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Genetic algorithm in mix proportioning of high-performance concrete

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Abstract

High-performance concrete is defined as concrete that meets special combinations of performance and uniformity requirements that cannot always be achieved routinely using conventional constituents and normal mixing, placing, and curing practices. Ever since the term high-performance concrete was introduced into the industry, it had widely used in large-scale concrete construction that demands high strength, high flowability, and high durability. To obtain such performances that cannot be obtained from conventional concrete and by the current method, a large number of trial mixes are required to select the desired combination of materials that meets special performance. Therefore, in this paper, using genetic algorithm that is a global optimization technique modeled on biological evolutionary process—natural selection and natural genetics—and can be used to find a near optimal solution to a problem that may have many solutions, the new design method for high-performance concrete mixtures is suggested to reduce the number of trial mixtures with desired properties in the field test. Experimental and analytic investigations were carried out to develop the design method for high-performance concrete mixtures and to verify the proposed mix design.

Keywords: High-performance concrete; Genetic algorithm; Mixture proportioning; Compressive strength; Workability

1. Introduction

1.1. High-performance concrete

The parts of the world in which large-scale concrete construction takes place have extended enormously. Due to the recent trends in construction industries (i.e., increased number of heavily reinforced concrete structures), construction of large and taller structures, and developments of construction techniques (i.e., efficient concrete pumping techniques), the industries and companies in general strive to cast massive volume of concrete. When this large volume of concrete is used for construction, the safety and durability of cast concrete become fundamental issues. To ensure these issues, much effort has been focused on the developments of high-performance concrete [1–10].

High-performance concrete is designed to give optimized performance characteristics for a given set of materials, usage, and exposure conditions, consistent with strength, workability, service life, and durability. Engineers and constructors all over the world are finding that using high-performance concrete allows them to build more serviceable structures at comparable cost. High-performance concrete is being used for structures in aggressive environments: marine structures, highway bridges and pavements, nuclear structures, tunnels, precast units, etc. [11,12].

The major difference between conventional concrete and high-performance concrete is essentially the use of chemical and mineral admixtures. The use of chemical admixtures reduces the water content, thereby at the same time reduces the porosity within the hydrated cement paste. The reduction in the water content to a very low value with high dosage of chemical admixtures is undesirable, and the effectiveness of chemical admixtures such as superplasticizer principally depends on the ambient temperature, cement chemistry, and fineness. Mineral admixtures, also called as cement replacement materials, act as pozzolanic materials as well as fine fillers; thereby, the microstructure of hardened cement matrix becomes denser and stronger. At ambient temperature, their chemical reaction with calcium hydroxide is generally slow. However, the finer and more vitreous the pozzolan is, the faster will be this reaction. If durability is of primary interest, then the slow rate of setting and hardening

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associated with the incorporation of fly ash or slag in concrete is advantageous. Also, the mineral admixtures are generally industrial by-products and their use can provide a major economic benefit. Thus, the combined use of superplasticizer and cement replacement materials can lead to economical high-performance concrete with enhanced strength, workability, and durability. It is also reported that the concrete containing cement replacement materials typically provides lower permeability, reduced heat of hydration, reduced alkali–aggregate reaction, higher strength at later ages, and increased resistance to attack from sulfates. However, the effect of cement replacement materials on the performance of concrete varies markedly with their properties [13].

To obtain the special combinations of performance and uniformity requirements, a near-optimum mix proportion of high-performance concrete is very important. However, there have not been any guide specifications on the mix proportion of high-performance concrete. Required mix proportions are therefore obtained by trial and error method that is based on existing data and by the method that is based on specifications for conventional concrete mixtures. Such methods for mix proportioning require large number of trial mixes to select the desired combination of materials, whereas a good mix proportioning procedure has to minimize the number of trial mixes and achieve an economical and satisfactory mixture with desired properties [14,15]. This paper presents a new design method for high-performance concrete mixtures using genetic algorithm to minimize the number of trial mixes and provide appropriate mix proportion.

Genetic algorithm, which is first formalized as an optimization method by Holland, is a global optimization technique for high dimensional, nonlinear, and noisy problem and a stochastic search technique based on the mechanism of natural selection and natural genetics [22]. Genetic algorithm, differing from conventional search techniques, starts with an initial set of random solutions called population. Each individual in the population is called a chromosome, representing a solution to the problem at hand. The evolution operation simulates the process of Darwinian evolution to create population from generation to generation. The success of genetic algorithm is founded in its ability to keep existing parts of solution, which have a positive effect on the outcome, and proceed with optimizing the nonoptimal part. The approach is global, as possible as many samples from different parts of the solution space are examined simultaneously. Then the transition rules, which combine and change those samples in order to improve the solutions already found, are probabilistic and not deterministic. This enables genetic algorithm to reach a global optimum without being fixed in local optima. Genetic algorithm, known as a very efficient heuristic algorithm that has been widely used in the various fields of engineering [23–27], gives therefore more accurate results than other algorithms in the mix proportioning problem having many local solutions.

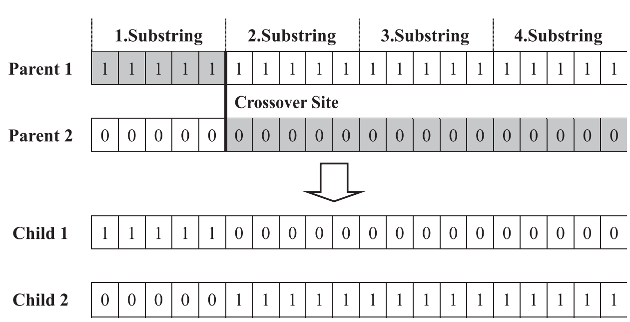

Fig. 1. Single-point crossover.

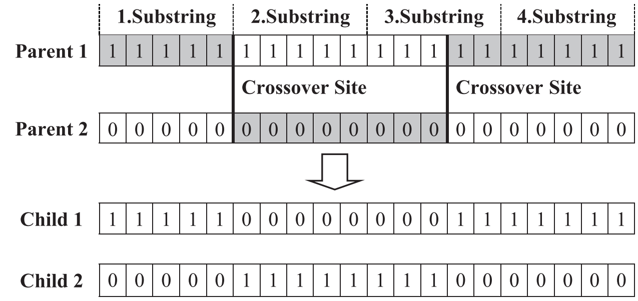

Fig. 2. Two-point crossover.

