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Cost optimization of high strength concretes by soft computing techniques

Erdogan Ozbay[1]*, Ahmet Oztas[2] and Adil Baykasoglu[3]

[1]*Civil Engineering Department, Mustafa Kemal University, 31200, Iskenderun, Turkey*
[2]*Civil Engineering Department, Epoka University, Tirana, Albania*
[3]*Industrial Engineering Department, University of Gaziantep, 27310, Gaziantep, Turkey*

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Abstract. In this study 72 different high strength concrete (HSC) mixes were produced according to the Taguchi design of experiment method. The specimens were divided into four groups based on the range of their compressive strengths 40-60, 60-80, 80-100 and 100-125 MPa. Each group included 18 different concrete mixes. The slump and air-content values of each mix were measured at the production time. The compressive strength, splitting tensile strength and water absorption properties were obtained at 28 days. Using this data the Genetic Programming technique was used to construct models to predict mechanical properties of HSC based on its constituients. These models, together with the cost data, were then used with a Genetic Algorithm to obtain an HSC mix that has minimum cost and at the same time meets all the strength and workability requirements. The paper describes details of the experimental results, model development, and optimization results.

Keywords: high-strength concrete; genetic algorithm; genetic programming; cost optimization.

1. Introduction

As recent earthquakes in various parts of the world, including Pakistan and Turkey, have tragically demonstrated that if the structures are not properly designed and constructed even moderate earthquakes can potentially cause huge property damage and loss of life. In the 2005 Kashmir earthquake, more than 73.000 people were killed and more than 3.3 million were left injured and homeless. Over 470.000 houses were completely destroyed, nearly 65% of the hospitals in the area were destroyed or badly damaged and an estimated 10.000 school buildings were affected (Bliss *et al*. 2006). In Turkey, during Adana-Ceyhan earthquake in 1998, Adapazar-Gölcük earthquake in 1999 and Bingöl earthquake in 2003 more than 20.000 people died and more than 90.000 buildings collapsed completely. The investigations carried out after these earthquakes have singled out the poor quality of construction as the major reason behind these devastating losses (Ozkul and Oztas 1998, Oztas 2003).

Concrete structures in active seismic zones are especially vulnerable to severe damage if there is lack of quality control during design and construction. Further compounding the problem is the fact that the concrete structures generally have higher mass and thus inherently attract more earthquake forces. However in most developing countries, because of economic reasons, the use of concrete structures remains high. Fortunately recent advances in the development of High Strength Concretes

* Corresponding author, Ph.D., E-mail: ozbay@mku.edu.tr

(HSC) offer opportunities for design of relatively light structures, even in the most seismically active regions of the world. By appropriate mix of water, cement, aggregate, and chemical and mineral admixtures it is possible to develop HSC with strengths in the range of 50 to 100 MPa. With proper attention to detailing and quality control structures designed with HSC are comparable in weight, strength, and ductility to metal-framed structures at generally much lower cost. As compared to the conventional concrete the cost of HSC is obviously higher which could a deterrent to its use in the developing countries. Therefore to make the use of HSC more wide-spread there obviously is need for methodology that produces concretes with desired strength and workability properties at minimum cost. This provides the main motivation for this paper.

A variety of ingredients and admixtures are employed world-wide to produce various high strength concretes. However a systematic optimization-based procedure that takes into account both the mechanical performance of concrete and its manufacturing costs is lacking. Several studies have been conducted that have employed optimization methodology in the construction materials area. Muthukumar and Mohan (2004) optimized mix proportions of polymer concrete to have minimum void. For each polymer concrete mechanical properties such as compressive strength, flexural strength, tensile strength and splitting tensile strength were first maximized and compared with the experimental data. Following Ashby (2000), they used the maximum values for all response quantities, and then carried out a combined multi-objective optimization strategy to recommend optimum polymer concrete mix design. Chung *et al.* (2004) proposed an optimization methodology that simultaneously considered the mechanical performance and the manufacturing cost from the early stage of design for composite laminated plates. Sahab *et al.* (2005) optimized the cost of reinforced concrete flat slab buildings. The objective function was the total cost of the building including the cost of floors, columns and foundations. The cost of each structural element included that of material and labor for reinforcement, concrete and formwork. Karihaloo and Kornbak (2001) demonstrated how rigorous mathematical programming techniques can be employed in the design of fiber-reinforced concrete mixes to achieve both high tensile strength and high ductility.

The aim of this paper is to present a methodology for minimizing cost of mix proportions for HSC to meet given design conditions. Data from 72 different mix designs is obtained to develop the mathematical models needs for the optimization study. Since the major barrier in use of HSC is its high cost, a unit cost model for HSC is developed using current market prices for materials and labor in Turkey. The Genetic Programming (GP) technique is used to capture the complex nonlinear relationship between the various design and performance variables. The minimum cost mix-design problem is then formulated in the form of a mathematical programming and solved using a Genetic Algorithm (GA) (Castilho *et al.* 2005, Al-Tabtabai and Alex 1999).

