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Innovation Approach for Modelling Compressive Strength of Fiber Reinforced Concrete Using Gene Expression Programming

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ABSTRACT: Recent advances in the field of construction materials have led to development of a variety of high performance concretes like steel fiber reinforced one (SFRC). It has been proved by many researches that the addition of steel fibers can improve various properties of concrete. The compressive strength of concrete (fc) is the main mechanical property in design of reinforced concrete structures. This paper deals with estimation of compressive strength of SFRC using gene expression programming (GEP) approach. In this regard, fine aggregate to cement ratio (FA/C), coarse aggregate to cement ratio (CA/C), water to cement ratio (W/C), fiber percentage (FP), superplastizer to cement percentage (SP/C) and fiber length to diameter ratio (L/D) were considered as the most important factors affecting the compressive strength of SFRC. To extract an accurate mathematical relationship from GEP approach, a comprehensive database was collected from literature with 115 mix design of SFRC. About 80% of the gathered database was used for training the model, while the rest was utilized for testing the model. The results indicate the acceptable performance of the developed GEP-based model, as the viewpoint of statistical parameters. The absolute fraction of variances for both training and testing datasets are more than 0.98 which approve a high correlation between the predicted values of the proposed model and the experimental results. At the end, a parametric study was carried out to investigate the efficiency of the developed model in predicting the tendency of compressive strength by changing the effective input variables.

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1. INTRODUCTION

Recent improvements in the field of concrete technology have led to the emergence of fiber reinforced concrete. It has been approved by many research studies that the addition of fibers can improve different mechanical properties of concrete such as tension, compression, shear, flexural strength, ductility, impact resistance and first cracking strength [1-5]. Fibers used in concrete are usually made of steel, glass, plastic or natural materials. Steel fiber reinforced concrete (SFRC) has been rapidly gaining in popularity as a result of its improved mechanical properties over plain concrete. As the viewpoint of concrete structure design, the concrete compressive strength is the most important mechanical property. Many factors can significantly influence the compressive strength including water-binder ratio (W/B), the size of the specimens, cement type, aggregate content, maximum aggregate size, aggregate type, curing type and period, type and amount of chemical admixtures and mineral additives, environmental factors and the specimen's testing method.

A genetic algorithm (GA), inspired by biological evolutionary process, is a global optimization technique which can be used to find a near optimal solution to a problem with many local solutions. The genetic algorithm, which was first formalized as an optimization method by Holland [6], is a meta-heuristic optimization technique for high dimensional and nonlinear problems. Genetic programming (GP) [7], as an extension of GA, is an artificial intelligence method which the solutions are computer programs (equations) with tree structures and can be used to predict the behavior of engineering systems. The developed equations can be easily manipulated in practical circumstances, noisy problems and stochastic search techniques based on the mechanism of natural selection and natural genetics. Gene expression programming (GEP) [8] is a recent extension of GP which evolves computer programs with different sizes and shapes encoded in linear chromosomes with a fixed length. There have been some scientific efforts in serving GEP to material and structural engineering tasks. The main advantage of the GEP-based approach is its capability in generating predictive equations without assuming the prior form of the mathematical relationship.

Nazari and Riahi (2012) used a gene expression programming model as a powerful tool for predicting the effect of nanoparticles on the compressive strength of the geo-polymers in the considered range [9]. Gandomi et al. (2013) developed a GEP based-model for estimating the shear strength of deep reinforced concrete beams and introduced

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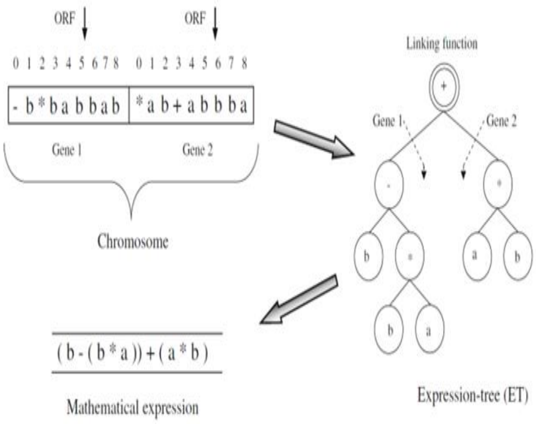

