Modeling effect of SiO₂ nanoparticles on the mechanical properties of the concretes

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Abstract In the present study, the effect of SiO₂ nanoparticles on the mechanical properties (compressive, flexural and tensile strength) of the binary blended concrete is studied. SiO₂ nanoparticles with two different sizes of 20 and 100 nm were used as partial cement replacement by 0.25, 0.5, 0.75, 1.0, 1.25, 1.5, 1.75 and 2.0%. According to the obtained results, during the first few days of curing, the concrete specimens made with 20 nm SiO₂ particles had a higher strength than those of 100 nm. It was interesting that in the last few days of curing, the situation was reversed. According to the SEM images, in the initial days of curing, a higher amount of C–S–H gel was formed around the 20 nm SiO₂ particles compared to that of 100 nm ones. As an explanation for this event, one can mention to the presence of more nucleation sites which caused a significant acceleration in early age strength. It was while that, the growth of the C–S–H gel around the 100 nm particles was higher in 84 days of moist curing. An artificial intelligence based model was also presented for simulating the mechanical properties of the binary blended concrete. To construct the model, training and testing of the model were conducted by using experimental results from 51 specimens. The input parameters were five independent variables which consist of the number of the days of curing, quantity of SiO₂ (%), quantity of SiO₂ (kg), quantity of cement (kg) and the size of SiO₂ nanoparticles. The training and testing results in the proposed model

confirmed a strong capability for predicting mechanical properties of the binary blended concrete.

Keywords SiO₂ nanoparticles · Mechanical properties · Binary blended concrete · C–S–H gel · Modeling

1 Introduction

As a newer building and construction material, in comparison with stone and steel, one can mention to the cement based concretes [1]. During the last century, the properties of concrete were very astonishingly improved as a result of embedding a wide range of supplementary cementing material [1].

Due to a high potential of nanoparticles in various of engineering applications, nanotechnology has recently attracted considerable scientific interest. Nanoparticles significantly improve the properties of engineering materials and distinguish them from the conventional grain-size materials of the same chemical composition [2].

According to the previous researches [3], SiO₂ nanoparticles can strongly affect the compressive, tensile and flexural strength of the concretes. In fact, they cause a lower setting time and permeability of water, as well as a higher resistance to the chemical reactions [3].

The role of SiO₂ nanoparticles can be stated as follows:

1. If a non-uniform distribution of small amounts of SiO₂ nanoparticles is provided in the cement paste, they are able to act as a nucleus to tightly bond with cement hydrate and further promote the cement hydration due to their high activity [4, 5].
2. It was shown that [3], SiO₂ nanoparticles, when are introduced to the hydrate matrixes, provide an obstacle

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to the growth of harmful crystals which are not favorable for the strength [6].

3. SiO₂ nanoparticles have also shown an important role as the filler in the cement based materials, and hence the increase of their strength. Besides, SiO₂ nanoparticles provide a leading stage to generate C–S–H agents through reaction with Ca(OH)₂. On the other hand, due to the high surface area to volume ratio of nano-sized particles, a potential for tremendous chemical reactivity is provided [7, 8].

The amorphous or glassy silica, as the major component of a pozzolan, reacts with calcium hydroxide formed from calcium silicate hydration. According to the surface area existing for reaction, the rate of the pozzolanic reaction can decrease or increase.

Genetic programming (GP) as generalization of genetic algorithms (GAs), was proposed by Koza [9, 10]. Three basic genetic operators including reproduction, crossover and mutation are present in the GP. Gene expression programming (GEP) as an advanced version of GP has recently attracted a lot of attention [11–20]. In GEP, individuals are encoded as linear strings of fixed size (genome), which are expressed later as non-linear entities with different sizes and shapes. These entities are known as expression trees (ETs). ETs are the expression of a chromosome, and they undergo the selection procedure, 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 operator. The chromosomes may consist of one or more genes which represents a mathematical expression. Two different languages are used for expression the mathematical code of a gene, including the language of the genes and the language of the ETs [8]. There are two important parts for each gene, i.e. the head and the tail. The mathematical operators, variables and constants (+, −, *, /, √, sin, cos, 1, a, b, c) are presented with the head while other variables and constants (1, a, b, c) are shown with the tail. A simple chromosome with a linear string including one gene is indicated in Fig. 1. The corresponded ET and mathematical equation are also shown in this figure. The translation process of the ET to Karva language is implemented by beginning to read from left to right in the top line of the tree and from top to bottom. Linking functions, i.e. addition, subtraction, multiplication, or division also cause that the genes join to each other [21].

