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An integrated approach for optimum design of HPC mix proportion using genetic algorithm and artificial neural networks

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Abstract. This study aims to develop a cost-based high-performance concrete (HPC) mix optimization system based on an integrated approach using artificial neural networks (ANNs) and genetic algorithms (GA). ANNs are used to predict the three main properties of HPC, namely workability, strength and durability, which are used to evaluate fitness and constraint violations in the GA process. Multilayer back-propagation neural networks are trained using the results obtained from experiments and previous research. The correlation between concrete components and its properties is established. GA is employed to arrive at an optimal mix proportion of HPC by minimizing its total cost. A system prototype, called High Performance Concrete Mix-Design System using Genetic Algorithm and Neural Networks (HPCGANN), was developed in MATLAB. The architecture of the proposed system consists of three main parts: 1) User interface; 2) ANNs prediction models software; and 3) GA engine software. The validation of the proposed system is carried out by comparing the results obtained from the system with the trial batches. The results indicate that the proposed system can be used to enable the design of HPC mix which corresponds to its required performance. Furthermore, the proposed system takes into account the influence of the fluctuating unit price of materials in order to achieve the lowest cost of concrete, which cannot be easily obtained by traditional methods or trial-and-error techniques.

Keywords: genetic algorithm; artificial neural networks; high performance concrete; minimum cost; optimization.

1. Introduction

The selection of HPC mix proportions is the process of choosing suitable concrete ingredients and determining their relative quantities with the object of producing as economically as possible concrete of certain required properties, namely workability, strength, and durability (Metha and Aïtcin 1990). Traditional HPC mixture proportion algorithms are based on a generalization of previous experience, available as tables or empirical formulas. Due to the uncertainty of concrete

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ingredients, such as fine and coarse aggregates, cement, chemical and mineral admixtures, traditional HPC mixture proportion algorithms are a trial and error process, which results in the waste of materials, laborers and time (Ji *et al*. 2006).

The main problem for HPC mix proportion design lies in establishing analytical relationships between the mix composition and the properties of concrete. Several researchers have suggested mathematical models to describe the relationship between components and materials behavior. Unfortunately, rational and easy-to-use equations are not yet available in design codes to accurately predict the properties of HPC. Furthermore, with the aforementioned models, the evaluation of the effects of each parameter on properties of concrete is almost impossible.

In recent years, there has been interest in a class of computing devices known as artificial neural networks (ANNs) that operate in a manner analogous to biological nervous systems. The neural network modeling approach is simpler and more direct thantraditional statistical methods, particularly when modeling nonlinear multivariate interrelationships (Yeh 2006). The main advantage of ANNs is that one does not have to explicitly assume a model form, which is a prerequisite in the parametric approach. Indeed, in ANNs a relationship of possibly complicated shape between input and output variables is generated by the data points themselves. In response to the complex interaction between concrete behaviors and concrete mix proportions, many researchers have applied neural networks to predict various properties of concrete. Most of the research has focused on two basic properties, namely compressive strength and workability of HPC (Kasperkiewicz *et al.* 1995, Öztaş *et al*. 2006, Yeh 1999, 2006). Unfortunately, during this study there is no research has been found on modeling the durability of HPC using neural networks. Due to the complex nature of material behavior of concrete, in this study ANNs are used to predict strength, workability and durability.

The key components in designing an HPC mix-proportion are not only the concrete properties, but also the cost of concrete in order to derive the optimum ingredients. Therefore, optimization techniques are usually employed. However, the optimum design of HPC is a very complicated issue because the most economical solution is subjected to various constraints.

Genetic Algorithms (GA) are an intelligent search method which can be applied to solve complex optimization problems in achieving the optimum solution to overcoming these restraints. A search procedure comprises natural selection, quick exploration and information collection in a search space. In contrast to most classical optimization methods, a GA requires no gradient information and involves procedures which can search for multiple optima rather than a single or local optimum. These characteristics make GA a powerful tool for solving optimization problems (Cheng and Li 1997, Goldberg 1989, Holland 1992, Nanakorn and Meesomklin 2001). GA has been applied to various kinds of problems and is considered to be an ideal tool for solvingoptimization problems (Lim *et al.* 2004, Nanakorn and Meesomklin 2001, Powell and Skolnick 1993).

Recently, Yeh (1999) applied neural networks incorporated with nonlinear programming to design the optimum mix proportions of HPC. Unfortunately, the aspect of durability of HPC has been overlooked. Integrating ANNs and GA, it is possible to apply analytical methods to search for the optimum mix proportion of HPC which corresponds to required performance and lowest cost.

The objective of this study is to develop an integrated approach using artificial neural networks (ANNs) and genetic algorithms (GA) for cost optimization of HPC mix proportion. In the present work, ANNs are used to predict the three main properties of HPC, namely workability, strength and durability, which are further used to evaluate fitness and constraint violations in the GA process. To achieve the objective, the following steps are taken:

1. Develop a database of HPC

2. Develop ANNs for predicting strength, slump and durability by using experimental data from the database
3. Develop the GA engine software by applying the static penalty function technique for optimization of HPC mix proportions
4. Incorporate the ANNs prediction software as a constraint evaluator into the GA engine software
5. Validate the proposed system by comparing the system's results with the results from trial mixes

2. Development of a database of HPC

The first step in developing the proposed system is to obtain accurate and reliable training and testing samples. Unfortunately, most of the data from previous research only emphasize strength and workability. The lack of data for durability of HPC is the main problem in the data collection process.

Durability is the fundamental property of HPC based on its impermeability and it is widely accepted that the ability of concrete to resist the ingress of chloride ions can result in a significantly more durable concrete (Bentz 2007, Graybeal and Tanesi 2007). The ASTM C 1202-97 Standard Test Method for Electrical Indication of Concrete's Ability to Resist Chloride Ion Penetration is used extensively in the concrete industry for assessing concrete quality and is now being included in concrete specification documents (Bentz 2007). The test approximates the amount of electrical current that is passed through a cylindrical concrete specimen when a 60 V dc potential difference is applied across the specimen for a period of 6 h.