Fig. 1. Chromosome with two genes and its decoding [8]

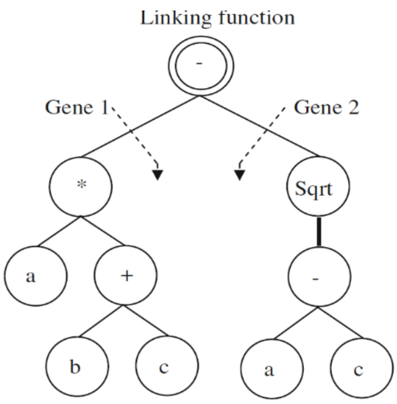

Fig. 2. Example of a GEP expression tree [8].

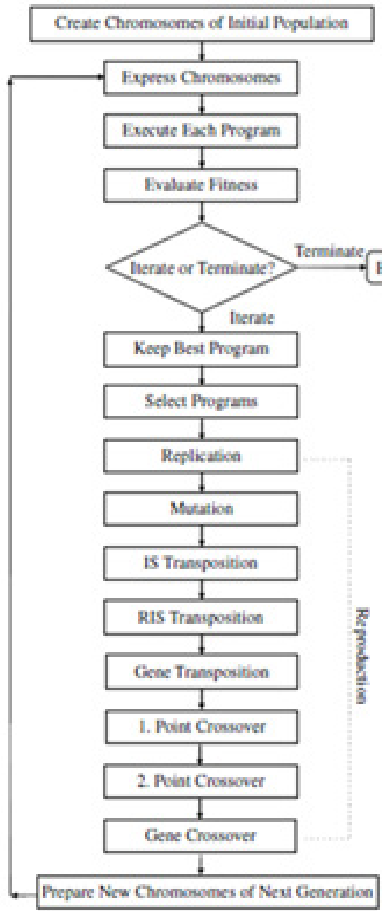

Fig. 3 .flowchart of the GEP [8].

a formula with better efficiency compared to other design codes [10]. Gandomi et al. (2009) proposed a new version of GP, called linear GP, for the formulation of the compressive strength of concrete cylinders confined by carbon fiber reinforced plastic and demonstrated the high performance of the developed model compared to available traditional equations [11]. Baykasoglu et al. (2008) studied the uniaxial compressive and tensile strengths of rocks that are widely used in the design stage of geotechnical structures using GP [12]. Kara (2012) studied the feasibility of using GEP to create an empirical model for the ultimate shear strength of SFRC beams without stirrups and approved the higher capability of the developed model in comparison to other available mathematical relationships [13]. González-Taboada et al. (2016) developed a GEP for estimation of structural recycled concretes using a comprehensive gathered database and proved their model was in good harmony with experimental results [14]. Jafari and Mahini (2017) developed a GEP model for design of lightweight concrete based on their experimental results and demonstrated its high accuracy [15].

Exact estimation of concrete compressive strength is one of the most important issues which civil engineers meet with it. This subject is so crucial in the case of high performance concrete such as SFRC. The main purpose of this paper is to utilize the GEP technique to build a predictive model for the 28 days' compressive strength (fc) of SFRC with cylindrical specimens of 150×300 mm. The proposed model is developed based on a comprehensive database obtained from the literature. A comparative study was conducted between the results obtained by the proposed model and experimental results found in the literature.

2. METHODOLOGY

Gene expression programming (GEP), like genetic algorithms (GAs) and genetic programming (GP), uses population of individuals, selects them according to their fitnesses and generate next populations based on genetic operators. The fundamental difference between the three algorithms returns to the nature of the individuals: In GAs the individuals are linear strings of fixed length (chromosomes), while in GP the individuals are nonlinear entities of different sizes and shapes (parse trees) and in GEP the individuals are encoded as linear strings of fixed length (the genome or chromosomes) which are afterwards expressed as nonlinear entities of different sizes and shapes (i.e. simple diagram representations or expression trees) [8].