The aim of the present study is to simulate of the effects of the process parameters including size of nano-SiO₂, curing age, quantity of SiO₂ (kg), quantity of SiO₂ (%), and quantity of cement (kg) on mechanical properties (compressive strength, split tensile strength, and flexural strength) of the binary blended concrete (BBC). In

addition, totally 51 data of mechanical properties in different conditions were collected, trained and tested by means of GEP. The obtained results have been compared by experimental ones to evaluate the software power for predicting mechanical properties of the BBC. Application of such rarely reported computer programs in this area as GEP to predict their properties is of interest.

2 Materials and methods

The chemical composition and physical properties of the Ordinary Portland Cements (OPCs) as the main cementing material are given in Table 1. SiO₂ nanoparticles in two different sizes (20 and 100 nm) were used in this work. Sand particles with a diameter less than 0.4 mm and fineness modulus of 2 were used as fine aggregate. Meanwhile, the crushed basalt stored in the laboratory with maximum size of 15 mm was used as coarse aggregate. Both fine and coarse aggregates were kept constant for all concrete mixes.

The mixtures including three series, i.e. St as the control specimens, S₂₀, and S₁₀₀ were prepared in the laboratory conditions. Natural aggregates, water, and cement as the starting materials were used to prepare of the St, while S₂₀ and S₁₀₀ were prepared with different contents of SiO₂ nanoparticles with the average size of 20 and 100 nm, respectively. The mixtures were prepared with the cement replacement of 0.25, 0.5, 0.75, 1.0, 1.25, 1.5, 1.75, and 2.0% of SiO₂ nanoparticles. The water to binder weight was set on 0.40 ratio for all of the mixtures [22] while the binder content of all mixtures was considered 400 kg/m³. For each mixture, cubic specimens of 100 mm and 180 × 40 × 40 mm were made for compressive strength and flexural strength tests, respectively. For split tensile strength, cylinders were made with the diameter of 140 mm and the height of 280 mm. [23].

3 Results and discussion

3.1 Compressive strength

The compressive strength values of the St, S₂₀ and S₁₀₀ series mixtures are shown in Table 2. As can be seen, in the S₁₀₀ samples, by increasing the amount of SiO₂ nanoparticles up to 1.5%, the compressive strength also increases. However, when this amount reaches 1.75%, the compressive strength finds a decreasing trend, although it is still higher than that of the plain cement concrete (St). As an explanation for this event, one can mention to the quantity of SiO₂ nanoparticles which is present in the mixture. This content of SiO₂ nanoparticles is higher than that required to

Fig. 1 Chromosome with one gene and its expression tree and the corresponding mathematical equation **Table 1** Chemical and physical properties of Portland cement (wt%)

Mater	SiO ₂	Al ₂ O ₃	Fe ₂ O ₃	CaO	MgO	SO ₃	Na ₂ O	K ₂ O	Loss in ignition
Chemical Properties	21.93	5.26	3.41	53.20	6.41	3.71	0.16	0.98	3.23
Physical Properties	Specific gravity (g/cm ³)			Specific surface (BET) (m ² /g)			Specific surface (Blain) (m ² /kg)		
	1.7			–			314		

