Computers and Concrete, *Vol. 18, No. 2 (2016) 155-163*
DOI: http://dx.doi.org/10.12989/cac.2016.18.2.155

Predicting of compressive strength of recycled aggregate concrete by genetic programming

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(Received November 4, 2015, Revised March 8, 2016, Accepted March 9, 2016)

Abstract. This paper, proposes 20 models for predicting compressive strength of recycled aggregate concrete (RAC) containing silica fume by using gene expression programming (GEP). To construct the models, experimental data of 228 specimens produced from 61 different mixtures were collected from the literature. 80% of data sets were used in the training phase and the remained 20% in testing phase. Input variables were arranged in a format of seven input parameters including age of the specimen, cement content, water content, natural aggregates content, recycled aggregates content, silica fume content and amount of superplasticizer. The training and testing showed the models have good conformity with experimental results for predicting the compressive strength of recycled aggregate concrete containing silica fume.

Keywords: recycled aggregate concrete; silica fume; compressive strength; gene expression programming

1. Introduction

Increasing costs and decreasing in natural resources, caused humankind turns towards recycling and reuse of wastes. Recently, this subject is also common in the construction industry. But unfortunately has not yet been fully applied throughout the world. One of these methods is recycling materials from construction and demolition (C&D) waste as alternative aggregate in new concrete (Xie *et al*. 2015). Being a lower quality of recycled aggregate concrete (RAC) than conventional concrete, researchers have done many experiments to find solutions for improving RAC quality. Generally, the use of recycled aggregate (RA) increases the drying shrinkage, creep, carbonation rate and water absorption, and decreases the compressive strength, modulus of elasticity and resistance to freezing and thawing of concrete compared to those of natural aggregate concrete. But with the use of appropriate mix design and mineral admixtures, the results can be improved (Kou and Poon. 2015).

Compressive strength of concrete is one of the most valuable mechanical properties because of

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

its direct relationship to both quality and other features. The compressive strength of RAC is greatly influenced by the recycled aggregate replacement ratio and the effective w/c ratio (Ulloa *et al*. 2013). Higher variation in terms of the compressive strength is observed for 100% replacement where it is comparatively low for lower replacement levels such as 20% to 50%. Alam *et al.* (2012) found almost 15% reduction in compressive strength as compared to control mix for 25% to 50% recycled concrete aggregate. Ajdukiewicz and Kliszczewicz (2002) used some different mixers to predict mechanical properties of HSC/HPC containing recycled aggregate. They crushed original concrete of about 35-70 MPa containing high quality aggregates and large amount of cement to make mixers. To maintain the connection between the crushed aggregates, they replaced different percentages of silica fume with part of cement. Finally, it was found properties of RAC can be improved satisfactorily by adding mineral/chemical additives. Ö. Çakır (2014)] replaced various ratios of RC instead of NA. Mineral additives used in this experimental work are silica fume (SF) and ground granulated blast furnace slag (GGBFS) at various ratios. The results showed replacing about 100% recycled aggregate instead of NA caused a 24 % reduction in compressive strength and as a total result, it is found to increase in replacing of RA proportion with NA, compressive strength decrease. Also, he found compressive strength of RAC containing 5% & 10% SF increase and it is in contrast to results found by using of GGBFS. Elhakam *et al*. (2012), studied concrete properties made of recycled coarse aggregates. Results showed the negative effects of using RC in making concrete, especially at higher contents. So they proposed three methods to enhance the quality of RAC properties. These methods included self-healing of recycled aggregates mixing method and adding silica fume. The results showed immersing recycled aggregates in water up to 30 days, especially for lower cement contents, improves RAC mechanical properties. Mixing water, cement, addition and recycled aggregates, then natural sand and natural coarse aggregates were added, two stages mixing approach enhance the properties of recycled aggregate concrete. Adding 10.0% silica fume as cement addition to recycled aggregates concrete enhanced properties of concrete.

Since making concrete at laboratory and measuring its properties, especially compressive strength, is time-consuming, so recently, researchers use of computational methods to predict concrete properties. Also some of these methods such as artificial neural networks and fuzzy logic have been used for predicting RAC properties. Genetic programming (Koza. 1995) is quite new modeling, proven to be superior to regression methods and neural networks because of obtaining explicit formulations for experimental studies (Elhakam *et al*. 2012). There are some studies done by GP for modeling concrete containing natural aggregate and both fresh and hardened properties of it in literature in later years (Nazari and Riyahi. 2011, Castelli *et al.* 2013). But about recycled aggregate, it is the first time in this paper.

2. Gene expression programming models and parameters

Gene expression programming (GEP) is, like genetic algorithms (GAs) and genetic programming (GP), a genetic algorithm as it uses populations of individuals, selects them according to fitness, and introduces a genetic variation using one or more genetic operator (Ferreira 2001). GEP is a kind of evolutionary algorithms which inherited the linear chromosomes of fixed length from genetic algorithms and the expressive parse trees of varied sizes and shapes from genetic programming. The fundamental steps of Gene Expression Programming are schematically represented in Fig. 1. The process is repeated for a certain number of generations or until a good solution has been found (Ferreira 2006). The genes of gene expression programming have all the same size. However, these fixed length strings code for expression trees (ET) of different sizes. All problems in GEP are presented by ETs which include operators, functions, constants and variables.

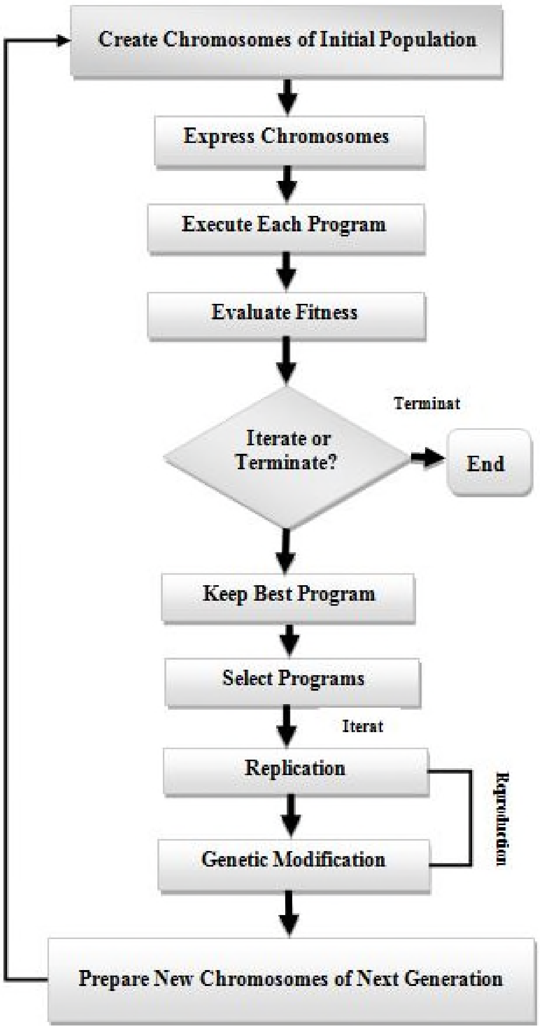


Fig. 1 Flowchart of Gene expression programming (Ferreira. 2006)

It is proven, the GEP proposes many advantages as compared with other classical regression techniques. Some functions define in advance in regression techniques where analyses of these functions are later performed while no predefined function is considered for the GEP approach. It is believed for modeling and obtaining clear formulations of experimental studies, like multivariate problems, GEP is more powerful than regression techniques and neural networks (Milani and Nazari 2012, Nazari *et al*. 2011, Bhargava *et al*. 2011, Ganguly *et al*. 2009, Podgornik *et al*. 2011).

