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PRACTICAL FORMULATION FOR ESTIMATING THE COMPRESSIVE STRENGTH OF SELF-COMPACTING FLY ASH CONCRETE USING GENE-EXPRESSION PROGRAMMING

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Abstract

This study aims to develop a gene expression programming (GEP)-based model for estimating the strength of self-compacting concrete (SCC) using fly ash (FA). The model considers the effects of six input variables, including the binder content, the FA proportion, the water/binder ratio, the fine aggregate content, the coarse aggregate content, and the superplasticizer dosage. The 28-day compressive strength of 114 concrete samples was used to generate the prediction model. The trial runs indicate that the GEP model with four genes and 120 chromosomes demonstrates strong performance, achieving a high coefficient of correlation and low errors (e.g., RMSE and MAE). The selected model is reliable, transparent, and easy to use in practice in designing the mix proportion for the SCC. The analysis of variable contributions demonstrates that the water/binder ratio and proportion of FA have the most significant influence on the strength of the SCC, while the fine aggregate content shows a comparatively minor effect. Thus, the strength of SCC could be increased significantly by reducing the water/binder ratio with a low proportion of FA content. The novel model from this study could help engineers in estimating the strength of SCC with reasonable FA content and choosing the appropriate mix proportion to achieve the design strength.

Keywords: self-compacting concrete; GEP model; FA content; water/binder ratio.

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1. Introduction

Self-compact concrete (SCC) is a type of concrete that is compacted by its own weight to produce strong concrete without the need for vibrating compaction [1]. The advantages of SCC include lower permeability of the concrete structure, shorter construction time, enhanced concrete quality, and reduced noise from vibration processes [1–3]. There are some factors that could affect the properties of SCC, such as binder content, proportions of coarse and fine aggregates, water/binder ratio, superplasticizer dosage, and the inclusion of supplementary admixtures [4, 5].

In the design and application of SCC, two fundamental properties must be simultaneously satisfied: fresh-state workability and hardened-state mechanical performance. While flowability, passing ability, and resistance to segregation govern the placement efficiency and homogeneity of SCC in complex formworks, the unconfined compressive strength (UCS) remains the most critical parameter for evaluating structural performance and reliability. UCS is a direct indicator of the load-bearing capacity of concrete, serving as the primary basis for mix proportioning, quality control, and compliance with structural design codes. In SCC incorporating supplementary cementitious materials such as fly ash, compressive strength not only reflects the degree of hydration and pozzolanic activity but also dictates the long-term durability and service life of the material. Therefore, reliable prediction

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of UCS is indispensable for optimizing mixture design, ensuring safety in structural applications, and promoting the sustainable use of industrial by-products.

Mix design for SCC has often been developed based on empirical rules and trial-and-error adjustments of paste, aggregates, and admixtures [6–9]. While straightforward, these methods assume constant material behavior and still require multiple trial batches to reach both slump-flow and strength. According to Wang, et al. [7], such "simple" formulas may lead to significant prediction errors when mixtures fall outside the calibration range. In general, empirical approaches do not adequately account for the interactions among water/binder ratio, binder type, and aggregate packing, all of which are critical factors influencing SCC performance [5, 10–12].

To improve prediction, many studies have turned to Artificial Intelligence (AI) models for SCC properties, especially the strength of mixes with fly ash or ground granulated blast furnace slag (GGBFS) [5, 10–12]. These methods reduce prediction errors and effectively handle complex nonlinear relationships [7, 10]. However, common "black-box" tools like Artificial Neural Networks (ANNs) and Adaptive Neuro-Fuzzy Inference System (ANFIS) remain difficult to interpret, and impractical for engineers since they rarely yield explicit or transferable formulations [13]. Thus, developing a practical, straightforward, and transparent AI approach is beneficial [5, 10–12].

Gene-Expression Programming (GEP) is an evolutionary algorithm and a branch of traditional genetic programming. In GEP, the solution is expressed as tree-like structures composed of input variables, constants, and functions [14, 15]. This "white-box" modeling approach can efficiently address scientific problems with some advantages, including generating accurate yet simple mathematical expressions or equivalent representations in various programming languages that are readily applicable in practice [15]. Thus, the GEP technique has been successfully applied to model, analyze, and simulate a wide range of civil engineering problems [12, 14, 16–18].