Traditionally, producing HPC has required high consumption of cement with low to intermediate replacement of pozzolan, resulting in a product that isn't environmentally friendly and which is of low durability. To improve this process, experiments were especially designed according to the concept of environmental friendliness together with the technique of high performance concrete production proposed by Metha and Aïtcin (1990).

Rigorous experimental programs were conducted in the laboratory to investigate the influence of using different pozzolanic materials, cement content and water-to-binder (W/B) ratios on workability, compressive strength and durability of HPC. The target 28 day compressive strength of HPC mixtures was designed in the range of 40-150 MPa, and the workability of concrete expressed in terms of slump was kept constant at 10-15 cm by varying the dosage of superplasticizer. In this experiment, a new type of superplasticizer called polycarboxylic ether (PCE) polymer was used in order to achieve the required workability, compressive strength and durability of concrete. Two types of pozzolanic materials were used, namely pulverized fly ash and condensed silica fume. The cementitious materials were varied from 400-600 kg/m^3 with W/B ranging from 0.2 to 0.4. Control specimens without using pozzolanic materials of concrete were also cast and tested.

In total, 55 mixtures were made and the specimens were tested for their properties. The durability of each mix was experimentally investigated by measuring the total charge passed through the concrete in accordance with ASTM C1202-97. To improve and expand the range of prediction, a database of HPC was produced by combining the experimental data together with the culled data from previous research (Feng *et al.* 2002, Lim *et al.* 2004, Nimityongskul *et al.* 2003, Shi 2004, Sirivivatnanon and Cao 1998, Tahir 1998, Wee *et al.* 1999, Zhao *et al.* 1998) based on similar types of materials as follows; 1) ordinary Portland cement; 2) class F fly ash; 3) condensed silica fume; 4) modified polycarboxylic ethers (PCE) or naphthalene formaldehyde condensate (NF); 5) natural river sand ($2.7 \le$ F.M. ≤ 3.1); and 6) crushed lime stone (10 mm $\le$ Max, size $\le$ 19 mm).

3. ANNs for prediction of HPC properties

3.1. ANNs Design and learning process

Based on the database achieved previously, ANNs were developed, trained and tested by using 201, 181 and 90 data sets to predict compressive strength, initial slump and durability, respectively. Table 1 illustrates the general details of the concrete evaluation in this study. To test the reliability of the models, 20% of the data sets were randomly selected as test sets, while the remaining 80% of the samples were used to train the network. The outputs of the networks were 28 day compressive strength, initial slump and the total charge passed in accordance with ASTM C1202. Based on the charge that passed through the sample, a qualitative rating was made of the concrete's permeability, as illustrated in Table 2.

In this study, the input parameters are considered as the proportions of concrete mixture. Although each component is described using only single term, these terms actually represent a variety of types. For example, a fly ash and cement can be classified in several types and composed of different chemical compositions. Apart from the component types, the properties of concrete are influence by the mixing proportion and mixing preparation technique. However, each mixture in the database is almost never described with all of the important details indicated; thus the prediction of

Table 1 Ranges of constituents and concrete properties for training the networks

Component	Data set of Compressive strength		Data set of Workability		Data set of Durability	
	Min (kg/m^3)	Max (kg/m^3)	Min (kg/m^3)	Max (kg/m^3)	Min (kg/m^3)	Max (kg/m^3)
Ordinary Portland cement	140	708	180	708	135	611
Fly ash	0	270	0	225	0	275
Silica fume	0	208	0	208	0	110
Water	111	270	108	207	120	220
Superplasticizer#1 (NF)	0	36.5	0	36.5	0	17.3
Superplasticizer#2 (PCE)	0	20.5	0	20.5		
Coarse aggregate	909	1270	894	1280	895	1167
Fine aggregate	310	834	489	1017	536	914
W/B	0.16	0.7	0.16	0.7	0.17	0.67
Initial slump			55 mm	245 mm		
f_c' (28 day)	23 MPa	127 MPa				
RCPT (28 day)					14 coulombs	5900 coulombs

Table 2 Chloride ion penetrability based on charge passed (ASTM C1202-97)

Charge Passed (coulombs)	Chloride Ion Penetrability
>4,000	High
2,000-4,000	Moderate
1,000-2,000	Low
100-1,000	Very Low
<100	Negligible

concrete properties from the available data is a highly uncertain task (Kasperkiewicz et.al. 1995). Hence, in this study, the concrete properties can be a function of cement content (C, kg/m^3), fly ash content (F, kg/m^3), silica fume content (SF, kg/m^3), water content (W), water to binder ratio (W/B), type and dosage of superplasticizer (NF or PCE, kg/m^3), coarse aggregate content (CA, kg/m^3), and fine aggregate content (FA, kg/m^3).

3.2. Performance of ANNs

In this study, the neural networks were developed and performed under MATLAB programming. The learning algorithm used was gradient descent with adaptive learning rate back-propagation. The error incurred during the learning process was expressed in terms of mean-squared-error (MSE).

A parametric study was carried out in this study, numbers of input neurons and numbers of hidden layers with various numbers of neurons in each layer were determined to achieve the most appropriate architecture of the trained network. After a number of trials, the best network architecture that minimizes the MSE of training data was selected as illustrated in Fig. 1. Fig. 1(a) and (b) show the