Table 2 Compressive strength of SiO₂ nanoparticles based samples

Sample	SiO ₂ nanoparticles (%)	Size of SiO ₂ nanoparticles (nm)	Quantity Of cement (kg)	Quantity of SiO ₂ (kg)	Compressive strength		
					7 days	21 days	84 days
St	0	20	400	0	25.4	33.15	41.78
S20	0.25	20	399	1	28.03	38.24	41.28
S20	0.5	20	398	2	29.98	39.84	43.24
S20	0.75	20	397	3	31.1	40.21	46.14
S20	1	20	396	4	32.19	42.85	47.24
S20	1.25	20	395	5	32.41	42.98	48.16
S20	1.5	20	394	6	31.1	40.34	48.01
S20	1.75	20	393	7	30.4	39.03	47.46
S20	2	20	392	8	27.14	37.95	45.47
S100	0.25	100	399	1	25.73	35.41	45.14
S100	0.5	100	398	2	26.13	37.21	47.78
S100	0.75	100	397	3	27.95	38.54	48.95
S100	1	100	396	4	28.64	39.11	49.24
S100	1.25	100	395	5	29.13	39.97	50.21
S100	1.5	100	394	6	30.07	39.14	51.78
S100	1.75	100	393	7	29.93	38.16	49.12
S100	2	100	392	8	27.84	37.45	47.32

Table 3 Flexural strength of of SiO₂ nanoparticles based samples

Sample	SiO ₂ nanoparticles (%)	Size of SiO ₂ nanoparticles (nm)	Quantity of cement (kg)	Quantity of SiO ₂ (kg)	Flexural strength (MPa)		
					7 days	21 days	84 days
St	0	20	400	0	4	4.2	4.5
S20	0.25	20	399	1	4.8	5	5.1
S20	0.5	20	398	2	4.9	5.2	5.4
S20	0.75	20	397	3	5.2	5.5	5.8
S20	1	20	396	4	5.4	5.7	6.1
S20	1.25	20	395	5	5.5	5.8	6.2
S20	1.5	20	394	6	5.2	5.5	5.9
S20	1.75	20	393	7	4.9	5.2	5.6
S20	2	20	392	8	4.5	4.9	5
S100	0.25	100	399	1	4.3	4.6	5.5
S100	0.5	100	398	2	4.5	4.8	5.8
S100	0.75	100	397	3	4.7	5	6.2
S100	1	100	396	4	4.9	5.2	6.5
S100	1.25	100	395	5	5	5.3	6.9
S100	1.5	100	394	6	5.1	5.4	7.1
S100	1.75	100	393	7	5	5.2	6.9
S100	2	100	392	8	4.8	5	6.6

Table 4 Split tensile strength of of SiO₂ nanoparticles based samples

Sample	SiO ₂ nanoparticles (%)	Size of SiO ₂ nanoparticles (nm)	Quantity of cement(kg)	Quantity Of SiO ₂ (kg)	Split tensile strength (Mpa)		
					7 days	21 days	84 days
St	0	20	400	0	1.4	1.6	2.1
S20	0.25	20	399	1	2.3	2.4	3.1
S20	0.5	20	398	2	2.5	2.8	3.3
S20	0.75	20	397	3	2.6	3	3.4
S20	1	20	396	4	2.7	3.1	3.5
S20	1.25	20	395	5	2.8	3.1	3.6
S20	1.5	20	394	6	2.5	2.7	3.1
S20	1.75	20	393	7	2.3	2.4	2.6
S20	2	20	392	8	2	2.1	2.4
S100	0.25	100	399	1	1.8	1.9	3.1
S100	0.5	100	398	2	2	2.1	3.6
S100	0.75	100	397	3	2.3	2.4	3.8
S100	1	100	396	4	2.5	2.7	4
S100	1.25	100	395	5	2.6	2.9	4.3
S100	1.5	100	394	6	2.7	3	4.5
S100	1.75	100	393	7	2.4	2.6	4.2
S100	2	100	392	8	1.8	2	3.7

combine with the liberated lime during the process of hydration. This means that an excess silica is leached out [24].