This paper aims to develop a simple, robust, and practical prediction model for estimating the compressive strength of SCC using the GEP technique. The novel model could be used conveniently by applying an accurate and transparent empirical equation or a Python implementation. In addition, this proposed model also provides engineers with a useful tool for selecting appropriate mix proportions and determining the optimal FA replacement ratio to achieve the desired design strength.

2. Data preparation

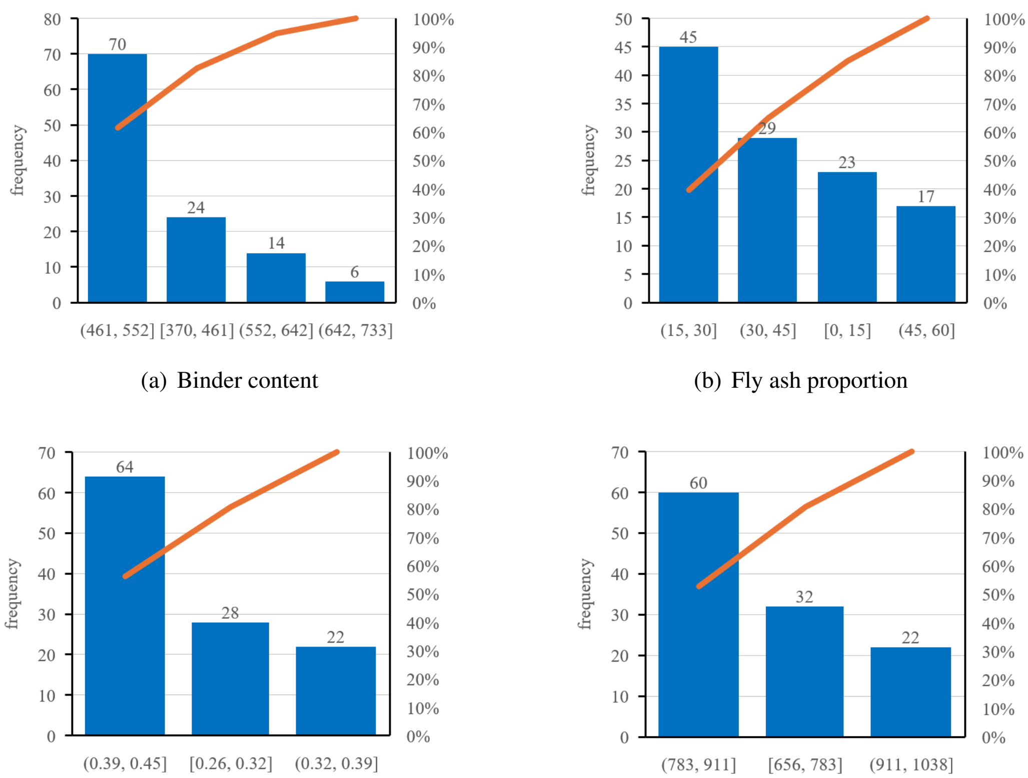
The dataset from the report of Belalia-Douma, et al. [10] was used in this study to develop a prediction model for estimating the compressive strength of SCC containing FA. The dataset includes 114 experimental test results, which were gathered from the research of Şahmaran, et al. [19], Muthupriya, et al. [20], Mahalingam, et al. [21], Güneyisi, et al. [22], Bingöl, et al. [23], Dhiyaneshwaran, et al. [24], Belalia-Douma, et al. [10], and among others. Six input variables, including total binder content, FA proportion, water/binder ratio, fine aggregate content, coarse aggregate content, and superplasticizer dosage, were investigated, and the output was the 28-day compressive strength of SCC concrete. Table 1 illustrates an example of the dataset.

In this study, Ordinary Portland Cement (OPC) was selected as the main binder, and part of it was replaced with Class F fly ash, a low-calcium by-product from coal-fired power plants [10]. The fine aggregate came from natural river sand, while the coarse aggregate was crushed granite, serving as the primary load-bearing skeleton of the concrete mix. To maintain workability at a low water/binder ratio and to allow the mixture to flow and compact under its own weight, a polycarboxylate ether (PCE)-based superplasticizer was added [10]. This type of high-range water reducer is particularly effective in self-compacting concrete, although its efficiency may vary depending on the specific mix proportions and material properties.

