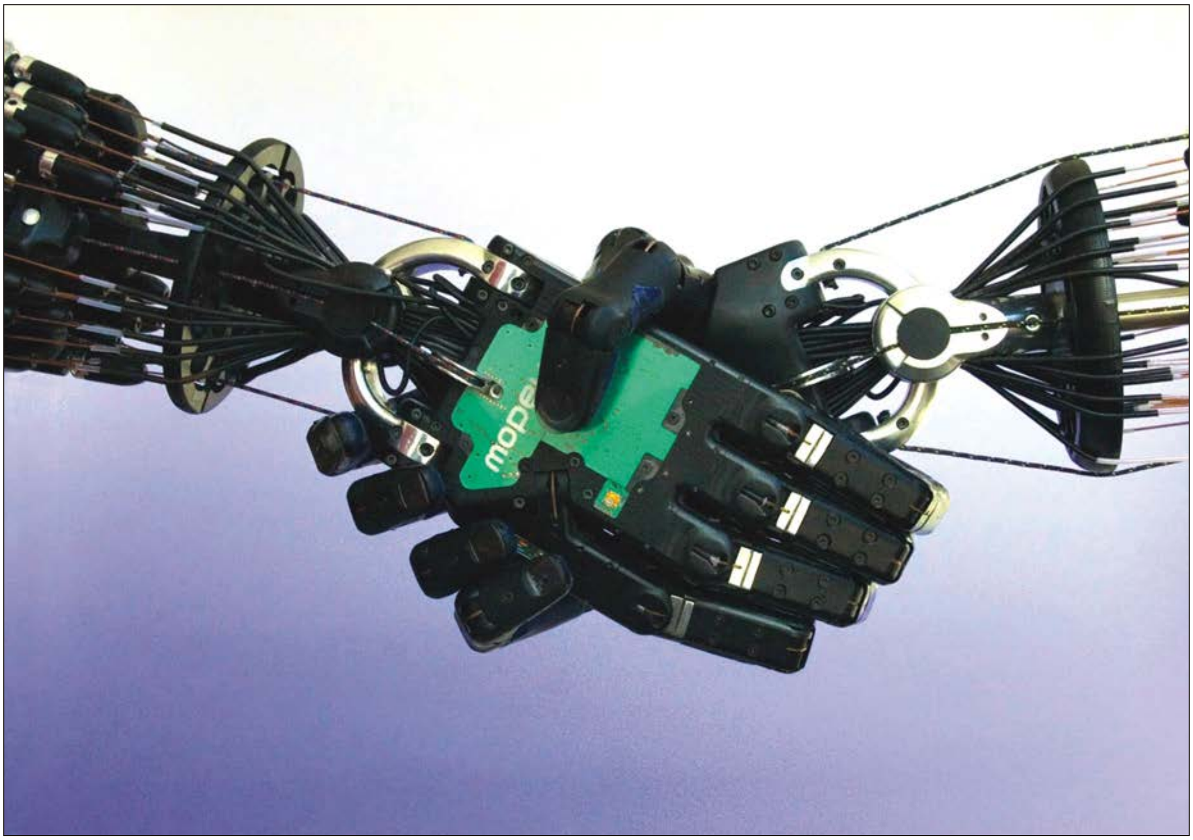

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Optimum Cost of Prestressed and Reinforced Concrete Beams using Genetic Algorithms

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ABSTRACT

This study aims at obtaining the cost of Prestressed Concrete (PC) beams and Reinforced Concrete (RC) beams. These beams are designed according to the requirements of the ACI 318-05 code. The objective function comprised the cost of concrete and the cost of reinforcement. Two computer models were developed for the cost optimization of PC and RC simple beams using MATLAB software. The design variables of RC simple beams were beam width, effective beam depth, number of flexural bars and reinforcement bar diameter. Beam width, effective beam depth, number of flexural bars, reinforcement bar diameter, number of tendons, tendon diameter and eccentricity of the centre of gravity of the tendons represented the design variables of PC simple beams. Practical design situations were considered using integer values for beam dimensions, number and diameter of bars/tendons. A catalogue of the common values of the beam dimensions and bar/tendon numbers and diameter dimensions were prepared for this purpose. A cost reduction of 27.9 and 16.7% for the 4 and 8 m span RC beams, respectively and 29.8 and 17.8% of the 10 and 20 m span PC beams was obtained by the GA model over the generalized reduced gradient method. The effect of concrete compressive strengths and wider design parameters bounds on the outputs of the optimization process were examined. The comparison showed that the GA models were smart in keep moving towards the optimum cost of the beams.