Additionally, in samples made with 100 nm of SiO₂ particles (S₁₀₀), the compressive strength has a lower value in comparison with that of 20 nm SiO₂ particles at 7 and

Table 5 Parameters of the GEP model

Parameter definition	Values
Chromosomes	30
Head size	8
Number of genes	2
Linking function	Multiplication
Mutation rate	0.044
Inversion rate	0.1
One-point recombination rate	0.3
Two-point recombination rate	0.3
Gene recombination rate	0.1
Gene transposition rate	0.1
Constants per gene	5
Weight of functions	7
Lower bound	10
Upper bound	10

21 days of curing. This is because of the lower pozzolanic activity of the 100 nm SiO₂ particles than the 20 nm ones. The lower pozzolanic activity is originated from two things: first the larger size of the samples containing the 100 nm SiO₂ particles, and second the decline of the content of the hydration in these samples. When the curing age reaches 84 days, the compressive strength also finds an increasing trend which is because of the growth of C–S–H gel.

Looking back at Table 2, one can notice that the concrete samples made with the 20 nm SiO₂ particles show a higher strength than those made with the 100 nm particles at early ages of curing. The highest response rates for the compressive strength of the S₂₀ series is related to the

samples containing 1.25% SiO₂ nanoparticles with the curing age of 84 days. In fact, during the hydration process of Portland cement, Ca(OH)₂ is formed at early ages. In continuation, due to the lower pozzolanic reactivity of the 100 nm SiO₂ particles, the consumption of Ca(OH)₂ occurs faster in the 20 nm samples [1].

From the point view of energy, it should be noted that a more heterogeneous nucleation sites in S₂₀ samples (as a result of the higher volume to surface area ratio), is formed which causes a faster early age strength, according to Eq. (1) [1, 25]:

$$I = AN_T \exp\left(\frac{-\Delta G^*}{KT}\right), \quad (1)$$

where I is the nucleation rate, ΔG^* is the critical free energy for nucleation, T is the absolute temperature, K is the Boltzmann's constant, A is a constant, and N_T is the number of nucleation sites.

If the temperature is constant, the velocity of the C–S–H gel formation in the 20 nm samples is higher than that of the 100 nm samples. This is because of the more nucleation sites in the 20 nm samples. The more early age strength in the S₂₀ series stems from here. According to the values presented in Table 2, the compressive strengths of the S₁₀₀ samples concrete at 84 days were fairly larger than those of the S₂₀ samples. The free energy of heterogeneous nucleation of the gel on the surface of the SiO₂ nanoparticles could be obtained from Eq. (2) [1, 26]:

$$\Delta G_{het} = -V_s \cdot \Delta G_V + A_{sg} \cdot \gamma_{sg} + A_{sp} \cdot \gamma_{sp} - A_{sp} \cdot \gamma_{pg}, \quad (2)$$

where V_s is the volume of solid nucleus, ΔG_V is the volume energy of solid nucleus, A_{sg} is the interface between solid nucleus and gel, A_{sp} is the interface between the solid nucleus and nano-particle, γ_{sg} is the surface free energy

Fig. 2 SEM images of the samples at 7 days; **a** control cement paste (without nanoparticles); **b** cement paste with SiO₂ content (particle size 100 nm) using a replacement content of 0.75%; **c** cement paste with SiO₂ content (particle size 20 nm) using a replacement content of 0.75%

Fig. 3 SEM images of cement paste with SiO₂ content (particle size 100 nm) at 84 days using a replacement content of **a** 1.5%; **b** 2%

Sub-ET 1

Sub-ET 1

Sub-ET 2

Sub-ET 2

(a)

(b)

Fig. 4 Expression tree of the GEP model for: **a** compressive strength; **b** flexural strength; **c** split tensile strength

between the solid nucleus and gel, γ_{sp} is the interface between the solid nucleus and nano-particle, and γ_{pg} is the surface free energy between nano-particle and the gel.

