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Genetic algorithm for cost optimization of modified multi-component binders

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Abstract

This paper describes the application of a genetic algorithm for the cost optimization of a modified multi-component binder (MMCB). An MMCB comprised of Portland cement (NPC), finely ground mineral additives (fly ash, ponded ash or granulated blast furnace slag), and a highly reactive powder component (usually silica fume, SF) was modified by a superplasticizer (SP). Strength models based on the experimental results were developed. The present work is oriented to the minimization of the MMCB cost for specific strength levels with the help of a changing range genetic algorithm (CRGA) to handle the nonlinear constraints imposed by the MMCB models. The developed CRGA is based on an approach that adaptively shifts and shrinks the size of the search space to the feasible region. The application of CRGA helps to minimize the cost of MMCB with a low resolution of the binary representation scheme and without additional computational efforts.

1. Introduction

The application of chemical admixtures and mineral additives has become one of the most important developments in modern concrete technology. Added to the concrete mixture, relatively small amounts of chemical admixtures radically alter the behavior of fresh and hardened concrete [1–3]. The performance of concrete can be significantly improved by the application of selected mineral additives, especially industrial by-products like granulated blast furnace slag (GBFS), fly ash (FA), and silica fume (SF) [4–12]. The replacement of Portland cement (NPC) with mineral additives brings considerable economical savings and also helps to conserve natural resources. The relatively large number of components makes the problem of concrete mixture design more complicated than ever before; and the significant differences in the cost of the components makes the problem more complicated. As discussed by

de Larrard [13], Dewar [14], Gutierrez and Canovas et al. [15] and Sobolev [12], full-scale research of the behavior of chemical admixtures and mineral additives in concrete is time-consuming and expensive, therefore the application of an expert system based on existing knowledge and research data is essential for the proportioning of a competitive concrete mixture.

Complete models (or expert systems) trying to predict the behavior and properties of "contemporary" concrete involving a large number of components and, therefore a large range of variables, are under development [14,16–18]. Just one recent example is the "The Virtual Cement and Concrete Testing Laboratory" developed by NIST [7,8]. The realization of these systems needs comprehensive computer models based on extensive experimental data and also on new design approaches which could predict the behavior of material, saving time and research resources.

It was demonstrated that reliable models in the form of second-order polynomial equations can be obtained using factorial experiment [1,12,16,17]. In general, cost optimization is a numerical optimization problem with a

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nonlinear objective function and nonlinear constraints. Usually, this kind of nonlinear programming problem cannot be solved by developing a deterministic method in the global optimization category [19]. Therefore, the present work adopted the specially developed Genetic Algorithm (GA) that does not require consideration of the landscape of a search space nor the shape of an optimized function for the solution cost optimization problem [20].

2. Background on modified multi-component binders

The properties of concrete with GBFS, FA and SF including ternary mixtures of NPC–FA–SF or NPC–GBFS–SF have been discussed in the literature [4,5,9–12]. Less information is available regarding the performance of ponded fly ash (PA) in concrete. It is suggested that the behavior of this type of concrete can be significantly affected by the fineness of the mineral additive and also by the application of an effective superplasticizer (SP) [1]. The concept of a modified multi-component binder (MMCB) was proposed to describe this system. MMCB includes a binder composed of NPC, finely ground mineral additive (FA, PA or GBFS), and a highly reactive powder component (usually SF or metakaolin), modified by a SP. The main idea of MMCB is to improve the reaction ability of the mineral additives by fine grinding. Consequently, the mineral additives react quicker, avoiding the delay of the development of concrete strength at an early age. It was hypothesized that the application of finely ground mineral additives (FGMA), as a component of the binder, provides better packing in the NPC–FGMA system, especially in combination with SF and SP. As demonstrated by Sobolev [1], better packing of MMCB results in low water demand and also provides better fluidity of the cement paste.