Key words: Genetic algorithm, cost optimization, prestressed concrete, RC beams, structural concrete, ACI-Code

INTRODUCTION

Optimum design of structural concrete, as a main construction material, attracted an increasing attention of researchers and professional engineers. The cost of reinforced concrete elements is affected by a number of cost items including the cost of formwork, concrete and reinforcement. Therefore, the minimum weight design is not necessarily the same as the minimum cost design. For reinforced concrete members the optimum cost design is a compromise between the amount of concrete, reinforcement and formwork. This compromise minimizes the total cost of the structure and satisfies the design requirements. In the cost optimization of reinforced concrete structures the cross sectional dimensions of elements and detailing of reinforcement (size and number of steel bars) should be obtained (Michalewicz and Schoenauer, 1996; Castilho and Lima, 2007; Khedr, 2007).

The analytical methods depend mainly on the assumption that the design variables are continuous. In reality most reinforced concrete members in construction have dimensions of discrete sizes. For example, the width is commonly increased by a certain step size, e.g., 5 cm (Choi and Kwak, 1990). The amount of reinforcement of a section is also represented by the number of bars. Therefore, from the practical situation, the problem should be defined as a cost optimization of reinforced concrete members with discrete variables rather than with continuous variables. There are a number of methods which have been developed for discrete optimization of structures. However, the use of these methods is limited to small and simple structures as most of these methods involve numerous design variables. Thus applying these methods to the optimization of large and complex problems is not an easy task (Belegundu and Chandrupatla, 1999; Rao, 1996; Ozgan and Ozturk, 2007).

Recently, new approaches using genetic algorithms have been introduced (Camp *et al*., 2003; Lee and Ahn, 2003; Sahab *et al*., 2004, 2005; Senouci and Al-Ansari, 2009; Perera and Vique, 2009). Genetic algorithm, which is first formalized as an optimization method by Holland (1998), is a global optimization method for high dimensional, nonlinear and noisy problem and a stochastic search technique based on the mechanism of natural selection and natural genetics (Pham and Karaboga, 2000; Goldberg, 1989).

A number of researchers succeeded in applying genetic algorithm to obtain optimum design of structural elements and structures based on certain objective function and prescribed constrains. Atabay (2009) presented a cost optimization model for three-dimensional beamless reinforced concrete shear-wall systems by genetic algorithm method. The shear-wall dimensions were considered as design variables and it has been aimed at searching the optimum shear-wall dimensions that minimize total material cost of shear-wall. The constraints of structural optimization problem were defined according to the requirements of the reinforced concrete code of Turkey.

Govindaraj and Ramasamy (2005) applied Genetic Algorithms to obtain the optimum detailed design of reinforced concrete continuous beams. The produced optimum design satisfied the strength, serviceability, ductility, durability and other constraints related to good design and detailing practice.

Sahab *et al*. (2005) presented a two-stage hybrid optimization algorithm based on a modified genetic algorithm. In the first stage, a global search is carried out over the design search space using a modified GA. In the second stage, a local search based on the discrete genetic algorithm solution is executed.

The current study, which was conducted at the department of civil Engineering, IU-Gaza in 2009, presents the cost optimization of structural RC beams and PC beams using the genetic algorithm optimization technique. All design steps of the RC and PC beams were performed according to the ACI 813-05 (ACI, 2005). Design of a beam starts with proportioning its sections to resist bending moment and choosing the required reinforcement, taking into account the minimum and maximum reinforcement ratios and spacing between the reinforcement bars and deflection limitations. Having done this step, the chosen sections are checked and designed for shear and torsion with considering minimum web reinforcement, spacing between stirrups and shear capacity of the section.

Two computer models were developed for the structural cost optimization of RC and PC simple beams using (MATLAB, 2009) software. The results of these optimization models were compared with the results obtained using a classical optimization models, the generalized reduced gradient method. The influence of using higher concrete compressive strength values and wider design parameters bounds on the results of the optimization process of the RC and PC beams were examined. This showed that the GA models were smart in keeping the total cost of the beams optimum.

GENETIC ALGORITHM OPTIMIZATION TECHNIQUE

Traditional search and optimization methods can be classified into two distinct groups, namely; direct and gradient-based methods (Deb, 1995; Reklaitis *et al.*, 1983). In direct methods, only objective function and constraints are used to guide the search strategy, whereas gradient-based methods use the first and/or second-order derivatives of the objective function and/or constraints to guide the search process.

