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COST AND CO_2 EMISSION OPTIMIZATION OF REINFORCED CONCRETE FRAMES USING ENHANCED COLLIDING BODIES ALGORITHM

A. Kaveh* and Sh. Ardalani
Centre of Excellence for Fundamental Studies in Structural Engineering, Iran University of Science and Technology, Narmak, Tehran-16, Iran

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ABSTRACT

This paper investigates discrete design optimization of reinforcement concrete frames using the recently developed meta-heuristic called Enhanced Colliding Bodies Optimization (ECBO) and the Non-dominated Sorting Enhanced Colliding Bodies Optimization (NSECBO) algorithm. The objective function of algorithms consists of construction material costs of reinforced concrete structural elements and carbon dioxide (CO_2) emissions through different phases of a building life cycle that meets the standards and requirements of the American Concrete Institute's Building Code. The proposed method uses predetermined section database (DB) for design variables that are taken as the area of steel and the geometry of cross-sections of beams and columns. A number of benchmark test problems are optimized to verify the good performance of this methodology. The use of ECBO algorithm for designing reinforced concrete frames indicates an improvement in the computational efficiency over the designs performed by Big Bang-Big Crunch (BB-BC) algorithm. The analysis also reveals that the two objective functions are quite relevant and designs focused on mitigating CO_2 emissions could be achieved at an acceptable cost increment in practice. Pareto results of the NSECBO algorithm indicate that both objective yield similar solutions.

Keywords: Meta-heuristic algorithms; enhanced colliding bodies optimization; non-dominated sorting enhanced colliding bodies optimization; reinforcement concrete frames; multi-objective optimization; CO_2 emissions.

1. INTRODUCTION

The growing of global climate change with the progress of human activity and rapid

*E-mail address of the corresponding author: alikaveh@iust.ac.ir (A. Kaveh)

industrialization has created a need to appraise the impact of the products used in construction process and has challenged many contractors and companies to come up with more environmentally friendly ways of construction. Most of global warming has being caused by increasing concentrations of greenhouse gases in the earth's atmosphere during the past 10 decades [1]. The Intergovernmental Panel on Climate Change [2] reported that carbon dioxide makes up approximately 77% of greenhouse gasses in which construction industry has a remarkable contribution.

Concrete as the most popular manufactured product with sustainability benefits including considerable compressive strength and durability, excellent thermal mass and long service life, contributes 5% per percent of annual anthropogenic global CO_2 production. Main contributor for it to happen is chemical conversion process used in the production of Portland clinker and cement production by fossil fuel combustion. With annual consumption approaching 20000 million metric tonnes of concrete, the manufacturing process releases 0.9 tonnes of CO_2 per tonnes of clinker [1]. In addition to the 1.6 billion tons of cement used worldwide, the concrete industry is consuming 12.6 billion tons of raw materials each year. Thus besides cement role in CO_2 emission, mining, processing, and transporting of raw materials consume energy in quantity and adversely affect theology of the planet [3]. Reducing atmospheric concentration of CO_2 caused by construction industry can be reached through innovative architecture, sustainable structural design and reducing the cement of concrete mixture [1].

The purpose of this study is presentation of an optimal design technique in order to achieve more sustainable, environmentally friendly and economically feasible structural design. The methods of structural optimization can be divided into two categories: exact methods and approximate methods. The exact methods are based on mathematical programming such as the lagrangian multipliers method, convex programming, linear programming and sequential unconstrained minimization techniques which their endeavor for finding an optimal solution grow polynomially with problem size, hence the application of exact methods limited to simple and deterministic polynomial problem instances. To overcome these problems, meta-heuristic methods are developed. These methods provides the practical possibility to improve upon the design process without the need for complex analysis, however they require a great computational effort because of a large number of iterations needed for the evaluation of objective functions and structural constraints.

The meta-heuristic algorithms are more general and can easily be implemented. Some examples of these methods are: Genetic algorithms (GA) [4], Particle swarm optimization (PSO) [5], Ant colony optimization (ACO) [6], Big bang-big crunch (BB-BC) [7], Charged system search (CSS) [8], Ray optimization (RO) [9], Dolphin echolocation (DE) [10], Min blast (MB) [11], Colliding Bodies Optimization (CBO) [12], Ant lion optimization [13], and Water evaporation optimization (WEO) [14], etc.

Some current design activities are focused on cost optimization of reinforced concrete structures using evolutionary optimization methods. Rajeev and Krishnamoorthy [15] applied a simple genetic algorithm to perform optimal design of planar reinforced concrete frames, Camp et al. [16] used genetic algorithm for flexural design of RC frames, Lee and Ahn [17] applied genetic algorithm to optimum design of two dimensional frames, Govindaraj and Ramasamy [18] used genetic algorithms for optimum detailed design of RC frames based on Indian standard specifications, Paya et al. [19] conducted a multiobjective comparison for RC building frames using simulated annealing, Kwak and Kim [20] studied an optimum design of RC plane frames using integrated genetic algorithm complemented with direct search, Kaveh and Sabzi [21] conducted a comparative study of heuristic big bang-big crunch, heuristic particle swarm and ant colony optimization for optimum design of RC frames, Akin and Saka [22] used harmony search algorithm for optimum detailed design of RC plane frames.

Recently, attention to the preservation of environment and reducing CO_2 emissions have been the focus of studies in optimum design of RC structures. Paya et al. [23] used simulated annealing for CO_2 optimization of reinforced concrete frames, Camp and Huq [24] applied the Big Bang-Big Crunch algorithm for CO_2 and cost optimization of RC frames. The objective of current study is optimal design of cost and CO_2 emissions in terms of cross section dimensions and reinforcement details applying the American Concrete Institute's Building Code [25] of practice. The optimization is carried out using enhanced colliding bodies optimization algorithm developed by Kaveh and Ilchi Ghazaan [26] based on the improvement of CBO performance originally developed by Kaveh and Mahdavi [27] using memory to preserve some historically best solution.

The rest of this paper is structured as follows: section 2 describes the formulation of optimization problem, section 3 contains the explanations of utilized meta-heuristic algorithm and in section 4, the results obtained for three benchmark frames are detailed and discussed. Finally, in section 5 the concluding remarks are presented.

2. FORMULATION OF THE RC FRAMES OPTIMIZATION PROBLEM

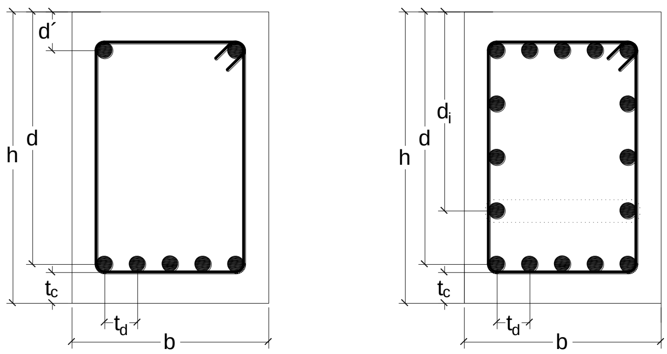
2.1 Design variables and section databases

The assessment of the objective functions requires the definition of the structure in terms of the design variables including cross-sectional dimensions of elements, area and type of steel bars and resisting capacity. Due to the discreteness of member dimensions and reinforcement sizes, large number of sections and different patterns of reinforcements, two section databases for beams and columns are created to reduce the elaboration of the problem. The identification numbers of the sections are related with all design variables. It is worth pointing out that the capacity of members is defined by applying ultimate strength design method. Two section databases are created based on ACI building code criteria and specified assumptions, which are, followed for both beams and columns sections.