2. Experimental study

2.1 Concrete mix proportioning

The key variables in the mix-design for HSC are water to cementitious material ratio (W/C), water content (W), fine aggregate to total aggregate ratio (s/a), and super plasticizer content (SP). In addition either fly ash (FA) or silica fume (SF) could be added to obtain desired properties. Thus the experimental program was divided into two categories. The first category considered W/C, W, s/a, SP and FA together with air entraining agent content (AE) as variables. The second category

Table 1 Standard L_{18} orthogonal array

Trial	Column no							
No	1	2	3	4	5	6	7	8
1	1	1	1	1	1	1	1	1
2	1	1	2	2	2	2	2	2
3	1	1	3	3	3	3	3	3
4	1	2	1	1	2	2	3	3
5	1	2	2	2	3	3	1	1
6	1	2	3	3	1	1	2	2
7	1	3	1	2	1	3	2	3
8	1	3	2	3	2	1	3	1
9	1	3	3	1	3	2	1	2
10	2	1	1	3	3	2	2	1
11	2	1	2	1	1	3	3	2
12	2	1	3	2	2	1	1	3
13	2	2	1	2	3	1	3	2
14	2	2	2	3	1	2	1	3
15	2	2	3	1	2	3	2	1
16	2	3	1	3	2	3	1	2
17	2	3	2	1	3	1	2	3
18	2	3	3	2	1	2	3	1

considered W/C, W, s/a, SP and SF as variables. Each category was further divided into two groups resulting in a total of four groups. Each group consisted of 18 specimens giving a total of 72 different concrete mixes that were prepared and tested. The first two groups considered 6 variables, as outlined earlier, while the other two groups had 5 variables. For use in the Taguchi design of experiments technique three levels of variation for each parameter in each group were defined. This necessitated use of standard L_{18} orthogonal array as shown in Table 1. The numbers 1, 2, and 3 in the table mean first, second and third level of each parameter, respectively. These levels were selected such that the specimens in the four main groups resulted in 28 day compressive design strengths in the ranges of 40 to 60, 60 to 80, 80 to 100, and 100 to 125 MPa, respectively.

Since there were only six parameters in the first two groups, the first and the last column of Table 1 were not used in preparing samples for these groups. The last two groups had five parameters and therefore the first and the last two columns of Table 1 were not taken into account for these groups. Based on these considerations, the specific mix proportions used in preparing various samples are as shown in Tables 2 and 3.

2.2 Material properties

A CEM I 42.5 R type cement was used in all concrete groups. It has a specific gravity of 3.12 and Blaine fineness of 3260 cm^2/g. Fly ash used was obtained from Sugozu power plant located in the southern part of Turkey. Its specific gravity and Blaine fineness were 2.36 and 2870 cm^2/g respectively. Silica fume used had 2.30 g/cm^3 specific gravity and its BET surface area was 210800 cm^2/g. Details of the compositions of cement, fly ash and silica fume are given in Table 4. A novel polycarboxylic type

Table 2 Mix proportions for group I and II

Group no	Mix no	W/C	W [lt]	s/a [%]	FA [%]	AE [kg/m^3]	SP [kg/m^3]
I. Group	M1	35	160	41	15	0.04	4.5
	M2	35	170	46	30	0.055	5.5
	M3	35	180	51	45	0.07	6.5
	M4	40	160	41	30	0.055	6.5
	M5	40	170	46	45	0.07	4.5
	M6	40	180	51	15	0.04	5.5
	M7	45	160	46	15	0.07	5.5
	M8	45	170	51	30	0.04	6.5
	M9	45	180	41	45	0.055	4.5
	M10	35	160	51	45	0.055	5.5
	M11	35	170	41	15	0.07	6.5
	M12	35	180	46	30	0.04	4.5
	M13	40	160	46	45	0.04	6.5
	M14	40	170	51	15	0.055	4.5
	M15	40	180	41	30	0.07	5.5
	M16	45	160	51	30	0.07	4.5
	M17	45	170	41	45	0.04	5.5
	M18	45	180	46	15	0.055	6.5
II. Group	M19	30	160	39	15	0.06	8
	M20	30	165	43	30	0.07	10
	M21	30	170	48	45	0.08	12
	M22	33	160	39	30	0.07	12
	M23	33	165	43	45	0.08	8
	M24	33	170	48	15	0.06	10
	M25	37	160	43	15	0.08	10
	M26	37	165	48	30	0.06	12
	M27	37	170	39	45	0.07	8
	M28	30	160	48	45	0.07	10
	M29	30	165	39	15	0.08	12
	M30	30	170	43	30	0.06	8
	M31	33	160	43	45	0.06	12
	M32	33	165	48	15	0.07	8
	M33	33	170	39	30	0.08	10
	M34	37	160	48	30	0.08	8
	M35	37	165	39	45	0.06	10
	M36	37	170	43	15	0.07	12

superplasticizer having a specific gravity of 1.07 and drinkable water with a pH of 7.44 at 18^{o}C were incorporated to achieve the desired workability. The coarse aggregate was a crushed limestone with a maximum particle size of 19 mm whereas natural river sand and crushed sand were used as fine aggregate. The grading of the aggregates is given in Table 5. The coarse and fine aggregates had specific gravities of 2.68 and 2.65 and mean water absorptions of 0.76% and 2.70% respectively.