In the last three decades, heuristic methods have been rapidly developed to solve optimization problems. These methods are based upon the principles of natural biological evolution; they are called Evolutionary Computations (EC). Heuristic methods such as Genetic Algorithms (GAs), Simulated Annealing (SA) and Tabu Search (TS) provide general ways to search for a good but not necessarily the best solution (Pham and Karaboga, 2000).

Genetic algorithms are numerical optimization techniques inspired by Darwin's theory of evolution. A GA starts searching design space with a population of designs (solutions), which are initially created over the design space at random. In the basic GA, every individual of population (design) is represented by a chromosome, a chromosome is an array of genes and a gene is an array of bits. A gene looks like: (11100010) and a chromosome looks like: (11000010, 00001110, 001111010, 10100011), each gene represents some data (beam width, beam depth, prestressing force, etc.) (Goldberg, 1989; Holland, 1998; Senouci and Al-Ansari, 2009; Sahab *et al.*, 2004).

GA uses four main operators, namely, selection, creation of the mating pool, crossover and mutation to direct the population of designs towards the optimum design. In the selection process, some designs of a population are selected by randomized methods for GA operations, for example: in creation of the mating pool, some good designs in the population are selected and copied to form a mating pool. The fitter chromosomes (better designs) have a greater chance to be selected. Crossover allows the characteristics of the designs to be altered. In this process different digits of binary strings of each parent are transferred to their children (new designs produced by the crossover operation). Mutation is an occasional random change of the value of some randomly selected design variables. The mutation operation changes each bit of string from 0 to 1 or vice versa in a design's binary code depending on the mutation probability. Mutation can be considered as a factor preventing from premature convergence. A flowchart presenting the working principle of a genetic algorithm is shown in Fig. 1. The following paragraphs explains briefly the four basic operators of genetic algorithms.

The Generalised Reduced Gradient (GRG) method was applied in the current study, as an example of classical optimization techniques, to compare its optimization results with those obtained from the GA optimization models.

The GRG method is a nonlinear optimisation program, which was developed by Lasdon *et al.* (1978), used by the Microsoft Excel Solver for solving optimization problems (minimisation and maximisation).

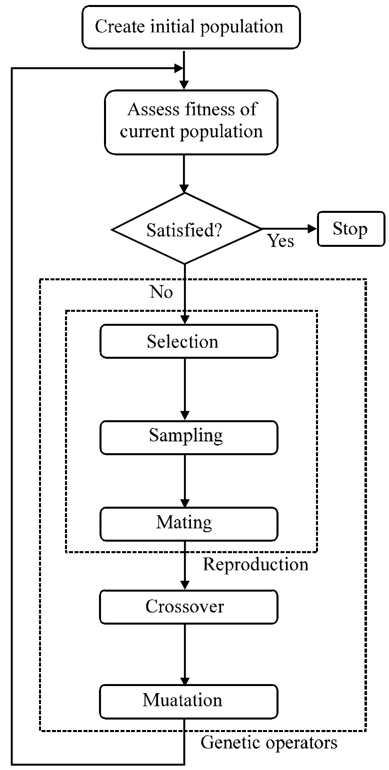

Fig. 1: Basic principle of a genetic algorithm

OPTIMIZATION PROBLEM FORMULATION

Two optimization models were developed for RC and PC beams. In the optimization models, objective functions, design variables, design constraints were defined. The fixed parameters of each design problem comprise the span of the beam, maximum aggregate size, cost m^{-3} of concrete, cost/ton of normal steel bars, cost/ton of prestressing tendons, modulus of elasticity of concrete, modulus of elasticity of prestressing tendons, tensile strength of prestressing tendons, modulus of elasticity of steel, the compressive strength of concrete, compressive strength of concrete at time of initial prestress, the yield strength of reinforcement, yield strength of prestressing tendons and the applied dead and live loads.

Objective function: The objective functions defined for the optimization model of the RC and PC beams, Z_o and Z_p, were the total cost of materials for concrete and steel reinforcement and steel tendons in case of prestressed concrete. The objective functions of the current models can be described as follows:

RC beams:

$$Z_o = C_c * \left[(A_c - A_s) * L - W_{str}/\gamma \right] + C_s * \left[\gamma * (A_s \times L) + W_{str} \right] \tag{1}$$

Subject to:

$$G_i(x_o) \leq 1 \qquad i = 1, 2, ..., n_g$$

$$x_j^l \leq x_j \leq x_j^u \qquad i = 1, 2, ..., n_s$$

$$x = (x_o)$$

PC beams:

$$Z_p = C_c * \left[\left(A_c - (A_s + A_{ps}) \right) * L - W_{str}/\gamma \right] + C_s * \left[\gamma * (A_s \times L) + W_{str} \right] + C_{ps} * \left[\gamma * (A_{ps} \times L) \right] \qquad (2)$$