2.1.1. Beams

For beams, the sections are considered as rectangular and singly reinforced, therefore the compression reinforcement at support and the tension reinforcement near mid-span are checked separately. This approach leads to a conservative and simple analysis. The area of steel varies from one #3 bar to a maximum of four #11 bars. The ratio of depth to width is varied between 1 and 2.5.

The last distance measured from the surface of the concrete member to the surface of the embedded reinforcing steel is taken as 380 mm. The assumed range and increment step of cross section dimension is different in each design example. Fig. 1a defines the geometry of a general rectangular singly reinforced concrete beam.



(a) (b)

Figure 1. General rectangular reinforced concrete beam and column

To evaluate flexural response of the beam elements, their capacity is defined using the ACI code. In order to ensure ductile failure, these must be designed as an under reinforced beam. The nominal resisting moment capacity of a singly reinforced concrete beam section is:

$$M_n = A_s f_y \left(d - \frac{a}{2}\right) \tag{1}$$

where A_s is the total area of tensile reinforcement, f_y is the yield strength of reinforcement, d is the distance from extreme compression fibers of the concrete to the centroid of tension reinforcement and a refers to the depth of equivalent rectangular compression block given as:

$$a = \frac{A_s f_y}{0.85 f_c' b} \tag{2}$$

where f_c' denotes the specified compressive strength of concrete and b is the width of section.

Taking the above mentioned rules into account, DB sections for beams containing the width, the height, the number of reinforcing bar, the steel ratio, the moments of inertia and the ultimate bending moment capacity can be created. Finally, the sections are arranged in the in order of increasing moment resisting capacities.

2.1.2 Columns

For columns, the sections are considered as rectangular tied and short, so the applied moment will not be magnified. The area of steel varies from four #3 bars to a maximum of twelve #11 bars. For the rebar topologies, an even number of bars with the same size are distributed along all four faces so that the column is symmetric about the axis of bending. Table 1 represents the pre-

Table 1: Column reinforcement combinations [24]

Index no.	Reinforcement combination	
	Width side	Height side
1	2	2
2	3	2
3	2	3
4	3	3
5	4	3
6	4	4

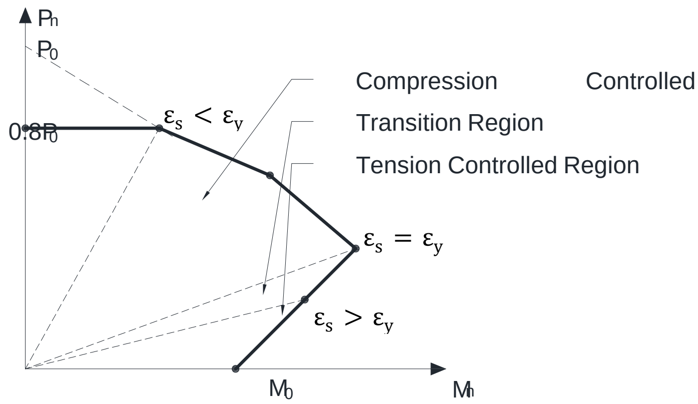


Figure 2. Column load-moment interaction diagram

specified reinforcement patterns for columns. The ratio of depth to width is considered between 1 and 2.5. Fig. 1b defines the geometry of a rectangular tied column.

Column sections are subjected to flexure in combination with axial forces, therefore the equilibrium of internal forces changes resulting different behavioral modes depending on the level of accompanying eccentricity. The sustainability and serviceability of column sections can be evaluated in a variety of the combination of bending moment and axial force derived by varying the applied axial strain. To find points corresponding to a specific value of strain distribution within the cross-section, rectangular stress block in the concrete must be determined. The same method is used to specify the stress distribution in reinforcement. Plotting values of load and moment capacities corresponding to different assumed values for the neutral axis depth (resulting different strain distribution) via an iterative calculation results in the contour chart called interaction diagrams. Fig. 2 shows a curve plot of controlling key points connected by linear relationships for a typical column section. The nominal axial load capacity for a given strain distribution defined by ACI Code is found by:

$$P_n = C_c + \sum_{i=1}^{n} F_{si} \tag{3}$$

where n is the number of reinforcement layer, C_c is the compressive force of concrete given as:

$$C_c = 0.85 f_c^{'} ab \tag{4}$$

And F_{si} is the force in each layer of reinforcement given as:

$$F_{si} = f_{si} A_{si} \qquad \text{if} \quad a \le d_i \tag{5a}$$
$$F_{si} = (f_{si} - 0.85 f_c^{'}) A_{si} \qquad \text{if} \quad a > d_i \tag{5b}$$

where f_{si} is the yield strength of reinforcement given as:

$$f_{si} = \varepsilon_{si} E_s \qquad - f_Y < f_{si} < f_Y \tag{6}$$

where E_s is the elastic modulus of reinforcement and ε_{si} is the strain of the ith layer of steel given as:

$$\varepsilon_{si} = 0.003 \left(\frac{c - d_i}{c} \right) \tag{7}$$

where c is:

$$c = \left(\frac{0.003}{0.003 - \varepsilon_y} \right) d_i \tag{8}$$

The nominal moment capacity for the specified strain distribution defined by ACI Code is found by:

$$M_n = C_c \left(\frac{h}{2} - \frac{a}{2} \right) + \sum_{i=1}^{n} F_{si} \left(\frac{h}{2} - d_i \right) \tag{9}$$

where a is:

$$a = \beta_1 c \tag{10}$$

and β is:

$$\beta_1 = 0.85 - 0.05 \frac{(f_c^{'} - 30)}{7} \ge 0.65 \quad \text{if} \quad f_c^{'} > 30\ MPa \tag{11a}$$

$$\beta_1 = 0.85 \qquad \text{if} \quad 30\text{ MPa} < f_c^{'} < 50\, MPa \tag{11b}$$

Considering the above information, DB sections for columns containing the width, the height, the number of reinforcing bar, the steel ratio, the moments of inertia and the combination of bending moment and axial force capacities can be created. Finally, the sections are arranged in increasing order of normalized areas for the P–M interaction diagram.

2.2 Structural constraints

Structural constraints are a series of restrictions in terms of the limitations and specifications provided by the ACI code. A structure should comply with these limitations in order to guarantee the feasibility of the solutions generated during iterative procedure. Making the solutions stand inside the feasible region is often a challenging effort and it is one of the complexities for handling the constrained problems. The most common method to overcome this issue is reducing the fitness value of merit functions by a product of eventual constraint and the objective function which leads the constrained problem convert to a sequence unconstrained problem. The use of exponential penalty-function allows us enforce the constraint on the objective function. To compute the capacity constraints violation, the internal forces by the action of the vertical and horizontal loads upon the RC element is required. In this study, the first order elastic analysis via matrix method is used to obtain the stress envelopes. With summing over the different constraints either in term of capacity or geometric, the total penalty of each design can be expressed as:

$$f_p(x) = \left(1 + \sum_{i=1}^{n} \max\big(0, C_i(x)\big)\right)^k \tag{12}$$

where x is the vector of design variables that are taken as the area of steel and the geometry of cross-sections of beams and columns, C_i is the normalized degree of violation of the ith constraint, n is the number of constraints and $k > 0$ is a penalty exponent required for tuning the penalty function. Since k reflects the solution quality, imposing a large k, results in severe penalty, which is reflected in rapid convergence to local optima (exploitation). Conversely, a small k reduce the severity of penalty, therefore a broadly search through the space region with slow convergence will be used to explore the solution (exploration). Depending on the case study, penalty exponent can be obtained through trial and error.