Table 1 The input and output quantities used in GEP approach models

	Maximum	Minimum
Input variables	Data used in the models	
Age of specimens (day)	3	90
Cement (kg/m^3)	250	500
Water (kg/m^3)	113	246.2
Natural aggregates (kg/m^3)	0	2044
Recycled aggregates (kg/m^3)	0	1797.7
Silica fume (kg/m^3)	0	115
Superplasticizer (kg/m^3)	0	15
Output variable		
Compressive strength (MPa)	14.9	97.5

In this paper, for the first time, we predict compressive strength RAC containing silica fume by GEP modelling. We used GeneXproTools software (Ganguly *et al*. 2009) to modelling data. Unluckily, there is no precious way to obtain the best performance and combination of parameters to achieve the highest accuracy. Thus, it causes complicating and time-consuming of modelling process. In this paper, different levels of effective GEP parameters used to acquire correlations of higher efficiency and lower complexity. Hence, for achieving the highest possible accuracy for entire models, at first, the lowest possible level of parameters such as, 1 gene, was utilized and then the model was trained by a combination of different input parameters. “Addition”, “subtraction”, “multiplication” and “division” be introduced in utilized GEP software, as linking functions. Considering addition and subtraction operating in a parallel way, “addition” was selected to try the models. In the same way, between multiplication and division, “multiplication” was considered. Appling multiplication instead of addition might implicate models; therefore, addition is preferred. To solve a problem, a chromosome with single-gene could be selected and then the modelling may proceed by increasing the length of the head. However, the number of genes could be increased and a function to link the sub-expression trees (sub-ETs) could be chosen when it becomes very large (Pouraliakbar *et al*. 2014).

It is not measurable the magnitude of a model complexity. As a whole, increasing the inputs of a model, increases complexity. For example, how much the number of genes increase, the model strongly complicates. However, about other utilized parameters, it acts as the same manner. There is not any specific definition of complexity. Consequently it may be considered definite combinations of input parameters together as a factor of complication. Also, continuing the generation to achieve higher levels of regression and better fitness in training data set causes complexity too (Pouraliakbar *et al*. 2014). Therefore by using different parameters, compressive strength was predicted and at the end, modelling results compared with experimental results.

To predict RAC compressive strength, the details of 228 samples constructed of 61 different mixers collected from literature (Ajdukiewicz and Kliszczewicz. 2002, Çakır and Sofyanlı. 2014, Modani and Mohitkar. 2014). This information includes the weight of concrete's components (age of the samples, cement, water, natural aggregates, recycled aggregates, sand, silica fume and superplasticizer) and compressive strength. Quantities about inputs and output values were presented in Table 1. Among 228 experimental samples, randomly selected 80% samples used as a training set for models and 20% samples used as testing set. For using GEP there are five major steps.

First of all is choosing fitness function, which in this problem, we measured the fitness f_i by using two following expressions

$$f_i = \sum_{j=1}^{c_t} \left(M - |C_{(i,j)} - T_j| \right) \tag{1}$$

Where M is the range of selection, $C_{(i,j)}$the value returned by the individual chromosome i for fitness case j (out of C_t fitness cases) and T_j is the target value for fitness case j. if $\left| C_{(i,j)} - T_j \right|$ (the precision) less or equal to 0.01, then the precision is equal to zero, and $f_i = f_{max} = C_t M$. In this case, M = 100 was used, therefore f_{max} = 1000. The advantage of this kind of fitness functions is that the system can find the optimal solution by itself (Ferreira. 2001).

$$E_i = \sqrt{\frac{\sum_{j=1}^{n} \left(C_{(i,j)} - T_j \right)^2}{\sum_{j=1}^{n} \left(T_j - \bar{T} \right)^2}} \tag{2}$$

Where $P_{(i,j)}$ is the value predicted by the individual program *i* for fitness case *j* (*out of n fitness cases or sample cases*); T_j is the target value for fitness case *j*; and $\bar{T}$ is given by the formula

$$\bar{T} = \frac{1}{n} \sum_{j=1}^{n} T_J \tag{3}$$

For a perfect fit, the numerator is equal to 0 and E_i= 0. So, the *RRSE* index ranges from 0 to infinity, with 0 corresponding to the ideal. As it stands E_i can not be used directly as fitness since, for fitness proportionate selection, the value of fitness must increase with efficiency. Thus, for evaluating the fitness f_i of an individual program *i*, the following equation was used

$$f_i = 1000 \cdot \frac{1}{1 + E_i} \tag{4}$$

Which obviously ranges from 0 to 1000, with 1000 corresponding to the ideal (Modani and Mohitkar 2014). The second major step is selection of terminals T and functions F to create chromosomes. In this case terminals set include of the independent variable. i.e., T= {*AS*, *C*, *W*, *NA*, *RA*, *SF*, *SP*} and about functions, four basic arithmetic operators $(+, -, *, /)$ and some basic mathematical functions $(Sqrt, x^3, \ldots)$were used the models. The weight of each function is 1, but you can increase the probability of a function being included in your models by increasing its weight in the Select/Weight column (www.gepsoft.com). The third major step is to choose the chromosomal architecture, namely the length of the head and the number of genes. In this case we used 2, 3 and 4 genes [Sub-ETs] and length of heads 8, 9, 10, 12 and 14 for models randomly. The fourth major step in preparing to use GEP is to choose the linking function to link the sub-ETs which in this problem we used multiplication and addition.

And finally, a combination of all genetic operators (*mutation, transposition and crossover*…) was utilized as set of genetic operators. All details of used parameters were presented in Table 2. Explicit formulations based on the approach models for f_c were obtained by Eq. (5)

