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# Cost and $CO_2$ Optimization for RC Short Column Sections Subjected to Axial Load and Uniaxial/Biaxial Bending Using the Social Spider Optimization Algorithm

**Alper Akin[1], Ibrahim Aydogdu[2], and Turhan Bilir[3]**

[1]*Trinity Meyer Utility Structures, Memphis, TN, USA. [1]Email: <alperakin@yahoo.com>,*
[2]*Department of Civil Engineering, Akdeniz University, TURKEY. [2]Email: < aydogdu@akdeniz.edu.tr>,*
[3]*Department of Civil Engineering, Bulent Ecevit University. [3]Email: < tbilir@ogu.edu.tr >.*

## ABSTRACT

The building construction industry consumes large amounts of energy and creates substantial pollution by producing a large portion of $CO_2$ emissions. In addition to the energy consumed from the operation of the building, the energy consumed from both materials in the construction phase must be reduced to minimize the life-cycle energy use of a building. In this study, an optimal design method for RC columns in buildings using Social-Spider Optimization (SSO) algorithm is proposed to reduce the cost and $CO_2$ emissions from the structural materials in the construction phase. Objective functions of the optimization problem are defined as the minimized cost, the $CO_2$ emission, and the weighted aggregate of the cost and $CO_2$. In the formulation of the objective functions, unit costs are based on the materials and labor required for the construction of RC columns and $CO_2$ emissions are associated with the transportation, processing, manufacturing, and fabrication of materials and the emissions of the equipment involved in the construction process. In the formulation of the optimum design problem, the sectional properties of RC columns with rectangular cross section that are subjected to axial force and bi-axial bending moment such as the dimensions of the rectangular cross section along x and y direction, the diameters of bars and their total number along x and y directions are taken as design variables. The design constraints are implemented from ACI 318-14 which consist of columns strength check under axial compression and biaxial bending, the minimum and maximum steel ratio, the minimum and maximum bar spacing and the minimum column width restrictions. The proposed SSO based optimal design method is applied to two numerical design examples to investigate the effective use of structural materials for the sustainable design of RC columns and to demonstrate the efficiency and robustness of the presented algorithm.

## INTRODUCTION

In the United States, the energy consumption in buildings and their construction is more than 54% of all energy consumption in country. International Energy Agency (IEA) [T'Serclaes 2007] also states that buildings and their construction produce 24% of all $CO_2$ emissions. In the construction industry, the studies on reducing the $CO_2$ emissions generated during building operation have been actively conducted since the 2000s. Nevertheless, $CO_2$ emissions must be reduced in all stages where reduction is possible. Buildings should be designed to reduce their $CO_2$ emissions from the earliest design stages to create environmentally friendly construction and buildings. $CO_2$ emissions can be reduced by reflecting the unit $CO_2$ emission of each structural material in the design stage.

For steel structures, $CO_2$ emission reduction can be generated by minimizing the total weight of steel material to produce sustainable structural designs; whereas, reinforced concrete (RC) structures are composed of different materials (steel and concrete) and unit price of each material and $CO_2$ emissions for two structural materials are different. Thus, reducing the $CO_2$ emissions of RC structural members requires establishing correlations between different materials and minimizing the total amount of $CO_2$ emissions from all materials.

In addition to the RC structures, the RC columns are also commonly preferred and used in steel construction because concrete material offers a great advantage to design this structure more economically and support large axial loads in a high-rise building. Using higher amounts of concrete causes larger $CO_2$ emission, has negative effects on the environment and causes global warming. Therefore, both minimizing cost of structure and $CO_2$ emissions must be taken into account in the design of RC columns. In most optimization studies, only the total cost or weight of the structure are considered for minimizing. $CO_2$ emissions should also be considered and minimized during the structural design phase for the sustainable design of buildings. Generally, the additional cost from $CO_2$ emissions is not considered in existing studies. $CO_2$ emissions can be transformed to cost then the additional costs from $CO_2$ emissions must be considered when evaluating the cost of RC column and producing a cost-effective design during the structural design phase. However, because of the complexity in structural design of RC columns, minimizing the cost and the $CO_2$ emission is not an easy task. Modern meta-heuristic optimization algorithms can be considered as efficient tools for these types of problems.

In this study, Social Spider Optimization (SSO) based design method for RC columns to minimize the $CO_2$ emissions and cost of a structural design is presented. The total amount of $CO_2$ emissions is converted to cost so that the construction cost and $CO_2$ emission cost are considered concurrently. Then, the optimization algorithm utilized in this study minimizes the total cost, including the additional cost generated from $CO_2$ emissions, while satisfying the stress and constructability constraints. The cross-sectional dimensions and the number and diameters of reinforced bars are used as the design variables in the proposed optimal design method. The proposed optimal design method employs SSO as an optimization tool and considers the unit prices and $CO_2$ emissions for the various strengths of concretes and steel bars.