2.2.1 Beam constraints

Structural capacity of reinforced concrete beams must be greater than the ultimate bending moment derived from the applied loading. The moment capacity penalty can be expressed in normalized form as below:

$$C_1 = \frac{|M_u| - \emptyset M_n}{\emptyset M_n} \tag{13}$$

where M_u is the ultimate applied moment and $\emptyset$ is the strength reduction factor. For compression controlled sections having a net tensile strain in the extreme tension steel equal to or smaller than 0.002 while the extreme fibers of compression face in concrete reaches its crushing strain of 0.003, $\emptyset$ is taken as 0.65 and for tension controlled sections having the strain values in tension reinforcement farthest from the compression face of a member greater than 0.005 while concrete reaches its crushing strain of 0.003, $\emptyset$ is taken as 0.9. Sections between these two extremes are called transition sections and the strength reduction factor is calculated by linear interpolation.

In order to prevent the possibility of sudden failure and improve the cracking behavior, the lower bound of reinforcement ratio is limited to:

$$\rho_{min} = \frac{\sqrt{f_c'}}{4f_y} \geq \frac{1.4}{f_y} \tag{14}$$

The minimum reinforcement ratio penalty is:

$$C_2 = \rho_{min} - \rho \tag{15}$$

To ensure the ductile behavior and the requirements for placing the reinforcing bars, the upper bound on the reinforcement ratio is limited to:

$$\rho_{max} = 0.85\beta_1 \frac{f_c'}{f_y} \frac{600}{600 + f_y} \tag{16}$$

The maximum reinforcement ratio penalty is:

$$C_3 = \rho - \rho_{max} \tag{17}$$

For controlling the deflection, the minimum thickness is limited depending on the manner in which beams are supported. In this study, the beams are considered as nonprestressed at both ends continuous with allowable thickness of:

$$h_{min} = \frac{l}{21} \tag{18}$$

where l is the beam span. The beam thickness penalty can be expressed as:

$$C_4 = \frac{h_{min} - h}{h_{min}} \tag{19}$$

If the rectangular compression-block depth is greater than the effective depth, the penalty is applied as:

$$C_5 = \frac{a - d}{d} \tag{20}$$

In order to place and compact concrete between bars satisfactorily and provide proportionate bond, the minimum clear spacing s_{min} should be d_b but not less than 1 in. Where d_b is the diameter of reinforcement bars. The bar spacing penalty is:

$$C_6 = \frac{s_{min} - s}{s_{min}} \tag{21}$$

Since the sections capacity is evaluated separately, the reinforcement topology including bar spacing and steel ratio could be different in both sections at the support and mid-span while the dimensions are the same. For this reason, the same procedure for determining constraint related to reinforcement topology must be performed for the section under negative bending moment.

2.2.2 Column constraints

A column section is acceptable when the design action effects defined by combination of M_n and P_n fall within the load-moment interaction diagram. The load-moment interaction penalty can be expressed as:

$$C_7 = \frac{r - r_0}{r_0} \tag{22}$$

where r is the radial distance between the origin of the interaction diagram and the corresponding pair under the applied loading and r_0 is the radial distance between the origin of the interaction diagram and the intersection of vector r with the load-moment curve.

For compression members, the minimum longitudinal reinforcement ρ_{min} is limited to 0.01. The minimum reinforcement penalty is:

$$C_8 = \rho_{min} - \rho \tag{23}$$

For compression members, the maximum longitudinal reinforcement ρ_{max} is limited to 0.08. The maximum reinforcement penalty is:

$$C_9 = \rho - \rho_{max} \tag{24}$$

The clear distance between longitudinal bars should be $1.5d_b$ but not less than 1.5 in. The longitudinal bar spacing penalty is

$$C_{10} = \frac{s_{min} - s}{s_{min}} \tag{25}$$

Since the bars are distributed along all four faces, the longitudinal bar spacing constraint must be checked in both width side and height side of the section.

3. OPTIMIZATION PROBLEM DEFINITION

3.1 Objective functions

The optimal design criterion for reinforced concrete frames involves two different objective functions: The first objective function is based on the most economical solution that accounts for the cost of materials in terms of the concrete, the steel and the labor cost in construction process. The second objective function quantifies the embedded CO_2 resulting from the use of materials, which involve emissions at different stages of the production, and the placement of concrete and steel in structure. The unit costs and CO_2 emissions were obtained from the 2007 database of the Institute of Construction Technology of Catalonia [28]. It is important to note that the calculation of GHG or CO_2 emissions of buildings does not contain transport emissions including transportation for building materials, construction equipment and workers, since transport distance from cradle to site is highly dependent on the case study. The general form of the objective function for current study can be expressed as:

$$\min: \ f(x) = \sum_{i=1}^{n} u_i m_i \, (x_1, x_2, \dots, x_r) \ \text{s.t:} \quad C_i(x_1, x_2, \dots, x_r) \leq 0 \tag{26}$$

where u_i represents the unit prices or unit CO_2 emissions of material and construction components, m_i is the measurements of the construction units, x_i are the design variables, n is the number of construction members, r is the number of design variables and C_i (i = 1,2,…,n) are the design constraints.

3.2 Proposed meta-heuristic algorithm

Meta-heuristic algorithms are often based on the simulation of natural evolution and the principle of preservation or the survival of the fittest, which is hypothetical population-based optimization procedure. In the other words, a meta-heuristic algorithm is an iterative process, which applies a set of agents to move through the design space and seek near–optimal solutions of the complex problems in a reasonably practical timescale. Although these optimization algorithms are usually non-deterministic, they make a reasonable trade-off between randomization and local search, this is why they can be used to find good feasible solution in an acceptable time especially in case of intractable real-world problems. This study presents the application of a novel population-based stochastic algorithm so called colliding bodies optimization (CBO) which simulates one fundamental law of physics, namely collision between two bodies.

3.2.1 Enhanced colliding bodies optimization method

Collision is a short-term interaction between two bodies in which they are pushed away from each other and tend to form the most stable configuration and achieve the lowest energy state. According to the law of energy and momentum conservation, in all collisions the total amount of momentum possessed by the two objects does not change i.e. the amount of momentum gained by one object is equal to the amount of momentum lost by the other object while the total kinetic energy after the collision may not be equal to the total kinetic energy before the collision and it changes to some other form of energy. What distinguishes different types of collisions is whether they conserve kinetic energy. When the total kinetic energy of system is lost, a perfectly inelastic collision occurs in which the two bodies stick together after the impact. Contrariwise if the total kinetic energy of system is conserved, a perfectly elastic collision occurs. The plot for this configuration is shown in Fig. 3.

In terms of this conception, the search ability of the CBO algorithm can be framed based on the interaction between colliding bodies (CBs) that are moving through predefined amplitude, starting with random initial position to find near–optimal solutions. Each colliding body as a solution candidate, containing a number of decision variables and characterized by its position and velocity. The laws of energy conservation as well as linear momentum conservation allow us to adjust the changes of these attributes in two-body collisions.

The magnitude of the body mass for each CB is defined in association with the respective fitness value given as:

$$m_i = \frac{\frac{1}{fit(i)}}{\sum_{j=1}^{n} \frac{1}{fit(j)}} \qquad i = 1,2,\ldots,n \tag{27}$$

where fit is the objective function value of the CBs and n is an even number of colliding bodies. In order to select pairs of objects for collision, CBs are sorted according to the value of their objective function in an increasing order and divided into two equal groups. Agents with upper fitness values (moving objects) and finite speed, push the corresponding agents with lower fitness values (stationary objects) which are at rest before the collision, towards better positions. The velocity of moving bodies before the collision is given as:

$$v_i = x_i - x_{i-\frac{n}{2}} \qquad i = \frac{n}{2} + 1,\ldots,n \tag{28}$$

where x_i is the position vector of the ith CB in moving group and $x_{i-\frac{n}{2}}$ is the ith CB pair position vector in the stationary group.

