OPTIMIZATION OF RC FRAMES BY AN IMPROVED ARTIFICIAL BEE COLONY ALGORITHM

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ABSTRACT

A new meta-heuristic algorithm is proposed for optimal design of reinforced concrete (RC) frame structures subject to combinations of gravity and lateral static loads based on ACI 318-08 design code. In the present work, artificial bee colony algorithm (ABCA) is focused and an improved ABCA (IABCA) is proposed to achieve the optimization task. The total cost of the RC frames is minimized during the optimization process subject to constraints on demand capacity ratios (DCRs) of structural members. Three benchmark design examples are tested using ABCA and IABCA and the results are compared with those of presented in the literature. The numerical results indicate that the proposed IABCA is an efficient computational tool for discrete optimization of RC frames.

1. INTRODUCTION

Optimization of reinforced concrete (RC) frames is a complex problem, due to the large number of variables that influence the design process, the different nature of the variables and the various reinforcement details available for the design problem at hand. For RC frames three different cost components of concrete, steel and formwork should be considered and in this case a combination of design variables must be such determined that the total cost is minimal. As designing and constructing of cost effective structures is of high importance, optimization of RC frames has been attracted much attention in recent decades.

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An exhaustive literature review has been achieved in [1] indicating that genetic algorithm (GA) has been widely employed in the scope of RC frames optimization. In the recent years, modern meta-heuristic algorithms were developed and employed for optimal design of RC frames. Kaveh and Sabzi [1-2] used heuristic big bang-big crunch (HBB-BC) and heuristic particle swarm ant colony optimization (HPSACO) algorithms for optimization of planar RC frames. Kaveh and Behnam [3] optimized 3D RC frames subject to natural frequency constraints by charged system search (CSS) algorithm. Gholizadeh and Aligholizadeh [4] employed bat algorithm (BA) to optimize 2D RC frames and they compared the results of BA with those of other meta-heuristics. Their study demonstrated that BA possesses better convergence rate with respect to the other algorithms.

In order to overcome the computational rigor of the traditional gradient-based optimization algorithms, meta-heuristic search techniques were developed and their high capabilities in tackling complex problems have been proved in the literature [5]. One of these meta-heuristics is artificial bee colony algorithm (ABCA) proposed by Karaboga [6] based on the intelligent behavior of a honey bee swarm. In ABCA, a colony of artificial bees including three groups of employed bees, onlookers and scouts who search for better food sources [7-8] is numerically modeled to achieve optimization task. Comparison of the computational performance of ABCA with some other meta-heuristics, such as genetic algorithm (GA), particle swarm optimization (PSO), differential evolution algorithm (DE) and evolution strategies (ES) [9] indicated that ABCA is a better global optimization algorithm and it can be effectively employed to solve engineering problems. Furthermore, the lesser adjustable parameters of ABCA makes it very popular in the different fields of science and engineering [10].

Besides all advantages of ABCA, it still suffers from shortcomings such as slow convergence, trapping in local optima and weak exploitation ability. In this paper, an improved ABCA (IABCA) is proposed to optimize the RC frames. Three design examples are presented and the numerical simulations demonstrate the efficiency of the proposed IABCA compared with other algorithms.

2. OPTIMIZATION PROBLEM FORMULATION

In this study, total cost of RC frames, including the cost of concrete, steel reinforcement and framework of all beams and columns, is considered as the objective function of the optimization problem as follows:

$$C = \sum_{i=1}^{nb} \left(C_C b_{b,i} h_{b,i} + C_S A_{S,b,i} + C_F (b_{b,i} + 2 h_{b,i}) \right) L_i + \sum_{j=1}^{nc} \left(C_C b_{c,j} h_{c,j} + C_S A_{S,c,j} + 2 C_F (b_{c,j} + h_{c,j}) \right) H_j \tag{1}$$

where C is objective function; nb is the number of beams; $b_{b,i}$, $h_{b,i}$, L_i and $A_{S,b,i}$ are the ith beam width, depth, length and area of the steel reinforcement, respectively; nc is the number of columns; $b_{c,j}$, $h_{c,j}$, H_j and $A_{S,c,j}$ are the jth column width, depth, length and area of the steel reinforcement, respectively; C_C, C_S and C_F are the unit cost of concrete, steel and framework, respectively. As mentioned in [1], in the present work the following unit costs

are also considered: C_C=105 \$/m^3, C_S=7065 \$/ m^3, C_F=92 \$/ m^2.