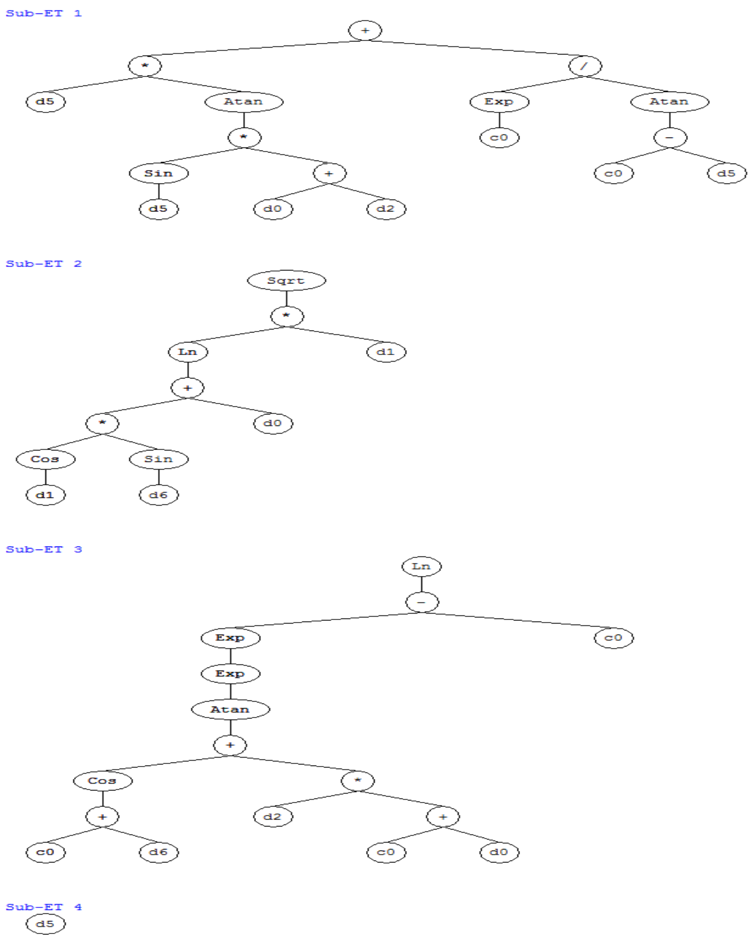


Fig. 2 Expression trees of GEP-9 approach model

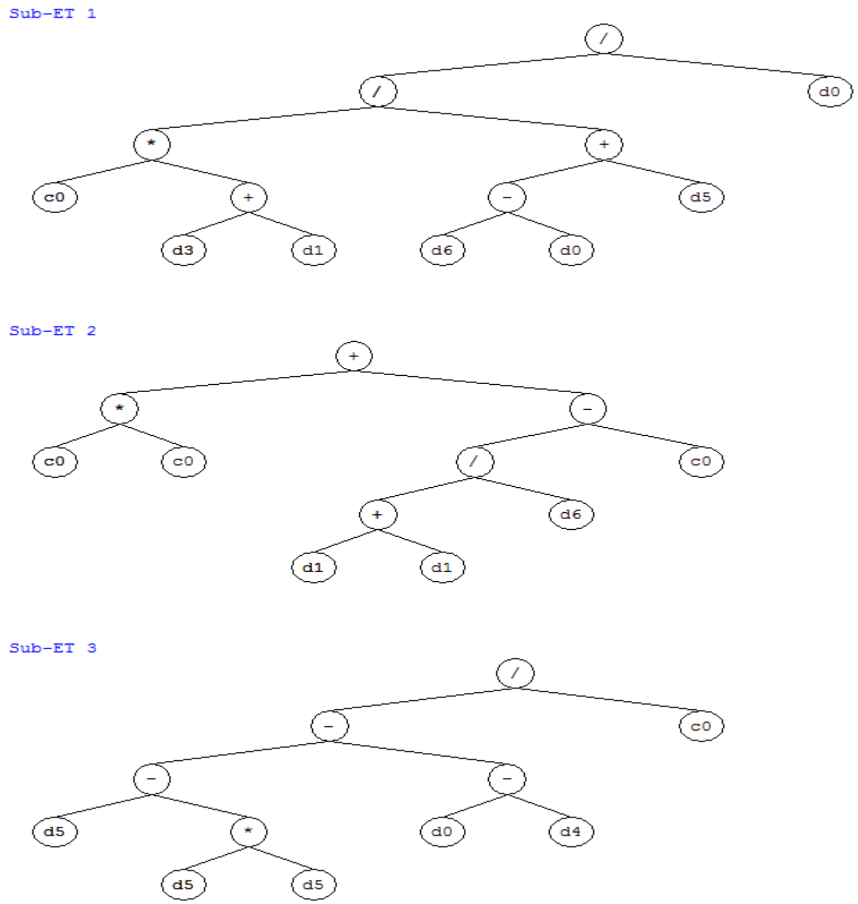


Fig. 3 Expression trees of GEP-12 approach model

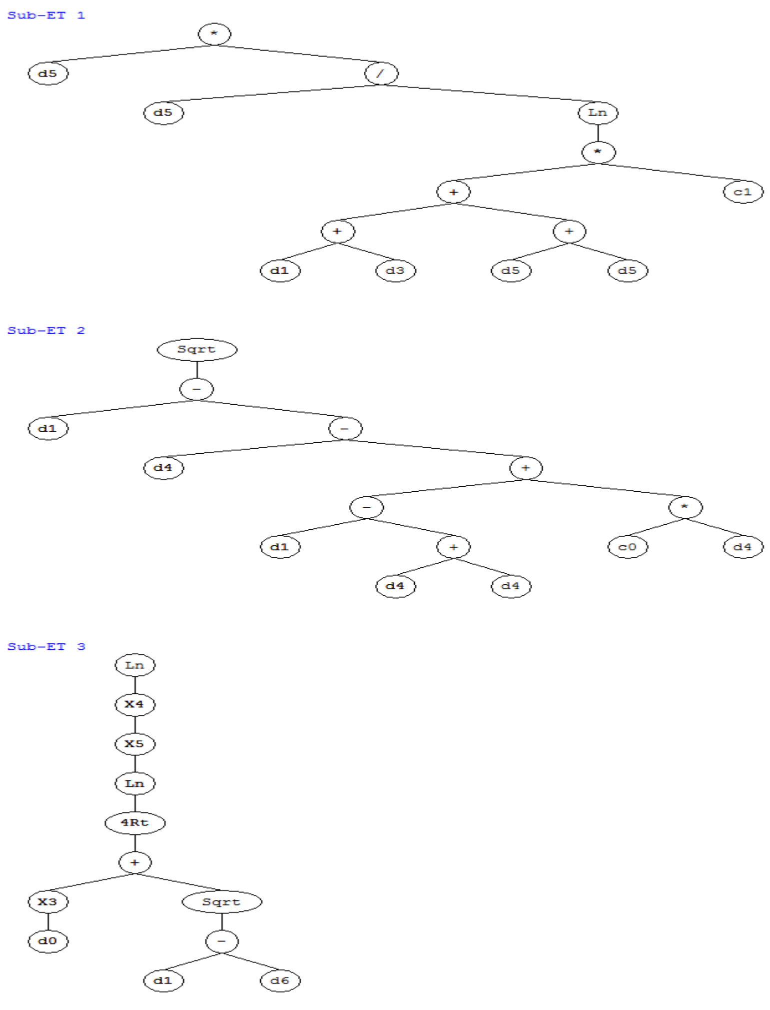


Fig. 4 Expression trees of GEP-14 approach model

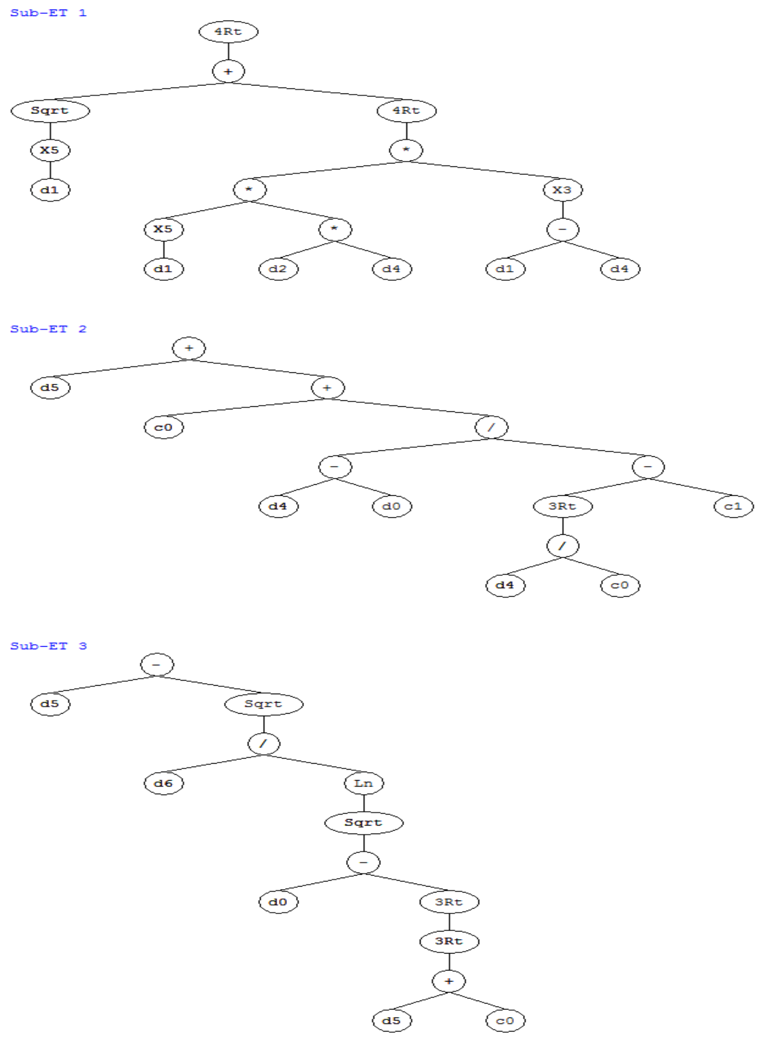


Fig. 5 Expression trees of GEP-19 approach model

Table 2 Utilized parameters for each GEP approach

Models set	Chromosomes	Head size	Number of genes	Linking function	Fitness function	Mutation	Inversion	Transposition	Constant per gene	Number of functions
GEP-1	30	10	3	Addition	Absolute with SR	0.044	0.1	0.1	2	6[a,1]
GEP-2	26	12	3	Multiplication	Absolute with SR	0.044	0.1	0.1	2	6[a,1]
GEP-3	40	14	4	Addition	Absolute with SR	0.044	0.1	0.1	2	6[a,1]
GEP-4	35	12	3	Multiplication	Absolute with SR	0.044	0.1	0.1	2	7[b,1]
GEP-5	35	8	3	Addition	Absolute with SR	0.044	0.1	0.1	2	8[c,2]
GEP-6	30	12	3	Addition	Absolute with SR	0.044	0.1	0.1	2	4[d,1]
GEP-7	30	8	2	Addition	Absolute with SR	0.044	0.1	0.1	2	6[a,1]
GEP-8	30	10	3	Addition	Absolute with SR	0.044	0.1	0.1	2	6[a,1]
GEP-9	40	12	4	Addition	Absolute with SR	0.044	0.1	0.1	1	10[e,4]
GEP-10	30	9	3	Addition	Absolute with SR	0.044	0.1	0.1	2	7[b,1]
GEP-11	60	8	3	Addition	Absolute with SR	0.044	0.1	0.1	2	7[f,1]
GEP-12	30	10	3	Addition	Absolute with SR	0.044	0.1	0.1	2	13[g,1]
GEP-13	30	8	3	Addition	RRSE	0.044	0.1	0.1	2	8[c,1]
GEP-14	30	8	3	Addition	RRSE	0.044	0.1	0.1	1	4[h,1]