After the collision, the attributes of each moving object is updated as follows:

$$v_i' = \frac{\left(m_i - \varepsilon m_{i-\frac{n}{2}}\right) v_i}{m_i + m_{i-\frac{n}{2}}} \qquad i = \frac{n}{2} + 1,\ldots,n \tag{29}$$

$$x_i' = x_{i-\frac{n}{2}} + r v_i' \tag{30}$$

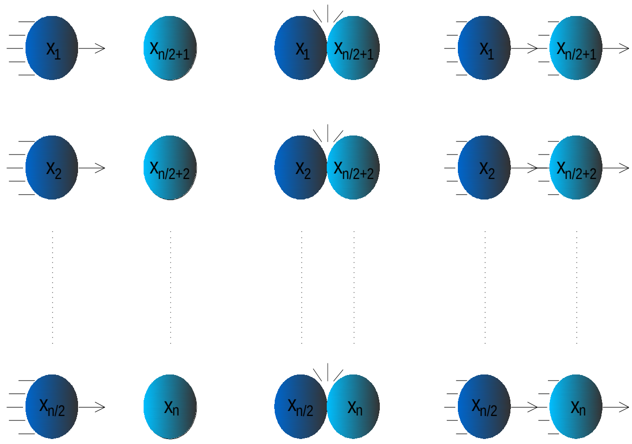


Figure 3. The collision between the sorted pairs of CBs

where m_i is the mass of the ith moving CB, v_i is the velocity of the ith moving CB before the collision, $m_{i-\frac{n}{2}}$ is the mass of the ith stationary CB pair, $x_{i-\frac{n}{2}}$ is the old position of the ith stationary CB pair, r is a random vector uniformly distributed in the range of (-1,1) and ε represents the coefficient of restitution defined as:

$$\varepsilon = 1 - \frac{\text{iter}}{\text{iter}_{\max}} \tag{31}$$

where "iter" is the number of iterations. Adjustment of this indicator changes the rate of intensification and diversification in the system and generally ranges between zero and one.

In addition, the attributes of each stationary object after the collision, which now has a velocity in the same direction of moving object is updated as follows:

$$v_i' = \frac{\left(m_{i+\frac{n}{2}} + \varepsilon m_{i+\frac{n}{2}}\right) v_{i+\frac{n}{2}}}{m_i + m_{i+\frac{n}{2}}}, \qquad i = 1, \dots, \frac{n}{2} \tag{32}$$

$$x_i' = x_i + r v_i' \tag{33}$$

where m_i is the mass of the ith stationary CB, $m_{i+\frac{n}{2}}$ is the mass of the ith moving CB pair,$v_{i+\frac{n}{2}}$ is the velocity of the ith moving CB pair before the collision and x_i is the old position of the ith stationary CB.

Historical solutions are repaired by employing the colliding memory (CM) which stores some best solution of every iteration found in previous population and substitute them to the current worst CBs vector. Introducing new best bodies into the population prevent population movement only to neighboring states and speed up the convergence rate without increasing the computational cost.

In order to break one or more members of the population out of local minima and produce a more efficient search, one component of the ith CB regenerated in a random manner in any given generation. The probability of choosing the component is expressed as Pro ranges between (0, 1).

Accord with the given definition, enhanced colliding bodies algorithm is a continuous variable based method improved by saving the best solutions and regenerating random members of population occasionally to produce a more efficient and reliable solution. The steps of this algorithm can briefly be outlined as follows:

Step 1: Randomly initialize the vector of CBs with n variables and evaluate their associated fitness function.

Step 2: Store some best solution of each iteration into the colliding memory and replace them to the current worst CBs vector.

Step 3: Calculate the mass value for each CBs using Eq. (27).

Step 4: Sort the fitness value of the objective function for each CBs in an increasing order, then determine the pairs of CBs for collision.

Step 5: Evaluate the velocity of moving bodies before the collision using Eq. (28).

Step 6: Update the velocities of stationary and moving bodies after the collision using Eq. (32) and Eq. (29), respectively.

Step 7: Update the positions of stationary and moving bodies using the generated velocities after the collision in step 6 and Eq. (33) and Eq. (30), respectively. If some bodies' new positions violate the boundaries, correct their position and return to the specified domain.

Step 8: Compare Pro with a random number, rn_i (i=1, 2… n), which is distributed uniformly between (0, 1), if rn_i < pro, randomly select a CB from both moving and stationary group and regenerate one related component accidentally.

Step 9: Return to step 2 until a terminating criterion is satisfied.

3.2.2 Nondominated sorting enhanced colliding bodies optimization

The proposed multiobjective algorithm is based on an improved version of the nondominated sorting genetic algorithm, called NSGA-II, which is proposed by Deb et al. [29]. The nondominated sorting genetic algorithm (NSGA) is based on some modifications to the ranking procedure of the individuals, originally proposed by Goldberg.

The basic design concept of NSGA-II is to find a set of non-dominated and evenly distributed solutions using two ranking techniques called non-dominated sorting and crowding approach. Each individual in population is assigned a rank on the basis of non-domination before selection. All non-dominated solutions are ranked 1. In the other words, these individuals are assigned the highest rank. Then this group of classified individuals are removed from the population and another set of non-dominated individuals from the remaining population are ranked. This group of classified individuals are also removed. This process continues until all individuals in the objective function space are classified. In order to provide a diversity and uniform distribution across the Pareto front, individuals at the same non-domination front are compared with a crowding distance. This helps the algorithm to explore the search space. After sorting procedure, the evolutionary operations are adopted to create new pool of offspring, and then the parents and offspring are combined.

Considering the basic concept of NSGA-II, in order to select pairs of objects for collision, CBs vector of every iteration is sorted by non-dominated sorting and crowding approach. Since agents in the first front have the maximum fitness value, they push the corresponding agents with the lower fitness value (stationary objects). The ranking techniques are also adopted to store some best CBs vector into the colliding memory.

4. DESIGN EXAMPLES

In order to demonstrate the efficiency and performance of the proposed algorithms, three symmetric multi-story and multi-bay benchmark problems of reinforced concrete frames are adapted and solved: The first example is a two-bay six-story frame originally designed by Rajeev and Krisnamoorthy [15] and redesigned by Camp et al. The remaining examples are a two-bay four-story frame and a two-bay six-story frame presented by Paya et al. [19] and redesigned by Camp et al. [24]. In order to compare the results with those of the previous researches, the same assumptions are followed. It is important to note that the assessment of the frames originally designed by Paya et al. [19] follows the Spanish Code of structural concrete [30].