An express method was developed for the evaluation of compressive and flexural strength of MMCB [1]. It involves the preparation of the mortars according to ASTM C349/C109, but with a sand-to-cement ratio (S/C) of 1.0. These mortars are produced at a reduced W/C adjusted to obtain a flow range of 105–115 mm. According to Sobolev [1], an S/C equal to 1.0 is the best value for the optimization of mortars with a SP and mineral additives. Because of extremely dense compaction and a very low water demand, an S/C of 1.0 corresponds to its minimum limit in high strength concrete at the maximum strength level. The compressive strength of mortar specimens ($40 \times 40 \times 160$ mm) cured for 8 h at 80 °C in a steam chamber was used as a control value of cement strength. Tested by this method, reference NPC demonstrated a compressive strength of 68.0 MPa (higher than the standard 28-day compressive strength of 55.2 MPa).

The resulting MMCB demonstrates a compressive strength (which is considered as one of the most important parameters of application) in a range of 75–135 MPa, a significant increase over reference NPC. The improved range of strength and especially the increased number of components constituting MMCB led to the development of a special procedure for the proportioning of the MMCB-based concrete mixtures [12]. An effective optimization of the performance characteristics at the level of MMCB (involving fewer components) was proposed to minimize the associated tests of concrete.

3. Models of MMCB: strength and cost optimization problem

In materials research, the development and exploration of the models is very important. Unlike actual tests, mathematical models describing concrete give a quick and inexpensive evaluation of the material. However, because of the typical inconsistency in the properties of the component materials, there is the risk of a possible discrepancy between the actual tests and the results of the model. Nevertheless, these results are important estimates which save the time and resources needed for research. It was demonstrated that second-order polynomial equations are appropriate for modeling the strength and rheological properties of MMCB systems [1,12]. Models were developed as a function of the composition for various MMCB systems including:

- NPC–SF–SP system;
- NPC–SF–FGPA–SP system;
- NPC–SF–FGBFS–SP system.

The models of MMCB compressive strength (f_c) were processed as second-order polynomial equations whose coefficients were computed by specially designed computer software. The basic equation of these models is

$$f_c = \sum_{i=0}^{n} \sum_{j=0}^{n} b_{ij} x_i x_j,$$

where n is the total amount of variable factors ($n = 2$ for NPC–SF–SP system and $n = 3$ for NPC–SF–FGPA–SP or NPC–SF–FGBFS–SP systems); b_{ij} the coefficients of polynomial equation; x_i, x_j the values of variable factors; and $x_0 = 1$.