GEP-15	30	8	3	Addition	RRSE	0.044	0.1	0.1	2	7[b,1]
GEP-16	30	12	3	Multiplication	RRSE	0.044	0.1	0.1	2	9[i,2]
GEP-17	30	10	3	Addition	RRSE	0.044	0.1	0.1	2	6[j,3]
GEP-18	40	12	4	Addition	RRSE	0.044	0.1	0.1	1	8[k,4]
GEP-19	30	12	3	Addition	RRSE	0.044	0.1	0.1	2	13[g,1]
GEP-20	30	12	3	Addition	RRSE	0.044	0.1	0.1	2	12[l,4]

[1] The weight of "$+,-,*$" functions were 4 $\times$ weight of other functions

[2] The weight of "$+,-,*$" functions were 7$\times$ weight of other functions

[3] The weight of "$*$" functions were 4$\times$ weight of other functions

[4] The weight of "$+,-,*$" functions were 3$\times$ weight of other functions

[a] The utilized functions were $+,-,*,/, sqrt, ,x^3$

[b] The utilized functions were $+,-,*,/, sqrt, x^3, x^2$

[c] The utilized functions were $+,-,*,/, sqrt, x^3, x^2, 3Rt$

[d] The utilized functions were $+,-,*,/$

[e] The utilized functions were $+,-,*,/, sqrt, exp, sin, cos, atan, ln$

[f] The utilized functions were $+,-,*, sqrt, x^3, x^2, 3Rt$

[g] The utilized functions were $+,-,*,/, sqrt, x^3, x^2, x^4, x^5, 3Rt, 4Rt, 5Rt, ln$

[h] The utilized functions were $+,-,*,/, sqrt$

[i] The utilized functions were $+,-,*,/, sqrt, x^3, exp, sin, cos$

[j] The utilized functions were $+,*, sqrt, x^3, x^2, pow$

[k] The utilized functions were $+,-,*,/, exp, sin, cos, atan$

[l] The utilized functions were $+,-,*,/, sqrt, x^3, x^2, x^4, 3Rt, 4Rt, exp, ln$

