Computers and Concrete, *Vol. 17, No. 4 (2016) 489-498*
DOI: http://dx.doi.org/10.12989/cac.2016.17.4.489

Empirical modeling of flexural and splitting tensile strengths of concrete containing fly ash by GEP

Mustafa Sarıdemir*

Department of Civil Engineering, Niğde University, 51240 Niğde, Turkey

(Received January 12, 2015, Revised December 18, 2015, Accepted January 25, 2016)

Abstract. In this paper, the flexural strength (f_{fs}) and splitting tensile strength (f_{sts}) of concrete containing different proportions of fly ash have been modeled by using gene expression programming (GEP). Two GEP models called GEP-I and GEP-II are constituted to predict the f_{fs} and f_{sts} values, respectively. In these models, the age of specimen, cement, water, sand, aggregate, superplasticizer and fly ash are used as independent input parameters. GEP-I model is constructed by 292 experimental data and trisected into 170, 86 and 36 data for training, testing and validating sets, respectively. Similarly, GEP-II model is constructed by 278 experimental data and trisected into 142, 70 and 66 data for training, testing and validating sets, respectively. The experimental data used in the validating set of these models are independent from the training and testing sets. The results of the statistical parameters obtained from the models indicate that the proposed empirical models have good prediction and generalization capability.

Keywords: flexural strength; splitting tensile strength; fly ash; genetic programming

1. Introduction

Concrete has become the most preferred building material in the rapidly developing and industrializing world. Fly ash (FA), which is a by-product of thermal power plants burning coal, is the material that contributes the durability and service life of concrete when used together with Portland or blended cement. Besides, the use of FA is both economical and changes the properties of concrete, improving workability, heat of hydration, segregation, strength, sweating, shrinkage and creep (Haque *et al.* 1984, Atiş 2003). Moreover, the storage and disposal problem of FA that is an industrial waste or by-product, is also eliminated by the use of FA instead of cement in concrete; else, FA has to be got rid of in landfills at a considerable cost (Atiş 2005).

The flexural strength (f_{fs}) and splitting tensile strength (f_{sts}) are the fundamental and important properties of concrete containing FA. These properties may be important in structural design of some specific applications like road, pavement and airport runway slabs. These properties are also usually determined by the experimental studies. These experimental studies can take a lot of time and are not very economical. Therefore, various artificial intelligent methods (neural networks, fuzzy logic, GEP, etc.) are used to determine these properties. The f_{fs} and f_{sts} values of concrete

*Corresponding author, Ph.D., E-mail: msdemir@nigde.edu.tr

http://www.techno-press.org/?journal=cac&subpage=8 ISSN: 1598-8198 (Print), 1598-818X (Online)

containing FA can be predicted in a very short time thanks to models developed on the basis of experimental data in the aforementioned methods. Therefore, artificial neural networks, fuzzy logic and GEP methods can be used to contribute experimental studies.

The purpose of this study is to predict the FA effect on the f_{fs} and f_{sts} values of concrete by the models built in the GEP, which is a more advanced version of genetic programming method. Therefore, two empirical models named as GEP-I and GEP-II are developed to predict the f_{fs} and f_{sts} values of concrete containing different proportions of FA. In the GEP-I model, 292 experimental data, belong to 54 different mixtures of concrete containing FA used for training, testing and validating sets in GEP, were collected from the available papers Atiş 2005, Siddique 2003 and 2004, Sekhar and Rao 2008, Jerath and Hanson 2007 and Kumar *et al.* 2007 to predict the f_{fs} values. Similarly, in the GEP-II model, 278 experimental data, belong to 111 different mixtures of concrete containing FA used for training, testing and validating sets in GEP, were collected from the available papers (Atiş 2005, Siddique 2003, 2004 and 2011, Sekhar and Rao 2008, Lam *et al.* 1998, Mohammed and Fang 2011, Haque and Kayalı, 1998, Bharatkumar *et al.* 2005, Kim *et al.* 1998, Mittal *et al.* 2006, Sukumar *et al.* 2008, Jau *et al.* 2004 and Yaprak *et al.* 2004) to predict the f_{sts} values. In the training, testing and validating sets of these models; age of specimen (AS), cement (C), water (W), sand (S), aggregate (A), superplasticizer (SP) and fly ash (FA) are used as input variables, whereas the f_{fs} and f_{sts} values in the training set are used as output. While the GEP-I and GEP-II models were trained with 170 and 142 of experimental data, it was also tested with 86 and 70 of them which were not used in the training phase, respectively. After the GEP-I and GEP-II models were trained, the equations depending on the input variables were obtained. These equations were verified with using the experimental data independent from the training and testing sets. The equation obtained from GEP-I model was validated with using the 36 experimental data obtained from the available paper Siddique 2003 independent from the training and testing sets. Similarly, the equation obtained from GEP-II model was verified with using the 66 experimental data obtained from the available papers Sekhar and Rao 2008 and Lam *et al.* 1998 independent from the training and testing sets. As the results of statistical parameters, it was observed that the f_{fs} and f_{sts} values evaluated from the training, testing and validating sets in the empirical models are close to experimental results.