Table 1. Example of a part of the dataset

Total Binder (kg/m^3)	Fly ash (%)	Water/ binder	Fine aggregates (kg/m^3)	Coarse aggregates (kg/m^3)	Superplasticizer (kg/m^3)	Compressive strength (MPa)
701	37	0.27	774	723	8.10	69.5
733	37	0.26	748	698	8.40	68.2
400	30	0.39	946	900	1.40	45.0
370	36	0.43	960	900	1.85	46.0
400	45	0.39	916	900	1.40	45.0
400	45	0.39	916	900	1.40	47.0

Table 2 shows the structure of the data used in this study. It can be observed that a wide range of total binders was employed; however, the popular binder content (cement and fly ash) ranges between 400 to 600 kg/m^3. Besides, FA was used in combination with cement at different proportions from 0 to 60%, which indicates that a high amount of FA was used in the study. Moreover, the water/binder ratio was low and fluctuated from 0.26 to 0.48. For the aggregate, the proportion of fine aggregate exceeded that of coarse aggregate, and the amount of each type of aggregate was from 600 to 1000 kg/m^3. Typically, the superplasticizer was used with a dosage of 1 to 13 kg/m^3. Finally, the compressive strength of the SCC at 28 days ranged from 17 to 87 MPa. Fig. 1 illustrates the distribution of the input and output data, while Table 3 provides the statistical analysis of the dataset.

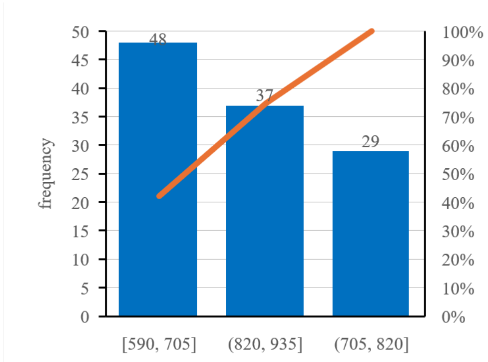


(a) Binder content

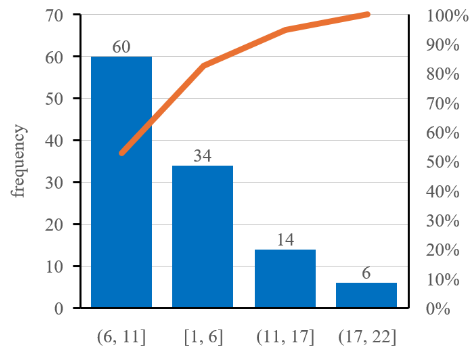
(b) Fly ash proportion

(c) Water/binder ratio

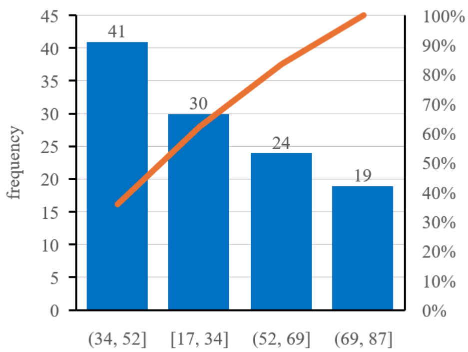
(d) Fine aggregate content



(e) Coarse aggregate content



(f) Superplasticizer content



(g) Compressive strength

Figure 1. Histogram of input and output variables

Table 2. Structure of the collected dataset

Parameters	Ranges	Number of data
Binder (d_0)	370-443(kg/m^3)	16
	443-515 (kg/m^3)	31
	515-588 (kg/m^3)	50
	588-660 (kg/m^3)	14
	660-733 (kg/m^3)	3
FA (d_1)	0-12 (%)	17
	12-24 (%)	26
	24-36 (%)	34
	36-48 (%)	20
	48-60 (%)	17
Water/binder (d_2)	0.26-0.30	19
	0.30-0.35	15
	0.35-0.39	28
	0.39-0.44	32
	0.44-0.48	20