Table 3 The obtained mathematical equations from different GEP approaches

Models set	Obtained equations for prediction of compressive strength of RAC
GEP-1	$\left((d5+d5)*\left(\frac{((6.803+6.803)-d5)}{(\sqrt{d5}-5.717)}\right)\right)+\sqrt{\left(((d5-9.723)+(d1-d0))+((d5-d0)+d4)\right)*\sqrt{d0}}+\sqrt{\left(d4+(\sqrt{d2+d2})\right)+\sqrt{d4}}$
GEP-2	$\sqrt{\sqrt{\left(\left(\left(((d0-d5)+(d1-d6))-\left(\frac{d1-(-9.952)}{d0}\right)+d0\right)-d5\right)\right)}}+\sqrt{\sqrt{\left(\left(((3.966+d1)+d0)-d4\right)-\left(d5-\left(\frac{d1}{-9.487}\right)\right)\right)}}-d6+\sqrt{d5-(-7.175)}$
GEP-3	$\sqrt{\left(d5-\left(d4-\left((d1+\sqrt{d2})+\sqrt{d2}\right)\right)\right)}-(d5+d4)+(d5)+\sqrt{d1-\left(\left(\left((d4-5.090)+\sqrt{d5*d3}\right)+\sqrt{d3*0.292}\right)+d4\right)}+\left(\frac{\left(\left(((d0*d5)*d5)+(d0*d0)\right)-d6\right)}{((5.065*d0)-(9.843-d0))+(d0+(5.065+d4))}\right)$
GEP-4	$\left(\sqrt{5.493+\sqrt{d0}}\right)+\left(\sqrt{8.876+d5}\right)+\left(\sqrt{-0.644+\sqrt{\left(d1-((d6+d5)+d4)\right)+\left((d1-d4)-(d6-(-9.842))\right)}}\right)$
GEP-5	$\left(\left(d5+\sqrt{\frac{d2}{7.961*7.961}}\right)+7.961\right)+\left(\sqrt{\sqrt[3]{\left(((d1)^3*d0)-(d1)^3\right)-d2}}\right)+\left(d5-\left(\frac{d4+d6}{(-6.693+d5)*(-8.941)}\right)\right)$
GEP-6	$\left(d5-\left(\left(\frac{((-7.858-9.925)-9.925)+d0}{\frac{-7.858}{-7.858}-d0}\right)-9.925\right)\right)+\left(d5-\left(\frac{\left((d4-d5)+\frac{d0}{4.036}\right)-((d5+d5)+d0)}{4.036}-0.203\right)\right)+(9.130*3.596)$
GEP-7	$\sqrt{\left(d3-(d6-d2)\right)+\left((4.528*4.176)*(d0-d5)\right)}+\left(\left(\left((d5-9.989)-\frac{9.989}{d0}\right)*\sqrt{\frac{d5}{0.684}}\right)+d5\right)$
GEP-8	$\sqrt{\left(((d5-d0)-(d4-d0))+((6.831*6.831)+d1)\right)*\sqrt{d0}}+\left((d5+d5)*\frac{(6.803+6.803)-d5}{\sqrt{d5}-5.778}\right)+\sqrt{d4}$
GEP-9	$\left((d5*(\tan^{-1}(\sin d5*(d0+d2))))+\left(\frac{[0.775]}{\tan^{-1}(0.775-d5)}\right)\right)+\sqrt{(\ln(\cos d1*\sin d6)+d0)*d1}+\left(\ln\left(\left[\left[\tan^{-1}\left(\cos(-4.377+d6)+\left(d2*(-4.377+d0)\right)\right)\right]\right]-(-4.377)\right)\right)+(d5)$

Table 3 Continued

GEP-10	$\sqrt{d1+\left(d0-\left(\frac{d1+d5}{d0}+(d4+d4)\right)\right)}+\sqrt{d1+\left(\left((d5*d5)-\frac{d6}{3.868}\right)-((d6+d5)+d4)\right)}+\left(d5+\left(d5+\sqrt{d0+((-8.894+d0)+d0)}\right)\right)$
GEP-11	$\left((d5*\sqrt[3]{d5})+(-1.791)\right)+\sqrt{(d1-d4)-\left((d4+(-2.611))+(d4+d5)\right)}+\sqrt[3]{d0*\left(\sqrt[2]{d2^2*9.607}+d1\right)}$
GEP-12	$\left(d5*\left(\frac{d5}{\ln\left(((d1+d3)+(d5+d5))*0.570\right)}\right)\right)+\sqrt{d1-\left(d4-\left((d1-(d4+d4))+(-1.548*d4)\right)\right)}+\ln\left(\left(\ln\sqrt[4]{d0^3+\sqrt{d1-d6}}\right)^5\right)^4$
GEP-13	$\left(\left((d5)+\sqrt[3]{(d1-d4)-(d4+d4)}\right)+d5\right)+\sqrt{\left(((d1-9.926)-d6)+(-9.904-9.926)\right)-d4}+\sqrt{\sqrt[3]{((d1*d0)+(-9.391*d4))^2}-9.935}$
GEP-14	$\left(\frac{\left(\frac{-5.807*(d3+d1)}{(d6-d0)+d5}\right)}{d6}\right)+\left((-5.807*-5.807)+\left(\frac{d1+d1}{d6}-(-5.807)\right)\right)+\left(\frac{(d5-(d5*d5))-(d0-d4)}{-5.807}\right)$
GEP-15	$\left(\left(((6.586+2.972)+(2.972*d5))+\sqrt{d0*2.972}\right)-d5\right)+\left(\frac{\left((d0-5.319)-\frac{d4}{d6}\right)*(5.319+2.632)}{d0}\right)+\sqrt{\left(((d5*d5)-(d4+9.966))-(d4+d4)\right)+d1}$
GEP-16	$\left(\cos\left(\cos\left(\frac{\sqrt{\sqrt{d0*d1}}+(\cos(d5-d4)+(9.225*9.225))}{9.225}\right)\right)\right)+\left(\cos\left(\cos\left(\frac{(\cos(9.108*d4)*(\sin(d2)-d5))-\cos(\cos d6)}{-8.055}\right)\right)\right)+((-9.740)*(-9.740))$
GEP-17	$\sqrt{d5+\left(\sqrt{\sqrt{\sqrt{d1}}*(d0+(-2.966))}\right)^2}+\left(4.548+\sqrt{d1+\left((-2.709+d5)^2+((d5+d4)*(-2.709))\right)}\right)+\left(\sqrt{\left(((d1+d2)*(d0+d1))*d6^{-1.935}\right)+d0}+d5\right)$
GEP-18	$\left(\sin d5*\left(d5*\left(\tan^{-1}\left(\left(\frac{d0}{\left(\frac{d5-0.838}{0.838}\right)}\right)*d0\right)\right)\right)\right)+\left(d5+\left(d0*\left(\sin 6.517+\left(\frac{\cos(d5-6.517)+d3}{d5}\right)\right)\right)\right)+\left(\left(-6.010+\tan^{-1}\left((\tan^{-1}d3)*\left(((d5+d5)*d5)-\sin d2\right)\right)\right)*-6.010\right)+\left((\sin((\sin d4)*d5))*d5\right)$

Table 3 Continued

GEP-19	$\sqrt[4]{\sqrt{d1^5}+\sqrt[4]{\left(d1^5*(d2*d4)\right)*(d1-d4)^3}}+\left(d5+\left(6.779+\left(\frac{d4-d0}{\sqrt[3]{\frac{d4}{6.799}}-7.674}\right)\right)\right)+\left(d5-\sqrt{\frac{d6}{\ln\sqrt{d0-\sqrt[3]{\sqrt[3]{d5+0.722}}}}}\right)$
GEP-20	$\ln\left(d0^2-\ln\left(d3-\left(-9.668*\left((d5*9.953)+(d1+d4)\right)\right)\right)\right)+\left(\ln\left((d1-d4)+\left(\left(((-5.329)-d6)-d5\right)-(-5.329)^2\right)\right)^2+d5\right)+\left(d3-\left(d3-\left(\left(\ln\left(\sqrt[3]{\frac{2.717+d0}{1.075}}\right)^3\right)^2+d5\right)\right)\right)$

$$f_c = f(AS, C, W, NA, RA, SP, SF) \tag{5}$$

As has been given in the literature, the equations were obtained from corresponding expression trees (ET) of 20 GEP models are presented in Table 3 where d0, d1, d2, d3, d4, d5 and d6 refer to AS, C, NA, RA, SF, SP and W respectively. The ETs of the best models (GEP-9, GEP-12, GEP-14 and GEP-19) were presented in Figs. 2-5.