The SSO algorithm, developed by [Cuevas, Cienfuegos, Zaldivar, & Perez-Cisneros, 2013], is based on the simulation of the cooperative behavior of social spiders. In this algorithm, individuals emulate a group of spiders which interact with each other based on the biological laws of the cooperative colony. In the algorithm, males and females (spiders) are considered as two different search agents. A set of different evolutionary operators, mimicking different cooperative behaviors typically observed in a colony, conduct with each individual according to their gender and they are modeled as two genders. This allows emulating the cooperative behavior of the colony in a more realistic way in addition to incorporating computational mechanisms to avoid critical flaws. The SSO algorithm has been used in a few engineering design problems [Esapour, Hoseinzadeh, Akbari-Zadeh, & Zare, 2015; Khorramnia, Akbarizadeh, Jahromi, Khorrami, & Kavusifard, 2015; Mirjalili, Saremi, & Mirjalili, 2015; Yu & Li, 2016] since its emergence and no study related to application of the SSO algorithm for optimum design of RC structures currently exists in the literature. Therefore, the proposed study is the first study on the application of the optimum SSO algorithm for the design of RC structures.

This paper is organized as follows. In Section 2, basic steps of the algorithm are described. Section 3 presents the mathematical model for the optimum design of RC columns. Numerical examples are presented in Section 4. Finally, in Section 5, conclusions are drawn.

## SOCIAL SPIDER OPTIMIZATION ALGORITHM

Social spider optimization (SSO) algorithm is one of the newest meta-heuristic search algorithm adopted from the natural behaviors of a spider colony. The spider colony consists of male and female spiders which have different tasks. In order to perform these tasks, the spiders use cooperative and mating operators. In the cooperative operator, the spiders move to new positions. The movement of each a spider is performed with respect to its own vibrations and other colony members. The vibrations of the spiders depend on the gender, distance between the spiders and their weights. In the mating operator, the dominant male spiders find the best female spiders for mating in their specific region and generate new spiders. The main steps of the SSO algorithm for the optimum design of RC columns problem are described as follows;

*Step 1*: Initial parameters of the SSO algorithm, which are the number of female spiders ($N_f$) and the number of male spiders ($N_m$), are determined in this step using equations (1) and (2) respectively.

$$N_f = round((0.9-0.25 \cdot rand)N_S) \tag{1}$$

$$N_m = N_S - N_f \tag{2}$$

where, rand is a random number between [0, 1], round is a function which rounds to the value of the nearest integer, $n$ is the number of design variables defined in the optimization problem.

*Step 2*: Initial RC column designs, assigned to the female ($f_{i,j}$) and the male ($m_{i,j}$) spiders, are generated randomly using equations (3) and (4). Then, these design are evaluated and their penalized costs ($Cost_p$) are calculated using equation (5).

$$f_{ij} = x_j^{low} + (x_j^{high} - x_j^{low})\ rand \quad i=1,\dots,N_f \ j=1,\dots,n \tag{3}$$

$$m_{kj} = x_j^{low} + (x_j^{high} - x_j^{low})\ rand \quad k=1,\dots,N_m \ j=1,\dots,n \tag{4}$$

$$Cost_p = Cost \cdot (1+C)^{\varepsilon} \tag{5}$$

where, $C$ is the total constraint violation value calculated from the sum of the values of constraints violation functions shown in equation (6), $\varepsilon$ is the penalty coefficient taken as 2.

$$C = \sum_{i=1}^{n_c} C_i\ ,\ C_i = \begin{cases} 0 \ for \ g_i(x_j) \leq 0 \\ g_i(x_j) \ for \ g_i(x_j) > 0 \end{cases} \ i=1,..,n_c \ j=1,\dots,n \tag{6}$$

where, $C_i$ represents the constraints violation functions for the stress and constructability constraints functions described in equations (16-22) and $n_c$ is the number of constraints functions defined in the optimization problem.

*Step 3*: After the evaluation process, the best spider which has the lowest design cost ($S_b$) and the worst spider which has the highest design cost ($S_w$) are determined. Then, the weights of the spiders are calculated as follows:

$$w_i = \frac{Cost_{high} - Cost_i}{Cost_{high} - Cost_{low}} \quad i=1,\dots,N_f \tag{7}$$

where, $Cost_{high}$, $Cost_{low}$ and $Cost_i$ are costs of the worst spider, the best spider and the $i^{th}$ spider respectively.