Table 3 Mix proportions for group III and IV

Group no	Mix no	W/C	W [lt]	s/a [%]	SF [%]	SP [kg/m^3]
III. Group	M1	24	150	35	5	13
	M2	24	155	37	10	15
	M3	24	160	39	15	17
	M4	26	150	35	10	15
	M5	26	155	37	15	17
	M6	26	160	39	5	13
	M7	28	150	37	5	17
	M8	28	155	39	10	13
	M9	28	160	35	15	15
	M10	24	150	39	15	15
	M11	24	155	35	5	17
	M12	24	160	37	10	13
	M13	26	150	37	15	13
	M14	26	155	39	5	15
	M15	26	160	35	10	17
	M16	28	150	39	10	17
	M17	28	155	35	15	13
	M18	28	160	37	5	15
IV. Group	M19	21	140	33	10	33
	M20	21	145	35	17	37
	M21	21	150	37	24	41
	M22	22	140	33	17	37
	M23	22	145	35	24	41
	M24	22	150	37	10	33
	M25	23	140	35	10	41
	M26	23	145	37	17	33
	M27	23	150	33	24	37
	M28	21	140	37	24	37
	M29	21	145	33	10	41
	M30	21	150	35	17	33
	M31	22	140	35	24	33
	M32	22	145	37	10	37
	M33	22	150	33	17	41
	M34	23	140	37	17	41
	M35	23	145	33	24	33
	M36	23	150	35	10	37

2.3 Concrete specimens and testing methodology

All concrete specimens were mixed as per ASTM C192 in a pan mixer by first mixing the dry ingredients for one minute and then adding the water with super plasticizer and mixing for another four minutes. Slump and air content of fresh concrete were then measured. From each mix, three

Table 4 Composition of cement, fly ash and silica fume

Chemical analyses [%]	CEM I 42.5 R	Fly ash	Silica fume
CaO	62.58	9.50	0.31
SiO_2	20.25	54.53	91.97
Al_2O_3	5.31	21.98	0.82
Fe_2O_3	4.04	5.26	1.32
MgO	2.82	1.99	1.28
SO_3	2.73	0.45	0.35
K_2O	0.92	1.70	1.49
Na_2O	0.22	0.76	0.49
Loss of ignition	3.02	2.27	1.33
Blaine fineness [cm^2/g]	3260	2870	21080
Specific gravity [g/cm^3]	3.12	2.36	2.30

Table 5 Aggregate grading

Sieve size (mm)	% Passing			
	I. Coarse aggregate	II. Coarse aggregate	I. Fine aggregate	II. Fine aggregate
19	100	94.40	100	100
16	100	65.70	100	100
12.5	100	25.00	100	100
8	62.70	1.10	100	100
4	7.90	1.10	97.40	92.70
2	3.00	1.10	92.10	68.40
1	2.60	1.10	87.50	40.20
0.5	2.60	1.10	63.30	29.00
0.25	2.60	1.10	13.50	22.70
0.125	2.60	1.10	4.40	14.90
Fineness modulus	6.20	7.30	2.40	3.30

150 mm cubes, three 100 mm diameter and 200 mm long cylinders, and three 150 mm cube samples were then prepared. The specimens were cast in three layers each of which was compacted for few seconds by a vibrating table. The specimens were demoulded after 24 hours and then stored in lime saturated water at a temperature of 21±2°C with 95±5% relative humidity until the date of testing.

The air content of freshly mixed concrete was determined by using the pressure method in accordance with ASTM C 231. The compressive strength and the split tensile strength of hardened concrete were determined at the 28th day according to the relevant ASTM standards. Water absorption test was performed for determining the volume of permeable voids in the hardened concrete according to the ASTM C 642. The test consisted of two major steps. First, the concrete specimens were immersed in water until the change in mass during a 24 hour period was less than 0.1%. This is called the saturated mass and is denoted by M_S. The specimens were then dried in a ventilated oven at a temperature of 105±5°C until the difference in mass during 24 hours was less