3. Results and discussion

Absolute fraction of variance (R^2) mean absolute error (MAE), root mean square error (RMSE), relative absolute error (RAE) and root relative squared error (RRSE) were presented in this paper as statistical evaluations for inevitable errors while training and testing the models according to the Eqs. (6)-(10), respectively.

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

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |t_i - o_i| \tag{7}$$

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

$$RAE = \frac{\sum_i |t_{i-} o_i|}{\sum_i |\, t_i - (1/n)\sum_i t_i|} \tag{9}$$

$$RRSE = \sqrt{\frac{\sum_i (t_i - o_i)^2}{\sum_i (t_i - (1/n)\sum_i t_i)^2}} \tag{10}$$

Here t is the target value, o is the output value and n is the number of all collected data. Statistical errors values for both training and testing the models were shown in Table 4. If (R^2) values are above 0.7 and closer to 1, predicted results are closer to experimental results. In addition, R^2 shows the fitness level of defined function on data set. Higher R^2 in training is a result of excellent fitness of the final function. On the other hand, this might cause deviation of the model in a way that cannot cover the unseen data and results in appreciable difference between training and testing errors and consequently higher regression values in both training and testing series are of interest. Usually higher values can be achieved by more complex models due to more tries and generations, lower complexity level was also always considered as mission. In the most cases of proposed models, the value of R^2 in testing is higher than in training. As it is known(www.gepsoft.com), it's not very important which fitness function be selected in GEP modelling so we used two fitness functions for the models. In this paper, cannot be compared these two fitness functions with each other exactly because of using different parameters in each model,

Table 4 Statistical parameters for predicting f_c values of RAC

Models set	MAE	RMSE	RAE	RRSE	R^2	MAE	RMSE	RAE	RRSE	R^2
			Training					Testing		
GEP-1	3.8988	5.1334	0.2404	0.2595	0.937	4.2089	5.6363	0.2767	0.3226	0.9185
GEP-2	5.033	6.9269	0.3104	0.3502	0.8867	3.5822	4.5158	0.2355	0.2584	0.9387
GEP-3	4.2683	5.692	0.2632	0.2878	0.9182	4.0583	5.1472	0.2668	0.2946	0.9312
GEP-4	5.3788	6.8446	0.3317	0.3461	0.8851	4.1653	5.2443	0.2739	0.3001	0.9116
GEP-5	4.8757	6.9767	0.3007	0.3527	0.8806	4.2333	5.7381	0.2783	0.3284	0.9164
GEP-6	5.1217	7.2173	0.3158	0.3649	0.8745	4.7775	6.3122	0.3141	0.3612	0.8852
GEP-7	4.48892	5.8036	0.2768	0.2934	0.917	4.6117	6.1479	0.3032	0.3518	0.8969
GEP-8	4.1106	5.2196	0.2535	0.2639	0.9332	4.9599	6.3464	0.3261	0.3632	0.8873
GEP-9	3.2388	4.676	0.1997	0.2364	0.9442	3.8207	4.7057	0.2512	0.2693	0.9361
GEP-10	5.0418	6.8557	0.3109	0.3466	0.8843	4.1029	5.7339	0.2698	0.3282	0.9034
GEP-11	4.8019	6.1847	0.2961	0.3127	0.9044	4.4792	5.79	0.2945	0.3314	0.9097
GEP-12	4.1085	5.4394	0.2534	0.275	0.9243	3.4061	4.7074	0.2239	0.2694	0.9332
GEP-13	5.1664	6.5466	0.3186	0.331	0.8912	4.4127	5.5758	0.2901	0.3191	0.8984
GEP-14	4.5452	5.7815	0.2803	0.2923	0.9145	4.4667	5.5654	0.2937	0.3185	0.9071
GEP-15	5.1769	6.5425	0.3193	0.3308	0.8914	4.8768	6.0197	0.3207	0.3445	0.8938
GEP-16	4.5321	5.7368	0.2795	0.29	0.9223	4.7349	5.9651	0.3113	0.3414	0.8986
GEP-17	5.3388	6.6981	0.3292	0.3386	0.887	4.2998	5.4566	0.2827	0.3123	0.9113
GEP-18	4.0585	5.1183	0.2503	0.2588	0.933	4.7616	5.9085	0.3131	0.3381	0.8964
GEP-19	4.555	5.9107	0.2809	0.2988	0.913	3.3956	4.2851	0.2233	0.2452	0.9414
GEP-20	4.7366	6.0376	0.2921	0.3052	0.9069	4.1974	5.2511	0.276	0.3005	0.9113

but about models with similar parameters, Absolute with SR has better results than RRSE results. R^2 Values for fitness function (1) in the training set ranges from 0.8745 to 0.9442 and for testing it is between 0.8852 and 0.9387. RRSE values of R^2, ranges between 0.8870 and 0.9155 for training and ranges from 0.8938 to 0.9414 for testing set.

There were few differences between experimental and predicted values statistically. So, all models can be applied for predicting compressive strength of RAC containing silica fume.

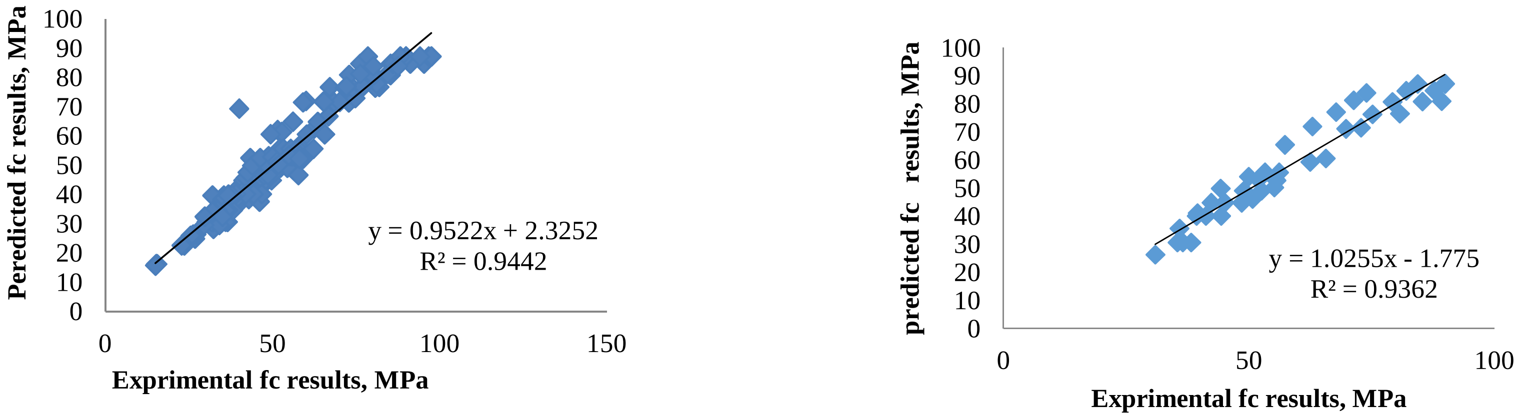
Also, if (MAE, RMSE, RAE, RRSE) values increase, reduce models performance. In some models, RMSE, RAE, MAE and RRSE values are higher in training than testing. Increase of error reduces the model performance. For instance, higher error levels of GEP-6, GEP-13and GEP-15 definitely decrease their performance. On the other hand, GEP-1, GEP-3, GEP-9 and GEP-19 have minimum introduced errors in both training and testing. It is concluded that the latter group has higher prediction accuracy in comparison with the first group. The minimum value of RMSE is 4.2851 for testing of GEP-19 and its maximum value is 7.2173 in training phase of GEP-6; however, the difference between the minimum and maximum was relatively high. The minimum value of MAE is 3.2388 for training of GEP-9 while its maximum 5.3788 belongs to GEP-4 in training. Also, details of other statistical errors were shown exactly for both fitness functions in Table 4. GEP-9 and GEP-12 are the best models for Absolute with SR and GEP-14 and GEP-19 are the best models of RRSE. The linear least square fit and fit line and the best models R2 values