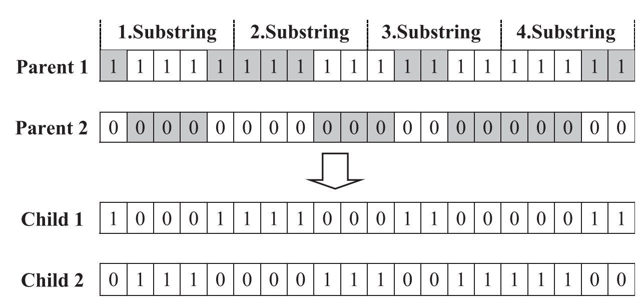

Fig. 3. Uniform crossover.

2. Genetic algorithm

The general form of genetic algorithm, as described in the book written by Goldberg, is composed of three major processes, i.e., selection, crossover, and mutation [28].

2.1. Selection

The fundamental principle of genetic algorithm starts from essentially Darwinian natural selection. The initial individuals were selected in this process. Selection provides the driving force in genetic algorithm, and selection pressure is critical in it. Typically, low selection pressure is indicated at the start of the genetic algorithm search in favor of a wide exploration of the search space, while high selection pressure is recommended at the end in order to exploit the most

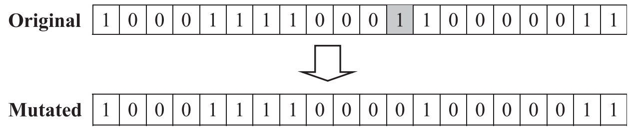

Fig. 4. Mutation.

promising regions in the search space. The selection directs genetic algorithm search toward promising regions in the search space.

2.1.1. Roulette wheel selection (proportional selection)

Roulette wheel selection is the best-known selecting method due to its simplicity. It is usually presented in every introduction to genetic algorithm. The basic idea is to determine selection probability; also called survival probability for each chromosome proportional to the fitness value. For chromosome with fitness, its selection probability is calculated as follows:

$$P_k = \frac{f_k}{\sum_{i=1}^{\text{pop-size}} f_i} \qquad (1)$$

where P_k is the selection probability of a chromosome from population k, f_k is the size of population k, and f_i is the size of whole population.

Therefore, a wheel can be made according to these probabilities. The selection process is based on spinning the roulette wheel pop − size times. Each time, a single chromosome is selected for the new population as described in the last selection.

2.1.2. Ranking selection

This theory introduced to overcome the scaling problems of the direct fitness-based approach. The idea sorts the population from the best to the worst and assigns the selection probability of each chromosome according to the ranking. This method ranks the individuals according to their normalized fitness. Two methods are in common use: linear ranking and exponential ranking.

2.1.3. Tournament selection

This approach contains both random and deterministic features simultaneously. This method randomly chooses a set of chromosomes and picks out the best one from the set for reproduction. The number of chromosomes in the set is called tournament size. A common tournament size is 2. This is called binary tournament. Selection probabilities are normally calculated and successive pairs of chromosomes are drawn using roulette wheel selection. After drawing a pair of the chromosomes with higher fitness, these are

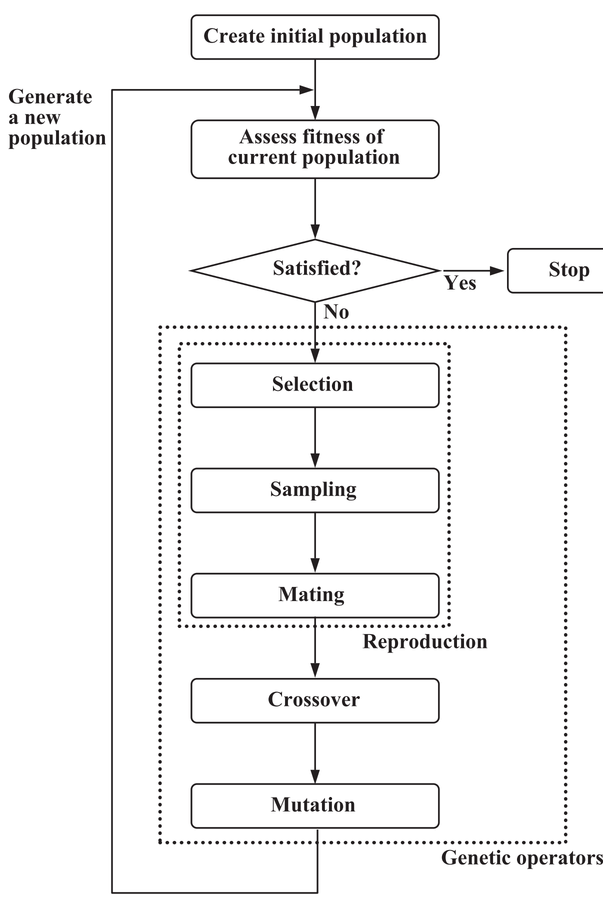

Fig. 5. Genetic algorithm process.

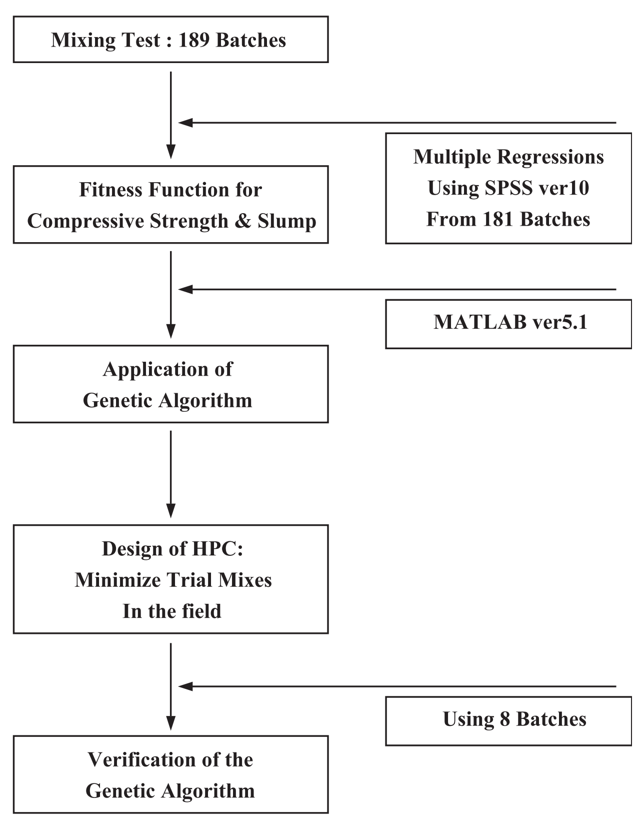

Fig. 6. Research procedure.

