1}{strength}\right)$, $(-slump) and\ (cost)$) equation 1-3 has been minimized the present study for the given constraints.

1) Available range constraint

   $Ce^{max} < Ce < Ce^{min}$

   $FA^{max} < FA < FA^{min}$

   $CA^{max} < CA < CA^{min}$

   $Wa^{max} < Wa < Wa^{min}$

   These lower and upper limit values have been determined by decreasing and increasing the minimum and maximum weights of cement, fine aggregate, coarse aggregate, and water by 10%, as shown in Table 1.

2) Ratio constraint

   According to Indian code the water cement ratio is minimum 0.35. Therefore the following constraint has been introduced

   $$\frac{Wa}{Ce} > 0.35$$

3) Absolute weight constraint

   All weights have been normalized based on a total mixture weight of 100 kg. Therefore, weight constraint is

   $Ce + FA + CA + Wa = 100$

5 Results

Using the experimental data, optimization by Genetic Algorithm (GA) has been carried out by MATLAB 2013. The mixture design has been assessed to achieve maximum strength and slump while minimizing cost, as summarized in Table 2. The results depicts that maximum compressive strength can be achieved as 51.3 N/mm2. It should be noted that, in that case, slump is 84.6mm. However, maximum slump can be obtained as 151.4 mm when the strength is 43.4mm. The optimized high, medium and low slump value corresponding to their compressive strength, cost and corresponding proportions are presented in Table 3. This result is very useful for obtaining desirable slump with lowest cost and highest compressive strength. Table 4 is presented by optimizing the slump with strength for M40 - M 15 grade of concrete. Percentage weight of cement, sand, coarse aggregate and water by optimizing slump and strength in a mix design are also presented in Fig 6. Table 4 and Fig. 6 clearly depict that if cement content increases, the strength increases. Further, strength of concrete has also been optimized with respect to the cost of different grade of concrete. The result is tabulated in Table 4. Moreover, the Table 4 and Fig. 7 also clearly depicts that when grade of concrete increases percentage of cement increases rapidly.

It is to be mentioned that the water–cement ratio plays a crucial role in determining both the strength and workability of concrete. As the water–cement ratio increases, workability improves; however, the compressive strength generally decreases due to higher porosity. Conversely, when the water–cement ratio falls below approximately 0.35, insufficient water is available for complete cement hydration, resulting in a honeycombed structure with unhydrated cement particles and reduced strength. Similarly, an increase in paste volume—i.e., higher cement content—initially enhances strength, but beyond an optimal limit, excessive cement can lead to higher shrinkage and cracking tendencies.

The model performance was evaluated using multiple statistical metrics for both compressive strength and slump prediction. For compressive strength, the R^2 value was found to be 0.78, indicating a good correlation between the actual and predicted values. The RMSE and MAE values were 2.52 and 2.31 respectively, showing that the prediction errors are small, while the MAPE value of 5.08% confirms that the model provides accurate and reliable predictions. In contrast, for slump prediction, the R^2 value was 0.68, which suggests a moderate level of accuracy. The RMSE and MAE values were 11.10 and 7.69 respectively, indicating higher deviations between actual and predicted values compared to compressive strength. The MAPE value could not be calculated for slump because several actual slump values are zero, making the percentage error undefined. Overall, the model performed better for predicting compressive strength than for slump, as reflected by its higher R^2 value and lower error metrics.

Table 2 Maximization of strength, slump and minimization cost

Strength (N/mm2)	**Slump (mm)**	**Cost (Rs)**	**Cement (kg)**	**Sand (kg)**	**Aggregate (kg)**	**Water (kg)**	
51.3	84.6	206.6	24.631	22.803	43.944	8.622	Max Strength
43.4	151.4	195.7	23.053	30.082	38.797	8.068	Maximum slump
15.1	63.7	120.5	11.447	30.505	49.294	8.754	Minimum cost

Table 3 Optimization of slump and strength

Grade of Concrete	**Target Strength (N/mm2)**	**Slump (mm)**	**Cement (kg)**	**Sand (kg)**	**Aggregate (kg)**	**Water (kg)**
M40	48.25	146.981	23.19	29.783	38.837	8.19
M35	43.25	78.841	18.758	27.638	46.12	7.483
M30	38.25	95.086	16.795	29.751	45.689	7.765
M25	31.6	94.972	14.855	31.063	46.545	7.537
M20	26.6	58.221	12.95	30.634	48.064	8.352
M15	20.775	63.002	11.685	30.469	49.131	8.715

Table 4 Optimization of cost and strength

Grade of Concrete	**Target Strength (N/mm2)**	**Cost (Rs)**	**Cement (kg)**	**Sand (kg)**	**Aggregate (kg)**	**Water (kg)**
M40	48.3	187.3	21.544	23.365	47.548	7.543
M35	43.3	167.6	18.489	26.404	48.251	6.856
M30	38.3	158.2	17.041	28.049	48.375	6.535
M25	31.6	144.7	14.967	30.082	48.713	6.238
M20	26.6	134.6	13.43	31.274	48.992	6.305
M15	20.8	127	12.331	31.357	49.184	7.128