Subject to:

$$G_i(x_p) \leq 1 \qquad i = 1, 2, ..., n_g$$

$$x_j^l \leq x_j \leq x_j^u \qquad i = 1, 2, ..., n_s$$

$$x = (x_p)$$

where, C_c is the cost of concrete per cubic meter, C_s is the cost of reinforcement steel per ton, Ac is the area of concrete cross section, As is the area of longitudinal reinforcement, L is the span of the beam, W_{str} is the weight of stirrups and γ is the unit weight of steel reinforcement, C_{ps} is the cost of prestressing tendons per ton, A_{ps} is the area of prestressing tendons. G_i is the i-th non-dimensional behavioral constraint function. x_j are the side constraints on design variables, where x_j^l and x_j^u are the lower and upper limits of the design variable x_j, respectively. n_g and n_s are the number of behavioural and side constraints, respectively. x_o and x_p are the design variable vector of the RC beams and PC beams, respectively.

Design variables and their bounds: Several design variables were given integer numbers with a predefined step size, these step sizes are chosen according to local practical conditions or depends on the availability in the local market. The bounds of the design variables were identified based the provisions of the ACI 813-05 code, aesthetic requirements, practical requirements and availability of material such as steel bar diameters.

RC beams: There were four design variables involved in the optimization problem of RC beam, namely:

- Beam width, b (integer values with step size of 5 cm)
- Effective beam depth, d (real values)
- Number of flexural bars, n_b (integer values with step size of 1)
- Diameter of flexural bars, d_b (integer values with step size of 2)

The bounds of the design variables were identified based on several requirements; including the provisions of the ACI code, aesthetic and practical requirements and availability of material.

PC beams: The design variables of the PC beam model are listed below:

b = Beam width (integer values)
d_p = Effective beam depth (real values)
n_b = Number of flexural bars (integer values)
d_b = Diameter of flexural bars (integer values)
n_t = Number of tendons (integer values)
d_t = Diameter of tendons (real values)
e = Eccentricity of the c.g of the tendons (real values)

Design constraints: The constraints are defined on the basis of the ACI318-05 requirements for reinforced concrete structures and architectural and practical considerations. The design constraints applied to RC and PC models represent the section flexural capacity, bar spacing, minimum and maximum reinforcement ratios, section shear capacity, stirrup's diameter and spacing and deflection limitations. In prestressed beam model, the maximum allowable concrete compressive and tensile stresses at initial prestress and service load stages are also considered as constraints.

Constraint handling: As GAs is an unconstrained optimization technique; it is necessary to transform the constrained cost optimization problem to an unconstrained one. Several methods for handling constraints by GAs have been proposed (Michalewicz and Schoenauer, 1996). Among them the rejecting strategy and methods based on a penalty approach. In the rejecting strategy, any design that violates one or more constraints is not accepted for the involvement in the GA process to create a new population. In a penalty method, a constrained optimization problem is converted to an unconstrained problem by adding a penalty for each constraint violation to the objective function. It converts the constrained nonlinear programming problem to an unconstrained minimization problem by penalizing infeasible solutions.

The success of this simple approach lays in the proper choice of these penalty parameters. The basic rule of choosing the penalty parameters is that they must be set so that all penalty terms are of comparable values with themselves and with the objective function values. This is intuitive because if the penalty corresponding to a particular constraint is very large compared to that of other constraints, the search algorithm emphasizes solutions that do not violate the former constraint. This way, other constraints get neglected and search process gets restricted in a particular way. Since, a proper choice of penalty parameters are the key aspect of the working of such a scheme, most researchers test different values of penalty parameter values and find a set of reasonable values. In this study, the technique suggested by Deb (1995) was used for handling constraint optimization problems for genetic algorithms. He devised the following fitness function, where infeasible solutions are compared based on only their constraint violation:

$$F(x) = \left\{ \begin{array}{lll} f(x) & \text{if } g_j(x) \geq 0, & \forall_j = 1, 2, \ldots\ldots, m \\ f_{max} + \sum_{j=1}^{m} \langle g_j(x) \rangle, & \text{otherwise} & \end{array} \right\} \quad (3)$$

The parameter f_{max} is the objective function value of the worst feasible solution in the population. Thus, the fitness of an infeasible solution not only depends on the amount of constraint violation, but also on the population of solutions at hand. However, the fitness of a feasible solution is always fixed and is equal to its objective function value.