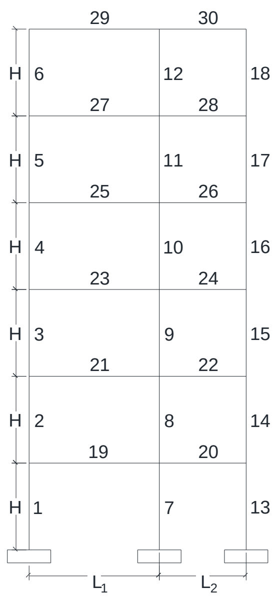


Figure 4. Two-bay six-story RC plane frame

4.1 Two-bay six-story frame

Fig. 4 illustrates the two-bay six-story frame originally designed by Rajeev and Krisnamoorthy [15] using standard GA algorithm and redesigned by Camp at al. [16, 24] using GA and BB-BC algorithm. The height of each story is 4 m and the span of the left and right bay is 6 m and 4 m, respectively. The optimal dimension of width for beam and column sections is considered between (200,460) mm and (150,560) mm, respectively. The step of increment for both beam and column sections is 30 mm. As shown in Fig. 4, the frame consists of 12 beams and 18 columns arranged in 4 beam groups and 3 column groups according to case 1 of Table 2. A factored uniformly distributed dead load of 30 $\mathrm{kN/m}$ is applied on each beam and the lateral equivalent static load of 10 kN is applied as joint load at each story level. Concrete has the compressive strength of 20 MPa and the unit weight of 2323 $\mathrm{kg/m^3}$. Reinforcement has the yield strength of 414 MPa and the unit weight of 7849 $\mathrm{kg/m^3}$. The number of DB sections created for beams and columns are 7128 and 9450, respectively, which results in a design space of 2.17e27. The frame has a total of 36 design variables, which define the geometry of the cross sections, the reinforcement bar size, and the number of reinforcing bars. Due to the number of design variables and the size of the design space, a small population of 12 with a typical stopping criterion of 3000 was required. In all cases the algorithm is executed fifty times to obtain the best statistical data of the results. Based on the examinations, the suitable values for the parameter Pro and CM are taken as 0.35 and $\mathrm{np}/2$, respectively. Where np is the number of population. The objective function is implemented to minimize the structural cost defined as:

$$f_k = \sum_{i=1}^{n_b+n_c} \{C_c b_i h_i + C_s A_{si} + 2C_f(b_i + h_i)\} l_i \tag{34}$$

where C_c is the unit cost of concrete, C_s is the unit cost of steel reinforcement, A_{si} is the area of reinforcing bars, C_f is the unit cost of formwork, n_b is the number of beams and n_c is the number of columns. The unit costs of concrete, steel and formwork are estimated as $\$735/\mathrm{m^3}$, $\$7.1$ /kg.

Table 2: Different type of grouping for two-bay six-story frame

Member type	Group no.	Grouping type					
		Case 1	**Case 2**	**Case 3**	**Case 4**	**Case 5**	**Case 6**
Beam	**1**	29	29	19-20	19-21	19-20	19-20
	2	30	30	21-22	20-22	21-22	21-22
	3	19-21-23-25-27	19-21-23-25-27	23-24	23-25	23-24	23-24
	4	20-22-24-26-28	20-22-24-26-28	25-26	24-26	25-26	25-26
	5	-	-	27-28	27-29	27-28	27-28
	6	-	-	29-30	28-30	29-30	29-30
Column	**1**	1-2-3-4-5-6	1-7-13-2-8-14	1-13	1-13	1-7	1
	2	7-8-9-10-11-12	3-9-15-4-10-16	2-14	2-14	2-8	2
	3	13-14-15-16-17-18	5-11-17-6-12-18	3-15	3-15	3-9	3
	4	-	-	4-16	4-16	4-10	4
	5	-	-	5-17	5-17	5-11	5
	6	-	-	6-18	6-18	6-12	6
	7	-	-	7	7	13	7-13
	8	-	-	8	8	14	8-14
	9	-	-	9	9	15	9-15
	10	-	-	10	10	16	10-16
	11	-	-	11	11	17	11-17
	12	-	-	12	12	18	12-18

Table 3: Best design for two-bay six-story frame

Member type	Group no.	GA [16]			BB-BC [24]			Present work		
		Width (mm	**Depth (mm)**	**Bars**	**Width (mm)**	**Depth (mm)**	**Bars**	**Width (mm)**	**Depth (mm)**	**Bars**
Beam	**1**	280	560	2#6+2#8	360	480	3#5+1#10	230	530	2#6+1#8
	2	330	480	1#5+2#7	330	430	1#9+1#10	200	370	1#6+1#8
	3	230	560	4#4+1#11	200	480	2#6+2#9	200	490	1#8+1#11
	4	200	480	1#6+2#5	230	330	2#5+2#6	200	430	3#4+2#7
Column	**1**	180	200	4#5	180	280	4#5	180	270	4#4
	2	180	460	4#7	280	250	8#5	210	330	4#5
	3	180	280	4#4	150	200	6#3	210	360	6#4
Best Cost ($)			24,959			23,664			23,081.57	
Average ($)			-			26,520.55			27,028.98	
Std deviation ($)			-			1,069.91			2,695.02	

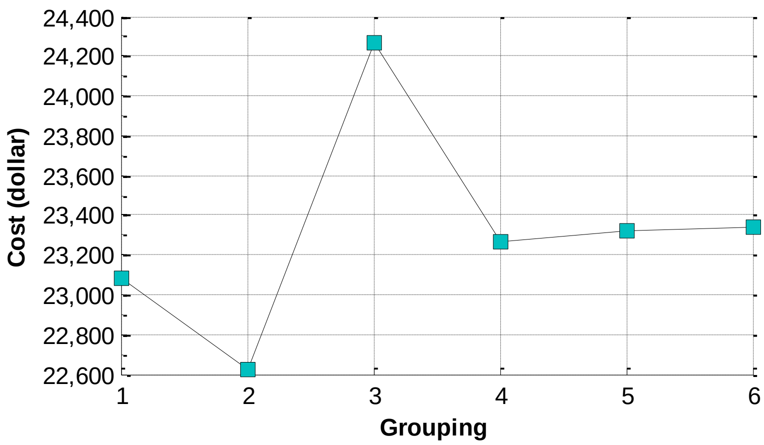


Figure 5. Best cost design for different cases of grouping

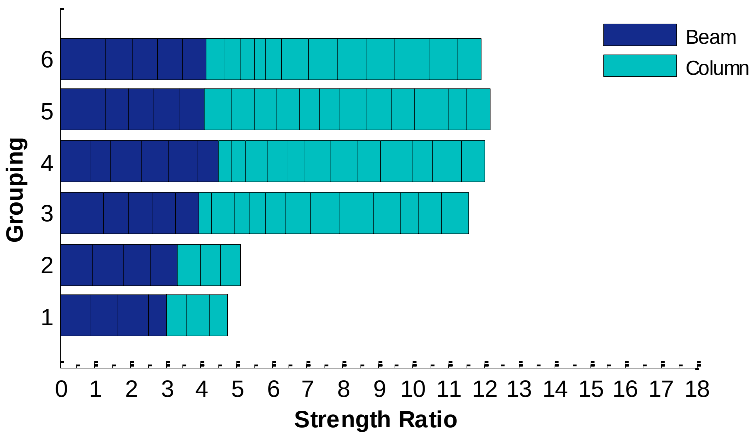


Figure 6. Strength ratio in the groups for different cases of grouping

Table 4: Best cost design in different size of the search space and number of iteration

Description	Case 1	Case 2	Case 3
Database of beam	7128	3330	3330
Database of column	9450	3898	3898
Search space	2.17e27	7.28e24	7.28e24
Iteration	3000	3000	800
Best cost ($)	23,081.57	22,450.4	23,008.15
Computation time (s)	3.19	2.56	0.46

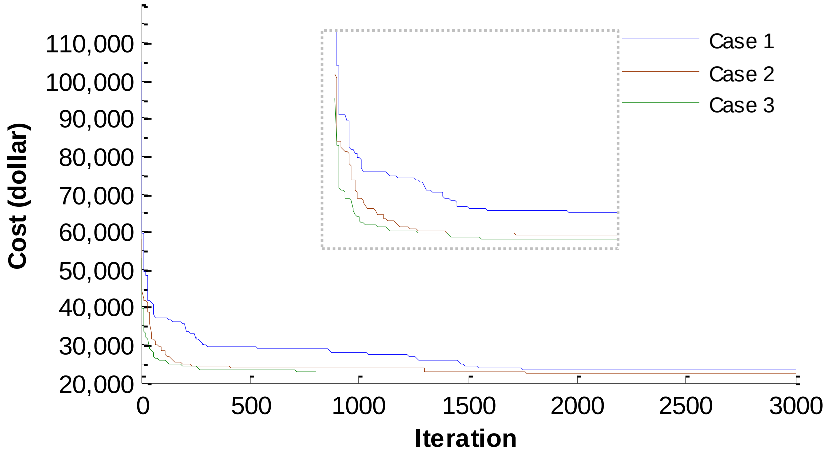


Figure 7. Convergence rate in different size of the search space and number of iteration and $\$54/m^2$, respectively

Table 3 compares the results obtained by the proposed algorithm with the previous solutions.