*Step 4*: In this step, all spiders use cooperative operator in order to generate new designs. In the colony, the female and the male spiders use different cooperative operators which are described as follows:

$$f_{i,j}^{k+1} = \begin{cases} f_{i,j}^{k} + \alpha \cdot vibc_i \left(x_{c,j} - f_{i,j}^{k}\right) + vibb_i \left(x_{b,j} - f_{i,j}^{k}\right) + \delta(rand-0.5) \ \ with \ probability \ PF & i=1,\dots,N_f \\ f_{i,j}^{k} + \alpha \cdot vibc_i \left(x_{c,j} - f_{i,j}^{k}\right) + vibb_i \left(x_{b,j} - f_{i,j}^{k}\right) + \delta(rand-0.5) \ with \ probability \ 1\text{-}PF & j=1,\dots,n \end{cases} \tag{8}$$

$$m_{i,j}^{k+1}=\begin{cases} m_{i,j}^{k}+\alpha\cdot vibf_i\left(x_{f,j}-m_{i,j}^{k}\right)+\delta(rand\text{-}0.5) & if\ w_{n_f+i}>w_{med} \quad i=1,\ldots,N_m \\ m_{i,j}^{k}+\alpha\cdot\left(\dfrac{\sum_{h=1}^{N_m} m_{h,j}^{k}\cdot w_{n_f+h}}{\sum_{h=1}^{N_m} w_{n_f+h}}-m_{i,j}^{k}\right) & if\ w_{n_f+i}\leq w_{med} \quad j=1,\ldots,n \end{cases} \tag{9}$$

where, $\alpha$, $\beta$ and $\delta$ rand are the random numbers between [0, 1]; $x_{c,j}$ and $x_{b,j}$ are the $j^{th}$ design variable of the nearest and the best spider; $vibc_i$ is the vibration between the $i^{th}$ spider and the nearest spider to the $i^{th}$ spider calculated using equation (10); $vibb_i$ is the vibration between the $i^{th}$ spider and the best spider calculated using equation (11); $vibf_i$ is the vibration between the $i^{th}$ spider and the nearest female spider to the $i^{th}$ spider calculated using equation (12); $w_{med}$ is the weight of the median spider; $k$ is the iteration number; $PF$ is the female movement parameter between [0, 1].

$$\begin{aligned} vibc_i=0 &\quad if(w_i\geq w_c) \\ vibc_i=w_c\cdot e^{-\sum_{j=1}^{n}(x_{c,j}-x_{i,j})^2} &\quad if(w_i<w_c) \end{aligned} \tag{10}$$

$$vibb_i=w_b\cdot e^{-\sum_{j=1}^{n}(x_{b,j}-x_{i,j})^2} \tag{11}$$

$$vibf_i=w_f\cdot e^{-\sum_{j=1}^{n}(x_{f,j}-x_{i,j})^2} \tag{12}$$

where $x_{b,j}$ is the $j^{th}$ design variable of the nearest female spider; $w_c$, $w_b$ and $w_f$ are the weights of the nearest spider, the best spider and the nearest female spider respectively. After the movement, the new designs are evaluated, their penalized costs are calculated using equation (5) and the colony is updated.
*Step 5*: The mating operator is performed in order to generate new designs. Only the dominant male spiders and the female spiders within the range of the dominant spiders use the mating operator. The dominant male spiders are determined by selecting male spiders whose weights are heavier than weight of the median spider. The female spiders in the range of the dominant male spiders are determined using following conditions:

$$\text{if } \sqrt{\sum_{j=1}^{n}(x_{m,j}-x_{f,j})^2}\leq\frac{\sum_{j=1}^{n}(x_j^{high}-x_j^{low})}{2\cdot n}\ ,\ m=1,\ldots,N_{Dm},\ f=1,\ldots,N_f \tag{13}$$

where, $x_j^{high}$ and $x_j^{low}$ are the upper and lower bounds of the design variable $x_j$; $x_{m,j}$ is the $j^{th}$ design variable of the $m^{th}$ dominant spider; $x_{f,j}$ is the $j^{th}$ design variable of the female spider; and $N_{Dm}$ is the number of dominant male spiders. If there are no female spiders in the range of the dominant male spiders, mating operation is not performed for the dominant male spider. After determination of female spiders, the new design is generated. Then, the new design is evaluated, its penalized cost is calculated using equation (5). If cost of the new design is less than the worst design in the colony, the worst design is replaced with the new design and the colony is updated.
*Step 6*: The termination criteria, which is the reaching maximum iteration number, is checked. If the termination criteria are satisfied, the algorithm is stopped. Otherwise, steps 3 to 6 are repeated.

## MATHEMATICAL MODEL FOR OPTIMUM DESIGN OF RC COLUMN SECTIONS

The optimization design problem of reinforced concrete column sections subject to axial force and uni-axial/bi-axial bending consists of identification of design variables, statement of objective function and constraints such that strength limitations and reinforcement arrangement rules specified by the concrete building code are satisfied.