Table 5 GEP models results compared with experimental results are used as test sets

Data used in models construction							Compressive strength (MPa)				
AS(day)	C(kg/m^3)	W(kg/m^3)	NA(kg/m^3)	RA(kg/m^3)	SP(kg/m^3)	SF(kg/m^3)	Exp.	GEP-9	GEP-12	GEP-14	GEP-19
3	500	180	485.5	1132	0	0	35.4	30.61475	30.61891	27.75674	33.28929
3	500	214.3	0	1567.7	0	0	30.9	26.2542	30.50182	25.77328	31.2384
3	454.5	126	1837.3	0	15	45.5	65.6	60.5716	65.54658	69.2146	59.48382
3	454.5	133.1	511	1191.4	15	45.5	62.4	59.33418	58.28499	53.24708	57.25867
3	454.5	176	0	1650	15	45.5	49.9	54.08107	57.02104	51.87096	48.60335
3	500	180	1745.6	0	0	0	36.5	30.6147	30.61891	40.13712	33.28929
3	500	180	485.5	1132	0	0	38.2	30.61475	30.61891	27.75674	33.28929
7	500	180	485.5	1132	0	0	39.3	40.08943	39.35715	38.46793	42.16529
7	500	214.3	0	1567.7	0	0	35.8	35.61661	39.34786	37.12998	40.87574
7	454.5	126	1837.3	0	15	45.5	72.8	71.49746	74.25948	73.46497	70.65067
7	454.5	133.1	511	1191.4	15	45.5	69.7	71.11525	67.01902	66.21663	68.71663
7	454.5	176	0	1650	15	45.5	57.3	65.42066	65.89096	64.7405	61.67548
7	500	180	1745.6	0	0	0	41.2	40.09206	39.35715	43.89649	42.16529
7	500	180	485.5	1132	0	0	44.3	40.08943	39.35715	38.46793	42.16529
14	500	180	485.5	1132	0	0	42.3	44.80019	45.29398	43.42144	45.38792
14	500	214.3	0	1567.7	0	0	39.5	41.13574	45.29308	42.32828	44.30892
14	454.5	126	1837.3	0	15	45.5	80.7	76.50014	80.19431	75.99974	73.96195
14	454.5	133.1	511	1191.4	15	45.5	75.1	76.32334	72.95552	72.00812	72.08632
14	454.5	176	0	1650	15	45.5	62.9	71.94006	71.83801	70.50267	65.36906
14	500	180	1745.6	0	0	0	45	44.80091	45.29398	46.25017	45.38792
14	500	180	485.5	1132	0	0	48.5	44.80019	45.29398	43.42144	45.38792
28	454.5	133.1	511	1191.4	15	45.5	79.2	80.73413	77.60496	76.66774	75.74282
28	454.5	176	0	1650	15	45.5	67.7	77.05091	76.48846	75.16761	69.21116
28	500	180	1745.6	0	0	0	48.9	49.10834	49.94345	49.22807	48.60369
28	500	180	485.5	1132	0	0	52.5	49.10805	49.94345	47.68343	48.60369
28	500	222.9	0	1567.7	0	0	50.7	46.11985	49.94333	46.6407	47.42498
28	454.5	126	1837.3	0	15	45.5	85.3	80.82828	84.84358	79.06075	77.58498
28	454.5	136	511	1191.4	15	45.5	89.2	80.9171	77.60495	76.58913	75.64525