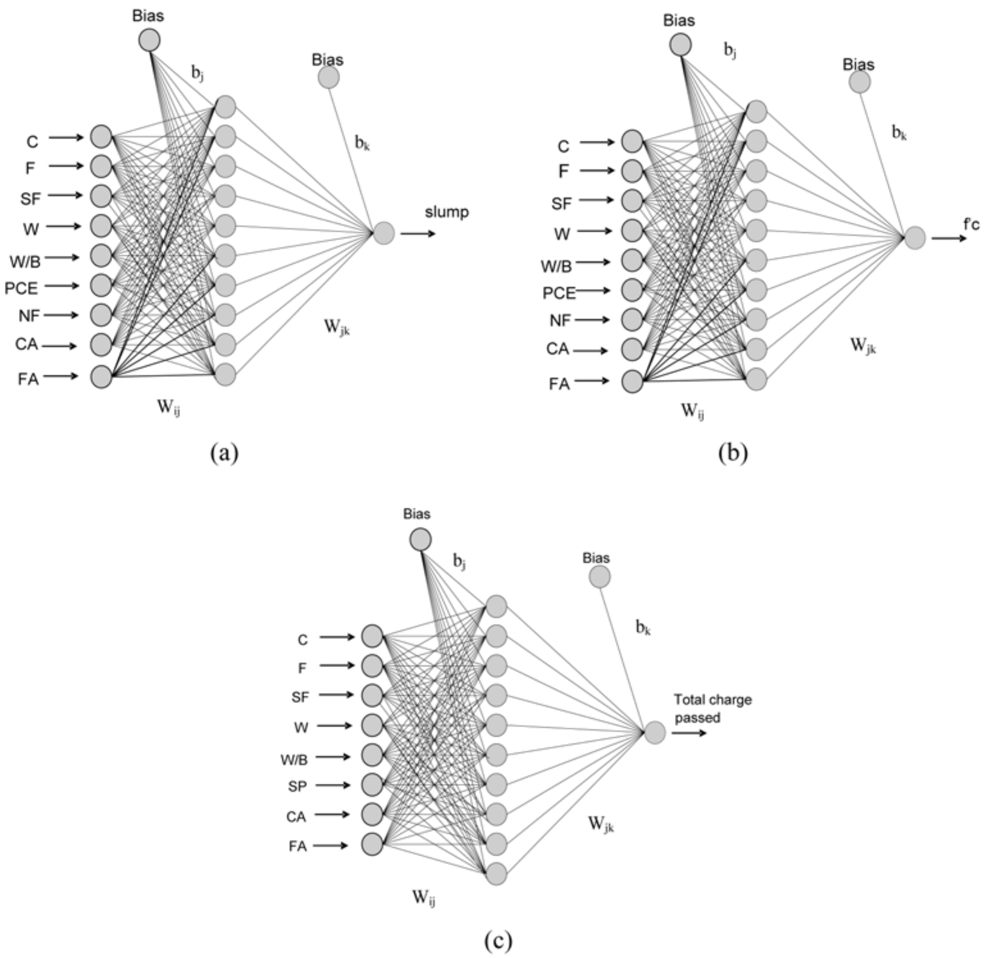

Fig. 1 Proposed neural networks architecture for (a) initial slump, (b) compressive strength, and (c) durability

Table 3 Statistical parameters of ANNs models

Statistical parameters	f_c' model		Slump model		Durability model	
	Training set	Testing set	Training set	Testing set	Training set	Testing set
RMSE	5.4 MPa	4.6 MPa	9.8 mm	12.7 mm	68 c*	112 c*
MAPE	3.96%	4.50%	5.99%	5.19%	6.40%	13.55%
R^2	0.9960	0.9977	0.9970	0.9950	0.9963	0.9814

*c = coulombs

architecture of the neural networks for predicting the initial slump and compressive strength, respectively. The proposed networks consisted of nine input variables and one output variable. Fig. 1(c) illustrates the architecture of neural networks for predicting the durability of concrete in terms of total charges passed. The network consisted of eight input variables and one output variable.

The statistical parameters of ANNs for predicting the HPC properties of training and testing sets are illustrated in Table 3. All statistical values in Table 3 demonstrated that the proposed ANNs models were appropriate and capable of accurately predicting the properties of HPC. The results also indicated that the proposed models were successful in learning the relationships between the different inputs and the output parameters.

4. GA process for optimum design of HPC mix proportions

In the optimal design of HPC mix proportions, a single objective (cost of concrete) was applied in this study. The task is to search for a combination of mix-proportions based on minimum cost of objective function subjected to various constraints. Since GA is directly applicable only to unconstrained optimization, it is necessary to use some additional methods for handling constraints by GA. The most popular in the GA community to handle constraints is to use penalty functions that penalize unfeasible solutions by reducing their fitness values in proportion to their degrees of constraints violation (Michalewicz *et al.* 1996, Smith and Coit 1997). In this research, a static penalty function was incorporated into the objective function to transform the constrained objective function into an unconstrained one. There were six constraints which were considered in this problem, namely available range of ingredients, required slump, required strength, required durability, rational ratio and absolute volume constraint. Recently, Kuri Morales and Quezada (1998) developed a static penalty approach to solve the constrained optimization problem. In this method, individuals were evaluated using the following formula:

$$eval(\bar{x}) = \begin{cases} f(\bar{x}) & \text{if } \bar{x} \in F \\ K - \sum_{i=1}^{n}\left(\frac{K}{m}\right) & otherwise \end{cases} \tag{1}$$

where $eval(\bar{x})$ is the overall objective function, $\bar{x}$ is the vector of solutions, $f(\bar{x})$ is the objective function, F is the feasible region, n is the number of non-violated constraints and m is the total number of constraints. Constraints can be equality or inequality. K is a large positive constant, and K should guarantee that an unfeasible individual must be graded worse than a feasible individual. Kuri Morales and Quezada (1998) introduced this constant as 1×10^9.

4.1. Objective/fitness function

Fitness is a quality value, which is a measure of the reproductive efficiency of living creatures according to the principle of survival of the fittest. In GA, fitness is used to allocate reproductive trials and thus is some measure of goodness to be maximized. This means that strings with higher fitness value will have higher probability of being selected as parents. Therefore, the objective function minimization problem has to be transformed into the fitness function maximization problem. In the optimal design of HPC mix proportions, cost of concrete was considered as the objective function $f(x)$, which was given by the following relationship:

$$f(x) = (C_cW_c + C_fW_f + C_{sf}W_{sf} + C_wW_w + C_{nf}W_{nf} + C_{pce}W_{pce} + C_{ca}W_{ca} + C_{fa}W_{fa}) \tag{2}$$