**Design variables**

The design variables in the optimum design problem are selected as the dimensions of columns in *x* and *y* directions, the diameter of reinforcement bars at the cross-section of column and numbers of reinforcement bars in both sides of the column as shown in Figure ***1***. A design pool is generated for the design variables from which the optimum design algorithm selects values randomly and Table 1 shows the lower and upper boundaries, increments and the total number of possible candidates for the design variables. The values in that pool are selected in accordance with examples in practice. In the table, the first line contains values of possible column dimensions, the second line contains values for the diameter of corner reinforcement bars (there are eight different bar diameters) and the third line represents the possible reinforced bar numbers for the side reinforcements. The optimum design algorithm developed takes the sequence number for the supplementary design variable. When two integer numbers are randomly selected from 1 to 32, the corresponding column dimensions in the first line of Table 1 become the column dimensions adopted for the column. Similarly, an integer number selected randomly between 1 and 8 specifies the bar diameters adopted for the reinforcement bars. This design variable pool is taken from available studies in the literature [Zielinski et al. 1995 and Govindaraj and Ramasamy 2007]. Formulation of the optimum design problem of rectangular RC columns subjected to axial force and bi-axial bending moment with the design variables described above and implementing the design limitations from ACI 318-14 [ACI 2014] results in the following discrete programming problem.

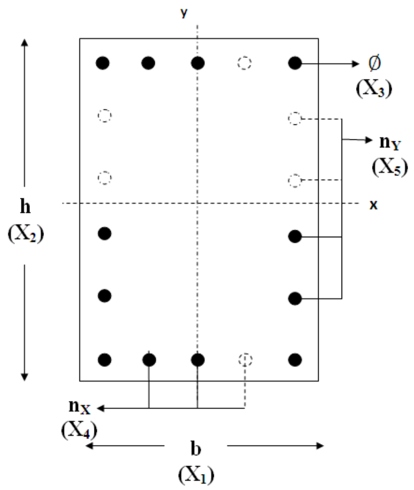


**Figure 1. Design variables for optimum design problem**

**Table 1. Design variable bounds for RC column design examples**

| Design Variables | | Lower Bound | Upper Bound | Increment (Step size) | Number of possible values in the range |
|---|---|---|---|---|---|
| $X_1$ and $X_2$ | $b$ and $h$ *(mm)* | 200 | 975 | 25 mm | 32 |
| $X_3$ | $\phi$*(mm)* | { 12,14,16,18,20,22,25,28} | | - | 8 |
| $X_4$ and $X_5$ | $n_x$ and $n_y$ | 0 | 7 | 1 | 8 |

**Objective Function**

In this study, the material cost and the weighted aggregate of cost and $CO_2$ of the RC columns are considered as the objective function. The objective function includes the cost of concrete, steel reinforcing and formwork which all are associated with labor and installation. The general formulations of optimization problem are given below. The cost and the weighted aggregate of the cost and $CO_2$ objective functions may be expressed mathematically as;

$$minimize \qquad f_{cost}(\boldsymbol{X})=\zeta_{cost}(C_s W_{st}+C_c V_c) \tag{14}$$

$$minimize \qquad f_{aggr}(\boldsymbol{X})=\zeta_{cost}f_{cost}(\boldsymbol{X})+\zeta_{CO_2}f_{CO_2}(\boldsymbol{X}) \tag{15}$$

where, $X$ is the vector which contains the sequence numbers of design variables, $C_s$ is the unit cost of steel, $C_c$ is the unit cost of concrete, $W_{st}$ is the weight of steel per unit length of the wall, $V_c$ is the volume of concrete per unit length of the wall, $A$, $E$ and $\rho$ are the cross sectional area, the $CO_2$ emission rate and the density of the structural material respectively, $N$ is the number of material defined in the structure design problem, $\zeta_{cost}$ and $\xi_{CO_2}$ are non-negative weights which are taken as 1 in this study. The $CO_2$ emission of the structural materials shown in Table 2 are adopted from literature studies [Park 2013 and 2014].

**Table 2. Unit $CO_2$ Emissions and Unit Price of the Structural Materials**

| Material | Strength | Unit Price | $CO_2$emission |
|---|---|---|---|
| Concrete | 24 MPa | 59.76 $/m$^3$ | 304.75 $CO_2/m^3$ |
| | 27 MPa | 62.50 $/m$^3$ | 324.76 $CO_2/m^3$ |
| | 30 MPa | 65.65 $/m$^3$ | 344.54 $CO_2/m^3$ |
| Steel | 400 MPa | 0.742 $/kg | 0.3857 $CO_2$/kg |
| | 500 MPa | 0.770 $/kg | 0.3962 $CO_2$/kg |

**Constraints**

The design philosophy of RC short columns covers the axial and flexural strength capacities, the reinforcement arrangement, and the cross-section of the column. In this optimum design problem, the constraints can be classified into two groups; strength constraints and section arrangement constraints. The constraints are expressed in a normalized form as given below.