2. Gene expression programming

Gene expression programming (GEP) is an expansion to genetic programming, which also develops computer programs of various forms and sizes; however, the developed programs are encrypted in a linear chromosome of constant length (Ferreira 2001). The chromosomes in the GEP are made up of multiple genes, every one gene encrypting a smaller sub-program. The chromosomes with length 27 are made up of three genes as shown in Fig. 1. In addition, three open reading frames (ORFs) and ORF codes for a sub-expression tree (Sub-ET) are shown in Fig. 1. Moreover, the functional and constructional organization of the linear chromosomes enables the free operation of significant genetic operators like mutation, crossover, recombination and transposition. First, the strength of the GEP is excessively simplicity in creating of genetic variety as the operators' study at the chromosome level. Second, the strength of GEP is made up of its matchless, multi-genic nature, which enables the development of more complex programs comprised of various sub-programs (Ferreira 2001, 2002 and 2003). There are two languages in the GEP called as the language of expression trees (ETs) and genes. In the GEP, in view of the

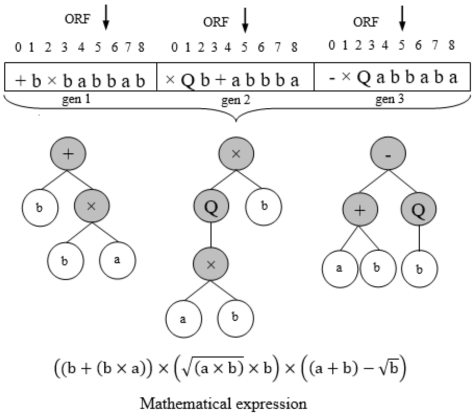


Fig. 1 Mathematical expression of GEP genes as sub-expression trees

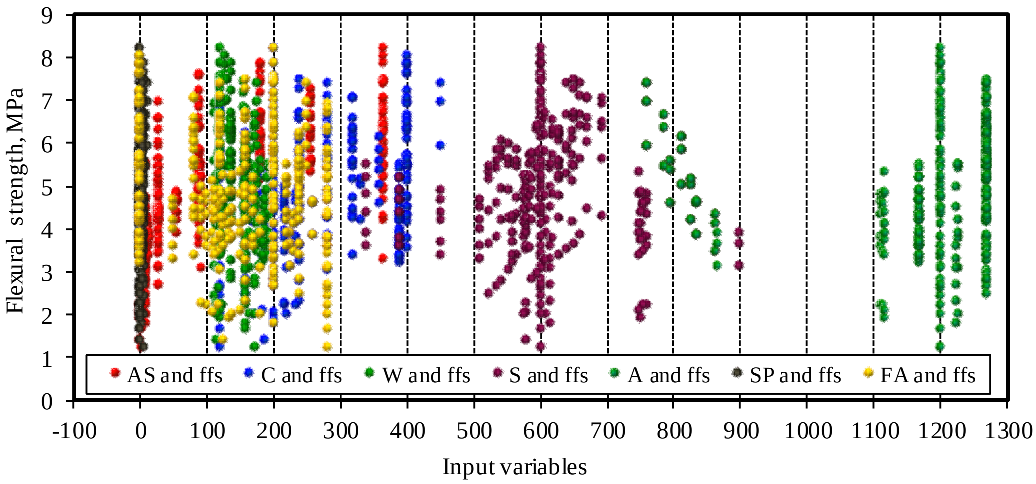


Fig. 2 Distribution of input variables and f_{fs} for GEP-I model

simple rules, which define the construction of ETs and their interplays, it is feasible to conclude the phenotype given the succession of a gene and the opposite. This bilingual and unique system is named as Karva language. The detailed information about GEP and this language is given in the papers (Ferreira 2001, 2002, 2003, Çevik and Cabalar 2009, Sarıdemir 2011, 2014).