It is clear that a semi-infinite set of member width, depth and steel reinforcement arrangements can be considered for RC structure elements. In this case, as the dimensions of the design space are very large, the computational burden of the optimization process increases. In order to reduce the dimensions of design space and consequently the computational cost, a countable number of cross-sections can be employed by constructing data sets in a practical range [4]. In the present study, the section databases constructed for beams and columns in [1] are employed. these databases of beams and columns are shown in Figs. 1 and 2, respectively. Further information about the databases can be found in [1].

Beam number	Width (mm)	Depth (mm)	Area (×10²mm²)	Moment of inertia (×10⁶mm⁴)	Number of bars Center (D19)	End (D22)	Factored moment resistance (kN.m) Center	End	Cost per unit length ($)
1	300	450	1350	2278.1	2	2	74.41	97.67	133.95
2	300	450	1350	2278.1	3	2	108.84	97.67	135.96
....	....	....	....	....	....	....	....	....	....
1013	450	900	4050	27338	10	12	761.3	1152.3	301.78
1014	450	900	4050	27338	12	12	893.43	1152.3	305.79

Figure 1. Database for the beams [1]

Column number	Width (mm)	Depth (mm)	Number of bars (D25)	P_0 (kN)	P_1 (kN)	P_3 (kN)	P_5 (kN)	M_2 (kN.m)	M_3 (kN.m)	M_4 (kN.m)	Cost per unit length ($)
1	300	300	4	1643.3	1314.7	429	692.7	22.19	81.98	70.52	133.72
2	300	300	6	1880.7	1504.6	405.7	1039.1	25.97	101.82	100.61	140.66
... ...	...	...	... ...	... .	... .	... .	... .	... ...	... ...	... ...	... ...
54	900	900	22	13128	10503	4961.3	3810	717.17	2230.7	1504.5	492.55
55	900	900	24	13366	10693	4954.9	4156.3	739.31	2326.2	1638.1	499.48

Figure 2. Database for the columns [1]

During the optimization prosecc, RC frames are analyzed for the following load cases according to ACI 318-08 code [11] and axial force and bending moments for each column and only bending moments for each beam are checked.

$$\begin{cases} \text{Load Case 1}: & 1.2\,DL+1.6\,LL \\ \text{Load Case 2}: & 1.2\,DL+1.0\,LL+1.4\,EL \\ \text{Load Case 3}: & 1.2\,DL+1.0\,LL-1.4\,EL \\ \text{Load Case 4}: & 0.9\,DL+1.4\,EL \\ \text{Load Case 5}: & 0.9\,DL-1.4\,EL \end{cases} \qquad (2)$$

where *DL*, *LL* and *EL* are dead, live and earthquake loads, respectively.

In order to design a beam the externally applied moment at mid-span (M_u^+), left (M_{uL}^-) and right (M_{uR}^-) joints of beams should be respectively less than the factored moment capacities at the middle (ϕM_n^+), and near the ends (ϕM_n^-). The factored moment capacity for beams is computed as follows [4]:

$$\phi M_n = \phi A_s f_y (d - \frac{A_s f_y}{1.7 f'_c b}) \tag{3}$$

where $\phi = 0.9$ is the strength reduction factor; A_s is the area of the tensile bars; f_y is specified yield strength of the reinforcing bars; d is the effective depth of the section which is measured as the distance from extreme compression fiber to centroid of the longitudinal tensile reinforcing bars of the section; f'_c is compressive strength of the concrete and b is the width of the cross-section.

A simplified linear P-M interaction diagram [1], shown in Fig. 3, can be employed to evaluate the strength of a column subject to bending moment and axial force
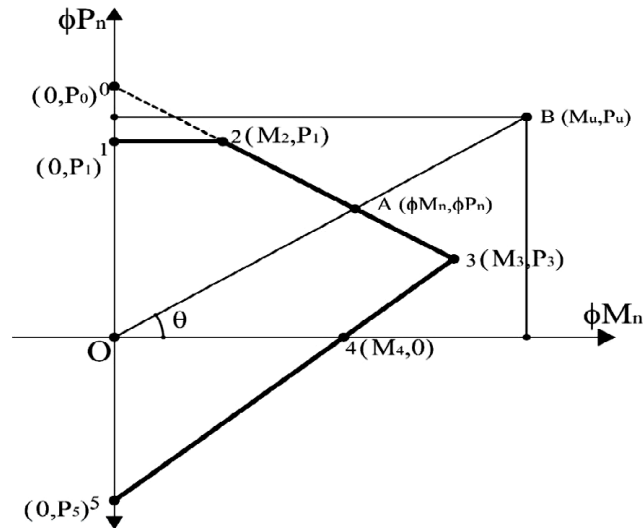