Table 1
Properties of cement

Properties	Cement
Specific gravity	3.15
Fineness (m^2/kg)	310
SiO_2 (%)	21.3
Al_2O_3 (%)	4.7
Fe_2O_3 (%)	3.1
CaO (%)	63.1
MgO (%)	3
Loss on ignition (%)	0.8

Table 3
Properties of fly ash

Properties	Fly ash
Specific gravity	2.13
Fineness (m^2/kg)	360
SiO_2 (%)	63.5
Al_2O_3 (%)	28.5
Fe_2O_3 (%)	4.2
CaO (%)	1.2
MgO (%)	0.8
Moisture content (%)	0.2
Loss on ignition (%)	3.6

inserted in the new population. The process continues until the population is full.

2.2. Crossover

Crossover simulates the sexual generation of a child or offspring from two parents. This is performed by taking parts of the bit string of one of the parents and the other parts from the other parent and by combining both in the child. The crossover rate is defined as the ratio of the number of offspring produced in each generation to the population size. This ratio controls the expected number (Crossover Rate × Population Size) of chromosomes to undergo the crossover operation. A higher crossover rate allows exploration in the large solution space and reduces the chances of settling for a false optimum; but if this rate is too high, it results in the wastage of a lot of computation time in exploring unpromising regions of the solution space. There are three kinds of crossover: single-point, two-point, and uniform crossover.

2.2.1. Single-point crossover

This kind of crossover operator is analogous to that of the binary implementation. The basic one is one-cut-point crossover. Let two parents be $u=[u_1, u_2, u_3...u_n]$ and $v=[v_1, v_2, v_3...v_n]$ if they are crossed after the kth position, and the resulting offsprings are shown as in Eqs. (2) and (3) and Fig. 1 shows a single-point crossover.

$$u = [u_1, u_2, u_3, \ldots\ldots, u_k, u_{k+1}, u_{k+2}, \ldots\ldots, u_n] \tag{2}$$

$$v = [v_1, v_2, v_3, \ldots\ldots, v_k, v_{k+1}, v_{k+2}, \ldots\ldots, v_n] \tag{3}$$

2.2.2. Two-point crossover

Two-point crossover is shown in Fig. 2. It differs from single-point crossover merely in the point that two random cuts are made; so three pieces have to be put together in order to produce an offspring.

2.2.3. Uniform crossover

Crossover can be implemented with uniform crossover operator, which has been shown to be superior to traditional crossover strategies for combinatorial problem. Uniform crossover first generates a random crossover mask and then exchanges relative genes between parents according to the mask. A crossover mask is simply a binary string with the same size of chromosome. The parity of each bit in the mask determines, for each corresponding bit in an offspring, which parent it will receive that bit from. It is illustrated in Fig. 3.

2.3. Mutation

The crossover operator is able to generate all possible values of genotypes even if the population contains only copy of a specific allele value. But as the genetic algorithm proceeds to generate new genotypes, it is always possible to lose the last copy of an allele value. The second operator prevents the population of genotypes from loosing a specific value of an allele. Mutation is performed with a given probability. The mutation rate is defined as the percentages of new genes to the total number of genes in the population and controls the rate at which new genes are introduced into the population for trial. If it is too slow, many genes that would have been useful are never tried out. But if it is too high, there will be much random perturbation, the offspring

Table 2
Properties of aggregates

Properties	Coarse aggregate	Fine aggregate
Fineness modulus	7.2	2.94
Specific gravity	2.7	2.61
Water absorption (%)	0.6	0.8
Unit weight (kg/cm^3)	1480	1590
Abrasion (%)	18.6	–

Table 4
Properties of silica fume

Properties	Silica fume
Specific gravity	2.1
Fineness (m^2/g)	2200
SiO_2 (%)	92
Al_2O_3 (%)	1.3
Fe_2O_3 (%)	2.4
MgO (%)	0.4
Moisture content (%)	0.1

Table 5
Properties of superplasticizer

Properties	Superplasticizer
Color tone	Deep brown
State	Liquid
Specific gravity	1.22
Solid content (%)	40.9
pH	7.5

will start losing their resemblance to the parents, and the algorithm will lose the ability to learn from the history of the search. Fig. 4 illustrates mutation.

Boundary mutation changes one of the parameters of the parent and changes it randomly either to its upper or lower bound, multi-nonuniform mutation changes all of the parameters of the parent based on a nonuniform probability distribution, nonuniform mutation changes one of the parameters of the parent based on a nonuniform probability distribution, and uniform mutation changes one of the parameters of the parent based on a uniform probability distribution.

After creating initial population composed of strings substituting for mix proportions, fitness increases through the repeating process of selection, crossover, and mutation. When fitness is satisfied, the repeating process is terminated and optimal solution is approached. This process is illustrated in Fig. 5.

3. Experimental program

3.1. Procedure

The 189 sets of mixtures were used for this experiment program. Based on the results of mixing test, using Statistical Packages for Social Science (SPSS) version 10, the fitness functions were developed from the 181 sets of mixtures [18,19]. After that, the fitness functions were applied in genetic algorithm, using MATLAB version 5.1 [20,21], and the results from genetic algorithm were compared to the eight sets of test mixtures for the verification and validity of the algorithm. This procedure is illustrated in Fig. 6.

3.2. Material properties

All materials except silica fume used in this experiment were produced in South Korea. Portland cement in accordance with ASTM type I was used. The coarse aggregate used was crushed granite with a specific gravity of 2.7 and a fineness modulus of 7.2, its maximum particle size is 19 mm. The fine aggregate was quartz sand with a specific gravity of 2.61 and a fineness modulus of 2.94. A naphthalene superplasticizer was used to keep the water to binder (W/B) ratio of concrete at a very low level. An air-entraining agent was used. A class F fly ash and a silica fume produced by Elkem, Norway, were used. The detailed properties of these materials are shown in Tables 1–6.