3. Empirical modeling of flexural and splitting tensile strengths of concrete containing fly ash

In the present study, two empirical models have been developed for predicting the (1, 3, 7, 14, 28, 56, 90, 91, 180, 256 and 365 days) f_{fs} and the (1, 3, 7, 14, 28, 56, 90, 91, 180 and 365 days) f_{sts} values of concrete containing different proportions of FA. While the first empirical model named as GEP-I are developed to predict the f_{fs} values of concrete containing FA, the second empirical model named as GEP-II are developed to predict the f_{sts} values of concrete containing FA. The

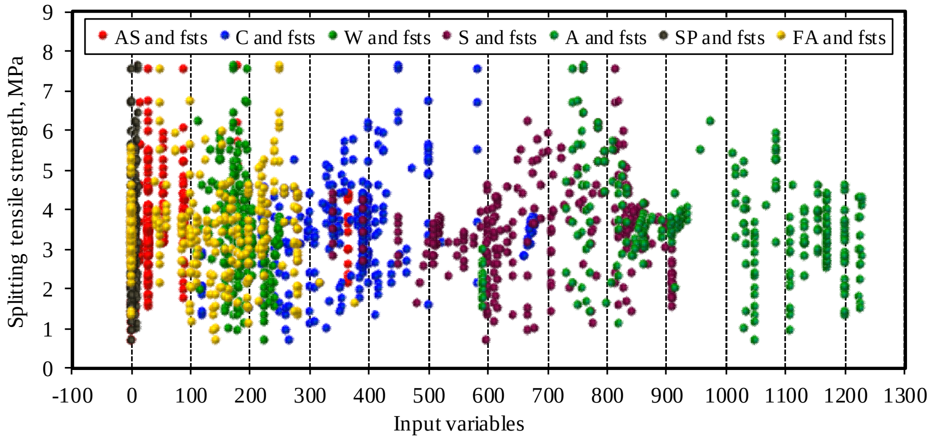


Fig. 3 Distribution of input variables and f_{sts} for GEP-II model

Table 1 The limit values used in GEP models

Input variable and meaning			Minimum	Maximum	Minimum	Maximum
			GEP-I		GEP-II	
d_0	AS	Age of specimen (day)	1	365	1	365
d_1	C	Cement (kg/m^3)	120	450	120	681
d_2	W	Water (kg/m^3)	112	195	112	252
d_3	S	Sand (kg/m^3)	280	898	280	910
d_4	A	Aggregate (kg/m^3)	760	1339	590	1228
d_5	SP	Superplasticizer (kg/m^3-l/m^3)	0	11	0	13
d_6	FA	Fly ash (kg/m^3)	0	280	0	377
Output variable and meaning						
	f_{fs}	Flexural strength (MPa)	1.24	8		
	f_{sts}	Splitting tensile strength (MPa)			0.67	7.62

distributions of input and output values used in these models are shown in Figs. 2 and 3. Besides, the limit values of input and output variables are given in Table 1. For generalization usability of these models, all experimental data were trisected into training, testing and validating sets for GEP. After that, the fitness function was selected, and the function set, the head size, the number of chromosomes, the number of genes and connection function were determined. The empirical models given the best results were obtained by the iteration running computer program. Finally, after the models were trained and tested, the ETs and equations depending on the input variables were obtained. These equations were verified with using the experimental data independent from the training and testing sets. So, the equations obtained from these models are used to predict the f_{fs} and f_{sts} values of concrete containing different proportions of FA.

In the development of GEP models, fundamental mathematical symbols (+, -, ×, /) and some mathematical functions (x^3, Tan, Sin, Sqrt, 1/x (Inv), Ln, $\sqrt[3]{\ }$, Mul3, Add3, Sub3) were utilized as shown in Table 2. Besides, the mutation, transposition and recombination were used as set of genetic operators. The Sub-ETs were connected by multiplication. After many tries, the head size

Table 2 GEP parameters used in proposed equations for f_{fs} and f_{sts}

	Parameter Definition	GEP-I	GEP-II
p_1	Number of generation	784	741.5
p_2	Arithmetic operators	+, -, ×, /	+, -, ×, /
P_3	Mathematical functions	x^3, Tan, Sin, Sqrt, 1/x, Ln, $\sqrt[3]{\ }$, Mul3, Add3	x^3, Tan, Sin, Sqrt, 1/x, Ln, $\sqrt[3]{\ }$, Mul3, Add3, Sub3
P_4	Number of chromosomes	30	
P_5	Head size	10	
p_6	Number of genes	5	
p_7	Linking function	Multiplication	
p_8	Mutation rate	0.044	
p_9	Inversion rate	0.1	
p_{10}	One-point recombination rate	0.3	
p_{11}	Two-point recombination rate	0.3	
p_{12}	Gene recombination rate	0.1	
p_{13}	Gene transposition rate	0.1	