Figure 3. A simplified linear P-M interaction diagram [1]

In a designed column the corresponding pair (M_u, P_u) under the applied loads does not fall outside the interaction diagram. In Fig. 3, if point B shows the position of the pair (M_u, P_u) and A is the crossing point of the line connecting B to the O and the interaction diagram, then the distance of the points A and B from O can be calculated. The ratio of the mentioned distances can be used as the constraint of the columns resistance. The angle between line OB and the horizontal axis (θ) is required to specify the point A. The lengths of OA (L_n) and OB (L_u) lines, can be computed as follows [4]:

$$L_n = \sqrt{(\phi M_n)^2 + (\phi P_n)^2} \tag{4}$$

$$L_u = \sqrt{(M_u)^2 + (P_u)^2} \tag{5}$$

Therefroe, if for a column section $L_u \leq L_n$ it can be concluded that the secction is suitable and safe enough. Besides the strength requirements, for columns of a frame, the dimensions of the top column (including width and height of the cross section *i.e.*, b_T, h_T) should not be larger than those of the bottom one (b_B, h_B), and also the number of reinforcing bars in the

top column (n_T) should not be greater than that of the bottom column (n_B) [4].

Formulation of a sizing optimization problem of RC frames is represented as follows [4]:

$$\text{Minimize: } F \quad \text{Subject to:} \tag{6}$$

$$g_1 = \frac{M_u^+}{\phi M_n^+} - 1 \le 0 \tag{7}$$

$$g_2 = \frac{\left| M_{uL}^- \right|}{\phi M_n^-} - 1 \le 0 \tag{8}$$

$$g_3 = \frac{\left| M_{uR}^- \right|}{\phi M_n^-} - 1 \le 0 \tag{9}$$

$$g_4 = \frac{L_u}{L_n} - 1 \le 0 \tag{10}$$

$$g_5 = \frac{b_T}{b_B} - 1 \le 0 \tag{11}$$

$$g_6 = \frac{h_T}{h_B} - 1 \le 0 \tag{12}$$

$$g_7 = \frac{n_T}{n_B} - 1 \le 0 \tag{13}$$

In this study, the constraints of the optimization problem are handled using the concept of exterior penalty functions method (EPFM) [12]. In this case, the pseudo unconstrained objective function is expressed as follows [4]:

$$\Phi = F(1 + P_{beam} + P_{column}) \tag{14}$$

$$P_{beam} = r_p \sum_{i=1}^{nb} \left(\left(\max\{0, g_1\} \right)^2 + \left(\max\{0, g_2\} \right)^2 + \left(\max\{0, g_3\} \right)^2 \right)_i \tag{15}$$

$$P_{column} = r_p \sum_{j=1}^{nc} \left(\left(\max\{0, g_4\} \right)^2 + \left(\max\{0, g_5\} \right)^2 + \left(\max\{0, g_6\} \right)^2 + \left(\max\{0, g_7\} \right)^2 \right)_j \tag{16}$$

where Φ and r_p are the pseudo objective function and positive penalty parameter, respectively; P_{beam}, and P_{column} are the penalty functions of beams and columns of the frame, respectively [4].

In this study, the presented optimization problem of RC frames is solved by ABCA and its improved version (IABCA) and they are described in the next sections.

3. ARTIFICIAL BEE COLONY ALGORITHM

The ABCA is a stochastic, population-based optimization algorithm proposed by Karaboga [6]. ABCA was inspired and developed based on the model of the foraging behavior of honey bee swarm. The colony of artificial bees consists of three groups of bees: employed bees, onlookers and scouts. A bee which has found a food source to exploit is called an employed

bee. Onlookers are those waiting in the hive to receive the information about the food sources from the employed bees and Scouts are the bees which are randomly searching for new food sources around the hive. The first half of the colony consists of the employed artificial bees and the second half includes the onlookers.The number of employed bees is equal to the number of food sources around the hive. The employed bee whose food source has been exhausted becomes a scout. Each cycle of the search consists of three steps: moving the employed and onlooker bees onto the food sources, calculating their nectar amounts and determining the scout bees and directing them onto possible food sources. A food source position represents a possible solution of the optimization problem at hand. The amount of nectar of a food source corresponds to the quality of the solution represented by that food source. Onlookers are placed on the food sources by using a probability based selection process. Every bee colony has scouts that are the colony's explorers. The explorers do not have any guidance while looking for food. If a solution representing a food source is not improved by a predetermined number of trials, then that food source is abandoned by its employed bee and the employed bee is converted to a scout.