Table 6 Experimental test results

Group no	Mix no	Slump [cm]	Air content [%]	Compressive strength [MPa]	Split tensile strength [MPa]	Water absorption [%]	Cost [YTL/m^3]
Group I	M1	18	2.8	53.3	5.8	2.06	115.73
	M2	23	3.2	45	4.8	2.02	111.8
	M3	26	3.6	45.9	5.8	1.77	106.5
	M4	23	3.4	44.2	3.96	0.72	104.5
	M5	25	4	29.6	2.38	0.62	88.5
	M6	24	2.5	42.3	2.97	0.77	118.2
	M7	20	4.2	41.5	3.82	0.82	103.4
	M8	21	2.8	42.5	3	1.15	101.1
	M9	24	3.4	32.3	2.95	1.11	85.4
	M10	27	4.1	43.5	2.83	1.23	96.4
	M11	23	5.4	49.5	3.31	1.56	128.5
	M12	26	5.2	46.1	3.16	1.33	111.3
	M13	22	4.2	54.2	3.17	1.24	94.1
	M14	20	3.6	54.2	3.14	1.52	110.3
	M15	24	3	51.4	3.96	1.22	106.7
	M16	18	3.1	50.9	3.7	2.17	90.1
	M17	27	3.8	47.4	3	2.23	87.3
	M18	26	3.7	57.2	3.8	1.78	114.2
Group II	M19	18	3.7	67.8	3.96	1.30	142.7
	M20	21	3.8	70.8	3.87	0.74	139.5
	M21	25	4.2	62.9	4.01	0.89	135.4
	M22	19	3.7	54.4	4.18	0.92	138.9
	M23	23	4.3	50.9	3.93	0.93	111.5
	M24	23	3.4	62.1	4.3	0.94	147.7
	M25	24	3.6	64.5	4.1	1.36	134.6
	M26	25	4.4	63.8	4.24	1.26	133.4
	M27	20	3.8	63.9	4.3	1.38	106.8
	M28	22	3.9	74.6	4.18	0.98	123.6
	M29	15	2.7	71.6	4.21	0.95	161.9
	M30	21	3	72.4	4.13	0.92	133.3
	M31	23	3.7	72.3	4.8	1.04	126.4
	M32	19	4	71.2	4.7	1.21	137.2
	M33	23	3.7	70.2	4.5	1.16	134.6
	M34	21	3.6	64.8	4.52	1.19	115.2
	M35	27	3.7	64.9	4.75	1.12	113.7
	M36	26	3.1	64.1	4.95	1.38	147

Table 6 Continued

Group no	Mix no	Slump [cm]	Air content [%]	Compressive strength [MPa]	Split tensile strength [MPa]	Water absorption [%]	Cost [YTL/m^3]
Group III	M37	22.5	3.5	95	5.15	1.62	224.3
	M38	24	3.4	95.5	5.02	1.59	268.2
	M39	23.5	3.6	93	5.46	1.41	314.1
	M40	24	3.7	83.1	5.44	1.90	248.7
	M41	25.5	3.8	83.7	5.09	1.81	290.8
	M42	24	3.4	82.4	5.13	1.90	221.7
	M43	24.5	3.6	82.3	4.99	1.55	219.7
	M44	23.5	3.8	82.6	5.14	1.53	233.7
	M45	25.5	3.4	82.8	4.89	1.42	274.2
	M46	25	3.7	85.3	4.99	1.29	292.2
	M47	26	3.8	86	6.56	1.35	245.6
	M48	24.5	3.1	84.2	6.29	1.32	265.7
	M49	24	2.8	87	5.49	1.15	268
	M50	22.5	2.4	88.1	5.91	1.28	225.6
	M51	23.5	3.3	90.5	6.25	1.32	267.6
	M52	22	2.7	86.3	5.89	1.70	245.3
	M53	24	2.8	81.2	6.11	1.51	260.1
	M54	23.5	2.5	82.3	6.19	1.66	219.6
Group IV	M55	25	1	115.9	8.29	0.62	393.4
	M56	19	1.2	104.7	8.64	0.77	411.8
	M57	24	0.8	102	6.72	0.48	487.8
	M58	18	1.4	97.4	7.36	0.60	393.4
	M59	19	1	95.1	1.82	0.81	465.1
	M60	20	1.1	105.7	10.93	0.70	344.5
	M61	19	0.9	102.1	9.75	0.69	375.6
	M62	21	1.1	108.5	11.12	0.61	375.7
	M63	19	0.8	108.9	7.91	0.59	446.8
	M64	17	0.8	106.3	10.04	0.51	450.5
	M65	19	1.1	102.8	9.41	0.54	379.3
	M66	20	0.9	98	6.04	0.59	403.8
	M67	18	0.6	89.8	6.11	0.62	422.1
	M68	19	1.3	94.1	6.25	0.56	354.6
	M69	20	0.8	102	7.97	0.68	426.3
	M70	18	1.3	94.1	7.34	0.62	400.9
	M71	17	0.9	94.9	7.30	0.67	420.7
	M72	27	0.6	109.3	7.32	0.39	353.4

than 0.1%. The dry mass is denoted by M_D. The water absorption (WA) by immersion is then expressed as the water uptake relative to the dry mass as follows.

$$WA = \frac{M_S - M_D}{M_D} \tag{1}$$

The overall test results of experimental study are given in Table 6. The last column in the table lists unit cost of each mix determined as discussed in the following section.

3. Cost assessment of mixes

An important first step in the cost optimization of HSC mix design is to have fairly accurate cost estimates for various mixes considered in the experimental program. Cost of each of the 72 mixes was determined in terms of Turkish lira (TL) per cubic-meter of concrete. (Currently 1 Turkish lira is approximately equal to 0.72 US dollars.) The cost included material costs, transportation cost, and administrative cost. The cost of curing, erection, and placing is essentially the same regardless of the mix design and thus was not considered in the cost estimates.

3.1 Cost of raw materials

Based on the current market prices in Turkey, the cost per ton of cement, water, fine and coarse aggregates, fly ash, air entraining agent, and superplasticezer are given in Table 7.