Parameters	Ranges	Number of data
Fine aggregate (d_3)	656-732 (kg/m^3)	17
	732-809 (kg/m^3)	22
	809-885 (kg/m^3)	14
	885-962 (kg/m^3)	51
	962-1038 (kg/m^3)	10
Coarse aggregate (d_4)	590-659 (kg/m^3)	38
	659-728 (kg/m^3)	11
	728-797 (kg/m^3)	18
	797-866 (kg/m^3)	19
	866-935 (kg/m^3)	28
Superplasticizer (d_5)	1-5 (kg/m^3)	33
	5-9 (kg/m^3)	38
	9-13 (kg/m^3)	30
	13-18 (kg/m^3)	8
	18-22 (kg/m^3)	5
Compressive strength (Y)	17-31 MPa	21
	31-45 MPa	34
	45-59 MPa	27
	59-73 MPa	16
	73-87 MPa	16

Table 3. Statistical analysis of input and output data

Variable	d_0	d_1	d_2	d_3	d_4	d_5	Y
Max	733	60	0.45	1038	935	21.84	86.8
Min	370	0	0.26	656	590	0.74	17
Range	363	60	0.19	382	345	21.1	69.8
Mean	523.49	28.75	0.37	852.87	742.63	8.01	48.23
SD	71.22	16.59	0.06	89.93	121.81	4.67	17.56
CoV	5072.54	275.09	0.00	8087.67	14 837.49	21.80	308.20

Note SD: standard deviation, and CoV: coefficient of variation.

3. Modelling the compressive strength of SCC using FA

3.1. GEP-based model development

Gene-expression programming (GEP) is a computational modeling technique that applies Darwin's principle of natural selection to solve scientific problems [25]. In GEP, the initial population is generated randomly, consisting of function sets and terminal sets [14]. The main operations, such as selection, mutation, transposition, and crossover, will be applied to create a new population. The output of the program will be evaluated by a fitness function. The solution of the GEP model is expressed by expression trees (ETs), which include several sub-ETs [14].

Pham, et al. [14] demonstrated that the GEP technique is able to generate prediction models with high accuracy and low errors. In addition, this technique was also applied in the research of Murad, et al. [26], Raheel, et al. [27], Al-Bodour, et al. [28], Namazi, et al. [29], Amin, et al. [30], Tung, et al.

[31], Onyelowe, et al. [32], Kumar, et al. [33], and among others. Furthermore, the GEP technique could provide transparent and practical equations, which could be ready to use in practice [14, 15].

In this study, GeneXpro Tools 5.0 software was applied to develop a GEP-based model for estimating the compressive strength of SCC using FA. Six input variables were considered, including the binder content (d_0), the FA proportion (d_1), the water/binder ratio (d_2), the fine aggregate content (d_3), the coarse aggregate content (d_4), and the superplasticizer dosage (d_5). The output variable was defined as the 28-day compressive strength of SCC (Y). The optimal parameters were achieved through trial runs. As a result, the model was developed with four to seven genes (sub-ETs), 120 to 200 chromosomes, and a head size of 9 to 10. Besides, the addition function (+) was applied to link sub-ETs, and the fitness function was root mean square error (RMSE). Fourteen different mathematical operators were utilized, including addition (+), subtraction (-), power of two (x^2), multiplication ($*$), square root ($\sqrt{}$), natural logarithm (ln), exponential (exp), power (x^y), power of three (x^3), cube root ($\sqrt[3]{}$), inverse ($1/x$), addition with four inputs ($x_1 + x_2 + x_3 + x_4$), subtraction with four inputs ($x_1 - x_2 - x_3 - x_4$), and multiplication with four inputs ($x_1 * x_2 * x_3 * x_4$). In summary, the parameter setting for the GEP-based model can be found in Table 4.

Table 4. Parameter setting for the GEP modelling

Parameter	Model
Input variables	6
Output variables	1
Chromosomes	120-200
Genes	4-7
Head size	9-10
Tail size	28
Gene size	65
Linking function	Addition
Fitness function	RMSE

In addition, K-Fold Cross Validation was applied to divide 114 data into training, testing, and validation subsets (K = 20). As a result, 80 (70%) and 17 (15%) points of data were used for model development (training and testing subsets). The remaining 17 (15%) points of data were used for independent validation purposes.