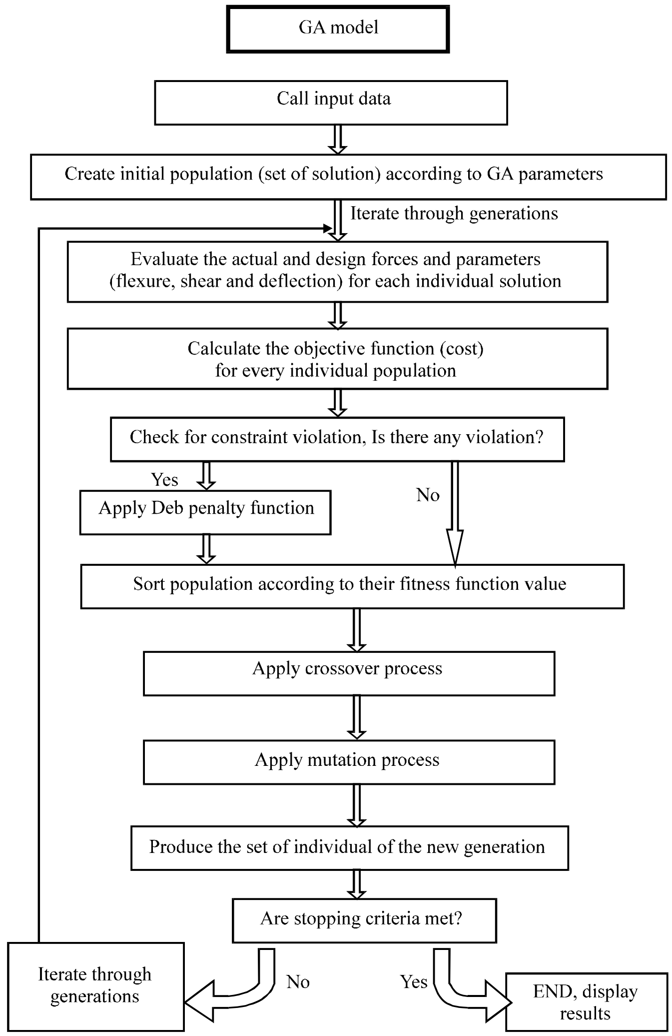

Fig. 2: Flowchart of the GA optimization process of RC and PC models

Cost optimization procedure: Figure 2 shows a flowchart of the algorithm of the developed models for the cost optimization of simply supported RC and PC beams. The cost optimization procedure starts with calling the constant parameters and then creating the population size which contains the first randomly created design variables. Afterwards, the design variables will be used to evaluate the actual and design forces and parameters (flexure, shear and deflection) for each individual solution. The objective function of each individual population is to be calculated. The optimizer will then check the constraints and identify if there is any constraint violation. In case of constraint violation, the Deb penalty function will be applied. Consequently, the fitness function values of all individuals will be calculated and then sorted according to these values. Cross over, mutation and selection operators will be applied to produce a set of individuals of the new generation. This process will be repeated until one of the stopping criteria is satisfied.

Design examples: A number of beams was designed and optimized in order to test and validate the proposed GA models. Two simply supported rectangular RC beams and two simply supported

Table 1: Bounds of the design variables of RC beams

Variables	Lower bound	Upper bound	Step size
Beam width (b, cm)	30	70	5
Effective beam depth (d, cm)	70	100	Continuous
Number of flexural bars (n_b)	4	12	1
Diameter of flexural bars (d_b, mm)	12	24	2

Table 2: Bounds of the design variables of PC beams

	Upper bound	Lower bound	Step size
Beam width (b cm)	30	70	5
Effective beam depth (d, cm)	80	120	Continuous
Number of flexural bars (n_b)	4	10	1
Diameter of flexural bars (d_b mm)	12	18	2
Number of tendons (n_t)	2	20	1
Diameter of tendons (d_t cm (in))	0.635 (0.25)	1.43 (0.5625)	0.159 (0.0625)
Eccentricity of the c.g of the tendons, e	10	50	Continuous

PC beams were examined in the current study. The following paragraphs describe the fixed parameters of each case, the upper and lower bounds of the design parameters and their step sizes.

RC beams: The RC beams have spans of 4 and 8 m, uniform dead load of 7.85 KN m'^{-1} in addition to the own weight of the beam, uniform live load of 12.5 KN m'^{-1}, concrete compressive strength f_c' = 24.5 MPa, steel yield strength f_y = 410 MPa, concrete cost Cc = 60 USD m^{-3} and cost of steel Cs = 450 USD t^{-1}. The bounds of the design variables of the RC beam are presented in Table 1.