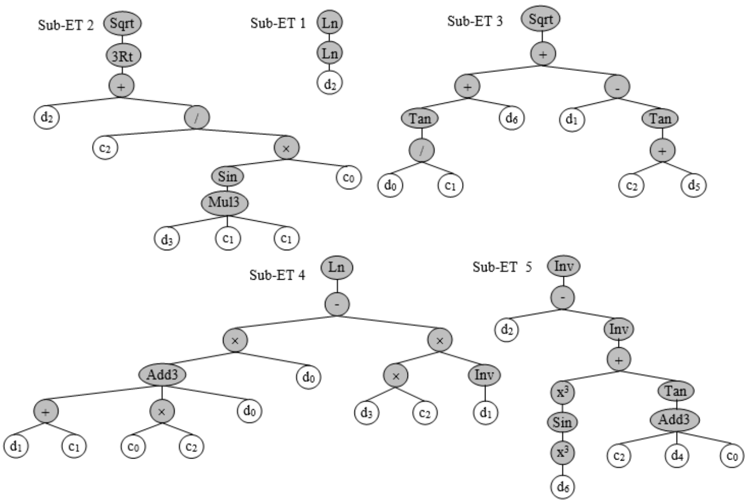


Fig. 4 Expression trees of GEP-I model proposed for f_{fs}

and number of chromosomes were detected to obtain the best results. The parameters used in the training of the GEP models are given in Table 2.

The ETs of the developed GEP-I and GEP-II models are seen in Figs. 4 and 5, respectively. The ETs of very complex problems require very long chromosome structures. Therefore, a large number of the Sub-ETs were employed in the GEP models. In the GEP-I and GEP-II models, the numbers of the employed Sub-ETs were five, and the linking functions for the connection of Sub-ETs were multiplication. The ETs of equations for f_{fs} and f_{sts} are seen in Figs. 4 and 5, where d_0, d_1, d_2, d_3, d_4, d_5 and d_6 imply to AS, C, W, S, A, SP and FA, respectively. For the GEP-I, the constants in the equation are in the Sub-ET2 c_0=2.014, c_1=-5.020, and c_2=-5.406, in the Sub-ET3 c_1=-1.974

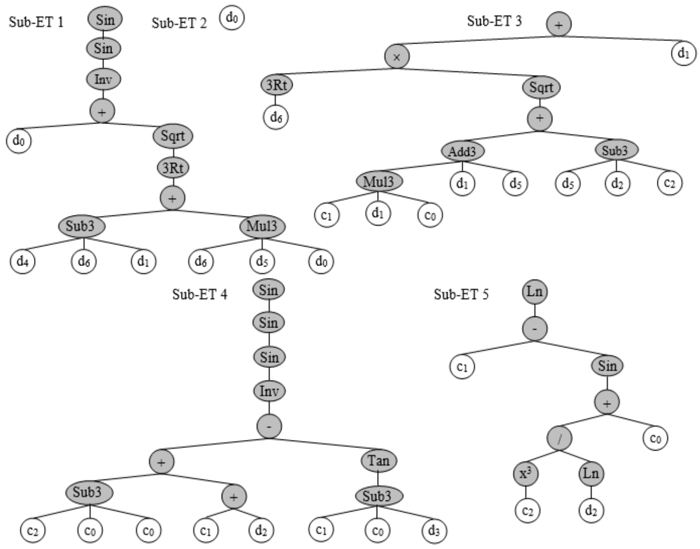


Fig. 5 Expression trees of GEP-II model proposed for f_{sts}

and c_2=5.144, in the Sub-ET4 c_0=-9.332, c_1=-5.799 and c_2=9.647, and in the Sub-ET5 c_0=6.400 and c_2=6.310. Similarly, for the GEP-II, the constants in the equation are in the Sub-ET3 c_0=2.372, c_1=0.776 and c_2=-8.240, in the Sub-ET4 c_0=-2.124, c_1=7.818 and c_2=-6.245, and in the Sub-ET5 c_0=-8.279, c_1=5.640 and c_2=6.413. The explicit equations of the GEP-I and GEP-II models for f_{fs} and f_{sts} are modified by Eqs. (2) and (3) depending on Eq. (1) and the above constant values.