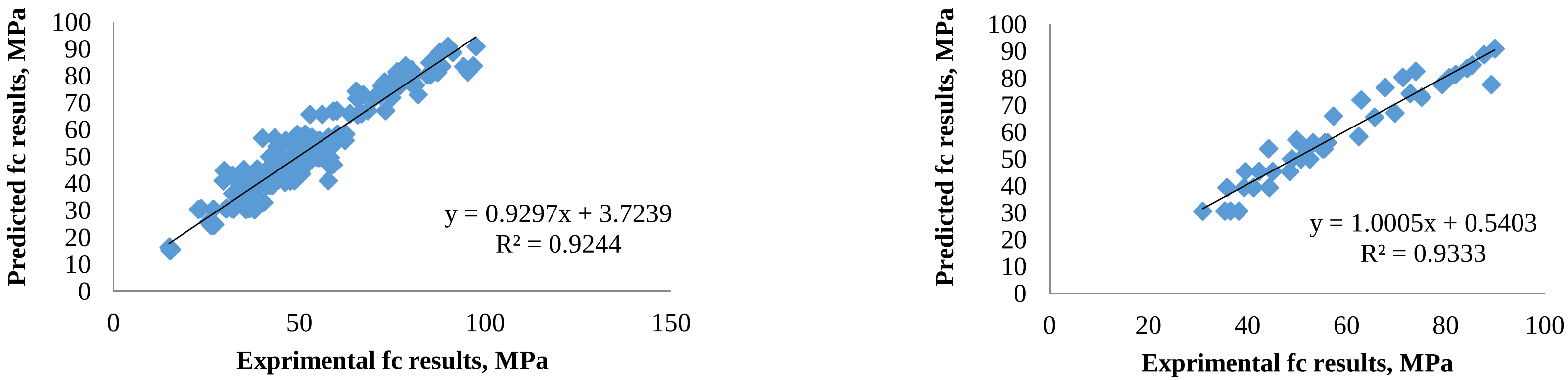
Table 5 Continued

56	500	214.3	0	1567.7	0	0	44.2	49.89514	53.72154	52.488	52.36012
56	454.5	126	1837.3	0	15	45.5	87.7	84.7044	88.62167	84.16189	83.2475
56	454.5	133.1	511	1191.4	15	45.5	82	84.64711	81.38306	82.4783	81.42828
56	454.5	176	0	1650	15	45.5	71.3	81.32273	80.26666	81.05027	75.0238
56	500	180	1745.6	0	0	0	51.9	53.07063	53.72155	54.3136	53.22375
56	500	180	485.5	1132	0	0	55.4	53.0705	53.72155	53.36689	53.22375
56	500	222.9	0	1567.7	0	0	55.1	50.18093	53.72154	52.37776	52.15466
90	454.5	126	1837.3	0	15	45.5	89.9	87.16184	90.84999	89.99595	89.56139
90	454.5	133.1	511	1191.4	15	45.5	84.3	87.11853	83.61138	88.3582	87.7544
90	454.5	176	0	1650	15	45.5	73.9	83.93025	82.49499	87.17697	81.41777
90	500	180	1745.6	0	0	0	53.2	55.61228	55.94987	60.22788	58.17599
90	500	180	485.5	1132	0	0	56.1	55.6122	55.94987	59.41627	58.17599
90	500	222.9	0	1567.7	0	0	55.6	52.75676	55.94987	58.51319	57.16581
90	454.5	126	1837.3	0	15	45.5	89.9	87.16184	90.84999	89.99595	89.56139



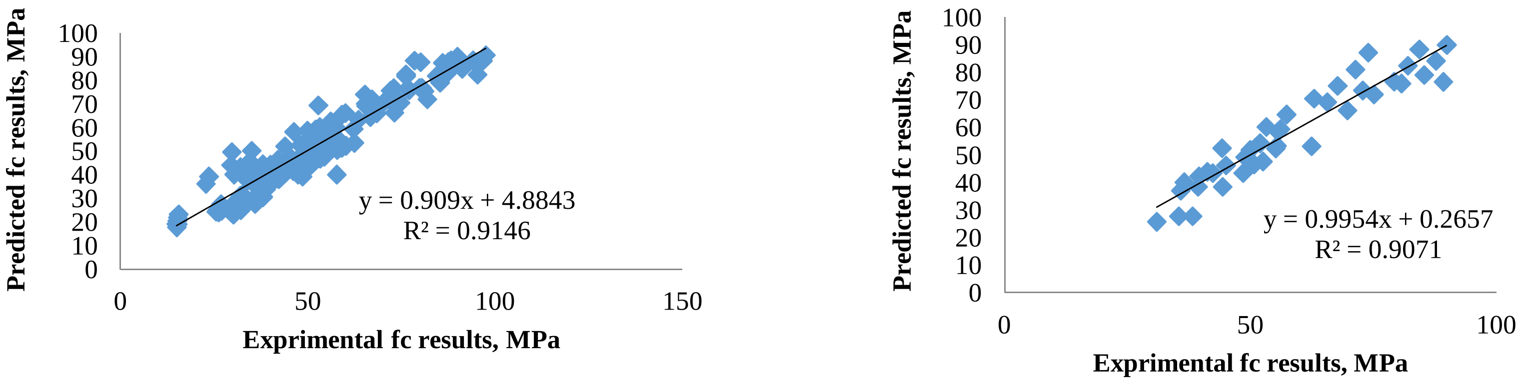
(a) Training (b) Testing

Fig. 6 Scattering Diagram of predicted vs experimental for training & testing models of GEP-9



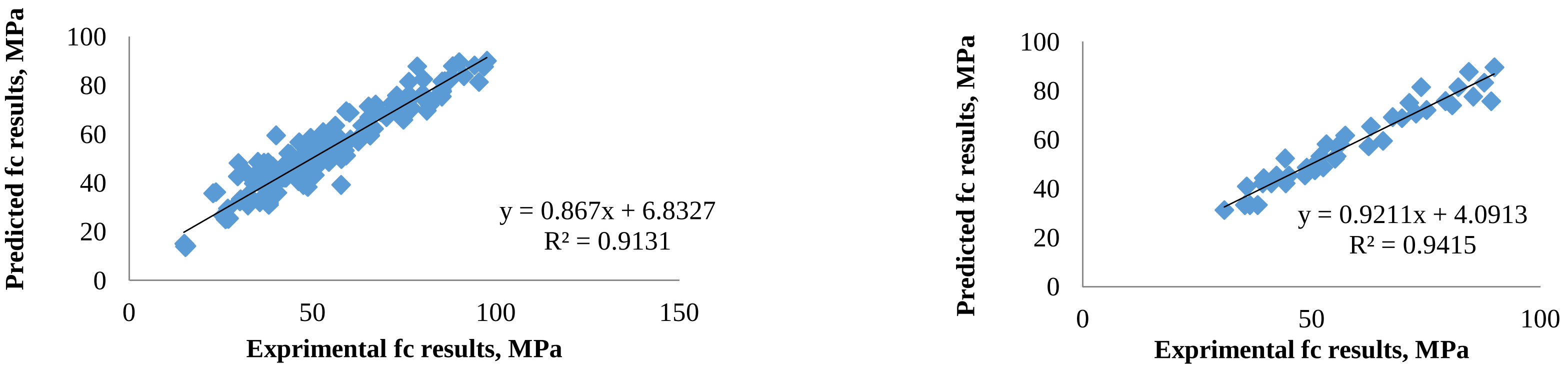
(a) Training (b) Testing

Fig. 7 Scattering Diagram of predicted vs experimental for training & testing models of GEP-12



(a) Training (b) Testing

Fig. 8 Scattering Diagram of predicted vs experimental for training & testing models of GEP-14



(a) Training (b) Testing

Fig. 9 Scattering Diagram of predicted vs experimental for training & testing models of GEP-19 of two fitness functions are shown in Figures 6-9 for the training and testing sets. These figures show clearly, the fc values obtained from the training and testing sets in GEP-9, GEP-12, GEP-14 and GEP-19 models are very close to the experimental results. Also, inputs values and experimental results with testing results obtained from best models were given and compared in Table 5. As we can see, GEP-19 has closer results to experimental results.

All results show GEP also is a good approach for predicting of RAC fc values like NAC as was done before by some researchers (Nazari and Riyahi. 2011, Castelli *et al*. 2013, Sonebi and Cevik 2009, Kara 2011, Gandomi *et al*. 2014, Sarıdemir 2011, Sarıdemir 2010, Sarıdemir 2014, Tanyildizi and Çevik 2010, Chen *et al*. 2014, Ozbay *et al*. 2008, Pérez *et al*. 2010).

4. Conclusions

As we know, the compressive strength is the most important properties of all concretes. For the first time, this study evaluates f_c of RAC in different ages, and proposes formulation for it by a novel application of GEP. To predict the compressive strength values of RAC, 20 models with different parameters were proposed. For running the models, data of some experimental studies were collected from literature. Almost all of the models indicate good results which are close to experimental results. Another reason for GEP capability for predicting f_c is about statistical parameters values (R^2, *MAE, RMSE, RAE, RRSE*) .This paper also proposes that GEP can be an alternative approach for prediction of f_c of recycled aggregate concrete containing silica fume and effective explicit formulation of many civil engineering problems. We hope to use of this approach in other RAC properties in nearer future.

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