Table 6
Properties of air-entraining agent

Properties	Air-entraining agent
Color tone	Colorless
State	Liquid
Specific gravity	1.05
Solid content (%)	6

Table 7
Mix proportion (40–80 MPa)

G_{max}	W/B (%)	W (kg/m^3)	G_v (%)	FA (%)
19 mm	30	160	32	0
	35	170	34	10
	40	180	36	20
	45			

G_v: volume of coarse aggregate.

3.3. Mix proportions

The mix proportions necessary to obtain a compressive strength between 40 and 80 MPa are presented in Table 7. There are nonsilica fume mixes. The W/B varies between 0.30 and 0.45, and the amount of fly ash used varies from 0% to 20% of the total binder. The range of G_v (the volume of coarse aggregate) is 32–36%. The range of water content (W) is 160–180 kg/m^3, and the content of superplasticizer and air-entraining agent are 0–2% and 0.010–0.013%, respectively, when expressed as a percentage of dry solids to the binder content.

The mix proportions necessary to obtain a compressive strength between 80 and 120 MPa are presented in Table 8. The silica fume dosage varies from 8% to 25%, the W/B ratio between 0.18 and 0.27. The range of the ratio of the weight of fine aggregate to the weight of all aggregate (s/a) is 35–39%. The range of W is 140–165 kg/m^3, and the content of superplasticizer is 2–5% of binder content.

Based on Tables 7 and 8, the 189 batches were mixed in this experiment. The 181 mixtures are listed in Tables 9 and 10 according to compressive strength. The eight mixtures for the verification and validity of the algorithm are listed in Tables 15 and 16.

3.4. Mixing

In many countries, most concrete today is batched and mixed in ready-mixed concrete plants where the batching is

Table 8
Mix proportion (80–120 MPa)

G_{max}	W/B (%)	W (kg/m^3)	SF (%)
19 mm	23, 25, 27	155, 160, 165	5, 10, 15
	20, 23, 25	145, 150, 155	10, 15, 20
	18, 20, 22	140, 145, 150	15, 20, 25

Table 9
Tested mixtures (40–80 MPa)

Number	f_c' (MPa)	Slump (mm)	W/B (%)	W (kg/m^3)	s/a (%)	FA (%)	AE (kg/m^3)	SP (kg/m^3)
1	74	215	30	160	48	10	0.069	8.00
2	74	245	30	160	48	20	0.069	8.00
3	71	200	30	160	46	0	0.069	8.00
4	72	210	30	160	45	10	0.069	8.00
5	69	205	30	160	44	20	0.069	8.00
6	69	240	30	160	42	0	0.069	8.00
7	68	210	30	160	42	10	0.069	8.00
8	65	225	30	160	41	20	0.069	8.00
9	66	210	30	170	47	0	0.074	8.50
10	66	260	30	170	46	20	0.074	8.50
11	65	225	30	170	44	0	0.074	8.50
12	65	205	30	170	43	10	0.074	8.50
13	63	200	30	170	42	20	0.074	8.50
14	64	245	30	170	41	0	0.074	8.50
15	63	225	30	170	40	10	0.074	8.50
16	63	260	30	170	39	20	0.074	8.50
17	61	220	30	180	45	0	0.078	7.50
18	62	195	30	180	44	10	0.078	7.50
19	62	250	30	180	44	20	0.078	7.50
20	62	210	30	180	42	0	0.078	7.50
21	61	210	30	180	41	10	0.078	7.50
22	58	200	30	180	40	20	0.078	7.50
23	61	225	30	180	38	0	0.078	7.50
24	61	210	30	180	38	10	0.078	7.50
25	61	240	30	180	37	20	0.078	7.50
26	63	145	35	160	51	0	0.059	5.71
27	63	250	35	160	50	10	0.059	5.71
28	62	240	35	160	50	20	0.059	5.71
29	63	175	35	160	48	0	0.059	5.71
30	63	195	35	160	47	10	0.059	5.71
31	59	245	35	160	47	20	0.059	5.71
32	63	185	35	160	45	0	0.059	5.71
33	62	230	35	160	44	10	0.059	5.71
34	59	240	35	160	43	20	0.059	5.71
35	60	195	35	170	49	0	0.063	4.86
36	58	225	35	170	49	10	0.063	4.86
37	56	200	35	170	48	20	0.063	4.86
38	59	195	35	170	46	0	0.063	4.86
39	58	240	35	170	45	10	0.063	4.86
40	58	225	35	170	45	20	0.063	4.86
41	57	220	35	170	43	0	0.063	4.86
42	55	225	35	170	42	20	0.063	4.86
43	55	195	35	180	48	0	0.067	3.86
44	54	195	35	180	47	10	0.067	3.86
45	52	200	35	180	46	20	0.067	3.86
46	56	150	35	180	44	0	0.067	3.86
47	51	190	35	180	44	10	0.067	3.86
48	48	170	35	180	43	20	0.067	3.86
49	53	190	35	180	41	0	0.067	3.86
50	46	220	35	180	40	10	0.067	5.14
51	48	210	35	180	40	20	0.067	5.14
52	51	170	40	160	52	0	0.040	4.00
53	49	95	40	160	52	10	0.040	2.57
54	49	220	40	160	51	20	0.040	4.00
55	50	210	40	160	49	0	0.040	4.00
56	49	205	40	160	49	10	0.040	4.00
57	49	220	40	160	48	20	0.040	4.00
58	50	230	40	160	46	0	0.040	4.00
59	49	195	40	160	46	10	0.040	4.00
60	47	210	40	160	45	20	0.040	4.00
61	49	205	40	170	51	0	0.043	2.13
62	48	195	40	170	50	10	0.043	2.13
63	46	175	40	170	50	20	0.043	2.13
64	47	190	40	170	48	0	0.043	2.13
65	47	195	40	170	47	10	0.043	2.13
66	46	195	40	170	47	20	0.043	2.13
67	47	170	40	170	45	0	0.043	2.13
68	46	200	40	170	44	10	0.043	2.13
69	44	180	40	170	44	20	0.043	2.13
70	45	210	40	180	49	0	0.045	2.25
71	44	205	40	180	49	10	0.045	2.25
72	43	205	40	180	48	20	0.045	2.25
73	45	210	40	180	46	0	0.045	2.25
74	44	200	40	180	46	10	0.045	2.25
75	44	210	40	180	45	20	0.045	2.25
76	44	220	40	180	43	0	0.045	2.25
77	42	195	40	180	42	10	0.045	2.25
78	43	220	40	180	42	20	0.045	2.25
79	47	180	45	160	53	0	0.036	3.56
80	46	140	45	160	53	10	0.036	3.56
81	45	130	45	160	52	20	0.036	3.56
82	45	160	45	160	50	0	0.036	3.56
83	43	160	45	160	50	10	0.036	3.56
84	45	170	45	160	49	20	0.036	3.56
85	44	120	45	160	47	0	0.036	3.56
86	43	160	45	160	47	10	0.036	3.56
87	44	200	45	160	46	20	0.036	3.56
88	46	175	45	170	52	0	0.038	1.89
89	42	130	45	170	51	10	0.038	1.89
90	42	100	45	170	51	20	0.038	1.89
91	43	190	45	170	49	0	0.038	1.89
92	42	165	45	170	48	10	0.038	1.89
93	42	190	45	170	48	20	0.038	1.89
94	43	200	45	170	46	0	0.038	1.89
95	42	185	45	170	45	10	0.038	1.89
96	42	180	45	170	45	20	0.038	1.89
97	42	230	45	180	51	0	0.040	2.00
98	42	210	45	180	50	10	0.040	2.00
99	41	175	45	180	50	20	0.040	2.00
100	42	170	45	180	47	0	0.040	2.00
101	41	185	45	180	47	20	0.040	2.00
102	43	175	45	180	44	0	0.040	2.00
103	40	220	45	180	44	10	0.040	2.00
104	38	170	45	180	43	20	0.040	2.00