$$f_{fs} \text{ or } f_{sts} = f(\mathrm{d}_0,\ \mathrm{d}_1,\ \mathrm{d}_2,\ \mathrm{d}_3,\ \mathrm{d}_4,\ \mathrm{d}_5,\ \mathrm{d}_6) = f(\mathrm{AS},\ \mathrm{C},\ \mathrm{W},\ \mathrm{S},\ \mathrm{A},\ \mathrm{SP},\ \mathrm{FA}) \tag{1}$$

$$\begin{aligned} f_{fs} = {} & \left[\mathrm{Ln}\left(\mathrm{Ln}(d_2)\right)\right] \times \left[\sqrt[6]{\frac{c_2}{\mathrm{Sin}(d_3 \times \mathrm{c}_1^2) \times c_0} + \mathrm{d}_2}\right] \times \left[\sqrt{\mathrm{Tan}\left(\frac{d_0}{c_1}\right) + \mathrm{d}_6 + \mathrm{d}_1 - \mathrm{Tan}(\mathrm{c}_2 + \mathrm{d}_5)}\right] \\ & \times \left[\mathrm{Ln}\left(\left((\mathrm{d}_1 + \mathrm{c}_1 + \mathrm{d}_0 + (\mathrm{c}_0 \times \mathrm{c}_2)) \times \mathrm{d}_0\right) - \left((\mathrm{d}_3 \times \mathrm{c}_2 \times \frac{1}{\mathrm{d}_1}\right)\right)\right] \times \left[\frac{1}{\mathrm{d}_2 - \frac{1}{\left(\left(\mathrm{Sin}(\mathrm{d}_6^3)\right)^3 + \mathrm{Tan}(\mathrm{c}_2 + \mathrm{d}_4 + \mathrm{c}_0)\right)}}\right] \end{aligned} \tag{2}$$

$$\begin{aligned} f_{sts} = {} & \left[\mathrm{Sin}\left(\mathrm{Sin}\left(\frac{1}{\mathrm{d}_0 + \sqrt[6]{(\mathrm{d}_4 - \mathrm{d}_6 - \mathrm{d}_1) + (\mathrm{d}_6 \times \mathrm{d}_5 \times \mathrm{d}_0)}}\right)\right)\right] \times [\mathrm{d}_0] \\ & \times \left[\left(\sqrt[3]{\mathrm{d}_6}\right) \times \left(\sqrt{\mathrm{c}_1 \times \mathrm{d}_1 \times \mathrm{c}_0 + \mathrm{d}_1 + 2\mathrm{d}_5 - \mathrm{d}_2 - \mathrm{c}_2}\right) + \mathrm{d}_1\right] \\ & \times \left[\mathrm{Sin}\left(\mathrm{Sin}\left(\mathrm{Sin}\left(\frac{1}{(\mathrm{c}_2 - 2\mathrm{c}_2 + \mathrm{c}_1 + \mathrm{d}_2) - \mathrm{Tan}(\mathrm{c}_1 - \mathrm{c}_0 - \mathrm{d}_3)}\right)\right)\right)\right] \times \left[\mathrm{Ln}\left(\mathrm{c}_1 - \mathrm{Sin}\left(\frac{\mathrm{c}_2^3}{\mathrm{Ln}(\mathrm{d}_2)} + \mathrm{c}_0\right)\right)\right] \end{aligned} \tag{3}$$

Finally, these modified equations for f_{fs} and f_{sts} are presented as Eqs. (4) and (5).

$$f_{fs} = [\mathrm{Ln}(\mathrm{Ln}(W))] \times \left[\sqrt[6]{\frac{-2.684}{\mathrm{Sin}(25.20 \times S)}} + K\right] \times \left[\sqrt{\mathrm{Tan}(-0.51 \times AS) + FA + C - \mathrm{Tan}(5.144 + SP)}\right]$$
$$\times \left[\mathrm{Ln}\left(((C + AS - 95.825) \times AS) - \frac{9.647 \times S}{C}\right)\right] \times \left[\frac{\left(\mathrm{Sin}(FA^3)\right)^3 + \mathrm{Tan}(12.71 + A)}{\left(\left(\mathrm{Sin}(FA^3)\right)^3 + \mathrm{Tan}(12.71 + A)\right) \times W - 1}\right] \tag{4}$$

$$f_{sts} = \left[\mathrm{Sin}\left(\mathrm{Sin}\left(\frac{1}{AS + \sqrt[6]{(A - FA - C) + (FA \times SP \times AS)}}\right)\right)\right] \times [AS] \times \left[\left(\sqrt[3]{FA}\right) \times \left(\sqrt{2.841 \times C + 2SP - W + 8.24}\right) + C\right]$$
$$\times \left[\mathrm{Sin}\left(\mathrm{Sin}\left(\mathrm{Sin}\left(\frac{1}{(5.821 + W) - \mathrm{Tan}(9.942 - S)}\right)\right)\right)\right] \times \left[\mathrm{Ln}\left(5.640 - \mathrm{Sin}\left(\frac{263.745}{\mathrm{Ln}(W)} - 8.279\right)\right)\right] \tag{5}$$