The best solution reported by the ECBO is 23,081.57$. The best ECBO design is 2.46 % less than the best solution given by BB-BC.

Five more types of grouping are considered for the design of frame listed in Table 2. The comparison of the solutions (Fig. 5) shows a maximum of 4.39% decrease in cost for the case 2 of grouping. Since the members in the same group have the same design variables, the capacity violations must be relatively close. More precisely, the internal force distributions in each group, which is highly related to the load pattern, should have insignificance difference as much as possible. Hence, the pattern of grouping should match closer to the internal force distributions while their number should compromise between the economic design and computing time. The information pertaining to compare the strength ratio between different cases of grouping has been quantified in Fig. 6.

One of the best approaches to handle the constraints is evaluating the fitness function in the feasible search space. This approach is called death penalty. The feasible region is achieved by rejection of infeasible individuals. Some of the geometric constraints can be applied during the process of creating DB sections. Therefore, no further calculations are necessary to enforce these constraints on the objective function. This technique is limited to problems in which the constraints are not dependent on the geometric information related to the structure. The remaining constraints to be checked in each iteration are the capacity (C_1, C_7) and the allowable thickness (C_4) restrictions. Taking the above mentioned procedure into account, the size of the search space is declined to 7.28e24 (Table 4). The algorithm could attain the similar best solution in a significant short iteration number of 800 and computational time of 0.46 s which is 6.93 times faster than Case 1. With the stopping criterion of 3000, it could decrease the solution by 2.73% with the computational time of 2.56 s, which is 1.24 times faster than Case 1. As shown in Fig. 7 the speed of convergence to the optimum value has had a considerable increase.

4.2 Two-bay four-story frame

Fig. 8 illustrates the two-bay four-story frame originally designed by Paya et al. [19] using SA algorithm and redesigned by Camp et al. [24] using BB-BC algorithm. The height of each story is 3 m and the span of each bay is 5 m. The optimal dimension of width for beam and column sections is considered between (150, 1200) mm and (250, 1200) mm, respectively. The step of increment for beam sections is 10 mm and for column sections is 50 mm. As shown in Fig. 8 the frame is consisted of 8 beams and 12 columns arranged in 4 beam groups and 8 column groups. The spacing considered between adjacent parallel frames is 5.00 m and the thickness of the slab for all story is 290 mm. Twelve load combinations that include counteracting effects of dead, live and wind loads are taken into account to determine the required strength of the members as listed below:

$$U=1.5D \tag{35a}$$
$$U=1.5D+1.6L1 \tag{35b}$$
$$U=1.5D+1.6L2 \tag{35c}$$
$$U=1.5D+1.6LT \tag{35d}$$
$$U=1.5D+1.6W1 \tag{35e}$$
$$U=1.5D+1.6W2 \tag{35f}$$
$$U=1.5D+1.44L1+1.44W1 \tag{35g}$$
$$U=1.5D+1.44L2+1.44W1 \tag{35h}$$
$$U=1.5D+1.44LT+1.44W1 \tag{35i}$$
$$U=1.5D+1.44L1+1.44W2 \tag{35l}$$
$$U=1.5D+1.44L2+1.44W2 \tag{35k}$$
$$U=1.5D+1.44LT+1.44W2 \tag{35l}$$

where D is the uniform dead load applied to each beam, L1 stands for the live load applied to only one beam in each story while the bays change alternatively, L2 is the uniform live load applied in a pattern opposite of L1, W1 is the wind load applied to the left side of the frame and W2 is the wind load applied to the right side of the frame. Table 5 lists the values of the uniform loads and wind loads at each story. Compressive strength of concrete varies in each story from 25 MPa to 50 MPa with the increment step of 5 MPa. The unit weight of concrete is 2323 $\mathrm{kg/m^3}$. Reinforcement has the yield strength of 500 MPa and the unit weight of 7849 $\mathrm{kg/m^3}$. The number of DB sections created for beams and columns is 98424 and 7584, respectively, which results a design space of 2.23e60. The frame has a total of 60 design variables. Hence, the population of 16 with a typical stopping criterion of 4000 was required. In this example two objective function is implemented to minimize cost and CO_2 emissions in terms of the materials and construction process. The general form of the cost function is defined as:

$$f_k = \sum_{i=1}^{n_b+n_c} \{C_c b_i h_i + C_s A_{si}\} l_i + \sum_{i=1}^{n_b} \{C_f\big(b_i + 2(h_i - t_i)\big) + C_t b_i\} l_i + \sum_{i=1}^{n_c} \{2C_f(b_i + h_i)\} l_i \qquad (36)$$

where C_t is the unit rate of scaffolding and t_i is the thickness of the slab. The CO_2 emission function has the same form of the cost function, however the unit values are different and also the scaffolding term is not considered. The unit rates for cost and CO_2 emissions are listed in Table 6.

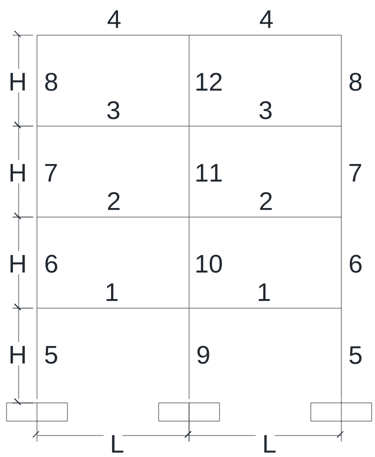


Figure 8. Two-bay four-story RC plane frame

Table 5: The applied loads on the frame

Action	Value
DL in story 1-3 (kN/m^2)	4
DL in story 4 (kN/m^2)	6
LL in story 1-3 (kN/m^2)	3
LL in story 4 (kN/m^2)	1
WL in story 1 (kN)	8.83
WL in story 2 (kN)	9.86
WL in story 3 (kN)	10.74
WL in story 4 (kN)	5.81

Table 6: Unit prices and CO_2 emissions

Description	Cost (€)		CO_2 (kg)	
	Beam	**Column**	**Beam**	**Column**
Steel B-500 (kg)	1.3	1.3	3.01	3.01
Concrete HA-25 (m^3)	78.40	77.80	132.88	132.88
Concrete HA-30 (m^3)	82.79	82.34	143.48	143.48
Concrete HA-35 (m^3)	98.47	98.03	143.77	143.77
Concrete HA-40 (m^3)	105.93	105.17	143.77	143.77
Concrete HA-45 (m^3)	112.13	111.72	143.77	143.77
Concrete HA-50 (m^3)	118.60	118.26	143.77	143.77
Form work (m^2)	25.05	22.75	3.13	8.90
Scaffolding (m^2)	38.89	—	4.86	—