The critical radius of nucleation (r) is:

$$r^* = \frac{2\gamma_{sg}}{\Delta G_V}. \quad (3)$$

And the free energy of critical radius of nucleation is:

Sub-ET 1

Sub-ET 2

Fig. 4 continued

$$\Delta G^* = \frac{16\pi\gamma^3}{3\Delta G_V^2} \cdot S(\theta), \quad (4)$$

where $S(\theta)$ is the shape factor and could be written as [1, 25]:

$$S(\theta) = \frac{(2 + \cos \theta)(1 - \cos \theta)^3}{4}. \quad (5)$$

And θ is the wetting angle and is constant during the growth of the nucleus. By combining the above equations:

$$\begin{aligned} \Delta G^* &= \frac{2}{3} \pi \left(\frac{2\gamma_{sg}}{\Delta G_V} \right)^3 \cdot \Delta G_V \cdot \frac{(2 + \cos \theta)(1 - \cos \theta)^3}{4} \\ &= \frac{\pi(r^*)^3 (2 + \cos \theta)(1 - \cos \theta)^3}{4} = \frac{1}{2} V^* \Delta G_V, \end{aligned} \quad (6)$$

Table 6 The range of the input parameters in the GEP model

Input	Output
Day of curing	7–84
Quantity of SiO ₂ (%)	0–2
Quantity of SiO ₂ (kg)	0–8
Quantity of cement (kg)	392–400
Nano particle size (nm)	20–100

where V^* is the critical volume of the nucleus.

According to the Eqs. (1)–(6), in S_{20} , the content of the formed nucleus does not reach V^* which causes C–S–H gel is stopped. However, in S_{100} , the volume of the nucleus reaches V^* , which causes a more C–S–H gel is formed at 84 days of moist curing.

3.2 Flexural and split tensile strengths

Tables 3, 4 and 5 show the flexural and split tensile strength values of the St, S_{20} and S_{100} series mixtures, respectively. As can be seen, mechanical properties of the S_{20} and S_{100} series have higher values than those of the control concrete St. Similar to what was discussed for the compressive strength, the flexural and split tensile strengths of the S_{100} series at the final days of curing are more than those of the S_{20} series.

3.3 Microstructure

Figure 2 shows the SEM micrographs of the cement pastes with (b, c) and without (a) nano-SiO₂ at 7 days. As can be seen, the C–S–H gel existed in isolation, surrounded by and connected with many needle-hydrates in the OPC paste. On the other hand, the SEM image related to the mixture containing nano-SiO₂ indicated a dense, compact formation of hydration products and a reduced number of the Ca(OH)₂ crystals (Fig. 2b, c).

As it was mentioned before, additions of nano-SiO₂ particles with different sizes influenced the hydration behavior as well as the microstructure of the cement paste, differently. As can be seen in Fig. 2, the samples made with 100 nm SiO₂ particles (Fig. 2b) have a structure of hydration products of the cement paste with less homogeneous, dense and compact (without visible pores) texture compared to the samples with 20 nm SiO₂ particles (Fig. 2c) at 7 days. In fact, when the SiO₂ nanoparticles with very small sizes fill in the pores of the cement paste, a coating is formed at the surface of the cement particles. Therefore, a uniform surface as well as uniform dispersion in the cement paste arise, resulting in a denser and more compact texture. These microstructural results can be

Fig. 5 The correlation of the measured and predicted compressive strength in **a** the training set; **b** the testing set

supported by compressive strength tests, and can describe all the behaviors previously obtained [1, 27].

As previously mentioned, in the samples made with 20 nm of SiO_2 particles, the compressive strength continuously improved until the SiO_2 content reached 1.25% at different days of curing (Fig. 3a here at 84 day of curing). Then, the strength was slightly decreased when the SiO_2 nanoparticles reach 1.5%. It is quite clear that with increasing the SiO_2 content in the cement (for example, 2%), the quantity of the cement in the mixture will naturally be reduced, which causes a lower hydration reactivity (Fig. 3b). Here, it could be stated that the reduction of the hydration reactivity had a greater impact than the increase of pozzolanic activity; thus, as a logical conclusion, a lower compressive strength was obtained for the cement mortar with 2% SiO_2 content [27].