The coefficients of polynomial equations representing the developed models of compressive strength are presented in Appendix A. The graphical representation of the strength of the NPC–SF–SP system is given in Fig. 1. Importantly, the SP parameter is taken as a percentage of SF (on a dry basis); therefore SP–SF parameters are dependent. All the other parameters are
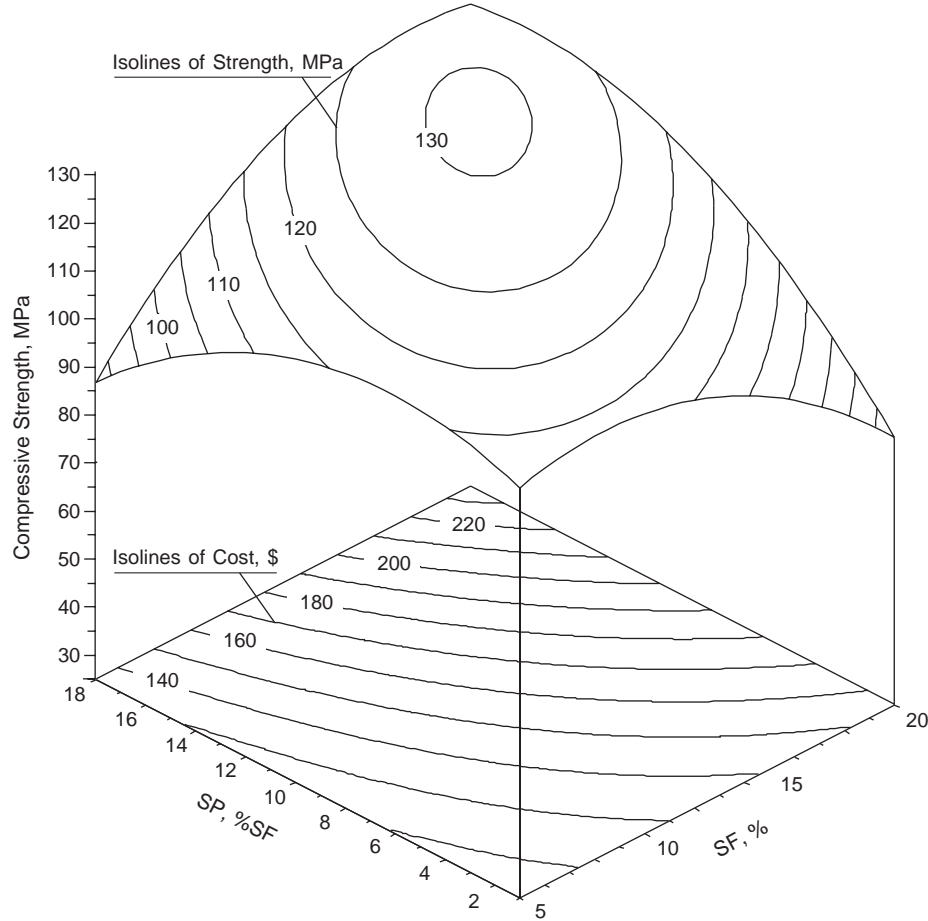
Fig. 1. The compressive strength and cost of the NPC–SF–SP binder.

considered as a percentage of the total content of MMCB; the remaining part is made up of NPC. The range of the variable factors used in the models is summarized in Table 1.

Cost optimization is another important application for the developed models (Fig. 1): it helps to estimate the proportions of the concrete and minimizes the costs associated with an actual test program, by omitting non-feasible compositions.

The design of the MMCB mixture of a specific strength and at a minimal cost comprises the global optimization problem (GOP) which could be resolved by finding an optimizer x^* such that

$$\varphi(x^*) = \min \varphi(X), \text{ where } X = [X_1, \ldots, X_n] \in R^n.$$

The objective function φ is defined for the search space $S \subseteq R^n$, which is the finite interval region in n-dimensional Euclidean space. The lower and upper bounds define the domains of variables:

$$l_i \leqslant x_i \leqslant u_i, \text{ where } 1 \leqslant i \leqslant n.$$

The search space in GOP is restricted to a feasible region (F, where $F \subseteq S$) by a set of constraints:

Table 1
The input characteristics of MMCB components

Component	Units	Bounds		Cost ($)
		Lower	Upper	
NPC	%	20	95	100
SF	%	5	20	350
FGPA	%	5	60	40
FGBFS	%	5	60	80
SP	% SF	1	15	2500
				5000

$$g_i(X) \leqslant 0, \text{ where } 1 \leqslant j \leqslant p,$$

$$f_r(X) = 0, \text{ where } 1 \leqslant r \leqslant q.$$

Usually the equality constraints can be substituted by pair of inequalities such as

$$f_r(X) \geqslant -\delta \text{ and } f_r(X) \leqslant \delta,$$

where δ is a small value to cover a tiny region. This case was considered in the research program and, consequently, the set of constraints consisted only of inequalities.

The cost of MMCB, C (as a function for optimization) is calculated by using the general formula

$$C = \frac{1}{100} \sum_{i=1}^{m} x_i c_i,$$

where m is the total amount of components ($m = 3$ for NPC–SF–SP system and $m = 4$ for NPC–SF–FGPA–SP or NPC–SF–FGBFS–SP systems); x_i the the dosage/proportioning of the i-component (NPC, SF, SP, and FGPA or FGBFS); c_i the cost of the i-component.