Table 7: Design results for cost objective for two-bay four-story frame

Member type	Group no.	BB-BC [24]				Present work			
		Concrete strength (MPa)	**Width (mm)**	**Depth (mm)**	**Bars**	**Concrete strength (MPa)**	**Width (mm)**	**Depth (mm)**	**Bars**
Beam	**1**	40	180	430	1#8+2#8	30	220	430	2#7+3#7
	2	40	180	450	1#10+2#8	30	250	450	2#7+4#5
	3	30	190	460	1#8+1#11	30	220	440	3#6+3#6
	4	25	220	530	4#4+1#10	25	220	430	1#9+3#7
Column	**1**	40	250	550	6#5	30	300	500	8#3
	2	40	250	300	4#5	30	300	400	6#4
	3	30	250	300	4#6	30	250	350	8#3
	4	25	250	300	6#6	25	250	350	12#4
	5	40	250	300	4#5	30	300	450	6[a]#4
	6	40	250	250	8#5	30	250	250	4#4
	7	30	250	250	6#4	30	250	300	4#3
	8	25	250	250	4#3	25	250	250	4#3
Best cost (€)		3540.88				3429.92			
Average (€)		3790.25				3682.09			
Std deviation (€)		139.28				156.51			
CO_2 emission (kg)		3778.24				3587.88			

Table 8: Design results for CO_2 objective for two-bay four-story frame

Member type	Group no.	BB-BC [24]				Present work			
		Concrete strength (MPa)	**Width (mm)**	**Depth (mm)**	**Bars**	**Concrete strength (MPa)**	**Width (mm)**	**Depth (mm)**	**Bars**
Beam	**1**	50	210	510	2#5+3#6	40	230	420	1#8+3#7
	2	30	220	530	2#5+1#10	40	240	510	4#4+3#6
	3	25	210	520	2#5+2#7	25	250	550	4#4+3#5
	4	25	240	590	4#4+1#9	25	260	560	2#6+3#5
Column	**1**	50	250	400	6#3	40	250	450	6[a]#3
	2	30	250	400	6[a]#3	40	250	400	6[a]#3

3	25	250	400	10#3	25	250	450	8#4
4	25	250	400	4#6	25	250	250	6#4
5	50	250	450	10#3	40	250	350	4#4
6	30	250	400	4#3	40	250	350	4#4
7	25	250	300	12#3	25	250	300	6#3
8	25	250	250	4#3	25	250	250	4#3
Best CO_2 emission (kg)		3327.29				3238.25		
Average (kg)		3650.33				3554.30		
Std deviation (kg)	127.81				216.83			
Cost (€)	3617.06				3525.27			

The results for single objective of cost function obtained by the proposed algorithm and the previous researches are compared in Table 7. The best solution reported by the ECBO is 3429.92 € with 3587.88 kg of CO_2 emissions. The best ECBO cost-design is 3.13 % less than the best solution given by BB-BC. Concrete represents 18.22% of the total cost, while reinforcing steel cost total about 25.55%. Table 8 compares the results for single objective of CO_2 emission functions. The best solution reported by the ECBO is 3238.25 kg with a cost of 3525.27 €. The best ECBO CO_2-design is 2.67 % less than the best solution given by BB-BC. The percentage comparison of the solutions indicates that the best CO_2 emissions design decreased the CO_2 emissions by 9.74% with a slight increase in cost of 2.77%. Since more environmentally friendly solutions are recommended by IPCC, on the other hand, the low-CO_2 emissions design could decrease the CO_2 emissions considerably at an acceptable cost increment in practice, it seems that designing the RC structures based on the CO_2 emissions is more logistical.

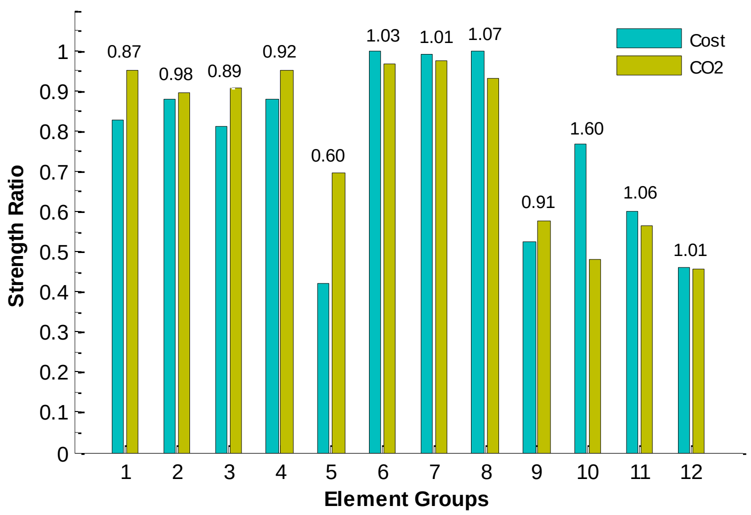


Figure 9. Strength ratio in element groups for both cost and CO_2 objective function

Table 9: Ratio between Cost and CO_2-optimized design variables

Group no.	Frame characteristics	
	Concrete strength	**Area of elements**
1	0.75	0.97
2	0.75	0.91
3	1.2	0.70
4	1	0.64
5	0.75	1.33
6	0.75	1.20
7	1.2	0.77
8	1	1.40
9	0.75	1.54
10	0.75	0.71
11	1.2	1
12	1	1

Table 10: Percentage of total cost and CO_2 emissions

Description	Cost (%)			CO_2 (%)		
	Beam	**Column**	**Total**	**Beam**	**Column**	**Total**
Steel	70	30	26	70	30	50
Concrete	52	48	18	60	40	35
Form work	33	67	46	18	82	15
Scaffolding	10	-	10	-	-	-
Total			100			100

Table 11: Results of the ECBO single objective and multiobjective designs.

Objective	Cost (€)	CO_2 (kg)
ECBO-Cost	3429	3587
NSECBO-Cost	3490	3475
ECBO-CO_2	3525	3238
NSECBO-CO_2	3520	3318

Fig. 9 compares the strength ratio in element groups for both cost and CO_2 objective functions. As can be seen, in beam groups the use of section capacity in low-cost design is lower than low-CO_2 emission design, while in column groups the use of section capacity is higher. This finding shows that there is a relationship between the geometry of frame and the objective functions. Table 2 indicates the ratio between cost and CO_2-optimized design variables. The dimension of beams are bigger over the low-CO_2 emission design than over the low-cost design.

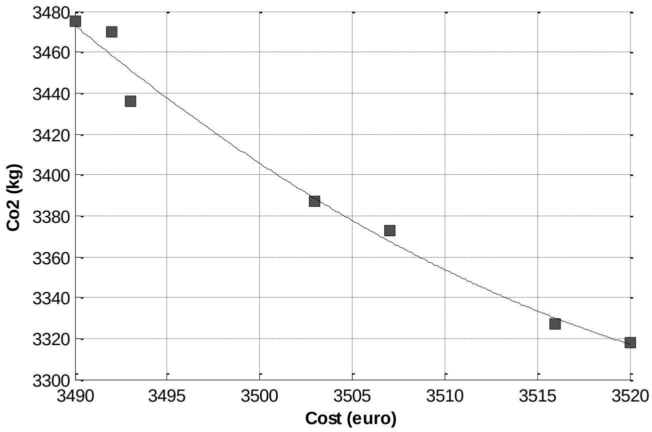


Figure 10. NSECBO Pareto front

In Table 10, the percentage of cost and CO_2 emissions is quantified for materials and construction components. Concrete, reinforcing steel, formwork and scaffolding represents approximately 26, 18, 46 and 10% of the total cost and 50, 35 and 15% of the total emissions, respectively.

Table 11 summarizes the results of the ECBO single objective and multi-objective designs. The best NSECBO design with lower cost is 3490 € with 3475 kg of CO_2 emissions which are 1.78% and 7.31% higher compared to single objective designs of cost and CO_2 emissions, respectively. Alternatively, the best NSECBO design with lower emissions is 3318 kg with a cost of 3520 €, which are 2.47% and 2.65% higher, respectively. Both objectives are closely related and result in similar solutions. All these lead to a tentative conclusion that the CO_2 and cost objectives should be considered together in RC structural designs. The Pareto front is presented in Fig. 10.