In GEP, individuals are encoded as linear strings of fixed size (genome) such as shown in Fig. 1 which are expressed later as non-linear entities with different sizes and shapes. These entities are known as expression trees (ETs). Usually, individuals are composed of only one chromosome, which, in turn, can have one or more genes, divided into head

Table 1. Statistical values of input and output variables.

Variables	Minimum	Maximum	Mean	Standard deviation
FA/C	0.95	3.93	1.89	0.80
CA/C	0.32	4.00	2.39	0.61
W/C	0.33	0.70	0.45	0.11
FP	0.01	3.00	0.68	0.52
SP/C (%)	0.00	1.50	0.49	0.61
L/D	19.23	100.00	58.78	21.20
f'_c (MPa)	17.93	59.70	39.00	9.93

and tail parts. ETs are the expression of a chromosome and they undergo the selection procedure (usually fitness proportionate), guided by their fitness value, so as to generate new individuals. During reproduction, the chromosomes, rather than the respective ET, are modified by the genetic operators. The structural organization of the GEP genes is better understood in terms of open reading frames (ORFs). In biology, an ORF or the coding sequence of a gene begins with the "start" codon, continues with the amino acid codons, and ends at a termination codon. In GEP, there are two languages: the language of the genes and the language of the ETs. In GEP, thanks to the simple rules that determine the structure of ETs and their interactions, it is possible to immediately infer the phenotype given the sequence of a gene, and vice versa [16].

This intelligible bilingual notation is called the Karva language. For example, a mathematical expression [a×(b+c)]-[√(a-c)] can be represented by a two gene chromosome or an ET, as shown in Fig. 2. This Figure shows how two genes are encoded as a linear string and how it is expressed as an ET [16].

The fundamental steps of GEP are schematically represented in Fig. 3. The process begins with the random generation of the chromosomes of the initial population. Then, these chromosomes are expressed and the fitness of each individual is evaluated using a set of fitness cases (also called the selection environment). Using roulette wheel sampling, the individuals are then selected according to their fitnesses (their performances in that particular environment) to reproduce with modifications, leaving progeny with new traits. The modification in the population is introduced by conducting single or several genetic operators on selected chromosomes, which include crossover, mutation and rotation. These new individuals are, in turn, subjected to the same developmental process: the expression of the genomes, confrontation of the selection environment and reproduction with modification. The process is repeated for a certain number of generations or until a good solution has been found [16].

3. EXPERIMENTAL DATABASE

The database used for the development of the model included the experimental results of 115 samples collected from several experimental studies [1,2,17,18,3,19,4,20,21,5,22]. In order to provide an accurate assessment of the compressive strength of SFRC using GEP model, the selection of effective factors on the compressive strength is so important. The most significant variables representing the behaviour of the compressive strength of SFRC were detected based on a literature review [1,2,5]. Six effective variables including fine aggregate to cement ratio (FA/C), coarse aggregate to cement ratio (CA/C), water to cement ratio (W/C), fiber percentage (FP), superplastizer to cement percentage (SP/C) and fiber length to diameter ratio (L/D) were used as the input variables of the model, while the concrete compressive strength (f_c) was considered as model output. The variable selection will affect the model generalization capability of GEP. The statistical parameters of input and output variables are given in Table .1.

For the analysis, the available database was randomly divided into training and testing subsets. The training data were taken for genetic evolution, while the testing data were used to evaluate the generalization capability of the model (model selection). The models with the best performance on both of the training and testing datasets were finally selected as the outcomes of the GEP runs. Among 115 data, 89 data were randomly taken for the training process (genetic evolution) and 26 data were considered for the validation phase to evaluate the performance of the developed model for unknown data.