The maximum axial load capacity of columns, $P_{n,max}$ should be greater than the factored axial design load acting on the column section, $P_d$ for all load combinations ($N_{lc}$= total number of columns);

$$g_1(x)=\frac{P_{d,i}}{P_{n,max}}-1\leq 0 \quad i=1,\ldots,N_{lc} \tag{16}$$

For a column section, the moment carrying capacity of column section in uni-axial or bi-axial bending case, $M_n$, obtained for each factored axial design load, $P_d$, should be greater than the applied factored design moment, $M_d$ ;

$$g_2(x)=\frac{M_{d,i}}{M_{n@P_{d,i}}}-1\leq 0 \quad i=1,\ldots,N_{lc} \tag{17}$$

The percentage of longitudinal reinforcement steel, $\rho$, in a column section should be between minimum and maximum limits permitted by the design specification ($\rho_{min}= 0.008$ *and* $\rho_{max} = 0.06$) ;

$$g_3(x)=\frac{\rho_{min}}{\rho}-1\leq 0 \quad and \quad g_4(x)=\frac{\rho}{\rho_{max}}-1\leq 0 \tag{18}$$

The width $b$ and the height $h$ of a column section should not be less than the minimum dimensions limit value given for the columns (*min. dimension*, $d_{min}$= *200mm*);

$$g_5(x)=\frac{d_{min}}{b}-1\leq 0 \quad and \quad g_6(x)=\frac{d_{min}}{h}-1\leq 0 \tag{19}$$

The ratio of the shorter dimension of the column section to the longer one should be greater than the permitted limit ($dr_{min} = 0.33$);

$$g_7(x)=\frac{dr_{min}}{b/h}-1\leq 0 \tag{20}$$

The total number of longitudinal reinforcing bars, $N_b$, in a column section should be smaller than specified maximum number of reinforcing bars, $N_{b,max}$, for detailing practice ($N_{b,max} = 24$);

$$g_8(x)=\frac{N_b}{N_{b,max}}-1\leq 0 \tag{21}$$

The minimum and maximum clear spacing between longitudinal bars, $a$, in a column section should be between minimum and maximum limits, $a_{min}$ and $a_{max}$, specified for detailing practice ($a_{min} = 50$ *mm and* $a_{max} = 300$ *mm*);

$$g_9(x)=\frac{a_{min}}{a}-1\leq 0 \quad and \quad g_{10}(x)=\frac{a}{a_{max}}-1\leq 0 \tag{22}$$

## NUMERICAL EXAMPLES

Two RC column design examples are originally developed in this study. Both consider ACI 318-14 structural design requirements and use discrete variable formulations. The objective functions presented in these examples, material cost and weighted cost are investigated and optimized separately. For both examples, the design loads and the considered load combinations are given in Table 3. Example 1 is subject to uniaxial bending and second example is subject to biaxial bending.

**Table 3. Design Loads for Numerical Examples and Load Combinations**

| Example | | $P_d$ (*kN*) | $M_x$ (*kNm*) | $M_y$ (*kNm*) |
|---|---|---|---|---|
| Ex.1 | Dead | 2480 | 472 | - |
| | Live | 1976 | 381 | - |
| | Earthquake | 360 | 571 | - |
| Ex.2 | Dead | 3987 | 371 | 281 |
| | Live | 2765 | 289 | 265 |
| | Earthquake | 730 | 426 | 386 |

| *Load Comb.* | *Dead* | *Live* | *Earthquake* |
|---|---|---|---|
| 1 | 1.4 | - | - |
| 2 | 1.2 | 1.6 | - |
| 3 | 0.9 | 1.0 | 1.0 |
| 4 | 0.9 | 1.0 | -1.0 |
| 5 | 0.9 | - | 1.0 |
| 6 | 0.9 | - | -1.0 |

In this study, the column examples are designed as short columns and the slenderness effect is not considered. For these examples, the unit weight of concrete and steel are taken as $25kN/m^3$ and $78.5kN/m^3$ respectively and it is assumed that single bar diameter is used in the RC section. In order to ensure that the obtained solution from the SSO is global or near global optimum, many runs were made in parallel. For these examples, the minimum and maximum percentages of section reinforcement are taken as 0.8% and 6% respectively. The clear distances between reinforcement bars are limited between 50 mm and 300 mm. The minimum width of column section is taken as 200 mm and the maximum number of reinforcement bars is restricted to 24. The maximum aspect ratio between column section dimensions is accepted as 3. Also, concrete cover used in capacity calculations is taken as 50 mm for both examples.