3.2. GEP-based model result

Several models were run with different setting parameters. Table 5 illustrates that GEP 02 achieved the highest coefficient of correlation (R-value) in both the training and testing phases. In addition, considering the complexity of the model, GEP 02 used four genes with 120 chromosomes to generate the solution, which is much simpler than other models. As a result, model GEP 02 was selected as the proposed GEP-based model for estimating the strength of SCC.

Fig. 2 presents the Python code of the model generated by GeneXpro Tools, while Fig. 3 shows the tree expressions of the selected GEP-based model with 4 sub-ETs. The mathematical formula obtained from the GEP 02 is presented as Eq. (1). This formula is simple, transparent, and ready to use in practice.

$$\begin{aligned} Y = &\left(-36.90 + (2d_5 - 17.57)^{-2} + d_1 + d_4\right)^{\frac{1}{2}} + d_2^{-9/4} \cdot 6.52^{\frac{1}{8}d_2} \\ &+ \left(e^{d_5 d_2} + d_4 + d_1 - 13.76 d_3^{d_2} d_2^2 d_5\right)^{\frac{1}{2}} - 0.1 d_2 (3.67 + d_1)^{1/2} (d_3 + 2d_5 + d_0)^{1/2} \end{aligned} \tag{1}$$

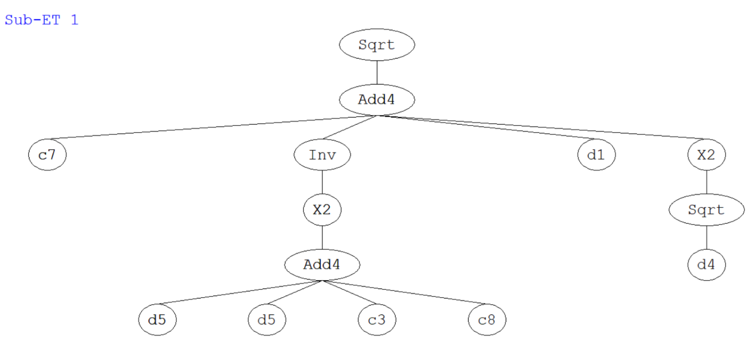
where Y is compressive strength of SCC (MPa); d_0 is total binder (kg/m^3); d_1 is FA proportion (%); d_2 is water/binder; d_3 is fine aggregate (kg/m^3); d_4 is coarse aggregate (kg/m^3); and d_5 is superplasticizer (kg/m^3).

Table 5. GEP model results with different setting parameters

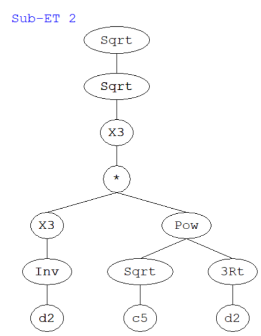
Model	Head size	Number of genes	Chromosomes	R-value	
				Training	Testing
GEP 01	10	6	180	0.913	0.903
GEP 02	9	4	120	0.920	0.939
GEP 03	10	7	200	0.912	0.908
GEP 04	10	4	150	0.910	0.881
GEP 05	9	5	200	0.915	0.918

```
from math import *

def gepModel(d):

    G1C7 = -36.9020087375773
    G1C3 = -8.99601892037385
    G1C8 = -8.565617778515
    G2C5 = 6.52284079200141
    G3C4 = -13.7560019998752
    G4C5 = -10.2319168431063
    G4C8 = 7.54635186350279
    G4C3 = 3.66730212583038

    y = 0.0

    y = sqrt((G1C7+(1.0/(pow((d[5]+d[5]+G1C3+G1C8),2.0)))+d[1]+pow(sqrt(d[4]),2.0)))
    y = y + sqrt(sqrt(pow((pow((1.0/(d[2])),3.0)*pow(sqrt(G2C5),gep3Rt(d[2]))),3.0)))
    y = y + sqrt((exp((d[5]*d[2]))+d[4]+d[1]+(pow(d[3],d[2])*(d[2]*d[2]*d[5]*G3C4))))
    y = y + (1.0/((G4C5*sqrt((1.0/(((G4C3+d[1])*pow(d[2],2.0)*(d[3]+d[5]+d[5]+d[0])*G4C8)))))))

    return y
```