PC beams: The PC beams had spans of 10 m and 20, uniform superimposed gravity dead load of 2 KN m'^{-1} in addition to the own weight of the beam, uniform live load of 3 KN m^{-2}, f_c' = 41.4 MPa, f_y = 410 MPa, yield strength of the steel tendon f_{yp} =1517 MPa, ultimate strength of the steel tendon f_{up} =1862, the initial prestressing before losses is assumed to be $f_{pi} \approx 0.70 \times f_{pu}$, Cc = 60 USD m^{-3} and Cs = 450 USD t^{-1}, Cps = 1000 USD t^{-1}. The bounds of the design variables of the PC beam are presented in Table 2.

ANALYSIS OF THE OPTIMIZATION RESULTS

The effect of higher values of the concrete compressive on the optimization process of the RC and PC beam models using the chosen and the extended design variables bounds are discussed here.

Results of RC and PC beams: The optimization process of RC beams and PC beams were carried out in order to search for an optimum solution for each case, the outputs of the optimization process (minimization of total cost) versus the number of generation are presented in Fig. 3 and 4.

The results of the GA optimization of the RC and PC beams together with those obtained from the Excel solver of Generalized Reduced Gradient (GRG) method are indicated in Table 3 and 4.

The optimum solutions of the 4 m- and 8 m-span RC beams using the GA model were 69.5 and 170.7 USD m^{-3}, respectively, while when using the Excel solver the corresponding values were 96.9 and 205 USD m^{-3}, respectively. The GA model showed a minimum cost of 231.5 and

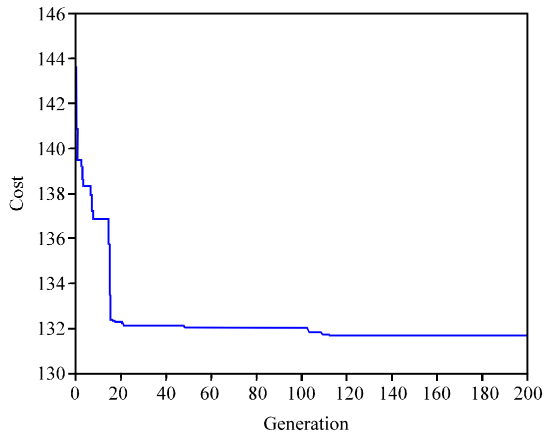

Fig. 3: Optimization process of RC beam

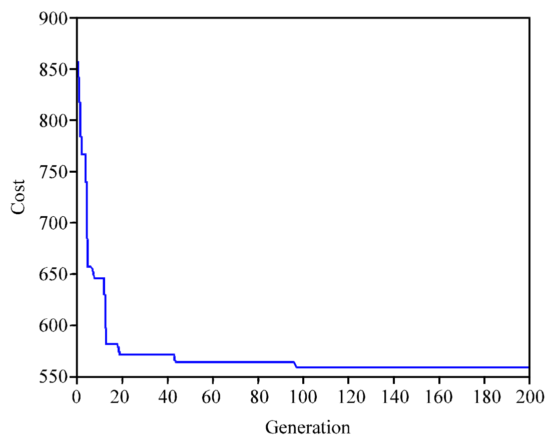

Fig. 4: Optimization process of PC beam

Table 3: Values of variables and cost function of the RC beams

	4 m span		8 m span	
Variables	GRG solver	GA	GRG solver	GA
Beam width (b)	40.0	30.0	35.00	30.0
Effective beam depth (d)	70.0	70.0	94.87	87.9
Number of flexural bars (n_b)	7.0	4.0	6.00	4.0
Flexural bars diameter (d_b)	16.0	16.0	14.00	18.0
Cost of concrete (USD m^{-3})	60.0	60.0	60.00	60.0
Cost of reinforcement (USD t^{-1})	450.0	450.0	450.00	450.0
Total cost (USD m^{-3})	96.9	69.5	205.00	170.7
Total cost saving (%)	27.9		16.70	

704.4 USD m^{-3} in case of the 10 and 20 m span PC beams, respectively. The Excel solver obtained a minimum cost of 329.9 and 857 USD m^{-3} for the 10 and 20 m span PC beams, respectively.