Numerical examples are optimized for the combinations of certain material strength properties and obtained optimum values for design variables and objective functions are illustrated in
Table ***4*** and Table 5. It is clearly seen from this table that the optimum RC column design having the minimum cost is obtained as \$61.04 and \$83.94 for examples 1 and 2 respectively by the SSO algorithm. The minimum costs are obtained by using high strength materials ($f_c$ = 30 MPa and $f_y$ = 500 MPa) for the

RC column design which results in approximately a 13% lower cost. Similar results are also obtained when the weighted aggregate of the cost and $CO_2$ objective function is used for both examples.

**Table 4. Optimum Values of Design Variables and Optimum Objective Functions for Example 1**

| | $f_c$ *MPa* | $f_y$ *MPa* | $b$ ($x_1$) *mm* | $h$ ($x_2$) *mm* | $\phi$ ($x_3$) *mm* | $n_x$ ($x_4$) | $n_y$ ($x_5$) | $f_{cost}$ *\$ / aggr.* |
|---|---|---|---|---|---|---|---|---|
| Objective: Cost | 24 | 400 | 700 | 950 | 22 | 3 | 2 | 70.74 |
| | | 500 | 675 | 950 | 22 | 3 | 2 | 70.49 |
| | 27 | 400 | 650 | 925 | 20 | 3 | 3 | 66.86 |
| | | 500 | 600 | 950 | 18 | 5 | 2 | 63.31 |
| | 30 | 400 | 575 | 950 | 20 | 3 | 2 | 61.48 |
| | | 500 | 550 | 950 | 16 | 6 | 3 | 61.04 |
| Objective: Aggregate | 24 | 400 | 675 | 950 | 18 | 6 | 3 | 283.30 |
| | | 500 | 625 | 950 | 20 | 6 | 2 | 273.95 |
| | 27 | 400 | 600 | 950 | 18 | 6 | 3 | 270.30 |
| | | 500 | 550 | 950 | 20 | 6 | 2 | 259.86 |
| | 30 | 400 | 550 | 950 | 18 | 6 | 2 | 259.38 |
| | | 500 | 525 | 950 | 18 | 6 | 2 | 251.17 |