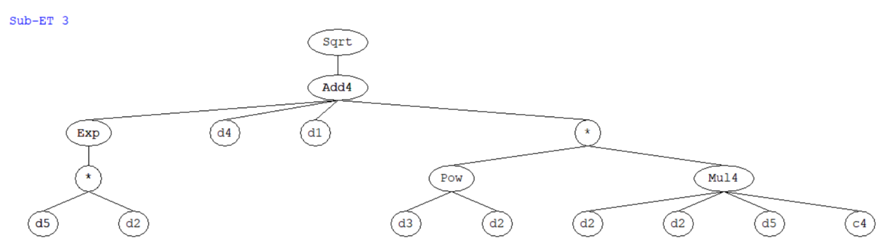
Figure 2. Python code of the proposed GEP model for estimating the compressive strength of SCC



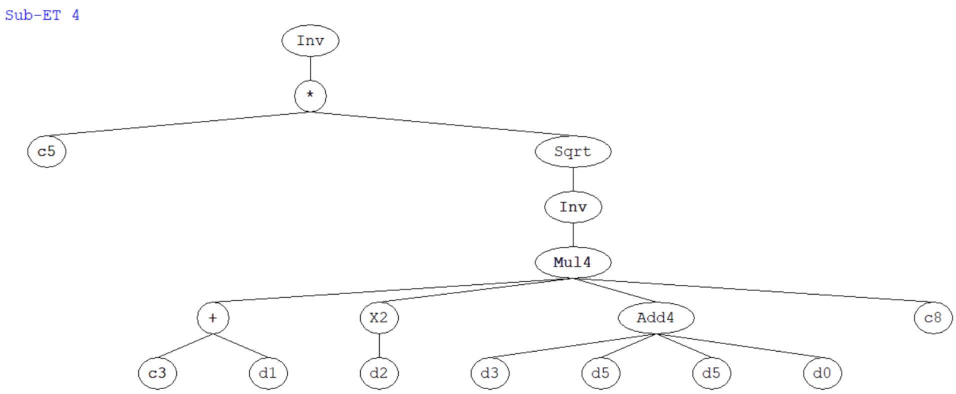
(a) Sub-ET 1



(b) Sub-ET 2



(c) Sub-ET 3



(d) Sub-ET 4

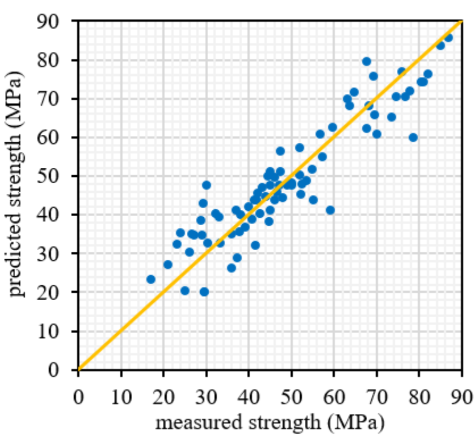
Figure 3. Tree expression of the proposed GEP model for estimating the compressive strength of SCC

3.3. *Model performance*

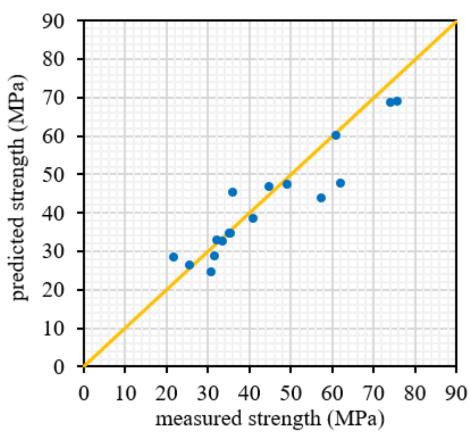
Fig. 4 illustrates the performance of the model during the training, testing, and validation phases. In addition, the coefficient of correlation (R), root mean square error (RMSE), and mean absolute error (MAE) were applied to evaluate the accuracy of the proposed model. Table 6 summarizes the statistical measures of the GEP-based model in training, testing, validation, and the entire data. It can be seen that the coefficient of correlation (R-value) of all phases is consistently high, ranging from 0.920 to 0.948. Furthermore, the RMSE and MAE errors of the model are acceptable and approximately 6.8 MPa and 5.5 MPa, respectively. These findings confirm that the proposed GEP-based model demonstrates strong predictive accuracy, reliability, and suitability for practical applications.