4. Evaluation of the models

Several statistical parameters have been employed to evaluate the performance of the models. In the present study, the error uncovered during the training, testing and validating sets in the GEP models can be described as an *R*-square (R^2) and is calculated using Eq. (6). In addition, in the sets of models, the mean-absolute-percentage-error (MAPE) and the root-mean-squared-error (RMSE) are calculated by Eqs. (7) and (8), respectively (Sarıdemir 2011 and 2014).

$$R^2 = \frac{\left(n\sum t_i o_i - \sum t_i \sum o_i\right)^2}{\left(n\sum t_i^2 - (\sum t_i)^2\right)\left(n\sum o_i^2 - (\sum o_i)^2\right)} \tag{6}$$

$$\mathrm{MAPE} = \frac{1}{n}\left[\frac{\sum_{i=1}^{n}\left|t_i - o_i\right|}{\sum_{i=1}^{n} t_i} \times 100\right] \tag{7}$$

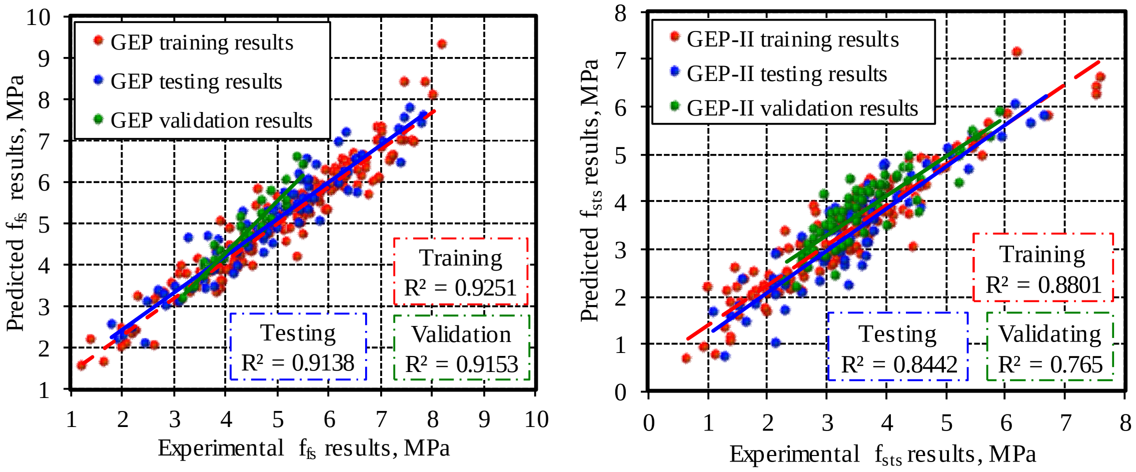
$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(t_i - o_i)^2} \tag{8}$$

Where, “*t*” is the experimental result, “*o*” is the result predicted by the models and “*n*” is the total number of experimental data.

The GEP-I and GEP-II models developed in the present study are used to predict the f_{fs} and the f_{sts} of concrete containing different proportions of FA. In the GEP-I model, as mentioned earlier, 170 and 86 experimental data were used for training and testing the results obtained from the available papers Atiş 2005, Siddique 2003 and 2004, Sekhar and Rao 2008, Jerath and Hanson 2007 and Kumar *et al.* 2007, respectively. In this model, 36 experimental data were also used for validating the results obtained from the available paper (Siddique 2003) independent from the

Table 3 Statistical parameters for GEP models

Statistical parameters	GEP-I			GEP-II		
	Training set	Testing set	Validating set	Training set	Testing set	Validating set
MAPE	6.8563	7.6802	7.9875	12.7654	12.7931	10.7255
RMSE	0.4102	0.4339	0.4580	0.4696	0.4857	0.4446
R^2	0.9251	0.9138	0.9153	0.8801	0.8442	0.7650



(a) (b)