generally automatic or semiautomatic. For instance, in the United States during the period 1966–1980, the proportion of manually batched concrete decreased from 54% to less than 25% [16]. Ready-mixed concrete is defined as concrete that is manufactured for delivery to a purchaser in a plastic and unhardened state. In consideration of the current trend of using ready-mixed concrete, concrete for the test was mixed according to the relevant flowchart shown in Fig. 7.

3.5. Compressive strength test

Specimens for compressive strength test were made in 100 × 200-mm cylinder molds. The test was conducted in accordance with ASTM C 684-95. The specimens were demolded at 24 h and cured in nonlime water at 20 ± 3 °C for 28 days then tested.

Table 10
Tested Mixtures (80–120 MPa)

Number	f_c' (MPa)	Slump (mm)	W/B (%)	W (kg/m^3)	s/a (%)	SF (%)	SP (kg/m^3)
1	115	185	18	140	35	15	31.10
2	122	200	18	140	35	20	32.10
3	123	190	18	140	35	25	36.50
4	113	215	18	145	35	15	27.70
5	116	220	18	145	35	20	28.70
6	119	210	18	145	35	25	28.70
7	109	220	18	150	35	15	28.20
8	115	200	18	150	35	20	33.90
9	117	200	18	150	35	25	34.40
10	105	210	20	140	35	15	21.90
11	109	185	20	140	35	20	21.40
12	119	210	20	140	35	25	31.30
13	112	190	20	145	37	10	19.30
14	118	190	20	145	37	20	22.50
15	104	205	20	145	35	15	20.90
16	107	210	20	145	35	20	20.90
17	115	220	20	145	35	25	26.10
18	106	190	20	150	37	10	16.60
19	106	190	20	150	37	15	18.10
20	106	185	20	150	37	20	19.50
21	105	210	20	150	35	15	20.90
22	108	200	20	150	35	20	27.70
23	112	190	20	150	35	25	28.70
24	103	205	20	155	37	10	18.10
25	104	190	20	155	37	15	18.60
26	105	200	20	155	37	20	21.00
27	104	210	22	140	35	15	16.50
28	108	200	22	140	35	20	21.40
29	116	210	22	140	35	25	21.90
30	103	200	22	145	35	15	19.30
31	105	220	22	145	35	20	20.90
32	112	220	22	145	35	25	25.00
33	102	210	22	150	35	15	23.00
34	107	220	22	150	35	20	20.90
35	108	220	22	150	35	25	26.10
36	104	210	23	145	37	10	16.10
37	105	210	23	145	37	15	15.10
38	107	200	23	145	37	20	21.90
39	103	205	23	150	37	10	14.60
40	103	190	23	150	37	15	14.60
41	104	200	23	150	37	20	18.60
42	97	230	23	155	39	5	18.50
43	103	200	23	155	39	10	18.80
44	102	210	23	155	39	15	18.30
45	103	200	23	155	37	15	14.60
46	100	190	23	155	37	20	13.70
47	94	230	23	160	39	5	16.80
48	98	230	23	160	39	10	13.80
49	98	230	23	160	39	15	19.80
50	94	235	23	165	39	5	19.80
51	97	230	23	165	39	10	18.00
52	100	215	23	165	39	15	17.10
53	103	200	25	145	37	10	17.60
54	103	190	25	145	37	15	13.40
55	104	190	25	145	37	20	21.00
56	101	200	25	150	37	10	12.70
57	102	205	25	150	37	15	13.70
58	103	200	25	150	37	20	14.60
59	95	200	25	155	39	5	14.80
60	97	210	25	155	39	10	18.30
61	99	230	25	155	39	15	19.80
62	99	200	25	155	37	10	12.20
63	99	200	25	155	37	15	11.70
64	93	200	25	155	37	20	14.20
65	89	230	25	160	39	5	16.80
66	91	215	25	160	39	10	13.40
67	86	230	25	165	39	5	16.80
68	98	230	25	165	39	10	15.70
69	92	225	25	165	39	15	16.60
70	88	180	27	155	39	5	10.90
71	93	190	27	155	39	10	12.90
72	94	220	27	155	39	15	15.80
73	87	220	27	160	39	5	11.90
74	91	200	27	160	39	15	13.80
75	90	235	27	165	39	5	15.40
76	90	235	27	165	39	10	13.90
77	89	220	27	165	39	15	15.30

3.6. Slump and air content test

ASTM C 143-90a procedure was followed to determine the slump of the fresh concrete immediately after completion of mixing. The air content in fresh concrete was measured according to ASTM C 231-91b.

4. Application of genetic algorithm and result

4.1. Determination of the fitness functions

When a specific mix proportion for high-performance concrete needs to be determined, compressive strength and slump are very important characteristics in the process of design. The fitness functions essential for genetic algorithm program are determined in terms of factors influencing compressive strength and slump. Therefore, the factors influencing compressive strength and slump must be determined.