Subjected to

$$W_k^l \le W_k \le W_k^u \tag{3}$$

(k = 1 to total number of ingredients)

and

$$g_i(x) = \left(1 - \frac{g_i}{g_i^a}\right) \tag{4}$$

(i = 1 to number of constraints)

$$\text{if } g_i(x) < 0 \text{ then } c_i = \frac{K}{m}$$

$$\text{if } g_i(x) \ge 0 \text{ then } c_i = 0$$

where $g_i(x)$ is *inequality constraint i*, g_i^a *is allowable value of constraint* g_i, c_i *is the static penalty value*, $f(x)$ is the cost function, C_c, C_f, C_{sf}, C_w, C_{nf}, C_{pce}, C_{ca}, and C_{fa} are the cost per unit weight of cement, fly ash, silica fume, water, sulphonate naphthalene formaldehyde condensate, modified polycarboxylic ethers, coarse aggregate and fine aggregate, respectively, W_c, W_f, W_{sf}, W_w, W_{nf}, W_{pce}, W_{ca}, and W_{fa} are the total weight per 1 m^3 of cement, fly ash, silica fume, water, sulphonate naphthalene formaldehyde condensate, modified polycarboxylic ethers, coarse aggregate and fine aggregate, respectively. W_i is total weight of each ingredient per 1 m^3 of concrete having upper bound (W_k^u) and lower bound (W_k^l). Based on the database used in this study, the lower and upper limited of each constituent material is shown in Table 4. Then, the equivalent unconstrained objective function can be expressed as:

$$F(x) = C_cW_c + C_fW_f + C_{sf}W_{sf} + C_wW_w + C_{sp}W_{sp} + C_{ca}W_{ca} + C_{fa}W_{fa} + \sum c_i \tag{5}$$

Now Eq. (5) has to be converted into fitness values. For minimization problems, the fitness function should be an inverse of the cost function. Therefore the fitness of an individual population can be written as:

$$\text{Fitness} = 1/\{(C_cW_c + C_fW_f + C_{sf}W_{sf} + C_wW_w + C_{sp}W_{sp} + C_{ca}W_{ca} + C_{fa}W_{fa}) + \sum c_i\} \tag{6}$$

4.2. Constraints of HPC mix-design

There were five constraints of HPC mix-design which were considered in this study, namely

Table 4 Range and limitation of constituents covered in this proposed method

Component	Available range and rational ratio constraints	
	Min (kg/m^3)	Max (kg/m^3)
Ordinary Portland cement	180	610
Fly ash	0	220
Silica fume	0	110
Water	110	220
Superplasticizer#1 (NF)	0	17.5
Superplasticizer#2 (PCE)	0	17.5
Coarse aggregate (10 mm ≤ Max, size ≤ 19 mm)	800	1200
Fine aggregate (2.7 ≤ F, M ≤ 3.1)	550	850
W/B	0.17	0.6

required compressive strength, required initial slump, required durability, lower and upper limit of ingredients and absolute volume. The upper and lower limits of ingredients are shown in Eq. (3). The compressive strength, initial slump, durability, and absolute volume constraints can be expressed as

$$f_c' \geq f_{cR}' \tag{7}$$

$$slump \geq slump_R \tag{8}$$

$$Q \geq Q_R \tag{9}$$

$$(W_c/G_c + W_f/G_f + W_{sf}/G_{sf} + W_w/G_w + W_{sp}/W_{sp} + W_{fa}/G_{fa} + W_{ca}/G_{ca})/1000 = 1.000 \tag{10}$$

where f_c' is the predicted 28 day compressive strength, slump is the predicted slump, and Q is the predicted total charge passed at 28 days. f_{cR}' is the required 28 day compressive strength, $slump_R$ is the required initial slump and Q_R is the required total charge passed at 28 days. G_c, G_f, G_{sf}, G_w, G_{sp}, G_{fa}, and G_{ca} are the specific gravity of cement, fly ash, silica fume, water, superplasticizers, fine aggregate and coarse aggregate, respectively.

5. Integration of ANNs with GA for cost optimization of HPC mix proportions

5.1. The architecture of the HPCGANN system

The prototype of the proposed system called High Performance Concrete Mix Design System Using Genetic Algorithm and Neural Networks (HPCGANN) was developed by applying a genetic algorithm (GA) optimization base with the static penalty function technique and employing artificial neural networks (ANNs) as constraints evaluators. The proposed system was developed using MATLAB programming. The architecture of the proposed system consisted of three main parts: 1) User interface; 2) ANNs prediction models software; and 3) GA engine software. The relationships among those parts are shown in Fig. 2.

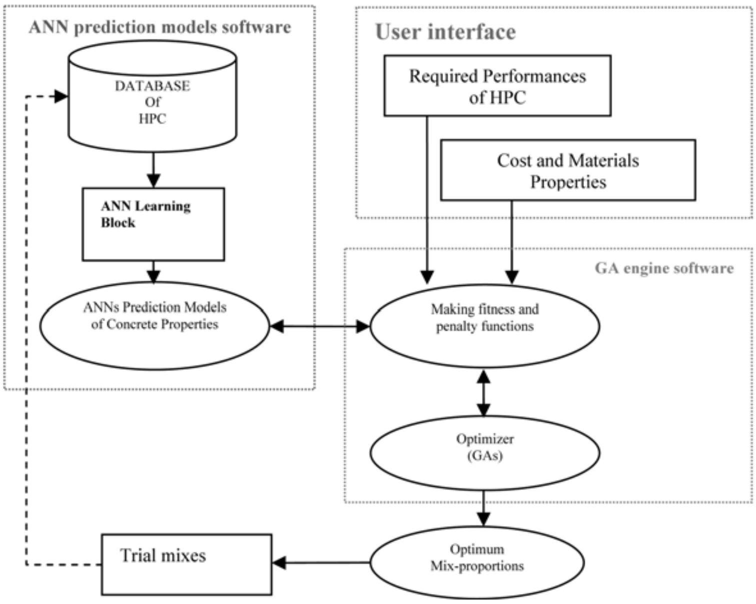

Fig. 2 Architecture of HPCGANN system

5.2. GA Engine software for optimum design of HPC mix proportions

In this study, the genetic algorithm program from Hock *et al*. (1996) was modified. Fitness function (Eq. 6) and constrained equations (Eqs. 7-9) were used to determine the optimal mix proportions of HPC for the required compressive strength, workability and durability. To obtain these, the trained ANNs described in the previous section were integrated with GA to predict the properties of each HPC mix used in the evaluation of fitness function in the optimization process.