4. MODEL DEVELOPMENT USING GEP

In this study, the goal of GEP is to find a high accurate formula for estimating the compressive strength of SFRC. This function can be expressed as follows:

$$f'_c = f\,(FA/C,\ CA/C,\ W/C,\ FP,\ SP/C,\ L/D)$$

There are several adjustment parameters which have to be set before implementation of GEP. In this regard, several runs have to be carried out to come up with a parameterization of the GEP to provide enough robustness and generalization to solve the problem. The number of programs in the population that the GEP will evolve is set by the population size (number of chromosomes). A run will take longer with a larger population size. The proper number of the population depends on the number of possible solutions and the complexity of the problem. Three levels were set for the population size (50, 150, and 300). The chromosome architectures of the models evolved by GEP include head size and the number of genes. The head size determines the complexity of each term in the evolved model. The number of terms in the model is determined by the number of genes per chromosome. Each gene codes for a different sub-expression tree or sub-ET. Three optimal levels were considered for the head size (3, 5, and 8) and the number of genes (1, 2, and 3). For the number of genes greater than one, the addition linking function was used to link the mathematical terms encoded in each gene. There are three levels considered for the population size parameter × three levels considered for the head size parameter × three levels considered for the number of genes equal to 27 different combinations of the parameters. Even if all of the previous parameter settings and the architecture are kept constant, the outcomes of the GEP might be different. This leads to extra difficulties in the selection of the optimal GEP model and parameter settings. To overcome this difficulty, on the basis of a trial and error study, as well as from recommendations by other researchers [31], all of these parameter combinations were tested and ten replications for each combination were carried out. Therefore, the overall number of GEP runs was equal to 27× 10 = 270. All of these combinations were tested to extract the best model. After 5,000 generations considered herein, a mass extinction or a neutral gene was automatically added to the model. In this study, basic arithmetic operators and mathematical functions were utilized to obtain the optimum GEP model. The mean absolute error function was used to calculate the overall fitness of the evolved programs. The program was run until there was no longer any significant improvement in the performance of the models. The GEP algorithm was implemented using Gene Xpro Tools [23].

5. RESULTS AND DISCUSSION

After running different GEP models, the best model was chosen on the basis of a multi objective strategy as below:

i. The simplicity of the model, although this is not a predominant factor.

ii. The best performance of the model for training dataset.

iii. The best performance of the model for testing data.

The first objective was controlled by the user through the parameter settings (e.g., the number of genes or head size which determines the upper limit for the size of the programs encoded in the gene). To examine how close, the predicted values were to the compressive strength steel fiber concrete, for indices, mean absolute error (MAE), mean absolute percentage error (MAPE), root mean square error (RMSE), and absolute fraction of variance (R2) were employed to evaluate the performance of models. These norms are formulated according to the following equations:

$$RMSE=\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(O_i-T_i\right)^2}$$

$$MAE=\frac{1}{n}\sum_{i=1}^{n}abs\left(O_i-T_i\right)$$

$$R^2=1-\frac{\sum_{i=1}^{n}(\mathrm{O}_i-\mathrm{T}_i)^2}{\sum_{i=1}^{n}O_i^2}$$

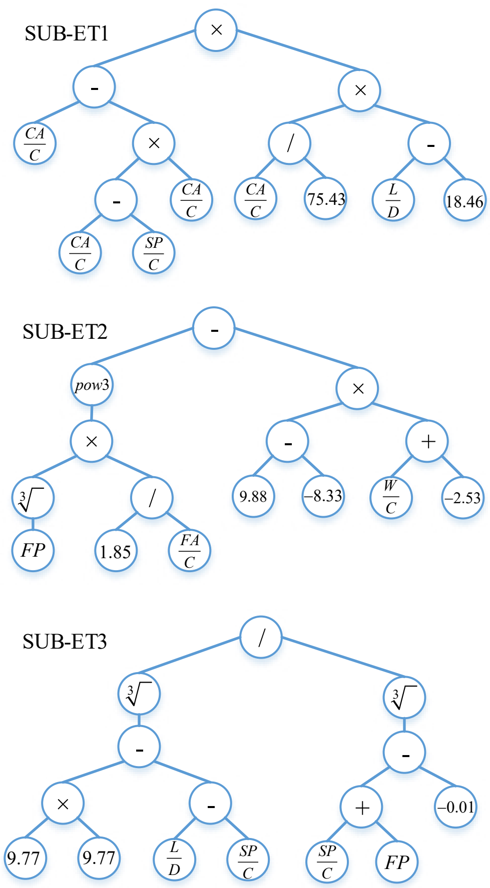

Fig. 4 .Expression tree for the best formula of compressive strength of SFRC.

$$MAPE=\frac{1}{n}\sum_{i=1}^{n}\frac{O_i-T_i}{T_i}\times 100$$

where O_i, T_i and n are the model output, experimental results of *i*th data and the number of data, respectively.