3.4 GEP modeling

In this study, the expression trees of GEP approach models for predicting the compressive strength, flexural strength and split tensile strength of OPC are given in Fig. 4a–c, respectively. It should be noted that the values of d0, d1, d2, d3 and d4 in Fig. 4 represent the values for input layers, i.e., day of curing, quantity of SiO_2 (kg), the size of SiO_2 nanoparticles, quantity of cement (kg) and quantity of SiO_2 (%) with the range given in Table 6.

In the GEP models, the number of the genes was two (Sub-ETs), and the linking function was multiplication. In the training and testing datasets, d0, d1, d2, d3 and d4 were considered as input parameters. Mechanical properties of the binary blended concrete (MPB) were also considered as independent output data. Among 51 experimental sets, 38 sets were randomly chosen as training set for the GEP

Fig. 6 The correlation of the measured and predicted flexural strength in **a** the training set; **b** the testing set

modeling and the remaining 13 sets were used as testing in order to generalize the capacity of the proposed models.

For the GEP-based formulations, the first step is to choose the fitness function. For this problem, firstly, the fitness, f_i , of an individual program, i , is measured by Eq. (7) [28]:

$$f_i = \sum_{j=1}^{C_t} (M - |C_{(i,j)} - T_j|), \quad (7)$$

where M is the range of selection, $C_{(i,j)}$ is 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 $|C_{(i,j)} - T_j|$ (the precision) is less than 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 for itself [28].

For the GEP approach models, chromosome 30 was observed to be the best of generation individuals which predicts the compressive strength. Explicit formulations based on the GEP approach models for f_s were obtained by:

$$\text{MPB} = f(d_0, d_1, d_2, d_3, d_4). \quad (8)$$

The related formulations could be obtained by the procedure shown in Fig. 4.

In the present study, in order to evaluate the capabilities of the GEP based models, the mean absolute percentage error (MAPE), root-mean-squared error (RMSE) and R-square (R^2) were estimated according to Eqs. (9)–(11), respectively [29]:

Fig. 7 The correlation of the measured and predicted split tensile strength in **a** the training set; **b** the testing set

$$MAE = \frac{1}{n} \left[\frac{\sum_{i=1}^n |t_i - o_i|}{\sum_{i=1}^n t_i} \right], \quad (9)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (t_i - o_i)^2}, \quad (10)$$

$$R^2 = \frac{(n \sum t_i o_i - \sum t_i \sum o_i)^2}{(n \sum t_i^2 - (\sum t_i)^2)(n \sum o_i^2 - (\sum o_i)^2)}, \quad (11)$$

where “t” is the experimental value, “o” is the predicted value, and “n” is total number of data.

The related equations to the GEP models obtained from Fig. 4a–c are in accordance with Eqs. (12), (13) and (14), respectively;

$$MPB_{compressivestrength} = \ln((d3 \ln(d2.d1) + 6.78) - d0) \times \ln(d0(\sqrt[3]{d3.d0} + \sin(-3.71d4))), \quad (12)$$

$$MPB_{flexuralstrength} = \ln\left(\left(\left(\sqrt[3]{d1} + 3.74\right) + \sqrt[3]{d0}\right) \cos(2.64d4)\right) \times \ln\left(7.60 + \sqrt{\frac{(d0d2) + d3}{d0.d2}}\right), \quad (13)$$

$$MPB_{splittensilestrength} = \sqrt[3]{d0 \exp\left(\cos^3 d0 \left(\sqrt[3]{\sqrt{d_2^2 + d1 + 0.18}}\right)\right)} \times \sqrt[3]{\ln\left(\left((\sin d4 - \sin d1) + \ln(0.18d2)\right)^3 + d2 \sin \sqrt{d1}\right)}. \quad (14)$$

Table 7 R^2 , MAPE and RMSE values of the GEP models

Statistics	GEP-CS		GEP-FS		GEP-STs	
	Training	Testing	Training	Testing	Training	Testing
R^2	0.96	0.98	0.84	0.88	0.85	0.78
MAE	0.371	0.363	0.486	0.574	0.537	0.474
RMSE	0.269	0.474	0.323	0.568	0.350	0.560
CS compressive strength						
FS flexural strength						
STs split tensile strength						