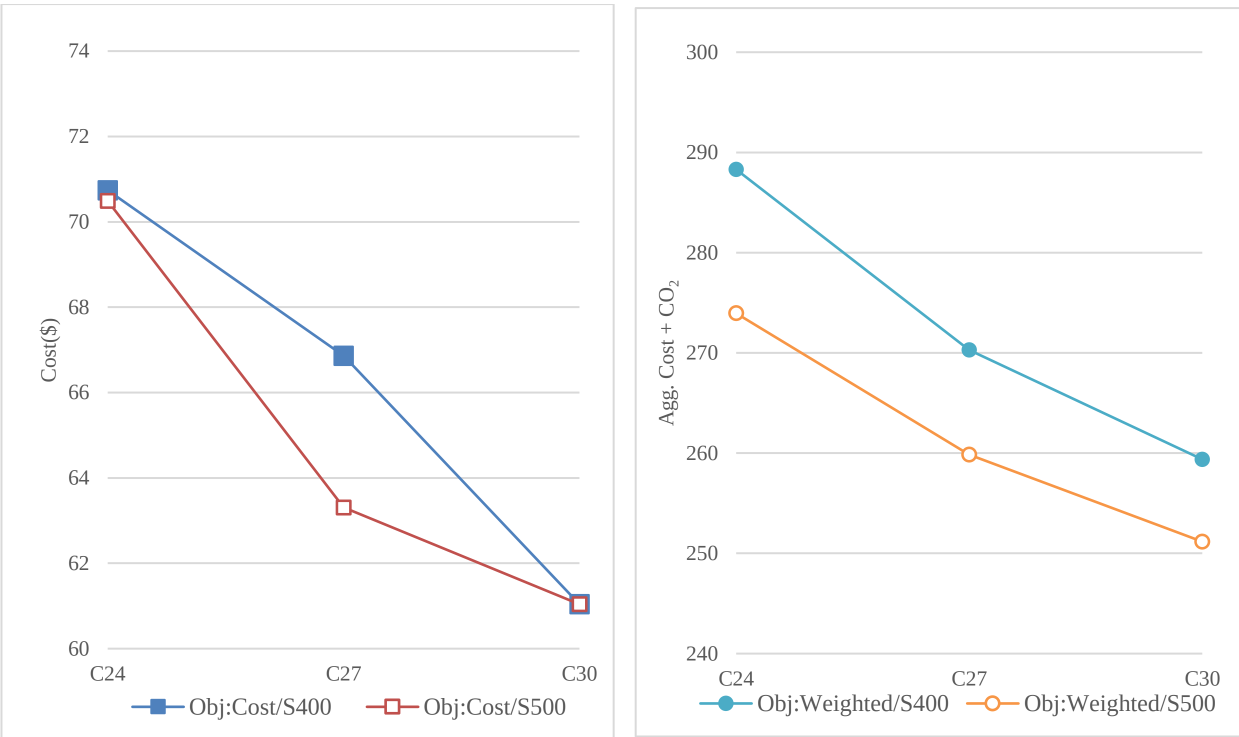


**Figure 2. Design variables for optimum design problem**

The distribution of optimum values with respect to different material strengths in the case of minimizing the cost and minimizing the weighted aggregated objectives are plotted in Figure 2 and Figure 3 respectively. It is concluded from these figures that the optimum cost values decrease when concrete strength is increased. Additionally, same relationship between the steel yield strength and the optimum values can be defined. It is obvious in Figure 2 and Figure 3 that higher optimum $CO_2$ emission values are obtained when lower yield strength of steel and compressive concrete strength are selected for the design. In other words, better results are obtained when higher material strength is utilized for RC column design.

**Table 5. Optimum Values of Design Variables and Optimum Objective Functions for Example 2**

| | $f_c$ MPa | $f_y$ MPa | $b$ ($x_1$) mm | $h$ ($x_2$) mm | $\phi$ ($x_3$) mm | $n_x$ ($x_4$) | $n_y$ ($x_5$) | $f_{cost}$ $ / aggr. |
|---|---|---|---|---|---|---|---|---|
| Objective: Cost | 24 | 400 | 925 | 950 | 20 | 6 | 4 | 96.43 |
| | | 500 | 875 | 975 | 22 | 5 | 2 | 92.34 |
| | 27 | 400 | 850 | 950 | 22 | 4 | 3 | 90.32 |
| | | 500 | 825 | 950 | 20 | 6 | 2 | 86.96 |
| | 30 | 400 | 775 | 950 | 22 | 4 | 2 | 83.76 |
| | | 500 | 775 | 950 | 25 | 2 | 2 | 83.94 |
| Objective: Aggregate | 24 | 400 | 875 | 975 | 22 | 6 | 2 | 378.27 |
| | | 500 | 850 | 950 | 25 | 5 | 2 | 375.23 |
| | 27 | 400 | 800 | 950 | 22 | 6 | 3 | 368.35 |
| | | 500 | 750 | 975 | 22 | 6 | 2 | 352.78 |
| | 30 | 400 | 750 | 950 | 22 | 5 | 2 | 352.83 |
| | | 500 | 650 | 950 | 25 | 6 | 2 | 343.17 |