Fig. 6 (a) Comparison of f_{fs} experimental results and GEP-I results, (b) comparison of f_{sts} experimental results and GEP-II results

training and testing sets. Similarly, in the GEP-II model, 142 and 70 experimental data were used for training and testing the results obtained from the available papers Atiş 2005, Siddique 2003, 2004 and 2011, Sekhar and Rao 2008, Lam *et al.* 1998, Mohammed and Fang 2011, Haque and Kayalı, 1998, Bharatkumar *et al.* 2005, Kim *et al.* 1998, Mittal *et al.* 2006, Sukumar *et al.* 2008, Jau *et al.* 2004 and Yaprak *et al.* 2004, respectively. In this model, 66 experimental data were used for validating the results obtained from the available papers Siddique 2003 and Haque and Kayalı, 19985 independent from the training and testing sets. The statistical parameter values with training, testing and validating sets obtained from the GEP-I and GEP-II models are presented in Table 3.

The performance of the GEP-I and GEP-II models for training, testing and validating sets can be seen in Figs. 6a-b, respectively. In these figures, the output results of the GEP-I and GEP-II models are compared with the experimental results. The horizontal axis of the figures are the experimental results in training, testing and validating sets, and the vertical ones are the output results of their corresponding GEP-I and GEP-II models. The results of training sets indicate that the GEP models are successful in learning the relationship between the different input variables and outputs. Besides, the results of testing sets indicate that GEP-I and GEP-II are able to generalize for predicting the f_{fs} and f_{sts} of concrete containing FA, and finally the results of validating sets indicate that the equations obtained from the models have good potential for predicting the f_{fs} and f_{sts} of concrete containing different proportions FA. In these figures, the R^2

values are separately seen for training, testing and validating sets. As can be seen in Figs. 6(a)-(b), the predicted results from the training, validating, and testing sets in the GEP-I and GEP-II models are found to be consistent with the experimental results.

Table 3 gives the statistical parameters of the GEP-I and GEP-II models calculated by the equations of MAPE, RMSE and R^2 for the f_{fs} and f_{sts} of concrete containing FA. It can be seen that the R^2 values in the training, testing and validating sets are 0.9251, 0.9138 and 0.9153, respectively, while the values of MAPE and RMSE are 6.8563 and 0.4102 in the training sets, 7.6802 and 0.4339 in the testing set, and 7.9875 and 0.4580 in the validating set for the GEP-I model. Similarly, for the GEP-II model, R^2 values in the training, testing and validating sets are 0.8801, 0.8442 and 0.7650, respectively, while the values of MAPE and RMSE are 12.7654 and 0.4696 in the training set, 12.7931 and 0.4857 in the testing set, and 10.7255 and 0.4446 in the validating set. The results show that the equations obtained from the GEP-I and GEP-II models are able to predict the f_{fs} and f_{sts} of concrete containing FA close to that of the experimental results.

5. Conclusions

The f_{fs} and f_{sts} values of concrete containing FA are an important problem and a difficult task to model its behavior. Because of this reason, the GEP is good tool to model the complex problems. In the present study, an enterprise is made to implement GEP models in predicting the concrete containing different proportions of FA. Two models named as GEP-I and GEP-II are proposed for predicting the f_{fs} and f_{sts} values of concrete containing FA. Two widely dispersed experimental databases made up of the f_{fs} and f_{sts} values are used for developing these models. The results predicted from training, testing and validating sets in the GEP-I and GEP-II are consistent with the experimental results. The high R^2 and the low RMSE and MAPE values of testing and validating sets show that the equations obtained from the GEP-I and GEP-II can be used for the prediction of the f_{fs} and f_{sts} values of concrete containing different proportions of FA. These statistical results also show that the proposed equations are reliable and accurate. As a result, this study indicates that the GEP can efficiently predict the f_{fs} and f_{sts} values of concrete containing different proportions of FA without trying any experimental study in a short time with small error rates.

Acknowledgements

This study has partially been supported by Niğde University, The Scientific Research Project Unit with the project number of FEB-2011/21. I am grateful for support.

References

Atiş, C.D. (2003), "High volume fly ash concrete with high strength and low drying shrinkage", *J. Mater. Civ. Eng.*, **15**(2), 153-156.

Atiş, C.D. (2005), "Strength properties of high-volume fly ash roller compacted and workable concrete, and influence of curing condition", *Cem. Concr. Res.*, **35**(6), 1112-1121.

Bharatkumar, B.H., Raghuprasad, B.K., Ramachandramurthy, D.S. Narayanan, B.K. and Gopalakrishnan, S. (2005), "Effect of fly ash and slag on the fracture characteristics of high performance concrete", *Mater. Struct.*, **38**(1), 63-72.