Table 7 Unit costs of the raw materials

Raw material	Unit cost (TL/ton)
Cement	100
Water	3
Fly ash	15
Aggregates (fine and coarse)	10
Superplasticizer (Glenium 51)	4160
Air entraining agent	40
Silica fume	585
Exchange rate	1 US \$ = 1.3 (TL)

Table 8 Input variables for GEP

Input variable	Description
x_1	Water to cement ratio (W/C)
x_2	Water content (W)
x_3	Fine aggregate ratio (s/a)
x_4	Replacement ratio of fly ash (FA)
x_5	Replacement ratio of silica fume (SF)
x_6	Content of air-entraining agent (AE)
x_7	Content of superplasticizer (SP)

3.2 Transportation and administrative cost

The prices shown in Table 7 are the costs at the source and do not include the cost of transporting the raw materials from the source to the plant and their delivery to the construction site. In addition there are administrative costs that take into consideration such items as advertising, energy, rents, insurance, office equipment, maintenance, depreciation, and overheads charges (Karihaloo and Kornbak 2001). These costs are obviously difficult to quantify. To get a reasonable estimate interviews were conducted with the managers of 22 ready-mix concrete plants located in different parts of Turkey. These interviews indicated that most managers break down the cost of HPC mixes as follows.

- Raw materials cost : 62%
- Transportation cost : 12%
- Administration cost : 26%

Furthermore these same plant managers estimated that 64.5% of the raw materials cost was actually the cost of the cement itself. Using this information, the transportation cost of cement can be determined as follows.

- Proportion of cement cost to the total cost = 62×64.5/100 = 40%
- Proportion of transportation cost to cement cost = 12×100/40 = 30%

Thus 30% of the cement cost was added to the total as its transportation cost. In the same way the transportation and administration cost for each component was calculated and added to the total. The total estimated cost of each of the 72 concrete mixes is shown in the last column of Table 6.

4. Mathematical models for cost and mechanical properties of HPC

In order to use optimization methodology the key design parameters such as slump, air content, compressive strength, split tensile strength, water absorption and the cost must be expressed as functions of variables in the HPC mixes. Thus we must develop equations that relate these properties of HPC to water to cement ratio (W/C), water content (W), fine aggregate ratio (s/a), replacement ratio of fly ash (FA), replacement ratio of silica fume (SF), content of air-entraining agent (AE), and content of superplasticezer (SP). Regression and Neural Networks are two of the most common techniques used in the literature to accomplish this. The success of regression techniques depends on the initial form of the model. Neural networks can handle complex relationships. However they do not give explicit mathematical equations and thus must be used as "black-boxes" in an optimization setting. More recently Gene-Expression Programming (GEP) has emerged as an attractive alternative. The technique can handle complex nonlinear relationships between various inputs and output variables and, once trained, results in a set of explicit expressions that can be used in any future analysis.

Gene-Expression Programming (GEP) is a natural extension of Genetic Programming (GP) and was recently developed by Ferriera (2002). A standard GP is a search strategy based on the rules of natural genetic evolution (Castilho *et al.* 2005). The GP works with population of individuals each representing a possible solution to a given problem. Each candidate solution, or individual, is represented as a string of bits analogous to chromosomes and genes in the evolution theory. A fitness score is assigned to each individual (Al-Tabtabai and Alex 1999). On the other hand a GEP starts with an *expression tree* (ET) written in the so-called Karva notation. For example, the

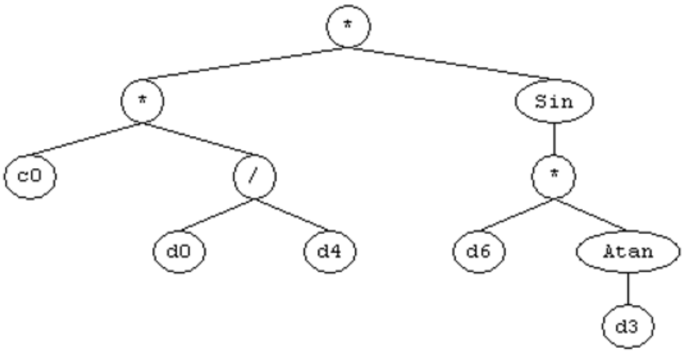

Fig. 1 A typical example of the GEP expression tree

algebraic expression $(c0(d0/d4)) \times \sin(d6(atan(d3)))$ can be represented by an ET as shown in Fig. 1. To read this tree we start at the bottom and move up. The left leaf indicates *d*0/*d*4 as the lowest expression. It then is multiplied by *c*0 to give the expression in the first set of parentheses. The right leaf starts with defining arc-tangent of *d*3 which then is multiplied by *d*6 and the resulting expression is then used as the argument to the sine function. The expressions from the two leafs are then multiplied to get the final expression. A GEP algorithm begins with the random values of parameters in the ET and applies standard genetic operations of selection, crossover, and mutation to find the best fit (Castilho *et al.* 2005, Goldberg 1989).

4.1 GEP Generated functions for HSC properties

Data from 56 randomly selected samples was used to train the GEP models. The data from the remaining 18 samples was used to test the models. Table 8 shows the HPC variables that were used as inputs to the models.