In the ABCA the number of food sources is set to ns which is equal to the number of employed or onlooker bees, and d is the dimension of each solution vector and the main steps of the algorithm are as follows [13]:

1. Selection of an initial population (X_1, …, X_{ns}) on a random basis.

$$X_i^{\mathrm{T}} = \{x_{i1}, x_{i2}, ..., x_{id}\} \tag{17}$$

$$x_{ij} = x_j^L + \mathrm{rand}(0,1) . (x_j^U - x_j^L) \tag{18}$$

in which, $i \in \{1, 2, ... , ns\}$, $j \in \{1, 2, ... , d\}$; x_j^L and x_j^U are the lower and upper bounds for the jth dimension, respectively.

2. Evaluation the fitness of each food source.

3. Each employed bee searches the neighbourhood of its current food source to determine a new food source using the following equation:

$$x_{ij}^{t+1} = x_{ij}^t + \Psi_{ij}(x_{ij}^t - x_{ik}^t) \tag{19}$$

where, $k \in 1, 2, ... , ns\}$, $j \in \{1, 2, ... , d\}$, $k \neq i$ and $\Psi_{ij} \in [-1,+1]$; t is iteration number.

4. Evaluation the nectar amount of the new food source and performing a greedy selection. (If the quality of the new food source is better than the current position, the employed bee leaves its position and moves to the new food source; in other words, If the fitness of the new food source is equal or better than that of X_i, the new food source takes the place of X_i in the population and becomes a new member.)

5. An onlooker bee selects a food source based on the information received from all of the employed bees.The probability p_i of selecting the food source i is determined as:

$$p_i = \frac{fit_i}{\sum_{i=1}^{ns} fit_i} \tag{20}$$

where fit_i is the fitness value of the food source X_i. After selecting a food source, the onlooker generates a new food source using Eq. (19). Once the new food source is generated, it will be evaluated and a greedy selection will be applied.

6.   If the fitness value of a food source cannot be further improved by a predetermined number of trials, the food source is considered abandoned and the employed bee associated with that food source becomes a scout. The scout randomly generates a new food source using the following equation:

$$x_{ij}^{t+1} = x_j^L + \text{rand}(0,1) \cdot (x_j^U - x_j^L) \tag{21}$$

The abandoned food source is replaced by the randomly generated one. In the ABCA, the predetermined number of trials for abandoning a food source is called *limit*, also in this algorithm at most one employed bee at each cycle can become a scout.

7.   If a termination condition is met, the process is stopped and the best food source is reported; otherwise the algorithm returns to step 3.

Many successful applications of ABCA have been reported in the literature however, some serious computational drawbacks such as slow convergence, trapping in local optima and weak exploitation ability encouraged researchers to modify ABCA [9–10]. As the exploration and exploitation abilities are not balanced in the ABCA in this paper, an improved ABCA (IABCA) is proposed to overcome this difficuilty. The next section describes IABCA.

4. IMPROVED ARTIFICIAL BEE COLONY ALGORITHM

To enhance the convergence rate and the convergence precision of ABCA and to resolve its premature convergence issue, an improvement to the original ABCA is conducted in the present work. In order to achieve this purpose, a mechanism of well-known bat algorithm (BA) [14–15] is included in the onlooker phase of ABCA and the resulted algorithm is termed as improved ABCA (IABCA). The robustness of BA lies in its interesting ability in making a satisfactory balance between exploration and exploitation characteristics. Automatic switch from exploration to more extensive exploitation is achieved in BA when the optimality is approaching [16]. The fundamental steps of IABCA is expressed as follows:

Initilization Phase

1.   Initilization algorithm parameters: number of generations (*ng*), *ns* and *limit*.
2.   Initilization parameters required for the mechanism taken from BA: $A^0=1$, $A_{\min}=0$, $r^0=0$, $r_{\max}=0$, $\alpha=0.9$, $\gamma=0.01$.
3.   Selection initial population using Eq. (18).

4. Evaluation the fitness of each food source.

Employed Bees Phase

5. Production new food sources using Eq. (19)
6. Evaluation the fitness of new food sources.
7. Application of greedy selection between the new and old solutions.
8. Calculation probabilities for source sites using Eq. (20).