Çevik, A. and Cabalar, A.F. (2009), “Modelling damping ratio and shear modulus of sand–mica mixtures using genetic programming”, *Expert Syst. Appl.*, **36**(4), 7749-7757.

Ferreira, C. (2001), “Gene expression programming: a new adaptive algorithm for solving problems”, *Complex Syst.*, **13**(2), 87-129.

Ferreira, C. (2002), “Discovery of the Boolean Functions to the Best Density-Classification Rules Using Gene Expression Programming”, Eds., Lutton, E. Foster, J.A. Miller, J., Ryan, C. and Tettamanzi, A.G.B., *Proceedings of the 4th European Conference on GP, EuroGP 2002*, **2278** *of Lecture Notes in Computer Science*, Springer-Verlag, Berlin, Germany, 51-60.

Ferreira, C. (2003), “Function finding and the creation of numerical constants in gene expression programming”, Eds., Benitez, J.M., Cordon, O., Hoffmann, F. and Roy R., *Advances in Soft Computing-Engineering Design and Manufacturing*, Springer-Verlag, 257-266.

Haque, M.N. and Kayalı, O. (1998), “Properties of high-strength concrete using a fine fly ash”, *Cement Concrete Res.*, **28**(10), 1445-1452.

Haque, M.N., Langan, B.W. and Ward, M.A. (1984), “High fly ash concrete”, *ACI Mater. J.*, **81**, 54-60.

Jau, W.C., Fu, C.W. and Yang, C.T. (2004), “Study of feasibility and mechanical properties for producing high-flowing concrete with recycled coarse aggregates”, *Int. Workshop on Sustainable Development and Concr. Technol.*, 89-102.

Jerath S. and Hanson N. (2007), “Effect of fly ash content and aggregate gradation on the durability of concrete pavements”, *J. Mater. Civ. Eng.*, **19**(5), 367-375.

Kim, J.K., Han, S.H., Park, Y.D. and Noh, J.H. (1998), “Material properties of self-flowing concrete”, *J. Mater. Civ. Eng.*, **10**(4), 244-249.

Kumar, B., Tike, G.K. and Nanda, P.K. (2007), “Evaluation of properties of high-volume fly-ash concrete for pavements”, *J. Mater. Civ. Eng.*, **19**(10), 906-911.

Lam, L., Wong, Y.L. and Poon, C.S. (1998), “Effect of FA and SF on compressive and fracture behaviors of concrete”, *Cement Concrete Res.*, **28,** 271-283.

Mittal, A., Kaisare, M.B. and Rajendrakumar, S. (2006), “Parametric study on use of pozzolanic materials in concrete”, *New Build. Mater. Constr. World*, 94-112.

Mohammed, B.S. and Fang, O.C. (2011), “Mechanical and durability properties of concretes containing paper-mill residuals and fly ash”, *Constr. Build. Mater.*, **25**(2)**,** 717-725.

Sarıdemir, M. (2011), “Empirical modeling of splitting tensile strength from cylinder compressive strength of concrete by genetic programming”, *Expert Syst. Appl.*, **38**(11), 14257-14268.

Sarıdemir, M. (2014), “Effect of specimen size and shape on compressive strength of concrete containing fly ash: Application of genetic programming for design”, *Mater. Design,* **56**, 297-304.

Sekhar, T.S. and Rao, P.S. (2008), “Relationship between compressive, split tensile, flexural strength of self-compacted concrete”, *Int. J. Mech. Solid.*, **3**(2), 157-168.

Siddique, R. (2003), “Effect of fine aggregate replacement with Class F fly ash on the mechanical properties of concrete”, *Cement Concrete Res.,* **33**(11), 539-547.

Siddique, R. (2004), “Performance characteristics of high-volume Class F fly ash concrete”, *Cement Concrete Res.*, **34**(3), 487-493.

Siddique, R. (2011), “Properties of self-compacting concrete containing Class F fly ash”, *Mater. Design*, **32**, 1501-1507.

Sukumar, B., Nagamani, K. and Raghavan, R.S. (2008), “Evaluation of strength at early ages of self-compacting concrete with high volume fly ash”, *Constr. Build. Mater.*, **22**, 1394-1401.

Yaprak, H., Şimşek, O. and Aruntaş, H.Y. (2004), “Effect of fly ash and blast furnace slag on properties of superplasticizer added concrete”, *Beton 2004 Congress Proceedings*, İstanbul, 707-715.

CC