The non-linearity of this equation is based on the dependency of the SP parameter from SF; therefore the dosage of the SP component (to be used in this formula as percent of MMCB) was calculated using the following expression:

$$X_{SP} = SF * SP/100.$$

The polynomial equation describing the strength of the MMCB mixture represents the single equality constraint for the specific design that is substituted by a pair of inequality constraints as mentioned before.

4. Development of a changing range genetic algorithm

GAs have a major application for global numerical optimization problems [21,22]. The advantage of a GA is that it does not require consideration of the landscape of a search space nor the shape of an optimized function [21]. Therefore GA is a universal tool for many optimization problems. There are numerous examples of GA applications to problems of civil engineering: optimization of water recourses [23–25], aerodynamic modeling [26,27] and optimization of structures [28–30].

Wu et al. [25] developed the self-adaptive boundary search strategy for the selection of penalty factor within a GA and the optimization for water distribution systems with the objective of obtaining the least cost solution of pipe sizes subject to the minimum allowable pressure requirements at the demand nodes. Poloni [26] used a hybrid GA for multi-objective aerodynamic shape optimization, where conventional GA was combined with the elitism method for selection of individuals. Adeli and Cheng [29] proposed the hybrid GA for structural optimization that integrated the penalty function method with the primal dual method. This approach evaluates the penalty function coefficient by using the Lagrangian method. Sarma et al. [30] applied an evolutionary algorithm to the design of steel space structures. A discrete multicriteria cost optimization model was presented by considering three design criteria: minimum material cost, minimum weight, and minimum number of different section types.

The optimization of the composition of construction materials is mainly limited to laminated composite panels [31–34]. Potgieter et al. [31] presented the stiffness optimization model of laminated plates by using GA.

Park et al. [32] applied GA to optimize the design of composite laminates for maximum strength. Only Grosset et al. [33] described the optimization of a composite laminate with multi-objective to minimize the cost and weight of a composition subjected to the constraint of allowable stiffness properties. Their approach is based on a conventional GA that has been adapted to optimization of composites.

Only a few researches deal with the optimization of concrete and MMCBs by using GA [35,36]. Eduardo et al. [35] presented the procedure for the optimization of construction of a concrete block wall using the fitness function. This considers the total cost of the construction and the decision variables for the optimization process: the material characterized by its hydration properties; the thickness of the lifts (layers); the placing frequency and the placing temperature. A conventional GA was used with elitism of the best individuals, tournament selection scheme, single point crossover and mutation genetic operators. Maruyama et al. [36] presented a method for the optimization of the proportions of a concrete mixture according to the required performance and described the solution of two proportioning problems by using GA—one of delayed setting time and high flowability in hot weather conditions and the other of accelerated setting and high flowability in cold weather conditions.

Still, the applications of GA to optimize the composition of construction materials are very limited. Even fewer papers deal with the cost-tailoring problem. Therefore the cost-composition problem of newly developed construction materials like MMCB needs further attention.

Various constraint-handling methods using GA were proposed for solving GOP. These methods can be grouped as follows [19,37,38]:

- methods based on penalty functions;
- methods based on repair algorithms;
- methods that use special representations and operators;
- hybrid methods.

The main idea of these methods is to produce a population of individuals only in a feasible region and then use the power of GA to search a feasible region for a global optimum. The developed method, named Changing Range GA (CRGA) also generates a population of individuals in a feasible region by converging (shrinking and shifting) the range of variables towards the feasible region [20]. The proposed method overcomes the drawbacks of a conventional GA applied to numerical optimization problems, when GA cannot provide high accuracy because a binary representation scheme for variables is used [38].

It is suggested that the method of shifting and shrinking the range of variables improves the

conventional GA [20]. According to this method, as generation trials progress, the range of every variable is reduced when compared with the previous one. Then, the new range is centered on a reference point. For the cost optimization of an MMCB mixture for a certain strength the best individual in the feasible region is used as a reference point [20].