Fig. 3 illustrates the flow diagrams of GA engine software for optimal design of HPC mix proportions. The inputs of the system were as follows: 1) required initial slump; 2) required compressive strength; 3) required chloride ion permeability in accordance with AASHTO 277 or ASTM C1202; 4) unit prices of materials; 5) specific gravity of each material; 6) type of pozzolans (fly ash, silica fume or blended fly ash and silica fume); and 7) type of superplasticizers (NF or PCE). Fig. 4 shows the user interface of the proposed system.

After introducing the input parameters, the integrated ANN-GA process was performed. The outputs of the system were as follows: 1) proportion of materials per 1 m^3 of concrete; 2) best fitness value; 3) concrete cost; 4) predicted compressive strength; 5) predicted initial slump; and 6) predicted chloride ion permeability, as shown in Fig. 5.

To find the minimum cost of mix proportions which were subjected to these constraints, the initial populations composed of C, F, SF, W, PCE, NF, FA and CA were created randomly from search space based on available range constraints and each variable was represented by 18-bit string. Then the fitness and penalty functions were performed. The genetic operators, namely selection, crossover and mutation, would result in an improved of the solution through the fitness values. The higher the fitness values the better the final solution. At the end of the final generation, the repeating process was terminated and the optimum solution is obtained.

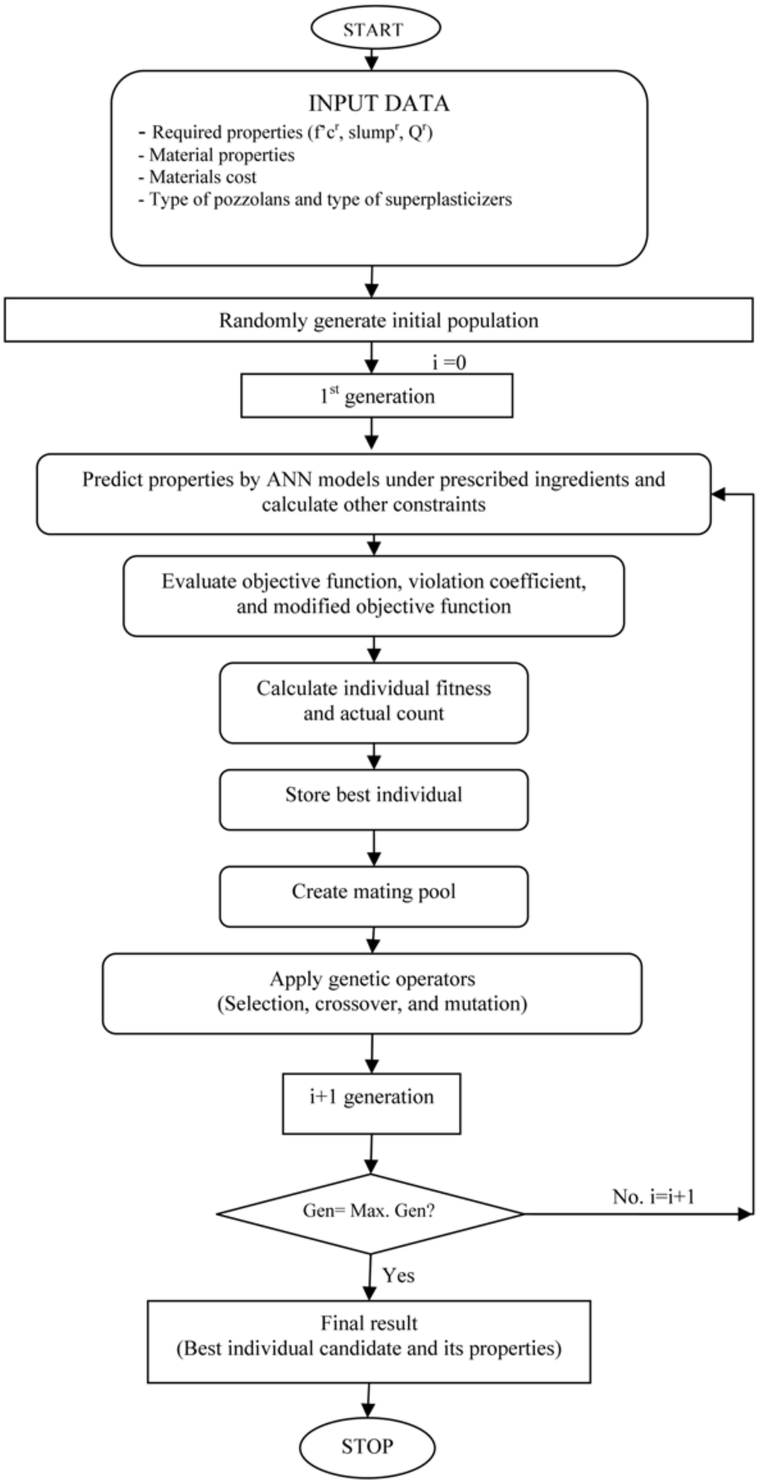

Fig. 3 Flow diagram of GA engine software for optimal design of HPC mix proportions