Table 6. Performance of the proposed GEP model

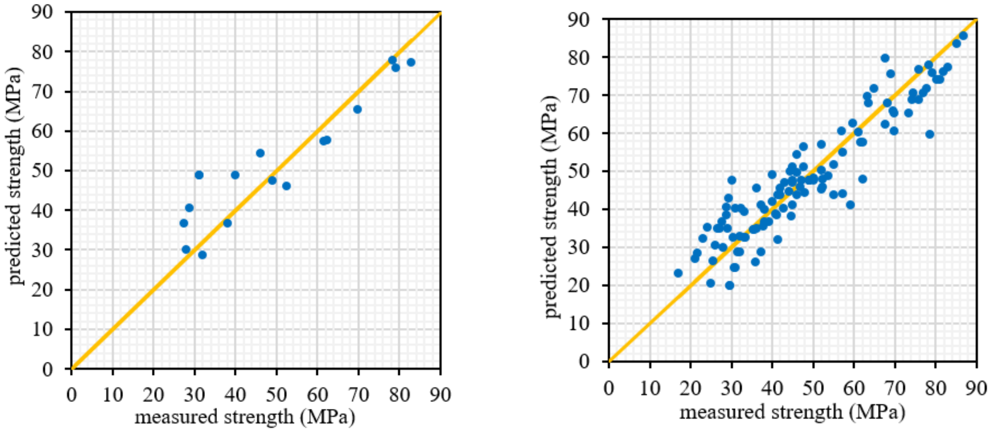
Phase	Training	Testing	Validation	All data
R-value	0.920	0.937	0.948	0.926
R^2	0.847	0.878	0.899	0.858
RMSE (MPa)	6.764	6.170	6.276	6.607
MAE (MPa)	5.475	4.419	5.333	5.297



(a) Training phase



(b) Testing phase



(c) Validation phase

(d) All data

Figure 4. Performance of the proposed GEP model

3.4. *Input significance*

The proposed GEP-based model identifies that the water/binder ratio has the greatest influence on the compressive strength of self-compacting fly ash concrete (as shown in Figs. 5 and 6). In this case, the examined variables were varied within the ranges specified in Table 3, while the remaining variables were kept constant at their mean values. Theoretically, the water/binder ratio is the dominant factor governing strength, as it directly controls the porosity of the hardened paste and the degree of cement hydration [34]. The fly ash (FA) proportion is the second most important parameter. At higher replacement levels, it appears that FA reduces early-age strength (it takes longer for pozzolanic reactions to occur than for cement hydration to happen) [35].

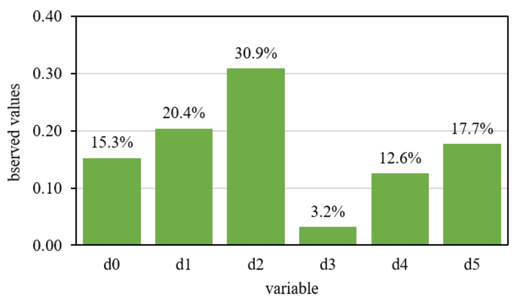
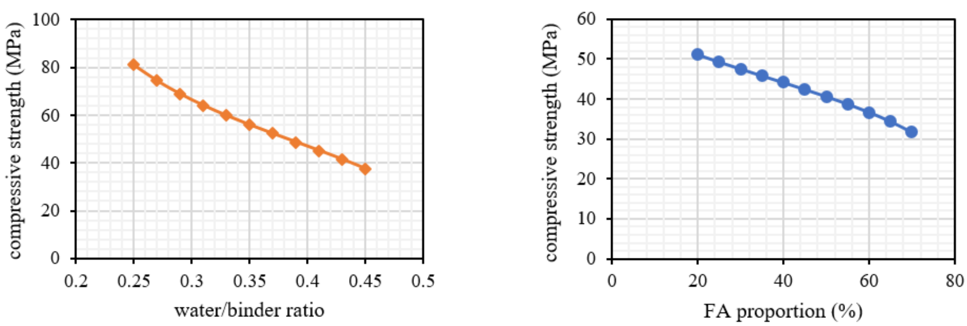