Therefore, the proposed method contains two procedures:

- shifting the region to the reference point so that the center of the new region coincides with the reference point;
- shrinking the size of region compared to its previous size.

As a result, the proposed strategy:

- increases accuracy without changing the resolution of a binary representation scheme;
- adaptively changes the probability of mutation to protect against convergence pressure which would otherwise result in a homogenous population;
- does not require additional computational effort.

The developed method is based on the following principles:

- *Shifting*: shifting is used to map the center of the next search space to the center of attraction. The center of

attraction, or the reference point, is identified by selecting the best from the subset of surviving individuals. This procedure is repeated continuously for the next subset of the individuals.
- *Shrinking*: shrinking is used to reduce the size of a search space. The reduction is performed for the range of every variable according to the previous range. The reduction of the range shrinks the search space to the feasible region and improves the accuracy of the variables without changes in the resolution of the binary representation scheme.
- *Randomization*: randomization is used to resist the convergence pressure which would result in a homogenous population. The shifting and shrinking procedures adaptively change the mutation rate of the GA and provide a diversity of population.

Fig. 2 illustrates the steps of the shifting and shrinking mechanism (SSM) of CRGA. Each rectangle represents the range of the variables whereas the vertical lines indicate the binary representation scheme with constant resolution (equal to 10). At the beginning, the lower and the upper bounds of the variables express the domain of the variables. After obtaining h_s individuals in the feasible region (one subset of the surviving individuals), the lower and upper bounds of each variable are changed because of the decreasing size of the search space relatively to the previous one.

For example, the lower and upper bounds of variable X_1, X_2, X_3 at the beginning of subset 2 are calculated to
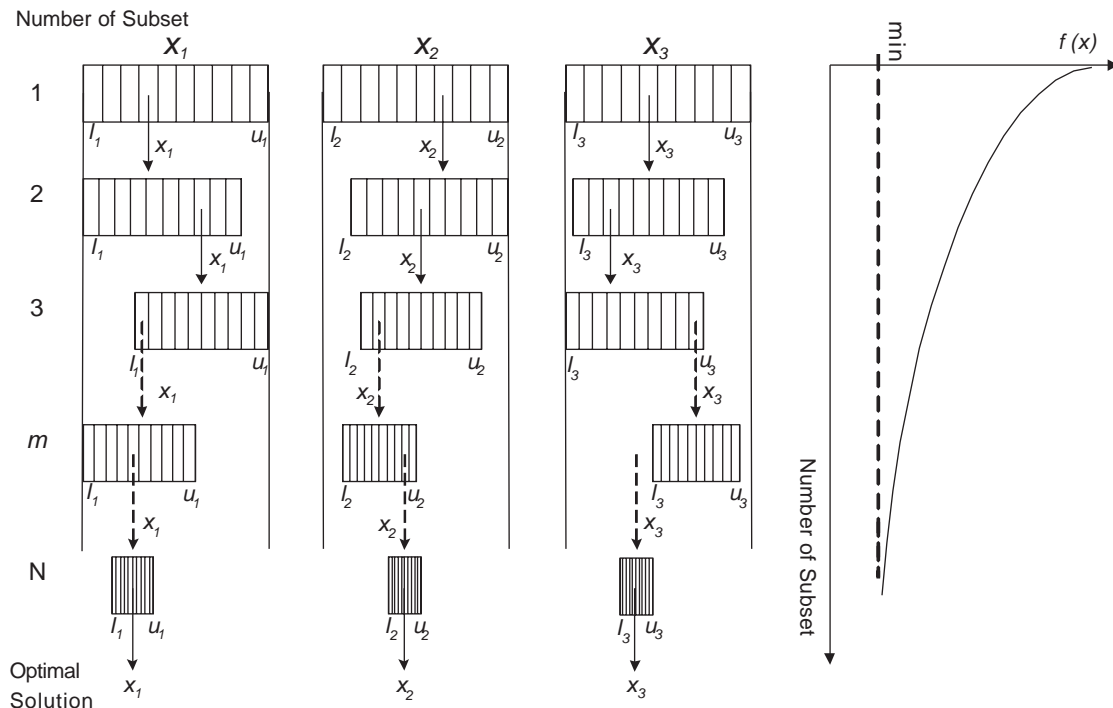