Onlooker Bees Phase

9. Selection *i*th source site based on probabilities of sites.
10.   If *rand > r_i*, production new food source using the following equation:

$$x_{ij}^{t+1} = \begin{cases} x_{ij}^t + \Psi_{ij}(x_{ij}^t - x_{ik}^t) + (1 - \Psi_{ij}).(x_{ij}^t - x_{best,j}) & \text{if } R_j < MR \\ x_{ij}^t & \text{otherwise} \end{cases} \tag{22}$$

where R_j, *MR* and Ψ_{ij} are random numbers between [−1,+1]; $x_{best,j}$ is *j*th dimention of the best solution found so far.

11.   Else if *rand ≤ r_i*, generation a new solution by local random walk as follows:

$$x_{ij}^{t+1} = \begin{cases} x_{ij}^t + \varepsilon.A_{ave} & \text{if } R_j < MR \\ x_{ij}^t & \text{otherwise} \end{cases} \tag{23}$$

where ε is random number between [−1,+1]; A_{ave} is average loudness

12. Evaluation the fitness of new solutions.
13. Application of greedy selection between the new and old solutions.
14. If *rand < A_i* & solution is improved, Updating loudness (A_i) and pulse rate r_i as:

$$A_i^{t+1} = \alpha.A_i^t \ , \ \ r_i^{t+1} = r_i^0.(1 - e^{-\gamma.t}) \tag{24}$$

Scout Bees Phase

15. Finding abandoned food sources
16. Generation new food sources on a random basis using Eq. (21).
17. If a termination condition is met, the process is stopped and the best solution is reported; otherwise the algorithm returns to step 5.

ABCA and IABCA are employed to tackle the stated optimization problem of some benchmark RC frames and the results are presented in the next section. In this paper, all of the required computer programs are coded in MATLAB [17] and a personal Pentium IV 3.0 GHz has been used for computer implementation.

5. NUMERICAL EXAMPLES

Three RC plane frames presented in [1, 4] are considered as the numerical examples of this study. In these examples, lateral equivalent static earthquake loads (*EL*) are applied as joint loads, and uniform gravity loads are assumed for a dead load *DL* = 22.3 kN/m and a live load *LL* = 10.7 kN/m. The assumed specified compressive strength of concrete and yield strength of reinforcement bars are f_c'=23.5 and f_y=392 MPa, respectively. For the first example *ns*=20 for the rest *ns*=30. The total number of generations is limited to 1000. For all examples, if the best solution is repeated in 40 consecutive iterations the algorithm will be terminated. The demand/capacity ratio (*DCR*) in the members of the optimum solutions, which is defined in the following equations, are given in all examples.

$$\text{For beams:} \quad DCR = \max\left\{\frac{M_u^+}{\phi M_n^+}, \frac{|M_{uL}^-|}{\phi M_n^-}, \frac{|M_{uR}^-|}{\phi M_n^-}\right\} \tag{25}$$

$$\text{For columns:} \quad DCR = \frac{L_u}{L_n} \tag{26}$$

5.1 Example 1: Three bay, four-story RC frame

The geometry, lateral equivalent static earthquake loads and grouping details of the four-story RC frame are shown in Fig. 4.
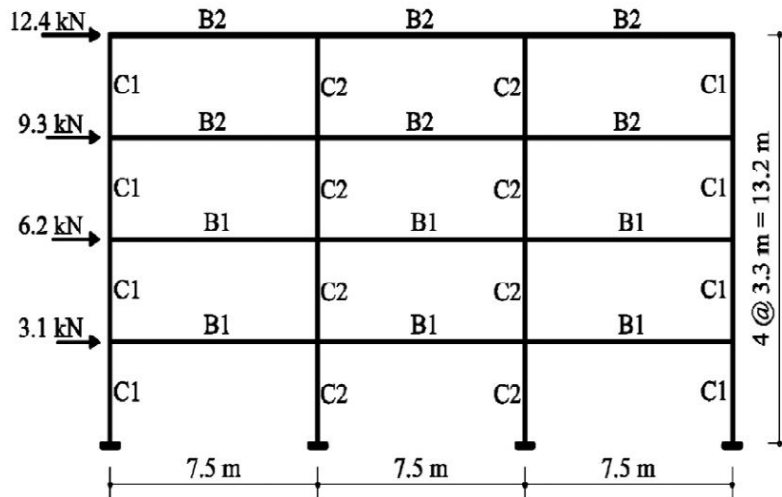

Figure 4. Three bay, four-story RC frame

The four-story RC frame is optimized by ABCA and IABCA meta-heuristics and the results are compared in Table 1.

The results presented in Table 1 indicate that both the optimum solutions found by ABCA and IABCA are feasible.