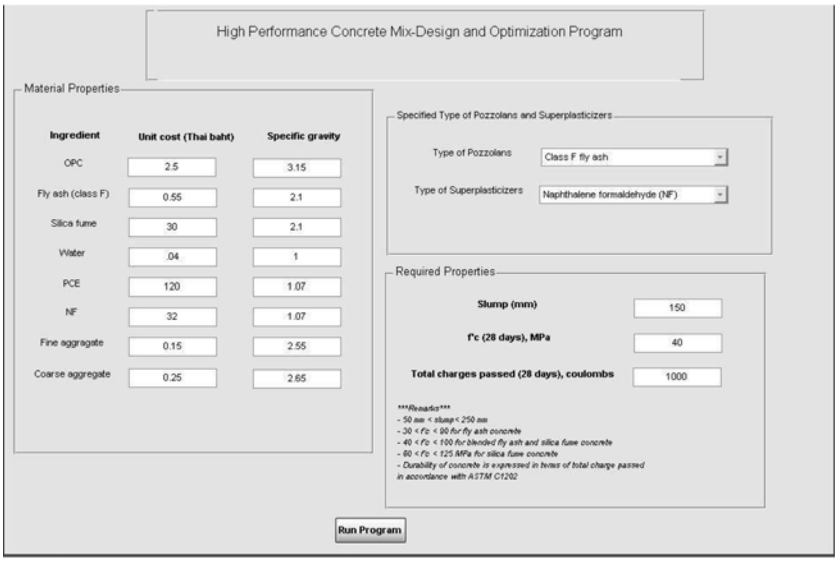

Fig. 4 User interface of HPCGANN system

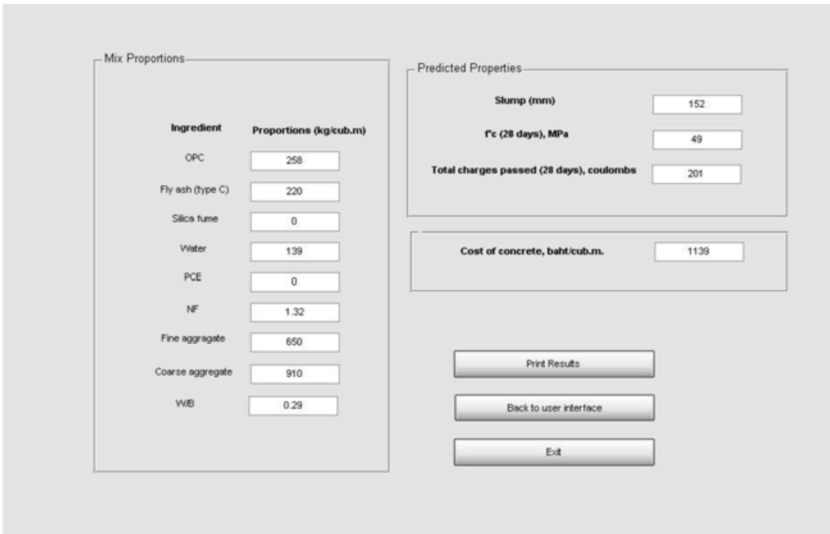

Fig. 5 Output of HPCGANN system

5.3. GA parameters

The genetic algorithm consists of many parameters which influenced its efficiency. Each of these parameters needs to be specified before a genetic optimization search can start. The following genetic parameters were enumerated in this study:

1) GA crossover type: simple crossover
2) Mutation probability: 0.03
3) Crossover probability: 0.6
4) Selection function: roulette wheel selection

5) Termination criteria: Generation = 200

6. Illustrative problems and system validation

To validate the system, two groups of ten samples, namely HPC with normal to high strength (40 MPa< f'_c <80 MPa) and high to very-high strength (80 MPa< f'_c <125 MPa), were investigated. Input data consisted of required initial slump, required compressive strength, required chloride ion permeability in accordance with ASTM C1202, unit prices of materials, specific gravity of each material, type of pozzolans and type of superplasticizers as shown in Tables 4-6. Unit prices of materials used in this study were based on the average price inthe Thai market as shown in Table 5. Table 6 shows the requirement constraints of each sample for HPC mix designs of 40-80 MPa and 80-125 MPa, respectively. These tests and observation on the designed mixes were performed in the laboratory by using a laboratory trial batch. Materials for the test samples were selected based on the abovementioned guidelines are as follows:

1) The Portland cement used was OPC (ASTM type I).

2) The fly ash used was class F fly ash for design of 40-80 MPa compressive strength.

Table 5 Unit prices and specific gravity of components

Component	Unit price (Baht/kg)	Specific gravity
Ordinary Portland cement	2.5	3.15
Fly ash	0.55	2.20
Silica fume	30.00	2.10
Water	0.04	1.00
Superplasticizer#1 (NF)	32.00	1.15
Superplasticizer#2 (PCE)	120.00	1.10
Coarse aggregate	0.25	2.65
Fine aggregate	0.15	2.55

Remark : 1 US$ is approximately equivalent to 35 baht.

Table 6 Required concrete properties and types of superplasticizers and pozzolans used

Mix. No.	Required slump (mm)	Required f'_c (MPa)	Required Q (coulombs)	Type of SP	Type of Pozzolan
1	150	40	1000	NF	F
2	150	50	1000	NF	F
3	150	60	1000	NF	F
4	150	70	1000	NF	F
5	150	70	1000	PCE	F
6	100	80	500	PCE	Blended F & SF
7	100	80	500	PCE	SF
8	100	90	500	NF	SF
9	100	100	500	NF	SF
10	100	110	500	NF	SF

3) Condensed silica fume was used for design of 80-125 MPa compressive strength.
4) Water was ordinary tap water.
5) The two types of chemical admixtures used were naphthalene formaldehyde condensate (NF) and poly-carboxylic ether (PCE) superplasticizer
6) The coarse aggregate was crushed limestone with the max size of 19 mm.
7) The fine aggregate was natural river sand with fineness modulus of 3.0.

Mixing was carried out in a laboratory pan mixer with a capacity of 70 liters. All specimens were cured in clean water at room temperature until testing. The workability of the fresh concrete was measured by using slump test in accordance with ASTM C 143. Compressive strengths at 28 days were obtained using a 150 mm cube. Durability of concrete was assessed by measuring the total charge passed at 28 days in accordance with ASTM C1202-92. Each quoted strength and charge passed value was the average of the three and two samples, respectively.