Fig. 2. Explanation of shifting and shrinking mechanism (SSM).

embrace the new search space with equal distances to the left side (lower bound) and the right side (upper bound) according to values x_1, x_2, x_3 (where x_1, x_2, x_3 are the value of variables designated by 1, 2, 3, respectively, at reference point). Then the new values of the lower and upper bounds of variable X_1, X_2, X_3 are limited to the lower and upper bounds of the domain of the variables (the dotted vertical lines in Fig. 2).

As generations progress, the density of vertical lines inside the rectangles is increased; this means that the optimal solution is obtained with better precision. The changing range of the variables can be considered as an additional mutation rate that explores more precisely the search space and speeds up convergence towards the optimal solution. The right side of Fig. 2 shows diagrammatically the changing $\varphi(x^*)$ at reference point versus set of generations in progress. It is predicted that the fluctuation of the $\varphi(x^*)$ will be significantly reduced as more sets of generations are developed [20].

5. The application of CRGA to the cost-optimization of MMCB

A software package utilizing a CRGA was developed and applied to the optimization of MMCB. The target compressive strength levels fell in the range of 60–130 MPa with 10 MPa increment. The margin of accuracy was considered at the level of up to $+1$ MPa (that corresponds to $\delta = 1$) for all the strength levels. Thus the equality constraint was converted to inequalities as

$$f_c \geqslant 0 \text{ and } f_c \leqslant \delta.$$

These limitations are applied because the cost function has a convex shape depending on strength; and the minimum cost is targeted by the optimization procedure. Tables 2 and 3 and Figs. 3–5 summarize the research results which are based on the best values obtained from 10 program runs with a standard deviation of less than 1%.

Two test cases were considered for cost optimization:

- the effect of SP cost (using NPC-SF-SP system);
- the effect of FGMA type (i.e. comparison of NPC–SF–FGPA–SP and NPC–SF–FGBFS–SP systems).

Prior to its full-scale application in the research program, the performance of the developed CRGA was compared with the conventional GA for selected compositions. The example of the trial runs evaluating

Table 2
The effect of SP cost on optimum composition of MMCB

Cost of SP ($)	Compressive strength (MPa)	SF (%)	SP (% SF)	Cost ($)
2500	130.0	12.7	10.2	162.7
	120.0	7.0	4.7	125.2
	110.5	5.0	1.0	113.7
5000	130.0	12.6	10.3	195.2
	120.0	6.7	5.3	133.7
	110.5	5.0	1.0	115.0

Table 3
The effect of FGMA type on optimum composition of MMCB

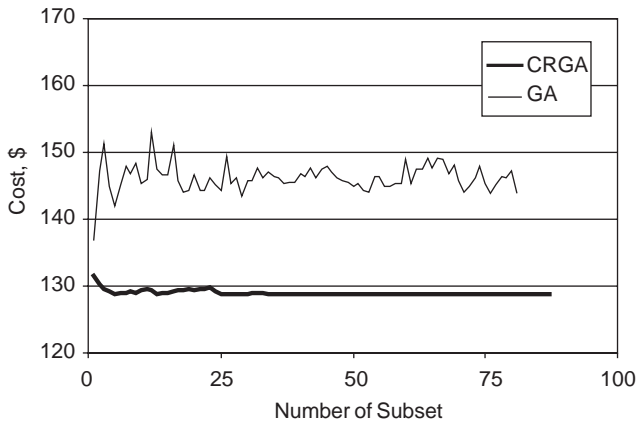| Type of FGMA	Compressive strength (MPa)	SF (%)	SP (%SF)	FGMA (%)	Cost ($)
FGPA	120.0	7.9	6.1	5.1	128.7
	110.0	6.1	4.6	11.9	115.9
	100.0	5.0	3.7	20.7	106.6
	90.0	5.0	2.6	31.9	99.6
	80.0	5.0	1.6	41.1	93.9
	70.0	5.0	1.0	49.5	89.0
	60.0	5.0	1.0	58.1	84.6
FGBFS	120.0	9.0	7.3	5.0	137.0
	110.0	5.9	5.2	5.0	120.5
	100.0	5.0	1.2	5.1	112.4
	90.0	5.0	1.0	17.3	108.5
	80.0	5.0	1.0	28.8	105.1
	70.0	5.0	1.0	39.2	101.9
	60.0	5.0	1.0	48.8	99.1