The best formula obtained by the GEP is equal to the following equation. The corresponding ETs for the best results are depicted in Fig. 4

$$ET=SUB-ET1+SUB-ET2+SUB-ST3$$

$$SUB-ET1=\left[\frac{CA}{C}-\left(\frac{CA}{C}-\frac{SP}{C}\right)\frac{CA}{C}\right]\left[\frac{1}{75.43}\frac{CA}{C}\left(\frac{L}{D}-18.46\right)\right]$$

$$SUB-ET2=\left[\sqrt[3]{FP}\,\frac{1.85}{FA/C}\right]^3-18.21\left(\frac{W}{C}-2.53\right)$$

$$SUB-ET3=\sqrt[3]{\frac{95.50+\frac{SP}{C}-\frac{L}{D}}{FP+\frac{SP}{C}+0.01}}$$

The statistical parameters of the developed GEP based model for training, testing and all data are given in Table 2. As you can see in this Table, the mean percentage error for

Table 2. Statistical parameters of the developed model.

	RMSE (MPa)	MAE (MPa)	MAPE (%)	R^2
Training data	5.26	3.75	10.73	0.98
Testing data	4.90	3.73	11.65	0.99
All data	5.18	3.75	10.96	0.98

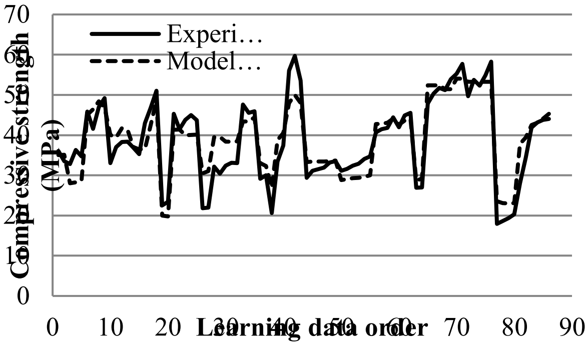

Fig. 5 .Comparison of experimental results with the predicted outputs for training dataset.

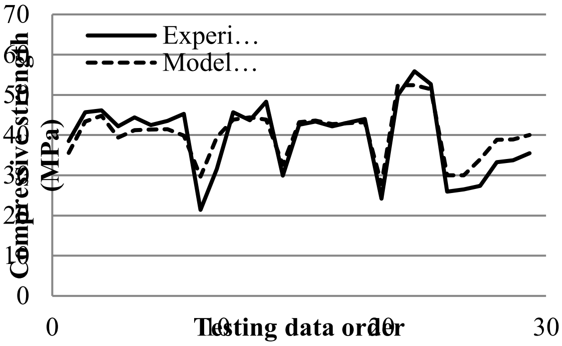

Fig. 6 .Comparison of experimental results with the predicted outputs for testing dataset.

training and testing data are 10.73% and 11.65%, respectively. Moreover, The R^2 values for both datasets are greater than 0.98 which indicate a high correlation between the predicted values of the developed model and experimental results.

The comparisons between the experimental results and the prediction outputs of the developed GEP model for training and testing datasets are illustrated in Figs. 5, and 6, respectively. As depicted in these Figures, there is a good harmony between the predicted and real values for both datasets.