All of the results obtained from experimental studies and predicted by using the training and testing results of the GEP models are given in Figs. 5, 6, 7. R^2 , MAPE and RMSE values are shown in Table 7 for the training and testing datasets. As can be clearly observed in Figs. 5, 6, 7, the values obtained from training and testing in the GEP models are very close to the experimental ones. The same figures also demonstrate that the predicted results of compressive strength, flexural strength and split tensile strength, obtained by the GEP models, for training (Figs. 5a, 6a and 7a) and testing datasets (Figs. 5b, 6b and 7b), are comparable with the experimental results. The training results for all mechanical properties confirmed a well learned model for establishing a non-linear relationship between the input and the output parameters with low error values. Comparing the results of GEP approach models with the experimental ones demonstrates a high generalization capacity of the proposed models and comparatively low error values. All of these findings exhibit a successful performance of the models for predicting mechanical properties of BBC in the training and testing stages [29].

The result of the testing phase in Figs. 5b, 6b and 7b shows that the GEP models are capable of generalizing between input and output variables with reasonably good predictions. The performance of the GEP models is shown in Table 7. The values of R^2 for the training set are 0.98, 0.84 and 0.85, and the values of R^2 for the testing set are 0.96, 0.84 and 0.78, respectively related to compressive strength, flexural strength and split tensile strength in the GEP model. The entire R^2 , MAPE and RMSE values show that the proposed GEP models are suitable and can predict the values of mechanical properties of BBC very close to the experimental values.

4 Conclusions

SiO₂ nanoparticles appear to affect the mechanical properties and the structure of high-strength cement pastes even in low concentration. Results showed that in the

samples made with the 20 nm SiO₂ particles, the compressive strength continuously improved until the SiO₂ content reached 1.25% and then slightly decreased as the SiO₂ content reached 1.5%. Additionally, after 7 and 21 days of curing, the compressive strength of the samples made with the 100 nm SiO₂ particles, had a lower value than 20 nm ones. From the point view of energy, although the S₂₀ samples had a more nucleation sites than the S₁₀₀ ones, most of the formed nuclei of the gel could not grow. In fact, the volume of nucleus was not able to reach V^* which causes the formation of C–S–H gel was stopped. GEP may be considered as a suitable approach for the evaluation of mechanical properties of BBC. The values of R^2 for the training set are 0.96, 0.84 and 0.85 and the values of R^2 for the testing set are 0.98, 0.88 and 0.78, respectively related to compressive strength, flexural strength and split tensile strength in the GEP model. The entire R^2 , MAE and RMSE values show that the proposed GEP models are suitable and can predict the values of mechanical properties of BBC very close to the experimental values.

References

1. Najigivi A, Khaloo A, Irajizad A, Abdul Rashid S (2013) Investigating the effects of using different types of SiO₂ nanoparticles on the mechanical properties of binary blended concrete. *Compos B* 54:52–58
2. Byung-Wan J, Chang-Hyun K, Ghi-ho T, Jong-Bin P (2007) Characteristics of cement mortar with nano-SiO₂ particles. *Constr Build Mater* 21:1351–1355
3. Stefanidou M, Papayianni I (2012) Influence of nano-SiO₂ on the Portland cement pastes. *Compos B* 43:2706–2710
4. Ji T (2005) Preliminary study on the water permeability and microstructure of concrete incorporating nano-SiO₂. *Cem Concr Res* 35(10):1943–1947
5. Li H, Xiao H, Ou J (2004) A study on mechanical and pressure-sensitive properties of cement mortar with nanophase materials. *Cem Concr Res* 34(3):435–438
6. Fernandez E, Gil FJ, Ginebra MP, Driessens FCM, Planell JA, Best SM (1999) Production and characterization of new calcium phosphate bone cements in the CaHPO₄-a-Ca₃(PO₄)₂ system: pH, workability and setting times. *J Mater Sci Mater Med* 10:223–230