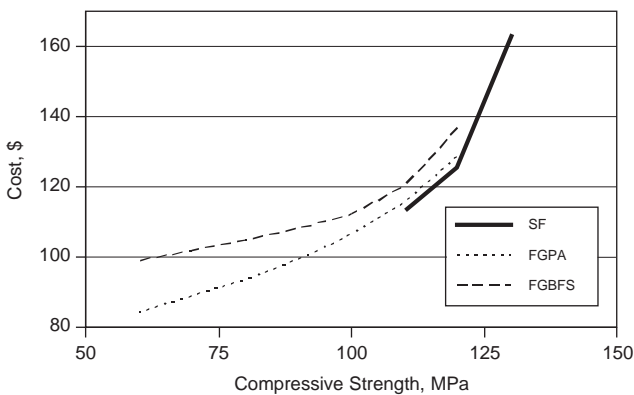Fig. 3. The comparison of CRGA and conventional GA.
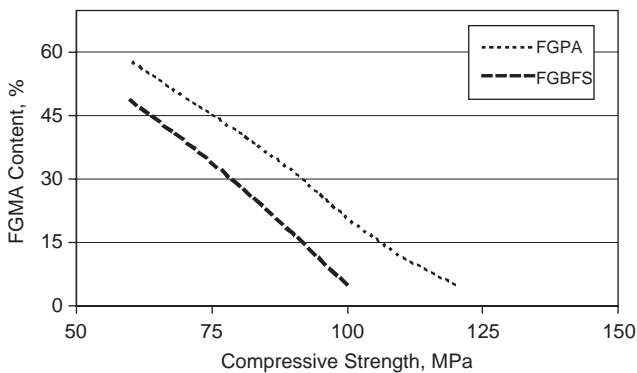

Fig. 4. Strength–cost relationship for MMCB.

Fig. 5. The effect of FGMA on strength of MMCB

the performance of CRGA and GA is presented for NPC–SF–FGPA–SP in Fig. 3. The obtained results clearly illustrate the advantage of CRGA over a conventional GA in finding the global optimum for the MMCB cost problem. A comparison of both curves shows that the SSMs lead to the global optimum. Otherwise, the GA population becomes homogenous and an additional mutation is needed to explore a more

feasible region. This role is performed by the "shifting and shrinking" mechanism.

The effect of SP cost on the optimum composition of MMCB is presented in Table 2. Indeed, the SP cost has little effect on the composition of MMCB: the proportioning of components at the minimum cost is virtually the same for specified strength levels. The MMCB with a compressive strength of 110 MPa represents the composition with the lowest possible content of SF and SP. Increasing strength to 130 MPa required a rise in SF and SP dosage by 7.6% and 9.3%, respectively, at a subsequent 43% increase in cost (for SP cost of $2500; Fig. 4). The effect of FGMA type on the optimum compositions of MMCB is summarized in Table 3 and Figs. 4–5. For this research SP cost was fixed at $2500. It is clear that the application of FGPA in MMCB is more effective when compared with FGBFS.

This is due to the better strength properties of MMCB containing FGPA and also because of the lower cost of FGPA. For example, a MMCB with a compressive strength of 120 MPa was designed with almost the same volume of FGMA at its minimum level of 5% (actually, 5.1% and 5% for FGPA and FGBFS, respectively, as per Table 3).