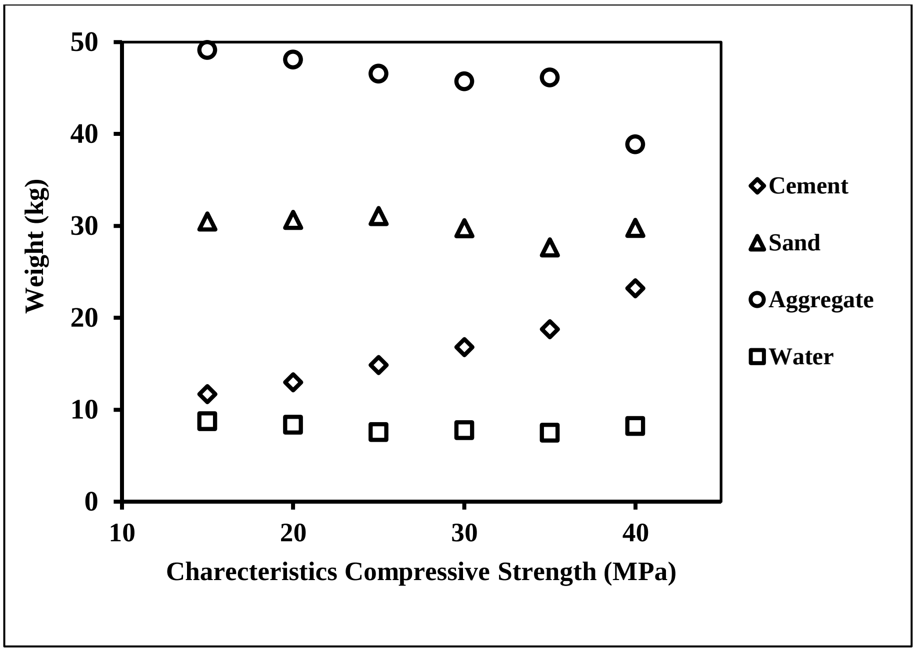


Fig. 6 - Percentage weight of cement, sand, coarse aggregate and water in a mix design by optimizing slump and strength

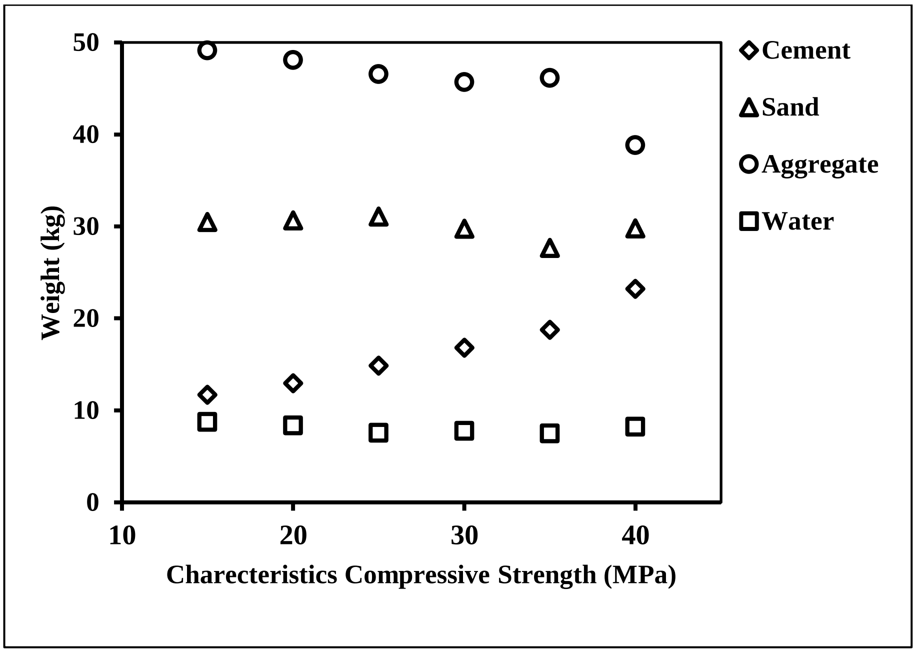


Fig. 7 - Percentage weight of cement, sand, coarse aggregate and water in a mix design by optimizing strength and cost

6 Conclusions

- The study developed a data-driven optimization framework combining Genetic Expression Programming (GEP) and Genetic Algorithm (GA) to determine optimal concrete mix proportions balancing strength, workability, and cost.
- Using experimental data from 62 concrete mixes, GEP-derived equations for compressive strength and slump were formulated and applied as basis functions for multi-objective optimization in MATLAB.

- The optimal mix achieved a maximum compressive strength of 51.3 N/mm² with a slump of 84.6 mm, while the maximum slump of 151.4 mm corresponded to 43.4 N/mm², clearly demonstrating the strength–workability trade-off.
- Optimized proportions for various slump ranges (high, medium, low) and concrete grades (M15–M40) were proposed, providing practically useful, performance-based mix designs adaptable to project requirements.
- The dataset, limited to 62 mixes using Portland Pozzolana Cement (PPC) and locally available aggregates, may restrict the generalizability of the results to other materials or regions. Durability parameters such as permeability, chloride resistance, and shrinkage were not considered, preventing long-term performance assessment. As the optimization outcomes are specific to the tested materials and conditions, validation with larger and more diverse datasets is recommended. Future research should also integrate environmental and sustainability indicators, incorporating durability, carbon footprint, and life-cycle cost into multi-objective optimization for more comprehensive mix design frameworks.
- Future studies should incorporate environmental and sustainability indicators, and explore multi-objective optimization including durability, carbon footprint, and life-cycle cost for more comprehensive mix design frameworks.
- The approach successfully illustrated that economical mixes can be designed without compromising performance, establishing a scientific alternative to traditional empirical mix design methods.
- The novelty of this study lies in integrating interpretable predictive modelling (GEP) with evolutionary optimization (GA) to minimize physical trials while enhancing decision-making flexibility in concrete design.

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