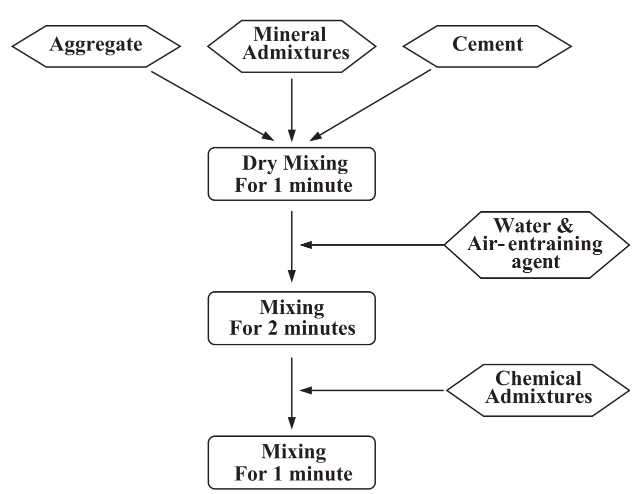

Fig. 7. Mixing flowchart.

Table 11
Fitness functions

Classification	Fitness functions	
40–80 MPa	Compressive strength	$f_c' = 122.14 - 0.84$ W/B $- 0.42$ W $+ 0.34$ s/a $- 0.09$ FA $+ 363.77$ AE
	Slump	Slump $= -463.21 - 3.05$ W/B $+ 5.21$ W $+ 0.54$ s/a $+ 0.11$ FA $- 6541.17$ AE $+ 41.67$ SP
80–120 MPa	Compressive strength	$f_c' = 170.37 - 1.87$ W/B $- 0.51$ W $+ 1.20$ s/a $- 0.49$ SF
	Slump	Slump $= -387.01 + 16.94$ W/B $+ 0.58$ W $- 1.23$ s/a $- 0.377$ SF $+ 1.163$ SP

f_c': compressive strength (MPa), Slump: slump of concrete (mm), W/B: water to binder ratio (%), W: water content (kg/m^3), s/a: fine aggregate ratio (%), FA: fly ash replacement ratio (%), SF: silica fume replacement ratio (%), AE: air-entraining agent content (kg/m^3), SP: superplasticizer content (kg/m^3).

4.2. Considering factors influencing compressive strength and slump for the determination of the independent variables

The factors influencing compressive strength and slump must be considered to determine the independent variables of the fitness functions in order to determine mix proportions by applying genetic algorithm to the fitness functions composed of selected independent variables. The factors to be considered in the fitness functions of compressive strength and slump are explained in the following sections.

4.2.1. Considering factors on compressive strength

The factors affecting compressive strength are water to binder ratio (W/B, %), water content (W, kg/m^3), fine aggregate ratio (s/a, %), replacement ratio of fly ash (FA, %), replacement ratio of silica fume (SF, %), and content of air-entraining agent (AE, %) [16].

When discussing effect of W/B on compressive strength, W/B ratio–porosity relation is indispensable. From the standpoint of strength, W/B ratio–porosity relation is undoubtedly the most important factor because, independent of other factors, it affects the porosity of both the cement paste matrix and the transition zone between the matrix and the coarse aggregate. W/B ratio–strength relationship in concrete can easily be explained as the natural consequence of a progressive weakening of the matrix caused by increasing porosity with an increase of the W/B ratio. Therefore, any increase of the water content tends to reduce compressive strength.

In a laboratory experiment, with a constant W/B ratio of 0.60, when the coarse/fine aggregate proportion and the cement content of a concrete mixture were progressively raised to increase the slump from 50 to 150 mm, a 12% decrease in the average 7-day compressive strength was observed.

The concrete without fly ash usually shows lower strength at 1 and 3 days, but strength gains can be substantial after about 7 days of curing. Highly active pozzolans are capable of producing high-strength in concrete at both early and late ages, especially when a water-reducing agent has been used to reduce the water requirement. It has been well known that silica fume has an effect on enhancing the strength of concrete and has been widely used in producing high-strength concrete.

For the most part, it is the W/B ratio that determines the porosity of the cement paste matrix at a given degree of hydration; however, when air voids are incorporated into the system, either as a result of inadequate compaction or through the use of an air-entraining admixture, they also have the effect of increasing the porosity and decreasing the strength of the system. It has been observed that the extent of the strength loss as a result of entrained air depends not only on W/B ratio of concrete mixture but also on the cement content. In short, as a first approximation, the strength loss due to entrained air can be related to the general level of concrete strength. At a given W/B ratio, high-strength concretes suffer a significant strength loss with increasing amounts of entrained air, whereas low-strength concretes tend to suffer only a little strength loss

Table 12
The coefficients of determination (R^2) (40–80 MPa)

The number of data	Strength fitness function (%)	Slump fitness function (%)
104	95.5	88.9
100	95.5	88.9
90	95.3	88.7
80	95.1	88.5
70	94.9	88.5
60	94.7	87.8

Table 13
The coefficients of determination (R^2) (80–120 MPa)

The number of data	Strength fitness function (%)	Slump fitness function (%)
77	90.5	74.2
70	90.5	74.2
65	90.5	74.0
60	90.5	74.0
55	90.3	74.0
50	90.1	73.3

Table 14
Significant levels for fitness function

Independent variables	Significant levels			
	40–80 MPa		80–120 MPa	
	Strength	Slump	Strength	Slump
W/B	.000	.102	.000	.000
W	.000	.000	.000	.580
s/a	.000	.553	.008	.832
FA,SF	.001	.706	.000	.000
AE	.000	.000	–	–
SP	–	.000	–	.002

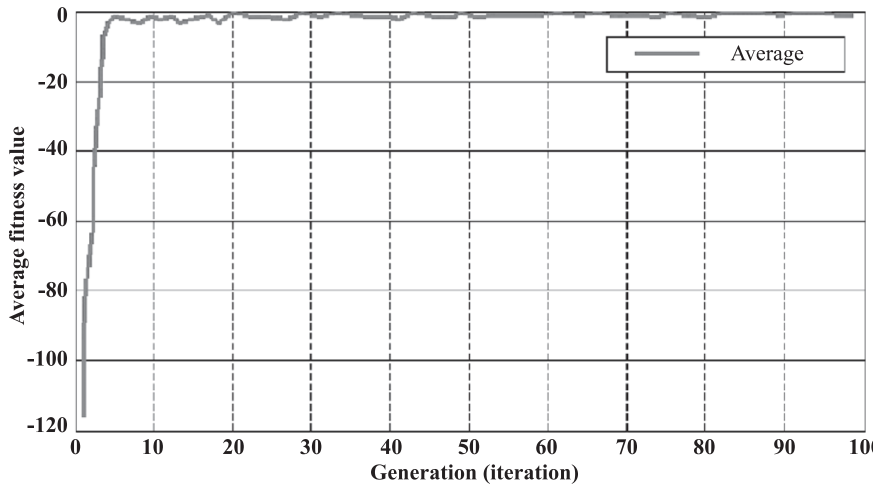

Fig. 8. Relation between error and the number of iteration.

or may actually gain some strength as a result of air entrainment.