MMCB containing FGBFS requires an increased dosage of SF and SP (by more than 1% each) adding up to about 5% of additional costs above the already more expensive compositions with FGBFS. This difference in cost increases at lower strength levels (when the design strength is less than 100 MPa) with a subsequent increase in FGBFS content, reaching 17% for 60 MPa binders (Fig. 5).

An MMCB with a strength of 100 MPa needs only 5% SF. Only 5.1% of FGBFS is allowed in this case at a SP dosage of 1.2%. Considerably higher volumes, i.e. 20.7% of FGPA can be used in this composition at a SP dosage of 3.7%. On the other hand, higher costs associated with the application of FGBFS could be offset by the superior corrosion resistance of this type of binder [1]. Consequently, the maximum FGPA content is 58.1% for an MMCB with strength of 60 MPa; by contrast, only 48.8% of FGBFS is needed to achieve the same strength level (Fig. 5). The models of MMCB containing FGMA are more conservative in the range of high strength (100–120 MPa); therefore high-strength NPC–SF–SP binders were designed at a slightly lower cost (Fig. 4).

6. Conclusions

(1) Evaluation tests demonstrated that CRGA performs better than a conventional GA in finding the global optimum in the case of an MMCB problem with non-linear constraints. This is achieved by the application of the "shifting and shrinking" mechan-

ism. The proposed CRGA is highly accurate in locating the global optimum. It is also very quick and very efficient (i.e. it does not require additional parameters or additional computational efforts).

(2) It was found that SP cost has little effect on the optimal composition of MMCB: the proportioning of components with minimum cost is virtually the same for given strength levels.

(3) The application of FGPA in MMCB is more effective than FGBFS. MMCB containing FGBFS requires an increased dosage of SF and SP which increases cost. It is clear that for a specific strength level the FGPA content in MMCB can be considerably higher than FGBFS. On the other hand, higher costs associated with the application of FGBFS may be offset by the superior corrosion resistance of this type of binder.

(4) The range of the strength values provided by MMCB from 60 to 130 MPa imparts the wide range of costs (from \$84.6 to \$162.7) associated with manufacturing of MMCB. The NPC–SF–FGPA–SP-based binder is more economical than NPC–SF–FGBFS–SP and plain NPC; for the reference level of 70 MPa it can provide 13% (NPC–SF–FGBFS–SP) and 11% (NPC) savings.

(5) The optimization of the strength characteristics at the level of MMCB helps to minimize the related tests of concrete. It was demonstrated that the second-order polynomial equations are suitable for modeling the strength of MMCB systems. The tabulated cost-optimized compositions can be used for the proportioning of the high performance concrete mixtures. It helps to minimize the costs associated with an actual test program by omitting the non-feasible compositions.

Acknowledgments

Appendix A

The coefficients of polynomial equations used in the models of compressive strength (adopted from [1,12])

Table A1
The coefficients of the strength model: NPC–SF–SP system

Description		Polynomial equation coefficients b_{ij} for i		
X_j	j	0	1	2
—	0	95.51029	3.70645	1.28067
SF	1		−0.23804	0.26747
SP	2			−0.21051

Table A2
The coefficients of the strength model: NPC–SF–FGPA–SP system

Description		Polynomial equation coefficients b_{ij} for i			
X_j	j	0	1	2	3
—	0	79.84697	5.68422	1.94891	−0.36482
SF	1		−0.29356	0.22903	0.01667
SP	2			−0.20957	−0.00331
FGPA	3				−0.00806

Table A3
The coefficients of the strength model: NPC–SF–FGBFS–SP system

Description		Polynomial equation coefficients b_{ij} for i			
X_j	j	0	1	2	3
—	0	82.47044	4.84009	2.00346	−0.74234
SF	1		−0.25912	0.22078	0.01194
SP	2			−0.20397	0.00416
FGBFS	3				−0.00403

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