The hidden functions connecting the input variables to the outputs were constructed by using the GEP software GeneXproTools 4.0 developed by Ferreira (2001). The program suggests many different equations for the prediction of HSC properties. The models with the highest accuracy on the training set are presented in Eqs. (2) to (6). The performance of these models on both the training set and the test set are tabulated in Table 9.

$$\mathrm{Slump} = F_1F_2F_3F_4F_5F_6F_7 \tag{2}$$

$$F_1 = \mathrm{atan}(\mathrm{atan}(\cos(\sin(x_1)))\sqrt{x_6+x_7})) \tag{2a}$$

$$F_2 = \mathrm{atan}\left(\sqrt{\sqrt{\sqrt{x_7}+(-4.058715+x_1)}+3.410736}\right) \tag{2b}$$

$$F_3 = \sqrt{\mathrm{atan}(\sin(x_7x_1)+1.30948)} \tag{2c}$$

$$F_4 = \sin(\mathrm{atan}(x_2^{x_7})+\mathrm{atan}(\sqrt{x_4})) \tag{2d}$$

$$F_5 = 0.197399 \tag{2e}$$

$$F_6 = 0.639318 \tag{2f}$$

Table 9 Statistical performance of the proposed GEP models

HSC property	Statistical parameter	Training set	Testing set
Slump	MSE	3.9	3.4
	RMSE	1.97	1.84
	MAE	1.49	1.40
	R	0.74	0.77
Air content	MSE	0.18	0.23
	RMSE	0.43	0.48
	MAE	0.31	0.37
	R	0.94	0.90
Compressive strength	MSE	52.57	46.73
	RMSE	7.25	6.83
	MAE	5.82	4.91
	R	0.94	0.95
Split tensile strength	MSE	2.45	1.82
	RMSE	1.56	1.35
	MAe	1.14	1.04
	R	0.80	0.84
Water absorption	MSE	0.06	0.09
	RMSE	0.25	0.3
	MAE	0.19	0.22
	R	0.84	0.85
Cost	MSE	49.89	41.45
	RMSE	7.06	6.43
	MAE	5.73	5.21
	R	0.99	0.99

MSE=Mean square error, RMSE=Root mean square error, MAE=Mean absolute error, R=Correlation coefficient

$$F_7 = \frac{x_7 x_6}{x_6 - x_2} + x_4 + x_2 \tag{2g}$$

Air content=F_1+F_2+F_3+F_4+F_5 (3)

$$F_1 = \frac{x_6}{\cos(\cos(x_7 - x_2) - (x_3 + x_4 - 6.2678))} \tag{3a}$$

$$F_2 = \cos\left(\frac{x_7}{x_1 + 26.0407} - x_5\right) \tag{3b}$$

$$F_3 = \cos\left(\sin\left((x_3 - x_7)\left(-\frac{6.562836}{x_1} + x_3\right)\right)\right) \tag{3c}$$

$$F_4 = \cos\left(\frac{\sin(x_7)}{x_1 / (x_7 - 12.2872)}\right) \tag{3d}$$

$$F_5 = \cos\left(\frac{-4.877961+2x_7}{2x_4-4.623352+x_1}\right) \tag{3e}$$

Compressive strength = $F_1F_2F_3F_4F_5F_6$ (4)

$$F_1 = 0.063232+0.063232x_2(x_5-0.063232)-0.063232x_5 \tag{4a}$$

$$F_2 = x_5(x_7+x_5)(9.616425-x_6-9.616425x_4)+5.672119 \tag{4b}$$

$$F_3 = x_5-0.211364 \tag{4c}$$

$$F_4 = -0.059722 \tag{4d}$$

$$F_5 = x_2-(-9.322021x_5-x_2x_5+x_4+x_3-(x_2+7.394745)) \tag{4e}$$

$$F_6 = 2x_4x_5x_6+41.3968+x_3+x_6-x_1 \tag{4f}$$

Water absorption = $F_1+F_2+F_3+F_4+F_5$ (5)

$$F_1 = \cos(-12.0105(x_5-x_6+x_6)) \tag{5a}$$

$$F_2 = \frac{2.848481}{x_6}-\frac{x_5}{x_3-x_4} \tag{5b}$$

$$F_3 = \frac{\cos((x_7-x_5)(8.127868-x_3))}{5.304779+x_4-8.127868x_6} \tag{5c}$$

$$F_4 = \frac{x_5}{x_2-5.23264(4.863953+x_6)} \tag{5d}$$

$$F_5 = \sin(\sin(\cos(-1.017425-x_5)(x_1+7.959504))x_5) \tag{5e}$$

Split tensile strength $=F_1+F_2+F_3+F_4+F_5$ (6)

$$F_1 = 1.8194285-x_5+0.331270\sin(x_7)+x_6x_5 \tag{6a}$$

$$F_2 = e^{\sin(x_7\sqrt{x_7}-5.039611+x_2)} \tag{6b}$$

$$F_3 = \cos(x_7+x_2+x_6-(2.575256-x_1-4.068206x_7)) \tag{6c}$$

$$F_4 = e^{\sin((x_7+1.22375-(x_2+1.652924))x_7)} \tag{6d}$$

$$F_5 = e^{-9.393646}+\sin(x_6x_7) \tag{6e}$$

Cost=$F_1+F_2+F_3+F_4+F_5+F_6+F_7+F_8$ (7)