7. Massazza F (1987) The role of the additions to cement in the concrete durability. *Cemento* 841:359–382
8. National Material Advisory Board (1987) Concrete durability: a multi-billion dollar opportunity, NMAB-437. National Academy Press, Washington
9. Saridemir M (2010) Genetic programming approach for prediction of compressive strength of concretes containing rice husk ash. *Constr Build Mater* 24:1911–1919
10. Kara IF (2011) Prediction of shear strength of FRP-reinforced concrete beams without stirrups based on genetic programming. *Adv Eng Soft* 42:295–304
11. Abdellahi M, Bahmanpour H, Bahmanpour M (2014) The best conditions for minimizing the synthesis time of nanocomposites during high energy ball milling: modeling and optimizing. *Ceram Int* 40:9675–9692
12. Abdellahi M, Bahmanpour M, Bahmanpour M (2015) Optimization of process parameters to maximize hardness of metal/ceramic nanocomposites produced by high energy ball milling. *Ceram Int* 40:16259–16272
13. Abdellahi M (2013) A new predictive model for calculating the hardness of metal matrix nanocomposites produced by mechanical alloying. *J Mater Res* 28:3270–3278
14. Abdellahi M, Bahmanpour M (2015) Rapid synthesis of nanopowders in high energy ball milling; optimization of milling parameters. *Ceram Int* 41:1631–1639
15. Abdellahi M, Bahmanpour M, Bahmanpour M (2014) Laminating; the best way to improve Charpy impact energy of nanocomposites. *Ceram Int* 40:16115–16125
16. Abdellahi M, Heidari H, Bahmanpour M (2014) A new predictive model for the bond strength of FRP-to-concrete composite joints. *Struct Concr* 15:509–521
17. Sabouhi R, Ghayour H, Abdellahi M, Bahmanpour M (2016) Measuring the mechanical properties of polymer–carbon nanotube composites by artificial intelligence. *Int J Damage Mech* 25:538–556
18. Abdellahi M, Bahmanpour M (2014) A novel technology for minimizing the synthesis time of nanostructured powders in planetary mills. *Mater Res* 17:781–791
19. Ghayour H, Abdellahi M, Bahmanpour M (2016) Artificial intelligence and ceramic tools: experimental study, modeling and optimizing. *Ceram Int* 41:13470–13479
20. Ghayour H, Abdellahi M, Bahmanpour M (2016) Effect of process parameters and synthesis method on the performance of thermoelectric ceramics: a novel simulation. *Ceram Int* 41:6991–6998
21. Wahab Khan M, Alam A (2012) Survey of application: genomics and genetic programming, a new frontier. *Genomics* 100:65–71
22. Gaitero JJ, Campillo I, Guerrero A (2008) Reduction of the calcium leaching rate of cement paste by addition of silica nanoparticles. *Cem Concr Res* 38(8–9):1112–1118
23. Sobolev K, Ferrada-Gutierrez M (2005) How nanotechnology can change the concrete world: part 1. *Am Ceram Soc Bull* 84(10):14–17
24. Jo BW, Kim CH, Tae G, Park JB (2007) Characteristics of cement mortar with nano SiO₂ particles. *Constr Build Mater* 21(6):1351–1355
25. Muller I (2007) A history of thermodynamics—the doctrine of energy and entropy. Springer, Berlin (**ISBN 978-3-540-46226-2**)
26. Reiss H (1965) Methods of thermodynamics. Dover Publications, Mineola (**ISBN 0-486-69445-3**)
27. Haruehansapong S, Tawich P, Somchai C (2014) Effect of the particle size of nanosilica on the compressive strength and the optimum replacement content of cement mortar containing nano-SiO₂. *Constr Build Mater* 50:471–477
28. Ali Aytel (2008) An application of artificial intelligence for rainfall-runoff modeling. *J Earth Syst Sci* 117:145–155
29. Saridemir M (2011) Empirical modeling of splitting tensile strength from cylinder compressive strength of concrete by genetic programming. *Expert Syst Appl* 38:14257–14268