4.2.2. Considering factors affecting the slump

The factors affecting the slump are W/B (%), W (kg/m^3), s/a (%), FA (%), SF (%), AE (%), and content of superplasticizer (SP, kg/m^3) [17].

In practice, predicting the effect of mix proportions on workability requires care since of the three factors, W/B ratio, aggregate/cement ratio, and water content, only two are independent. For instance, if aggregate/cement ratio is reduced but W/B ratio is kept constant, water content increases and consequently workability also increases. If, on the other hand, water content is kept constant when aggregate/cement ratio is reduced, then the W/B ratio decreases and as a result workability decreases somewhat but is not seriously affected.

Fly ash consists essentially of small spherical particles of aluminosilicate glass that is produced on combustion of pulverized coal in thermal power plants. With fresh concrete mixtures that show a tendency to bleed or segregate, it is well known that incorporation of finely divided particles generally improves workability by reducing the size and volume of voids. The finer a mineral admixture, the less of it will be needed to enhance the cohesiveness and the workability of a freshly mixed concrete. The small size and the glassy texture of fly ash can possibly reduce the amount of water required for a given consistency. Compared to normal Portland cement and typical fly ash, silica fume shows particle size distributions that are two orders of magnitude finer. This is why on the one hand the material is highly pozzolanic, but on the other hand it creates problems of handling and increases appreciably the water requirement in concrete unless water-reducing admixtures are used. In conclusion, silica fume has an effect on decreasing the workability of high-performance concrete.

The most important application of air-entraining admixture is for concrete mixtures designed to resist freezing and thawing cycles. A side effect from entrained air is the improved workability of concrete mixtures, particularly with those containing less cement and water, rough textured aggregate, or lightweight aggregate. In addition, entrained air reduces drastically concrete permeability, absorptiveness, and shrinkage age that are practical properties as important as compressive strength.

Superplasticizer, also called high-range water-reducing admixtures because they are able to reduce three to four times more water in a given concrete mixture than normal water-reducing admixtures, can be used to increase the slump for a given W/B ratio.

4.3. Multiple regression modeling and fitness function

The 181 sets of mixtures were used for finding fitness functions of compressive strength and slump by multiple regression modeling. For a system with n inputs (independent variables) and one output (dependent variable) y, the general least square (or linear regression) problem is to find out the unknown parameters β of the linear model as shown in Eq. (4).

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots\ldots + \beta_{n-1} x_{n-1} + \beta_n x_n \qquad (4)$$

Independent variables of the fitness functions, selected in consideration of influence on compressive strength and slump, were W/B (%), W (kg/m^3), s/a (%), FA (%), SF (%), and AE (%) for dependent variable of compressive strength (f_c') and W/B, W, s/a, FA, SF, AE, and SP (kg/m^3) for dependent variable of the slump of concrete (slump, cm),

Table 15
Tested mixtures (40–80 MPa)

Number	f_c' (MPa)	Slump (mm)	W/B (%)	W (kg/m^3)	s/a (%)	FA (%)	AE (kg/m^3)	SP (kg/m^3)
1	41	205	45	180	47	10	0.040	2.00
2	57	230	35	170	42	10	0.063	4.86
3	66	195	30	170	46	10	0.074	8.50
4	75	205	30	160	49	0	0.069	8.00

Table 16
Tested mixtures (80–120 MPa)

Number	f_c' (MPa)	Slump (mm)	W/B (%)	W (kg/m^3)	s/a (%)	SF (%)	SP (kg/m^3)
1	88	245	27	160	39	10	13.80
2	96	225	25	160	39	15	16.80
3	102	202	23	155	37	10	18.60
4	112	190	20	145	37	15	19.00

respectively. In this study, SPSS version 10 was used for multiple regressions [18,19]. The modeling results (fitness function) for compressive strength and slump are listed in Table 11 together with the significant levels for fitness function in Table 14. Generally, the coefficients of determination (R^2), over 70%, are required to verify the compatibility of a regression model. In addition, the change of the coefficients of determination (R^2) according to the change of the number of data needs to be observed to verify the compatibility of the number of data. The compatibilities of a regression model and the number of data were examined, as shown in Tables 12 and 13. The coefficients of determination (R^2) converged. Therefore, it was concluded that those were compatible.

4.4. Application and verification of genetic algorithm

Based on the programs made by Houck et al. [29], four genetic algorithm programs were developed for finding the design of high-performance concrete mixtures using MATLAB version 5.1 [20,21]. In the first program—called GAST1—W/B, W, s/a, FA, and AE for a specific compressive strength in the range of 40 to 80 MPa were determined. In GASLUMP1 program, using the results of GAST1, SP for a specific slump was determined. In the third program, called GAST2, W/B, W, s/a, and SF for a specific compressive strength in the range of 80 to 120 MPa were determined. In the fourth program, called GASLUMP2, using the results of GAST2, SP for a specific slump was determined. In this research, ranking selection based on normalized geometric distribution was used. The number of selected initial individuals was changed from 15 to 75 because the change of number of initial individuals is useful for finding an optimum value; that is, too large or too small number of initial individuals leads to the local solutions. Crossover was performed based on one-point, two-point, and uniform crossover theory. Four mutation methods were used in this study: boundary mutation, multi-nonuniform mutation, nonuniform mutation, and uniform mutation.