$$F_1 = 1.77612+x_6 \tag{7a}$$

$$F_2 = x_7\sqrt{x_6-1.839264}+(e^{x_7}+e^{-6.377655})2x_5 \tag{7b}$$

$$F_3 = x_6 \tag{7c}$$

$$F_4 = \ln(x_2)-x_4-9.869721x_5-x_1-\sqrt{x_5}-x_5 \tag{7d}$$

$$F_5 = \ln(x_2+\sqrt{x_7}(x_2x_3)-(x_2-1.943757)/1.943757) \tag{7e}$$

$$F_6 = 8.616821+x_2-(x_7/4.487457)-x_6-x_5x_3 \tag{7f}$$

$$F_7 = x_6 \tag{7g}$$

$$F_8 = x_7 - 0.997254x_1 \tag{7h}$$

5. Optimization problem for minimizing HPC costs

An optimization problem is formulated in order to obtain the best possible values for the HSC variables for minimum. There are seven design variables as identified in Table 8. The objective function is to minimize the cost given by Eq. (7). To obtain mixes that physically make sense upper and lower bounds are placed on desired mechanical characteristics of the mixes. The first constraint defines the lower and upper limit for compressive strength. The compressive strength itself is determined from Eq. (4). The upper limit of compressive strength was set based on the maximum value of compressive strength obtained during the experimental program. Thus compressive strength constraint was defined as follows.

$$113.9 \text{ MPa} \geq \text{Compressive strength} \geq 50.5 \text{ MPa} \tag{8}$$

Similarly the upper and lower bounds for slump, air content, water absorption, and split tensile strength were set to their ranges observed during the experimental program. The actual values of these quantities were computed using Eqs. (2), (3), (5), and (6).

$$270 \text{ mm} \geq \text{Slump} \geq 150 \text{ mm} \tag{9}$$

$$5.4\% \geq \text{Air content} \geq 0.6\% \tag{10}$$

$$11.1 \text{ MPa} \geq \text{Split tensile strength} \geq 1.8 \text{ MPa} \tag{11}$$

$$2.2\% \geq \text{Water absorption} \geq 0.4\% \tag{12}$$

In addition the following bounds were defined for the design variables. Once again the actual numerical values indicated were based on their values used in the experimental program.

$$45 \geq x_1 \geq 22 \text{ water to cement ratio (W/C)} \tag{13}$$

$$180 \geq x_2 \geq 130 \text{ water content (W)} \tag{14}$$

$$51 \geq x_3 \geq 35 \text{ fine aggregate ratio (s/a)} \tag{15}$$

$$45 \geq x_4 \geq 0 \text{ replacement ratio of fly ash (FA)} \tag{16}$$

$$0.08 \geq x_5 \geq 0 \text{ replacement ratio of silica fume (SF)} \tag{17}$$

$$41 \geq x_6 \geq 4.5 \text{ content of air-entraining agent (AE)} \tag{18}$$

$$24 \geq x_7 \geq 0 \text{ content of superplasticizer (SP)} \tag{19}$$

The solution of this mathematical optimization problem was obtained by using a Genetic Algorithm (GA) implemented in Mathematica (Bhatti 2000). The GA is a useful and effective stochastic technique for minimizing the HSC costs. The main advantage of GA is that it does not require gradient or derivative information. Furthermore GA systems are particularly adept at locating a global optimum using a random yet directed searching operator. Therefore, one is assured that the optimum solutions reported are truly the best solutions. The GA used in this study

Table 10 Optimal mix proportions and their expected HSC properties

No	W/B [%]	W [lt/m^3]	s/a [%]	FA [%]	SF [%]	AE [kg/m^3]	SP [kg/m^3]	Compressive strength [MPa]	Slump [cm]	Air content [%]	Water absorption [%]	Split tensile strength [MPa]	Cost [YTL/m^3]
1	30	170	48	45	0.0	0.08	12.0	58.23	26	3.83	0.99	3.27	78.20
2	37	165	48	30	0.0	0.06	12.1	65.99	25	3.54	1.35	4.85	71.30
3	37	170	43	16	0.0	0.07	12.3	54.38	24	3.30	1.81	10.21	83.07
4	24	155	37	0.0	10.0	0.0	16.4	73.12	23	3.30	1.66	5.44	82.63
5	45	180	46	15	0.0	0.05	6.5	50.05	27	3.47	1.76	1.87	83.24
6	27	154	36	0.0	14.0	0.0	12.7	51.06	24	3.35	1.60	3.87	84.50
7	33	160	43	45	0.0	0.06	12.0	62.28	24	4.32	1.58	10.23	84.27
8	33	160	39	30	0.0	0.07	12.0	59.79	19	3.37	0.94	4.03	85.05
9	30	156	39	9.0	0.0	0.02	9.7	113.86	27	3.07	0.67	5.96	123.19