4.3 Two-bay six-story frame with unequal bays

Fig. 11 illustrates the two-bay six-story frame originally designed by Paya et al. [19] using SA algorithm and redesigned by Camp et al. [24] using BB-BC algorithm. The story height and bay span of the frame and the search space specifications are the same as defined for the two-bay four-story frame in Example 2. As shown in Fig. 11 the frame is consisted of 12 beams and 18 columns, which are arranged in 6 beam groups and 12 column groups. The type of grouping, spacing considered between adjacent parallel frames, the thickness of the slab, the strength and the unit weight of concrete and steel, the load patterns and the magnitude of loads except the wind loads are the same as in Example 2. Table 12 lists the values of the wind loads at each story. The frame has a total of 90 design variables and the design space of 3.34e90. The general form of the objective functions are given in Eq. (36).

Table 13 compares the results for single objective of cost function obtained by the proposed algorithm with those of the previous researches. The best solution reported by the ECBO is 5697.98 € with 5834.72 kg of CO_2 emissions. The best ECBO cost-design is 2.29% less than the best solution

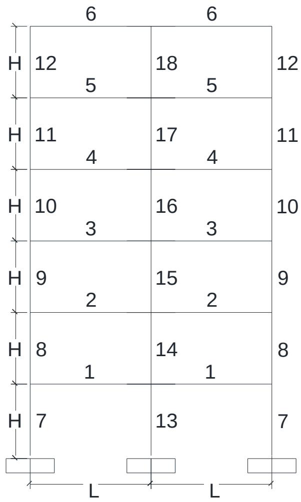


Figure 11. Two-bay six-story RC plane frame

Table 12: Wind loads for two-bay six-story frame

Action	Value
WL in story 1	8.83
WL in story 2	9.86
WL in story 3	10.74
WL in story 4	11.62
WL in story 5	12.36
WL in story 6	6.62

given by BB-BC. Table 14 compares the results for single objective of CO_2 emission functions. The best solution reported by the ECBO is 5682.82 kg with a cost of 5913.02 €. The best ECBO CO_2-design is 2.16% less than the best solution given by BB-BC. The percentage comparison of the solutions confirm the previous findings.

Table 13: Design results for cost objective for two-bay six-story frame.

Member type	Group no.	BB-BC [24]				Present work			
		Concrete strength (MPa)	**Width (mm)**	**Depth (mm)**	**Bars**	**Concrete strength (MPa)**	**Width (mm)**	**Depth (mm)**	**Bars**
Beam	**1**	45	180	420	3#5+2#9	50	220	410	1#10+2#9
	2	30	210	500	1#8+3#7	40	270	470	3#7+4#6
	3	30	200	500	2#6+3#7	35	220	440	2#6+3#7
	4	30	200	470	1#8+3#7	35	270	480	3#5+3#6
	5	25	210	520	1#10+3#6	30	260	480	3#7+3#6
	6	25	230	570	2#6+2#7	30	250	460	2#7+3#6
Column	**1**	45	250	650	6[a]#3	50	250	300	6#3
	2	30	250	500	6#3	40	250	450	8#4
	3	30	250	400	4#4	35	250	500	10#3
	4	30	250	400	4#6	35	300	300	8#3

	5	25	250	300	6#6	30	250	450	4#6
	6	25	250	250	6#6	30	250	300	6^a#5
	7	45	250	400	12#4	50	350	650	6^a#5
	8	30	250	400	12#5	40	250	250	6^a#3
	9	30	250	350	10#6	35	300	500	6#4
	10	30	250	300	8#6	35	250	450	8#3
	11	25	250	300	6#4	30	250	250	4#4
	12	25	250	250	6#4	30	250	250	4#3
Best cost (€)		5831.70				5697.98			
Average (€)		6416.73				6236.61			
Std deviation (€)		219.05				369.43			
CO_2 emission (kg)		6306.40				5834.72			

Table 14: Design results for CO_2 objective for two-bay six-story frame

Member type	Group no.	BB-BC [24]				Present work			
		Concrete strength (MPa)	**Width (mm)**	**Depth (mm)**	**Bars**	**Concrete strength (MPa)**	**Width (mm)**	**Depth (mm)**	**Bars**
Beam	**1**	35	230	560	1#7+1#11	50	300	500	1#9+2#8
	2	30	220	550	3#4+2#8	50	290	530	3#6+3#7
	3	25	250	620	4#4+4#5	45	230	450	3#7+3#7
	4	25	230	550	1#8+3#6	45	250	430	2#6+3#7
	5	25	230	550	1#8+1#10	40	250	490	1#9+3#6
	6	25	230	550	1#8+3#6	30	260	510	3#7+3#5
Column	**1**	35	250	500	6^a#3	50	250	350	6#4
	2	30	250	450	4#6	50	250	250	4#3
	3	25	250	450	4#5	45	250	500	6#4
	4	25	250	400	6#5	45	350	350	10#3
	5	25	250	300	6#5	40	250	300	6#3
	6	25	250	250	4#7	30	250	450	4#7
	7	35	700	250	4#3	50	250	300	4#3
	8	30	700	250	8#3	50	250	500	8#3
	9	25	700	250	6^a#3	45	250	500	8#3
	10	25	500	250	10#3	45	300	500	8#3
	11	25	250	250	4#7	40	250	350	4#4
	12	25	250	250	4#3	30	250	250	4#3
Best CO_2 emission (kg)		5808.70				5682.82			
Average (kg)		6392.72				6134.52			
Std deviation (kg)		279.59				403.39			
Cost (€)		5948.81				5913.02			

5. CONCLUDING REMARKS

This study aimed to evaluate the usefulness of the ECBO and NSECBO through the optimization of three multi story-multi bay frames design based on the ACI Code including architectural and reinforcement detailing. The algorithm is applied to two objective functions: The cost of material and the embedded CO_2 emissions during the construction process. Based on the present work, the following conclusions can be derived:

1. The ECBO design improved the results from both objective functions in a reasonably practical time over the designs developed by the BB-BC algorithm. Moreover, in comparison with other evolutionary approaches, the ECBO algorithm is simple to implement and it required a few premature to be set. These finding proved that ECBO–based methodology can be applied as an effective and powerful algorithm to arrive at a realistic design solutions for real complex problems. Other algorithms like those presented in Kaveh [43] can also be utilized to the present problem.
2. Conclusive solution of the algorithm is improved through selecting more rational groups of the elements. This implies that grouping in which the members in the same group are similar in the internal force distribution results in more economical solutions.
3. Considerable reduction of the size of the search space by rejection of infeasible individuals during the process of creating DB sections and eliminating the related terms of violation from the penalty function can reduce the calculation time and give a very rapid convergence in the early iterations toward the feasible solution. Moreover, with the same number of iterations and qualifications, the best solution decreases significantly.
4. Investigating the relationship between the two objective functions of cost and CO_2 emissions indicates that although the CO_2 emissions function causes a relative increase in the cost, it decreases the CO_2 emissions by 9.74%. Due to the growing efforts and the IPCC recommendation to reduce the atmospheric concentration of CO_2 caused by construction industry, it appears that optimal design of RC structures with respect to the CO_2 emissions as the key control point of the low carbon economy and a sustainable environment is more rational.
5. Comparison between the cost and CO_2-optimized design variables indicates that the geometry and physical dimension of elements are different in a way that the beams area are bigger over the low-CO_2 emission design than over the low-cost design.
6. The results of the ECBO single objective and multi-objective designs reveal that both objectives functions yield similar solutions and economical solutions also perform well in terms of CO_2 emissions.

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