Table 4: Values of variables and cost function of the PC beams

	10 m span		20 m span	
Variables	GRG solver	GA	GRG solver	GA
Beam width (b, cm)	50.0000	30.0000	50.0000	30.0000
Effective beam depth (d, cm)	80.0000	80.5000	90.7700	105.0200
Number of flexural bars (n_b)	4.0000	4.0000	4.0000	4.0000
Flexural bars diameter (d_b mm)	16.0000	12.0000	16.0000	12.0000
Number of tendons (n_t)	4.0000	6.0000	13.0000	12.0000
Diameter of tendons (d_t in)	0.5625	0.5625	0.5625	0.4375
Eccentricity of the c.g of the tendons (e)	37.3600	37.6100	42.7500	48.0500
Cost of concrete (Cc USD m^{-3})	60.0000	60.0000	60.0000	60.0000
Cost of steel reinforcement (USD t^{-1})	450.0000	450.0000	450.0000	450.0000
Cost of prestressing reinforcement (USD t^{-1})	1000.0000	1000.0000	1000.0000	1000.0000
Total cost (USD m^{-3})	329.8800	231.5300	857.0400	704.4200
Total cost saving (%)	29.8000	17.8000		

This means that the developed GA model showed 27.9 and 16.7% saving in cost for the 4 and 8 m span RC beams, respectively, over the Excel solver based on the generalized reduced gradient method. These results showed a higher cost savings than that obtained by Govindaraj and Ramasamy (2005). In their study, they compared the GA results with that obtained by Kanagasundaram and Karihaloo (1991) who applied linear programming optimization. A total cost saving of 11.28% for 4 m span RC beam was reached by Govindaraj and Ramasamy (2005) over that of the linear programming optimum cost. The higher cost saving obtained by the present study over Govindaraj and Ramasamy (2005) finding the can be attributed to the fact that they used the beam dimension alone as a variable and they applied several steel reinforcement templates in their GA model.

Also, 29.8 and 17.8% reduction in cost were obtained by the GA model in case of the 10 and 20 m span PC beams over the excel solver, respectively. This shows the efficiency of GA in finding optimum solutions, even with only the basic GA operators. This finding also indicates the advantage of using GA technique in cost optimization over classical optimization methods. This conclusion agrees very well with Senouci and Al-Ansari (2009) and Perera and Vique (2009), who provided structural engineers with a robust GA optimization model which capable of obtaining optimum design of structural beams.

Effect of compressive strength on the optimization process: The effect of using higher values of concrete compressive strengths while fixing the applied live and dead load (excluding the beam own weight) on the behaviour of the optimization process of the 8 m span RC beam and 20 m span PC beam models was investigated. Concrete compressive strengths of 25, 30, 35 and 40 MPa for the RC beams and 35, 40, 45 and 50 MPa for the PC beams were applied. The outputs of conducting the optimization process on the RC beam and the PC beam models using these higher values of f_c' are included in Table 5 and 6, respectively.

Table 5 and 6 show that when, f_c' of the 8 m span RC beam increases from 25 to 40 MPa, the total cost increases from USD 131.68 to 139.35 and when, f_c' of 20 m span PC beams increases from 35 to 50 MPa, the total cost increases from USD 604.62 to 658.46. The results indicated that as f_c' increases, the GA optimizer decreases the dimensions of the concrete section in order to find the

Table 5: Effect of compressive strength on outputs of optimization of 8m-span RC beam

f_c 'MPa	Cost of concrete m^{-3} (USD)	Cost of beam (USD)	b (cm)	d (cm)	n_b	d_b (mm)	ρ
25	60.0	131.7	30	78.3	4	16	0.0034
30	63.0	133.0	30	71.2	4	18	0.0047
35	65.5	135.4	30	70.0	4	18	0.0048
40	68.0	139.4	30	70.0	4	18	0.0048

Table 6: Effect of compressive strength on outputs of optimization of 20 m span PC beam

f_c' MPa	Cost of concrete m^{-3} (USD)	Cost of beam (USD)	b (cm)	e (cm)	n_b	d_b (mm)	d_p (mm)	n_t	d_t (in)
35	65.5	605.4	30	49.9	4	12	107.1	8	0.5000
40	68.0	615.5	30	49.8	4	12	106.1	20	0.3125
45	72.0	630.7	30	49.0	5	12	103.9	19	0.3125
50	76.0	658.5	30	47.3	4	12	101.3	16	0.3750

Table 7: Current and extended design variables bounds for the 8 m span RC beam

	b (cm)		d (cm)		n_b		d_b (mm)	
Design variables bounds	Min	Max	Min	Max	Min	Max	Min	Max
Current bounds	30	70	70	100	4	12	12	24
Extended bounds	10	80	30	120	2	16	12	26