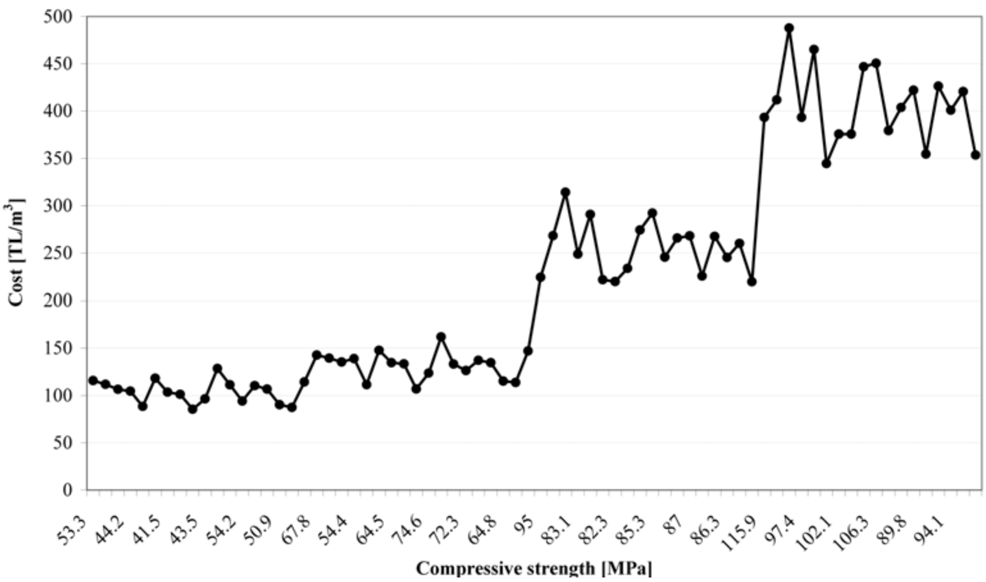

Fig. 2 Cost versus compressive strength change of concrete mixtures

employed a roulette wheel selection method. The crossover was performed based on one-point crossover theory with a probability of 0.9. Uniform mutation method was used with a probability of 0.01. The number of generations was restricted to 1000. The optimal cost and design variable values are given Table 10. By varying the upper and lower limits on the desired strength and workability parameters, various optimum designs with desired properties can easily be obtained. Fig. 2 presents the cost change of the 72 concrete mixtures according to their compressive strength. As seen in that figure that cost of the concrete mixtures increased with the increasing of the compressive strength. Moreover, when the ingredients of the concretes mixtures, which was presented in Table 2 considered, cost of the concrete directly related to the superplasticizer and silica fume dosages. Fig. 3 illustrates cost versus compressive strength of the optimum mixtures that was also given in Table

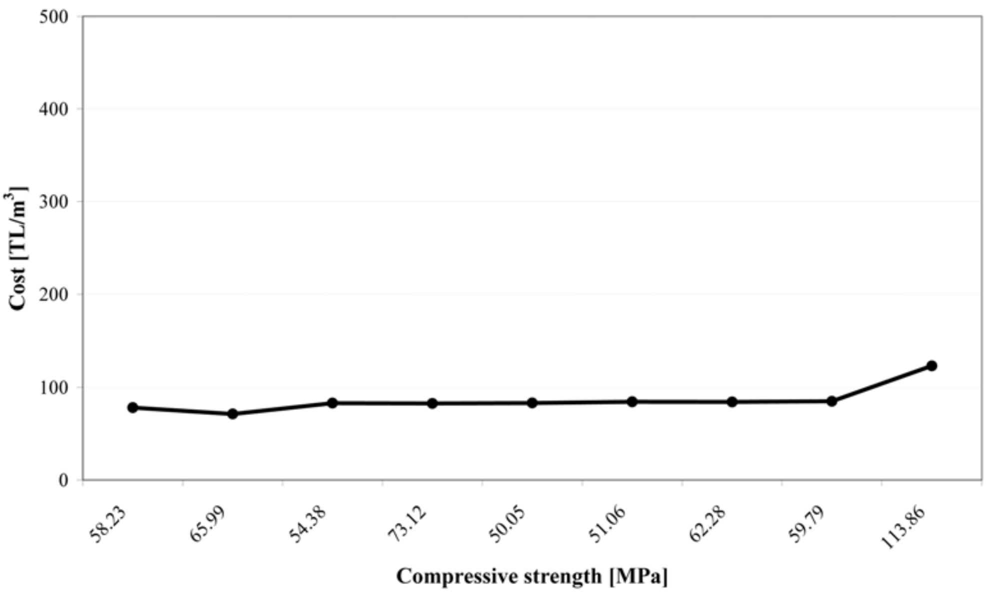

Fig. 3 Cost versus compressive strength change of optimum concrete mixtures

10. According to the Fig. 3, it can be concluded that high strength concrete can be produced with low costs.

6. Conclusions

In this work soft computing approaches of GEP and GA are used to determine parameters of high strength concrete that result in a minimum cost mix. GEP method was used to develop equations for prediction of mechanical properties of HSC using data obtained from an extensive set of samples designed for this study. The GEP was deemed to be a very useful tool to capture complex nonlinear relationships between input and output parameters. One of its main advantages is that it gives explicit mathematical equations that are necessary for generating optimization models. In the second part of the study optimum proportions of HPC mix are generated based on the equations derived by GEP analysis. Optimization models are solved by using GA. The paper demonstrates the effectiveness of using the soft computing approaches in modeling HPC material behavior. As a practical contribution the paper presents specific values for various HPC ingredients to obtain a minimum cost mix. The methodology can easily be adapted to handle specific situations as the prices change or if an HPC with different characteristics is desired.

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