7. Discussion of the results obtained from the proposed system

Fig. 6 shows the optimization histories of the illustrative samples. The results of mix proportions computed by the system are illustrated in Table 7. For the results of 40-80 MPa concrete, intermediate to high volume replacement of fly ash was selected with low cement consumption in each mix. The compressive strength and durability of 40-80 MPa concrete were controlled by low W/B and cement content, whereas the slumps were kept in the range of requirements by dosage of superplasticizers and fly ash. Cost of concrete was mostly controlled by the proportion of cement and superplasticizer. For the results of 80-125 MPa concrete, 5-20% of condensed silica fume replacement was selected with high cement consumption. The compressive strength and durability

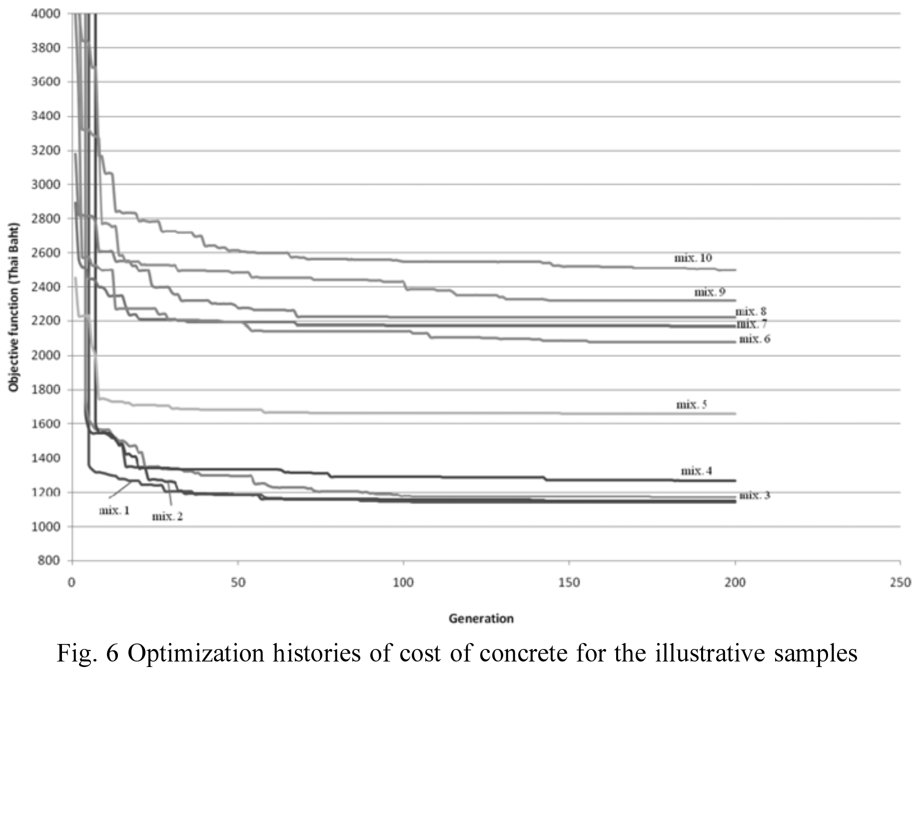

Fig. 6 Optimization histories of cost of concrete for the illustrative samples

Table 7 Mix proportion results from proposed system

Component	Mix designation									
	Mix.1	Mix.2	Mix.3	Mix.4	Mix.5	Mix.6	Mix.7	Mix.8	Mix.9	Mix.10
OPC (kg/m^3)	258	258	277	312	367	448	406	431	422	450
Fly ash (kg/m^3)	220	220	114	150	176	130	0	0	0	0
Silica fume (kg/m^3)	0	0	0	0	0	10	20	20	20	20
Water (kg/m^3)	139	124	112	112	141	131	112	116	111	110
NF (kg/m^3)	1.32	1.36	1.34	1.35	0	0	5.03	5.0	6.6	11.0
PCE (kg/m^3)	0	0	0	0	2.54	2.02	0	0	0	0
Fine aggregate (kg/m^3)	650	653	650	654	702	677	728	806	672	663
coarse aggregate (kg/m^3)	910	945	1093	1036	917	955	1128	1015	1150	1146
W/B	0.29	0.26	0.29	0.24	0.26	0.22	0.26	0.26	0.25	0.23
Predicted slump (mm)	152	151	155	159	160	159	155	187	158	132
Predicted f'c (Mpa)	49	53	60.1	70.2	70.1	80.0	88.7	90.1	100.0	110.1
Predicted Q (coulombs)	201	177	812	416	178	285	125	77	149	120
Cost (Thai baht)	1139	1148	1173	1268	1660	2082	2172	2219	2321	2468

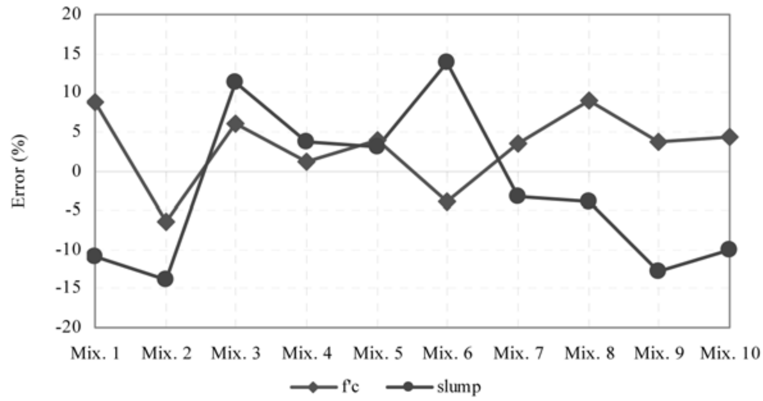

Fig. 7 Percentage errors of predicted and measured values

of 80-110 MPa concrete were controlled by very low W/B incorporated with the pozzolanic reaction and filler effect from condensed silica fume, whereas the slumps were kept in the range of requirements by higher dosages of superplasticizers. The cost of concrete was mostly controlled by the proportion of silica fume and superplasticizers. Fig. 7 shows the relationships of percentage error of predicted and measured values with various mix designations. The percentage error of predicted and measured values of slump and compressive strength were found to be ±15% and ±10%, respectively. The predicted durability of concrete was within the range of measured values illustrated in Table 8. Based on the results obtained from Tables 7-8 and Fig. 7, it can be concluded that the proposed system was successful in design of HPC mix proportions from the viewpoint of workability, compressive strength, durability and economy.