Table 1: Optimum designs of three bay, four-story RC frame

| Element | | ABCA | | | | IABCA | | | |
| | | Dimensions | | Reinforcements | | Dimensions | | Reinforcements | |
Type	Group	Width (mm)	Depth (mm)	Positive moment	Negative moment	Width (mm)	Depth (mm)	Positive moment	Negative moment
Beam	B1	300	500	3-D19	5-D22	300	450	3-D19	6-D22
	B2	300	500	3-D19	5-D22	300	450	4-D19	5-D22
Column	C1	400	400	6-D25		350	350	8-D25	
	C2	350	350	4-D25		350	350	4-D25	
Frame cost ($)		22916				21751			
Structural analyses		3980				4185			
Max. DCR for beams		0.939				0.999			
Max. DCR for columns		0.981				0.902			

Furthermore, the convergence histories of ABCA and IABCA meta-heuristics are depicted in Fig. 5.

The results indicate that the optimum cost obtained by IABCA is less than that of the ABCA however, it is evident that the convergence rate of the proposed IABCA is much better than that of the ABCA. This RC frame has been optimized by Kaveh and Sabzi [1] and their optimum cost and the number of required analyses are 22207 $ and 8500, respectively. Thus, the solution found by IABCA is better than that of Kaveh and Sabzi [1] in terms of frame cost and computational burden.
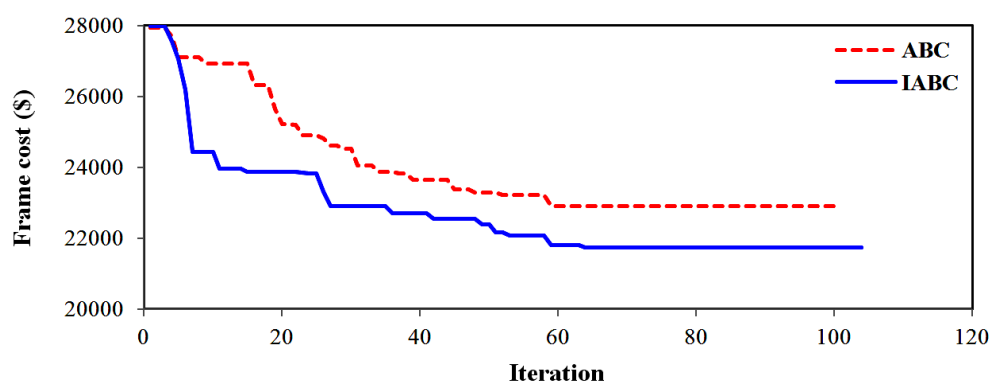

Figure 5. Convergence history of ABCA and IABCA for three bay, four-story RC frame

5.2 Example 2: Three bay, eight-story RC frame

The geometry of the three bay, eight-story RC frame, its element groups and lateral equivalent static earthquake loads are shown in Fig. 6.

The ABCA and IABCA meta-heuristics are employed for optimization of the eight-story RC frame and the results are compared in Table 2. The convergence histories of ABCA and IABCA are shown in Fig. 7.
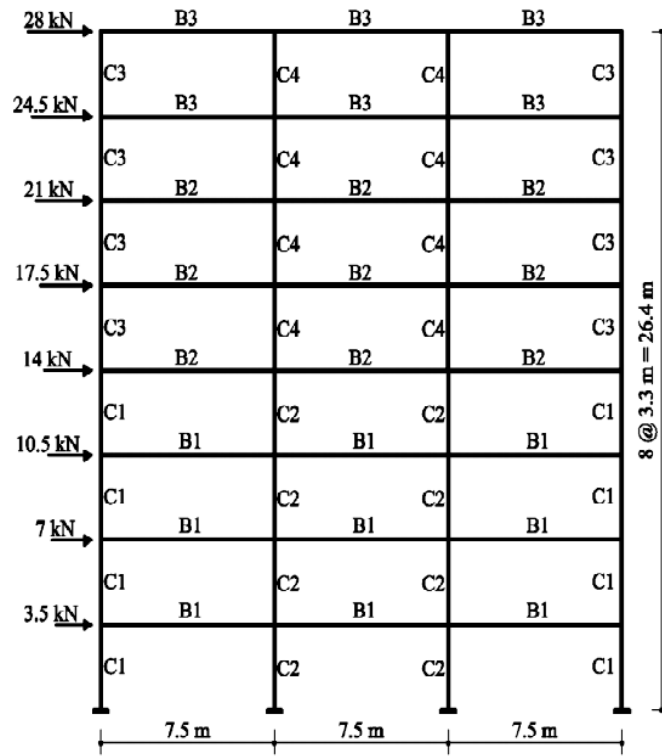
Figure 6. Three bay, eight-story RC frame