Moreover, for further verification of the GEP-based prediction model, a parametric analysis was performed to investigate the response of the predicted compressive strength of the GEP model with change of predictor variables. The robustness of a design equation is determined by examining how well the predicted target values agree with the underlying physical behavior of the investigated system. For this purpose, the trend of compressive strength with changing one input variable is monitored, when the values of all other variables are kept in their mean values. Figure Fig. 7 presents the tendency of the ultimate load strength predictions to the variations of

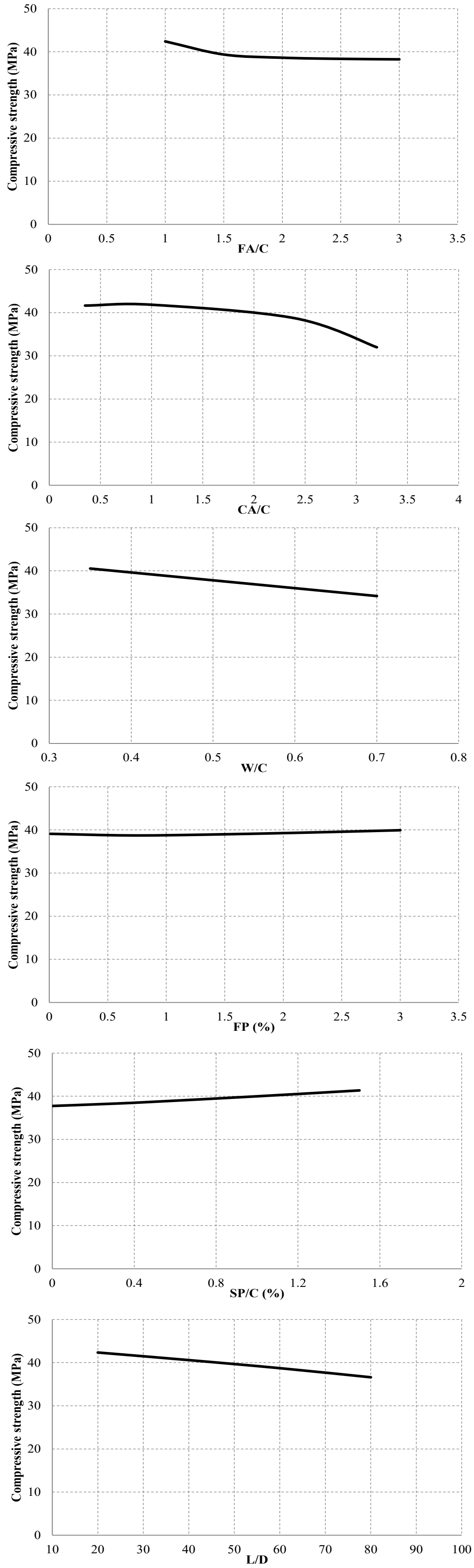

Fig. 7 .Ultimate load strength parametric analysis in the GEP-based model.

the effective input variables. As depicted in this Figure, the coarse aggregate to cement and water to cement ratios and also fiber length to diameter ratio have the most important effects on the compressive strength of SFRC. When the CA/C increases, the compressive strength of SFRC decreases because the amount of cement in the concrete mixture is reduced. With increasing the L/D of fiber, the compressive strength diminishes. It can be related to the inadequate compaction of concrete mixture for higher L/D ratios. Lower W/C ratio causes higher compressive strength because of the lower porosity of concrete and better interfacial transition zone condition. It can be concluded that the developed GEP model can correctly predict the trend of compressive strength with changing the input variables. What is so interesting here is that the amount of steel fiber in the mix design of SFRC has relatively no effect on the compressive strength.

6. CONCLUSION

In this study, a sub-branch of genetic programming, called gene expression programming (GEP), was utilized to formulate the compressive strength of steel fiber reinforced concrete. In order to achieve the best mathematical equation, different architectures of GEP were considered. The results of this study are as follows:

- The proposed model is mathematically so simple which can be used by civil engineers and can give a good estimation of compressive strength of SFRC for further experimental work.
- The mean absolute percentage error of the proposed model is about 11% for all data in the gathered database.
- The developed model can predict the compressive strength of SFRC mean absolute error of 3.75 MPa.
- The amount of steel fiber in the mix design of SFRC has the least effect on the compressive strength compared to other important variables.
- Water to cement and coarse aggregate to cement ratios have the most important effects on the compressive strength of SFRC in the proposed GEP based model.
- The developed GEP model has the ability to predict the trend of compressive strength with changing the input variables.

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