Table 8 Comparison of predicted 28 day total charge passed with measured total charge passed

Mix No.	Predicted Q (coulombs)	Measured Q (coulombs)	Chloride ion penetrability (ASTM C1202)
1	201	275	Very low
2	177	365	Very low
3	812	710	Very low
4	416	603	Very low
5	178	102	Very low
6	285	217	Very low
7	125	209	Very low
8	77	108	Negligible
9	149	128	Negligible
10	120	72	Negligible

8. Conclusions

This paper presented an integrated approach using artificial neural networks (ANNs) and genetic algorithms (GA) for cost optimization of HPC mix proportion. In the present work, ANNs were used to predict the three main properties of HPC, namely workability, strength, and durability, which were further used in the evaluation of fitness and constraint violations by the GA process. A system prototype, called High Performance Concrete Mix-Design System using Genetic Algorithm and Neural Networks (HPCGANN), was developed using MATLAB. The system serves as a tool in a performance and cost based design of high performance concrete mix proportion. Experimental investigations were carried out to validate the proposed method by comparing the predicted performance with tested results from trial batches. Based on the results obtained in the present study, the following conclusions can be drawn.

- The results indicate that the ANNs software in the proposed system can be used very efficiently to predict the initial slump, compressive strength and durability of high performance concrete across a wide range of mix proportion parameters.
- Using the trained ANNs integrated with GA can enable the design of HPC mix which corresponds to its required performance. Furthermore, the proposed system takes into account the influence of fluctuating unit prices of materials in order to achieve the lowest cost of concrete, which cannot be easily obtained by traditional methods or trial-and-error techniques.
- Although the capability of the proposed system was limited to the data located within the available range of training data in the ANNs software, the available range of the system could be easily expanded by retraining the neural networks with additional data from trial mixes.
- The proposed system was proven to be an effective mix design of near optimal mix proportions with reasonable accuracy. Furthermore, using the proposed technique can save time, reduce trial mixes, reduce waste materials and decrease cost for high performance concrete production.

References

Bentz, D.P. (2007), “A virtual rapid chloride permeability test”, *Cement Concrete Comp*., **29**(10), 723-731.

Cheng, Y. and Li, F.D. (1997) “Multiobjective optimization design with Pareto genetic algorithm”, *J. Struct. Eng.*, **123**, 1252-1261.
Feng, N., Feng, X., Hao, T. and Xing, F. (2002), “Effect of ultrafine mineral powder on charge passed of the concrete”, *Cement Concrete Res.*, **32**, 623-627.
Goldberg, D.E. (1989), *Genetic algorithms in search, optimization, and machine learning*, Addison-Wesley, Reading.
Graybeal, B. and Tanesi, J. (2007), “Durability of an ultrahigh-performance concrete”, *J. Mater. Civil Eng.*, **19**, 848-854.
Holland, J.H. (1992), *Adaptation in natural and artificial systems*, University of Michigan Press, Michigan.
Houck, C.R., Joines, J. and Kay, M. (1996), “A genetic algorithm for function optimization: A matlab implementation”. ACM.
Ji, T., Lin, T. and Lin, X. (2006), “A concrete mix proportion design algorithm based on artificial neural networks”, *Cement Concrete Comp.*, **36**, 1399-1408.
Kasperkiewicz, Racz, J. and Dubrawski, A. (1995), “HPC strength prediction using artificial neural networks”, *J. Comput. Civil Eng.,* **9**, 279-284.
Kuri Morales, A. and Quezada, C.C. (1998), “A Universal eclectic genetic algorithm for constrained optimization”, *Proceedings 6th European Congress on Intelligent Techniques & Soft Computing, EUFIT'98,* 518-522.
Lim, C.H., Yoon, Y.S. and Kim, J.H. (2004), “Genetic algorithm in mix proportioning of high-performance concrete”, *Cement Concrete Res.*, **34**, 409-420.
Metha, P.K. and Aïtcin, P.C. (1990), “Principles underlying the production of high-performance concrete”, *Cement Concrete Aggr.,* **12**, 70-78.
Michalewicz, Z., Dasgupta, D., Riche, R.L. and Schoemauer, M. (1996), “Evolutionary algorithms for constrained engineering problems”, *Comput. Indust. Eng.*, **30**(4), 851-870.
Öztaş, A., Pala, M., Özbay, E., Kanca, N., Çağlar, E. and Bhatti, M.A. (2006), “Predicting the compressive strength and slump of high strength concrete using neural networks”, *Constr Build Mater.*, **21**, 384-394.
Nimityongskul, P., Plengkham, K. and Piyarakskul, S. (2003), “Techniques and Methods of High-Strength Concrete Producing in Thailand”, *Proceeding of 1st National Convention on Concrete*, Thailand, 7-16.
Nanakorn, P. and Meesomklin, K. (2001), “An adaptive penalty function in genetic algorithms for structural design optimization”, *Comput. Struct.*, **79**, 2527-2539.
Powell, D. and Skolnick, M.M. (1993), “Using genetic algorithms in engineering design optimization with non-linear constraint”, (Ed. Kaufmann, M.), *Proceedings of the 5th International Conference on Genetic Algorithm,* San Mateo.
Shi, C. (2004), “Effect of mixing proportions of concrete on its electrical conductivity and the rapid chloride permeability test (ASTM C1202 or AASHTO 227) results”, *Cement Concrete Res.*, **34**, 537-545.
Sirivivatnanon, V. and Cao, H. T. (1998), “Binder dependency of durability properties of HPC”, *Proceedings of Canadian International Symposium of HPC and Reactive Powder Concrete*, Canada.
Smith, A.E. and Coit, D.W. (1997), *Constraint handling techniques-penalty functions*, Oxford University Press and Institute of Physic Publishing.
Tahir, M.A. (1998), *Model for predicting strength development of concrete incorporating fly ash of variable chemical composition and fineness,* School of Civil Engineering, Asian Institute of Technology, Pathumthani.
Wee, T.H., Suryavanshi, A.K. and Tin, S.S. (1999), “Influence of aggregate fraction in the mix on the reliability of the rapid chloride permeability test”, *Cement Concrete Res.*, **21**, 59-72.
Yeh, I.C. (1999), “Design of High-Performance Concrete Mixture Using Neural Networks and Nonlinear Programming”, *J. Comput. Civil Eng.*, **13**, 36-42.
Yeh, I.C. (2006), “Analysis of strength of concrete using design of experiments and neural networks”, *J. Mater. Civil Eng.*, **18**, 598-604.
Zhao, T.J., Zhou, Z.H., Zhu, J.Q. and Feng, N.Q. (1998), “An alternating test method for concrete permeability”, *Cement Concrete Res.,* **28**., 7-12.