Table 2: Optimum designs of three bay, eight-story RC frame

| Element | | ABCA | | | | IABCA | | | |
| | | Dimensions | | Reinforcements | | Dimensions | | Reinforcements | |
Type	Group	Width (mm)	Depth (mm)	Positive moment	Negative moment	Width (mm)	Depth (mm)	Positive moment	Negative moment
Beam	B1	300	550	3-D19	5-D22	300	500	3-D19	6-D22
	B2	300	500	3-D19	6-D22	300	500	3-D19	6-D22
	B3	300	500	3-D19	5-D22	300	500	3-D19	5-D22
Column	C1	400	400	8-D25		400	400	8-D25	
	C2	450	450	8-D25		450	450	10-D25	
	C3	350	350	8-D25		350	350	8-D25	
	C4	350	350	4-D25		350	350	6-D25	
Frame cost ($)		48077				47897			
Structural analyses		15020				16215			
Max. DCR for beams		0.989				0.985			
Max. DCR for columns		0.990				0.959			

The results demonstrate that the solution of IABCA is slightly better than the optimum design of ABCA. Also, both the presented optimum designs in Table 1 are feasible.
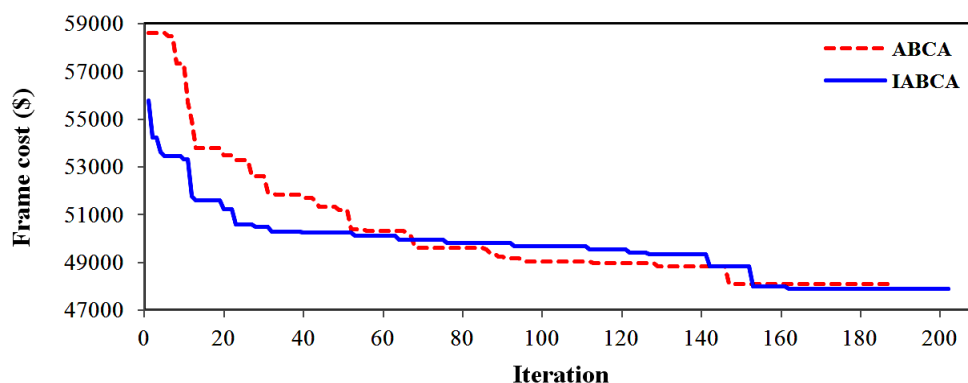
Figure 7. Convergence history of ABCA and IABCA for three bay, eight-story RC frame

The optimum cost obtained by IABCA in this example and its required analyses are respectively less than 48263 $ and 39500 of the solution reported in [1].

5.3 Example 3: Three bay, twelve-story RC frame

Fig. 8 depicts the geometry, element groups and lateral loading of the three bay, twelve-story RC frame.

Table 3 compares the optimal solutions obtained by ABCA and IABCA meta-heuristics. In addition, the convergence histories of the meta-heuristics are shown in Fig. 9. The optimum design found by IABCA is better than that of the ABCA.