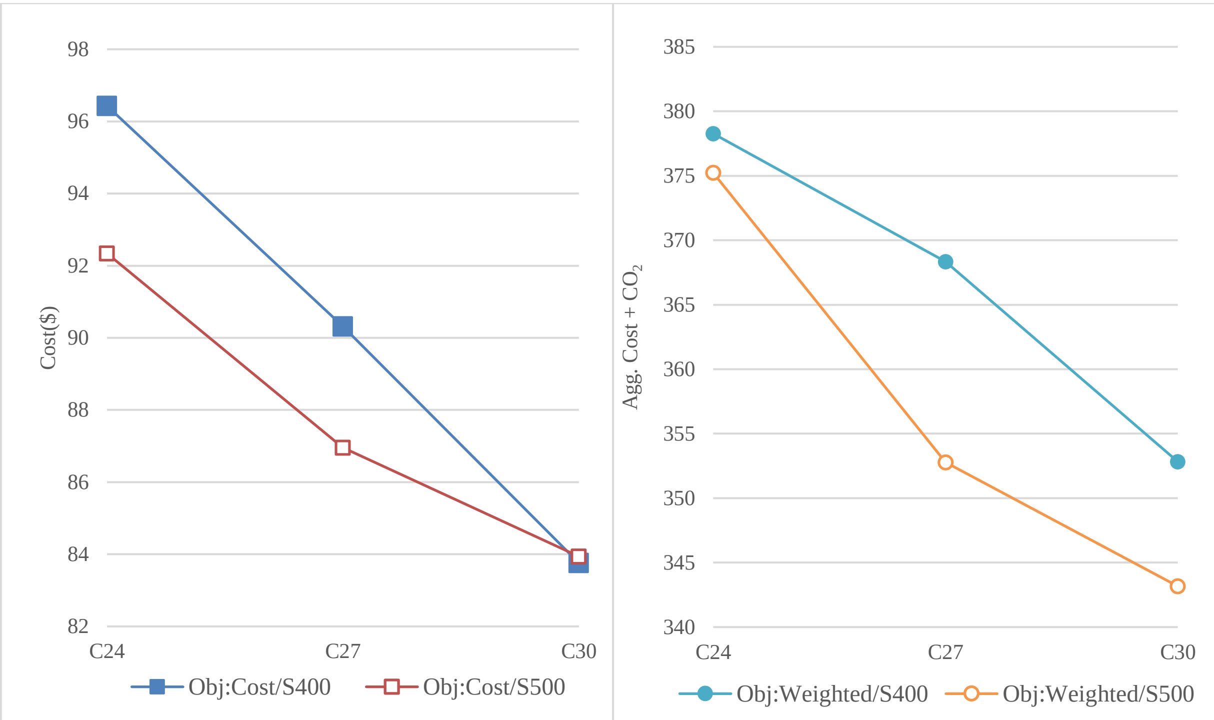


**Figure 3. Design variables for optimum design problem**

## CONCLUSION

In this study, we present SSO based optimization algorithm for RC columns that simultaneously considers the structural cost and $CO_2$ emissions at the structural design phase and we apply the technique to numerical examples to evaluate its effectiveness. The SSO shows good performance and is powerful and efficient in finding the optimum solution for the optimum cost design of RC columns. Evaluations are based on design optimizations using either cost or weighted aggregate of the cost and the $CO_2$ objective functions developed with a SSO algorithm. A sensitivity analysis indicates that both the cost and $CO_2$ formulation are highly sensitive to changes in applied loads, concrete compressive strength, yield strength of steel, and unit cost functions in the objective function formulation.

SSO algorithm is both computationally efficient and capable of generating low-cost and low-$CO_2$ emission RC column designs that satisfy safety, stability, and material constraints. Three different compressive strength values of concrete ($f_c$=24, $f_c$=27 and $f_c$=30Mpa) and two different yield strength values of steel ($f_y$=400 and $f_y$=500MPa) are used in the RC section design. In total, both design examples are optimized twelve times by taking different objectives and different materials.

According to the obtained optimized results, some outcomes are acquired. The first one is that optimizing RC columns considering the minimizing $CO_2$ emission objective function has great influence on optimum cost. Therefore, the minimizing $CO_2$ emission objective function should be considered in the optimum design to obtain sustainable designs. The second outcome is that when higher strength materials are selected in the design, better optimum cost values and optimum $CO_2$ emissions are obtained. The third one is that higher steel cost ratio and steel amounts are obtained in the minimization of $CO_2$ emission problem. Thus, higher steel amounts should be used in order to get less $CO_2$ emission. The fourth one is that usage of higher steel yield strength reduces the steel amount and steel cost percentage. We confirmed that increasing the amount of steel while decreasing the amount of concrete can be an effective way to reduce the structural costs and $CO_2$ emissions of the RC columns. As a result, it is concluded that the use of high-strength materials for RC columns effectively reduces $CO_2$ emissions. The unit cost and $CO_2$ emission of high-strength materials are greater than those of general-strength materials, but lower amounts of the former materials are required because of their increased strength, which in turn reduces the overall costs and $CO_2$ emissions.

## REFERENCES

ACI 318-14 (2014). "Building code requirements for structural concrete and commentary." *American Concrete Institute*, USA.

Cuevas, E., Cienfuegos, M., Zaldivar, D., and Perez-Cisneros, M. (2013). "A swarm optimization algorithm inspired in the behavior of the social-spider." *Expert Systems with Applications*, 40(16), 6374-638.

Esapour, K., et al. (2015). "A new sufficient method based on levy-social spider technique for optimal economic dispatch of thermal power unit." *Journal of Intelligent & Fuzzy Systems*, 28(3), 1137-1143.

Govindaraj, V. and Ramasamy, J.V. (2007). Optimum detailed design of reinforced concrete frames using genetic algorithms. *Engineering Optimization*. Vol. 39, 4, pp. 471-494.

Khorramnia, R., et al. (2015). "A new unscented transform for considering wind turbine uncertainty in ED problem based on SSO algorithm." *Journal of Intelligent & Fuzzy Systems*, 29(4), 1479-1491.

Mirjalili, S. Z., et al. (2015). "Designing evolutionary feedforward neural networks using social spider optimization algorithm." *Neural Computing & Applications*, 26(8), 1919-1928.

Park H.S., et al. (2013). "Cost and CO2 Emission Optimization of Steel Reinforced Concrete Columns in High-Rise Buildings," *Energies*, Vol.6, no. 11, pp. 5609-5624.

Park, H.S., et al. (2014). "Evaluation of the influence of design factors on the CO2 emissions and costs of reinforced concrete columns." *Energy and Buildings*, Vol.82, no. pp. 378-384.

T'Serclaes, P. (2007). "Financing Energy Efficient Homes: Existing Policy Responses to Financial Barriers." *International Energy Agency*, Paris, France.

Yu, J. J. Q., and Li, V. O. K. (2016). “A social spider algorithm for solving the non-convex economic load dispatch problem.” *Neurocomputing*, 171, 955-965.

Zielinski, Z.A., Long, W. and Troitsky, M.S. (1995). “Designing reinforced concrete short tied columns using optimization technique.” *ACI Structural Journal*. Vol 92, 5, pp. 619-626.