Table 8: Current and extended design variables bounds for the 20 m span PC beam

	b (cm)		e (cm)		n_b		d_b (mm)		d_p (cm)		n_t		d_t (in)	
Design variable	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max
Current bounds	30	70	10	50	4	10	12	18	80	120	2	20	0.25	0.5625
Extended bounds	10	80	5	60	2	20	12	22	40	130	2	24	0.25	0.5625

least cost since increasing f_c' increases the unit cost of concrete. Thus one can conclude that the GA optimizer do a remarkable effort in order to decrease the amount of material as its cost increases. The obtained outputs in Table 6 indicated also that the GA optimizer tends to use the least possible amount of steel since it is the most expensive material. The amount of reinforcing steel used is close to the minimum ratio permitted by the ACI Code (i.e., ρ_{min} = 0.0033). This finding agrees with (Senouci and Al-Ansari, 2009) who conducted a parametric study using a developed GA optimization model to obtain optimum design of composite beams. They noted that as the input parameters are changed the GA model responds very well in satisfying the applied constraints without losing the capability to obtain cost savings.

Effect of compressive strength on optimization results using wider design variables bounds: The bounds (ranges) of the design variables represent the space of problem from which the optimizer searches for the optimum solution. This space should be wide enough to comprise optimum solutions, therefore, the influence of the design variables bounds on the optimization outputs of the models was examined, the design variables bounds of the 8 m span RC beams and 20 m span PC beams were extended as shown in Table 7 and 8.

The optimization process of the GA models of 8 m span the RC and 20 m span PC beams using the wider design variables bounds was carried out and the corresponding optimization outputs are included in Table 9 and 10.

Table 9: Effect of compressive strength on optimum cost of RC beam using wider bounds

f_c' MPa	Cost of concrete m^{-3} (%)	Cost of beam (%)	b (cm)	d (cm)	n_b	d_b (cm)	ρ
25	60.0	102.9	20	87.7	2	22	0.0043
30	63.0	104.3	20	84.9	2	22	0.0045
35	65.5	104.1	20	81.2	2	22	0.0047
40	68.0	105.3	20	79.3	2	22	0.0048

Table 10: Effect of compressive strength on optimum cost of PC beam using wider bounds

f_c' MPa	Cost of concrete m^{-3} (%)	Cost of beam (%)	b (cm)	e (cm)	n_b	d_b (mm)	d_p (mm)	n_t	d_t (in)
35	65.5	481.6	20	48.6	2	14	114.6	28	0.2500
40	68.0	495.6	20	42.5	2	18	106.5	19	0.3125
45	72.0	518.6	20	44.4	2	12	112.9	30	0.2500
50	76.0	532.6	20	32.8	2	12	94.8	20	0.3750

The optimization results presented in Table 9 and 10 indicate that the total cost of the beam is reduced by about 30 and 25 dollars on average for the RC and the PC beams, respectively. This proves that when opening the design variable bounds as much as possible, the search space will be widened giving the GA optimizer a higher chance to obtain better solutions, due to better ability of manoeuvring.

CONCLUSIONS

This study aimed at developing cost optimization models for structural concrete beams using basic genetic algorithms. Two GA models were proposed to obtain the optimum design of simply supported reinforced concrete beams and prestressed concrete beams based on ACI 318-05. An Excel solver which uses the generalised reduced gradient method (representing classical optimization methods) was prepared in order to compare its results with those obtained from the GA models.

Numerical design examples were utilized to verify and validate the proposed models. Simply supported 4 m span and 8 m span reinforced concrete, RC, beams, 10 m span and 20 m span prestressed concrete, PC, beams were applied. The GA optimization results showed 27.9 and 16.7% reduction in cost for the 4 m and 8 m span RC beams, respectively, over the Excel solver based on the generalized reduced gradient method. Percentages of 29.8 and 17.8% reduction in cost were also obtained by the GA model in case of the 10 and 20 m span PC beams over the Excel Solver, respectively. This shows the capability of GA in finding optimum solutions, even with only the basic GA operators. This finding also indicates the superiority of using GA technique in cost optimization over classical optimization methods. The influence of applying higher concrete compressive strengths and wider design parameters bounds on the optimization process of the RC and PC beams were examined. The results proves that when opening the design variable bounds as much as possible, the search space will be widened giving the GA optimizer a higher chance to obtain better solutions, due to better ability manoeuvring. The results also revealed that the GA models were smart in keep moving towards the optimum cost of the beams.

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