Figure 5. Variable importance



(a) Effect of water/binder ratio

(b) Effect of Fly ash proportion

Figure 6. Effects of key variables on the strength of SCC using FA

Other factors, including the total binder, the coarse aggregate, and the superplasticizer, all play a moderate role, but are still significant. The binder increases the material available for hydration, the coarse aggregates modify the mechanical skeleton and influence the quality of the interfacial transition zone, while the superplasticizer enhances compaction and workability at low water/binder ratios, thereby promoting strength development. By contrast, the fine aggregate content shows a minor impact on the predicted compressive strength. This finding is consistent with the EFNARC guidelines [36] which indicates that fine sand contributes primarily to the flowability and stability of self-compacting mixtures rather than to their strength.

4. Proposed mix proportions for SCC

The proposed GEP-based model, as expressed in Equation (1), can be applied to optimize the mix proportions of self-compacting concrete (SCC) incorporating fly ash (FA). For example, assuming a target compressive strength of 50 MPa, the total binder content, fine aggregate, coarse aggregate, and superplasticizer were kept constant at their mean values, as presented in Table 3.

Table 7 presents several mix designs with reasonable input proportions to achieve the target strength. The SCC could achieve the strength of 50 MPa when the mix proportion consists of 525 kg/m^3 binder, 25% FA, the water/binder ratio of 0.35, 850 kg/m^3 of fine aggregate, 743 kg/m^3 of coarse aggregate, and 8 kg/m^3 of superplasticizer. The suggested mix proportion shows good agreement with the experimental results reported by Liu [37].

Table 7. Optimization and selection of SCC mixes

Mix design	Binder (kg/m^3)	FA (%)	Water/ binder	Fine aggregate (kg/m^3)	Coarse aggregate (kg/m^3)	Superplasticizer (kg/m^3)	Estimation of Compressive strength (MPa)
Mix 1	525	20	0.35	850	743	8	52.56
Mix 2	525	25	0.35	850	743	8	51.03
Mix 3	525	30	0.35	850	743	8	49.65
Mix 4	525	35	0.35	850	743	8	48.38
Mix 5	525	40	0.35	850	743	8	47.21

5. Conclusions and recommendations

This study developed a novel model for estimating the strength of SCC using FA. The GEP technique was applied to generate a prediction model considering the effects of binder content, FA proportion, water/binder ratio, fine aggregate content, coarse aggregate content, and superplasticizer dosage. The output variable was the 28-day compressive strength of SCC. The selected model demonstrated strong performance, with a high coefficient of correlation (R = 0.926), and low prediction errors (RMSE = 6.5 MPa, and MAE = 5.0 MPa). The GEP-based model is robust, transparent, and practical for mix design applications. Besides, the analysis of variable contributions indicates that the water/binder ratio and FA content have a strong influence on the strength of SCC. A reduction in the water/binder ratio leads to a significant increase in strength, whereas an increase in the FA content results in a remarkable decrease in the strength of SCC. Furthermore, several mix proportions were recommended to achieve a target compressive strength. The practical model developed in this study offers engineers an effective tool for predicting the strength of SCC incorporating FA and for selecting appropriate mix proportions to satisfy specific design requirements.

This study focused primarily on predicting the compressive strength of self-compacting fly ash concrete. While strength is a critical criterion, in practice, workability can be equally important.

However, the database employed in this study did not provide sufficient detail to develop a meaningful predictive model for workability. Consequently, the scope of this research was limited to strength prediction. Future studies should address the influence of mix proportions on flow behavior and explore the feasibility of developing predictive models for workability.

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