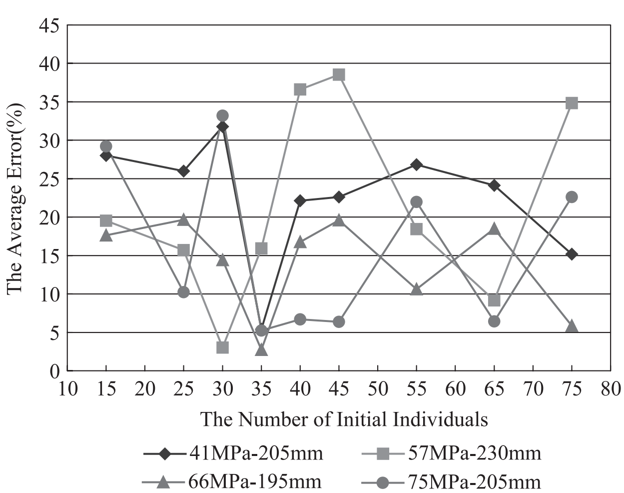

Fig. 9. Relation between error and the number of initial individuals (40–80 MPa).

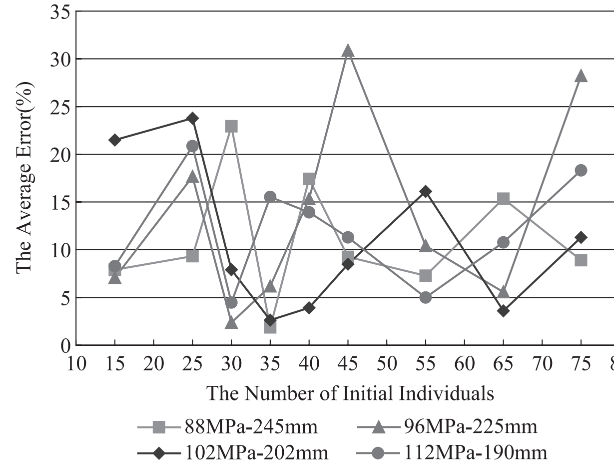

Fig. 10. Relation between error and the number of initial individuals (80–120 MPa).

Each input and output data of the program consist of compressive strength and slump. In the programs, after creating initial population of strings composed of W/B, W, s/a, FA, SF, AE, and SP, fitness increases through selection, crossover, and mutation. When errors between input data and output data become minimized, fitness is satisfied (Table 14). Then, the repeating process is terminated and optimal solution is approached. The fitness functions for compressive strength and slump listed in Table 11 were used in GAST1, GASLUMP1, GAST2, and GASLUMP2 in order. Fig. 8 shows that an error decreases when the number of iteration increases.

To verify the accuracy and usefulness of the genetic algorithm programs, eight sets of test mixtures listed in Tables 15 and 16 were compared to the results obtained in the genetic algorithm programs.

Table 17
The results from genetic algorithm and error (40–80 MPa)

Number	W/B (%)	W (kg/m^3)	s/a (%)	FA (%)	AE (kg/m^3)	SP (kg/m^3)	Average error (%)
1 (error %)	44	179	46	10	0.045	2.30	5.40
	(2.22)	(0.56)	(2.13)	(0)	(12.50)	(15)	
2 (error %)	35	171	42	10	0.065	5.56	3.03
	(0)	(0.59)	(0)	(0)	(3.17)	(14.40)	
3 (error %)	31	164	46	10	0.070	8.15	2.73
	(3.33)	(3.53)	(0)	(0)	(5.41)	(4.12)	
4 (error %)	30	160	53	0	0.075	9.17	5.25
	(0)	(0)	(8.16)	(0)	(8.70)	(14.63)	

Table 18
The results from genetic algorithm and error (80–120 MPa)

Number	W/B (%)	W (kg/m^3)	s/a (%)	SF (%)	SP (kg/m^3)	Average error (%)
1 (error %)	27	161	37	10	14.30	1.88
	(0)	(0.63)	(5.13)	(0)	(3.62)	
2 (error %)	24	163	38	15	16.24	2.35
	(4)	(1.88)	(2.56)	(0)	(3.33)	
3 (error %)	22	150	37	10	17.57	2.62
	(4.35)	(3.23)	(0)	(0)	(5.54)	
4 (error %)	20	141	38	14	20.95	4.48
	(0)	(2.76)	(2.70)	(6.67)	(10.26)	

After introducing specific compressive strength and slump, the genetic algorithm programs for the mix proportioning of high-performance concrete were performed. To find mix proportions with a minimum of error, the number of initial individuals to make a value with a minimum error in compressive strength and slum was changed from 15 to 75. The mix proportion with a minimum average error in compressive strength and slump was obtained with a number of initial individuals of 30 and 35. Figs. 9 and 10 show, respectively, the relation between the average of error in compressive strength and slump and the number of initial individuals.

The average errors in compressive strength and slump and comparative results varied with the mixtures from the genetic algorithm programs, and the eight sets of test mixtures are listed in Tables 17 and 18. The range of errors in W/B, W, s/a, F/A, S/F, AE, and SP are 0–4%, 0–4%, 0–8%, 0%, 0–7%, 4–13%, and 3–10%, respectively. The results show that the errors in W/B, W, s/a, F/A, and S/F are smaller than those of AE and SP. The values of two chemical admixtures are small and have decimal values. Therefore, though the values change on a very small scale, the errors of two chemical admixtures tend to have large values when the errors are expressed in the unit of percentage. Therefore, the errors of chemical admixture are considered to be not so large.

5. Conclusions

The object of this research is to propose a mix design method for high-performance concrete using genetic algorithm, which is a stochastic search technique based on the mechanism of natural selection and natural genetics. In this paper, genetic algorithm was developed to present a new design method for high-performance concrete mixtures to minimize the number of trial mixes and provides a reasonable mix proportion. Experimental and analytic investigations were carried out to develop genetic algorithm for mix proportioning of high-performance concrete and to verify the proposed mix design. Based on the results of this research, the following conclusions were drawn.

1. By applying the genetic algorithm for design of high-performance concrete mixtures, the number of trial mixtures with desired properties in the field can be reduced. This method is a new and alternative method to the current design method that has no exact design criteria.
2. Two small or large numbers of initial individuals made genetic algorithm find local solutions. The numbers of initial individuals for finding a global solution—the design of high-performance concrete mixtures with specific compressive strength and slump—were 30 and 35.
3. It is believed that the errors of chemical admixtures are not so large because the values of two chemical admixtures are small and have decimal values. Therefore, though the values change on a very small scale, the errors of two chemical admixtures tend to have large values when the errors are expressed in the unit of percentage.
4. The applicability of genetic algorithm for the mix design of high-performance concrete was observed in this paper, and a new method for design of high-performance concrete mixtures using genetic algorithm was provided.

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