Table 3: Optimum designs of three bay, twelve-story RC frame

| Element		ABCA				IABCA			
		Dimensions		Reinforcements		Dimensions		Reinforcements	
Type	Group	Width (mm)	Depth (mm)	Positive Moment	Negative moment	Width (mm)	Depth (mm)	Positive moment	Negative moment
Beam	B1	350	550	3-D19	7-D22	350	600	3-D19	6-D22
	B2	350	550	3-D19	6-D22	300	550	3-D19	6-D22
	B3	350	550	3-D19	5-D22	300	500	3-D19	6-D22
Column	C1	450	450	12-D25		450	450	10-D25	
	C2	600	600	12-D25		600	600	12-D25	
	C3	400	400	8-D25		400	400	8-D25	
	C4	500	500	10-D25		500	500	8-D25	
	C5	350	350	8-D25		350	350	8-D25	
	C6	400	400	4-D25		400	400	4-D25	
Frame cost ($)		82103				80413			
Structural analyses		16130				19030			
Max. DCR for beams		0.993				0.992			
Max. DCR for columns		0.982				0.939			
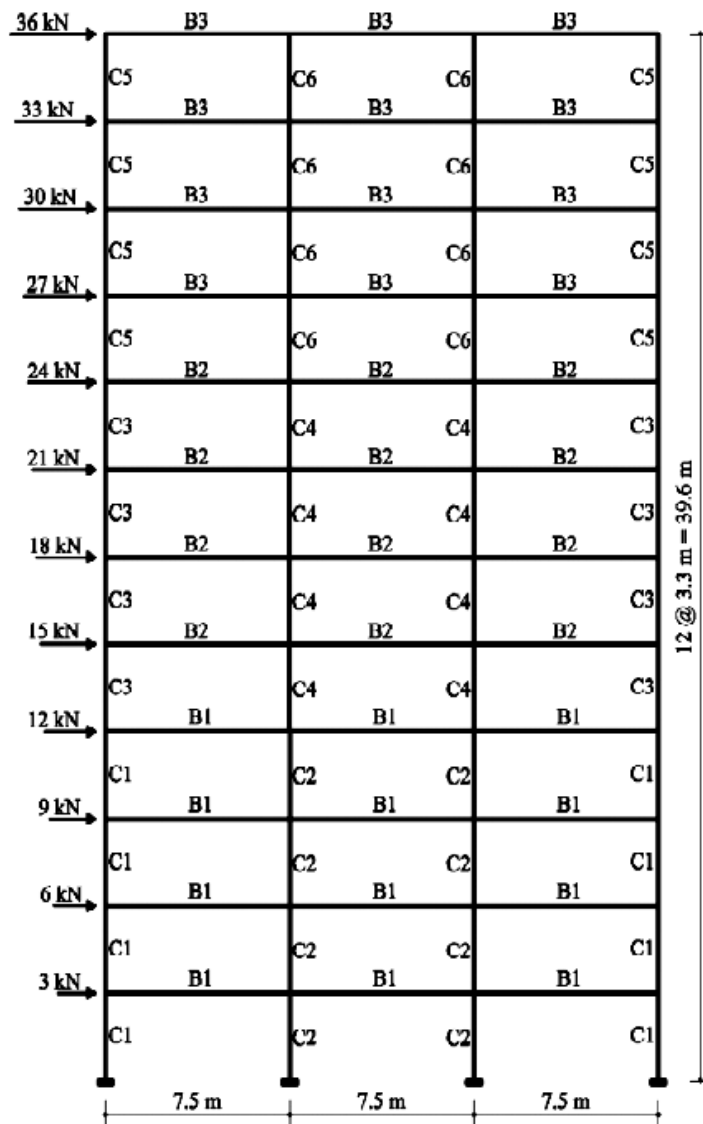
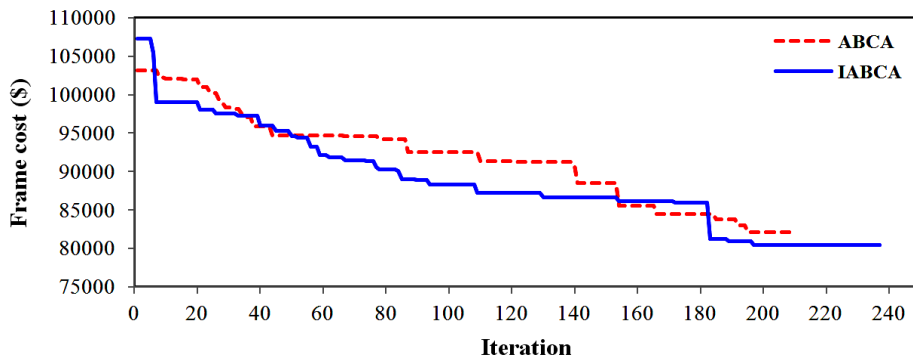Figure 8. Three bay, twelve-story RC frame

Figure 9. Convergence history of ABCA and IABCA for three bay, twelve-story RC frame

As well as the previous examples, in the present example also the optimum cost obtained by IABCA is less than that of the reported in [1]. Furthermore, the IABCA requires 16215 structural analyses which is less than the number of 54600 structural analyses required by the algorithm presented in [1].

6. CONCLUSIONS

The main objective of the current study is to develop an optimization model that is capable of obtaining the optimum design for reinforced concrete frames in terms of cross section dimensions and reinforcement details. The optimization task is carried out using ABCA and IABCA meta-heuristics, while still satisfying the strength and serviceability constraints of the ACI318M-08.

In this paper a computational strategy is applied to improve premature convergence issue of the ABCA and accuracy of the optimal frame costs. In this case, the performance of ABCA is improved by integrating a mechanism of bat algorithm (BA) in the onlooker phase of the ABCA. In the presented design examples, the optimum costs found by IABCA are slightly better compared with those of other algorithms. However, the computational demands of IABCA is considerably less in comparison with the other algorithms.

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