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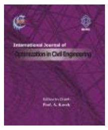

MOUTH BROODING FISH ALGORITHM FOR COST OPTIMIZATION OF REINFORCED CONCRETE ONE-WAY RIBBED SLABS

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ABSTRACT

In this paper, the optimum design of a reinforced concrete one-way ribbed slab, is presented via recently developed metaheuristic algorithm, namely, the Mouth Brooding Fish (MBF). Meta-heuristics based on evolutionary computation and swarm intelligence are outstanding examples of nature-inspired solution techniques. The MBF algorithm simulates the symbiotic interaction strategies adopted by organisms to survive and propagate in the ecosystem. This algorithm uses the movement, dispersion and protection behavior of Mouth Brooding Fish as a pattern to find the best possible answer. The cost of the system is considered to be the objective function, and the design is based on the American Concrete Institute’s ACI 318-08 standard. The performance of this algorithm is compared with harmony search (HS), colliding bodies optimization (CBO), particle swarm optimization (PSO), democratic particle swarm optimization (DPSO), charged system search (CSS) and enhanced charged system search (ECSS). The numerical results demonstrate that the MBF algorithm is able to construct very promising results and has merits in solving challenging optimization problems.

Keywords: mouth brooding fish algorithm; cost optimization; meta-heuristic algorithms; one -way ribbed slabs.

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1. INTRODUCTION

Optimization algorithms can be divided into two general categories of Gradient-based methods and metaheuristics. Metaheuristic algorithms are recent generation of the optimization

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approaches to solve complex problems. These methods explore the feasible region based on both randomization and some specified rules through a group of search agents.

The formulation of metaheuristic algorithms is often inspired by either natural phenomena or physical laws. Every metaheuristic algorithm consists of two phases: exploration of the search space and exploitation of the best solutions found. One of the main problems in developing a good metaheuristic algorithm is to keep a reasonable balance between the exploration and exploitation abilities [1].

There are several the well-known metaheuristic algorithms such as genetic Algorithm (GA) is introduced by Goldberg [2]. It is inspired by biological evolutions theory. Particle swarm optimization (PSO) is introduced by Eberhart and Kennedy [3]. It simulates social behavior, and it is inspired by the migration of animals in a bird flock or fish school. Ant Colony Optimization (ACO) is presented by Dorigo et al. [4]. It imitates foraging behavior of ant colonies. Simulated Annealing (SA) presented by Kirkpatrick et al. [5], harmony Search (SA) introduced by Geem et al. [6], Big Bang–Big Crunch algorithm (BB–BC) presented by Erol and Eksin [7]. Charged System Search (CSS) proposed by Kaveh and Talatahari [8]. Ray optimization (RO) proposed by Kaveh and Khayatazad [9]. water evaporation optimization (WEO) proposed by Kaveh and Bakhshpoori [10], colliding bodies optimization (CBO) algorithm originated by Kaveh and Mahdavi [11-12] and Kaveh et al. [13]. It simulates collision between two colliding bodies.

One of the recently developed metaheuristics is Mouth Brooding Fish algorithm (MBF) by Jahani and Chizari [14]. It is based on mouth brooding fish life cycle. This algorithm uses the movements of the mouth brooding fish and their children's struggle for survival as a pattern to find the best possible answer.

The main objective of the present study is to maximize or minimize one/some objective functions under some specific limitations. Thus, in this paper, the mouth brooding fish algorithm is used for optimization problems.

A reinforced concrete one-way ribbed slab (one-way waffle slab) comprises of hollow slabs which depth is more than solid slabs. For buildings with the small superimposed loads and the relatively large spans this system is the most economical such as in schools, hospitals, and hotels. Since the concrete in the tension zone is ineffective; this region is kept open between the ribs or filled with lightweight material to reduce the slab weight.

The present paper is organized as follows: In the next section, formulation of optimization problems is presented. In section 3, standard algorithm is briefly introduced. Section 4 consisting of the study of optimization of one civil constrained function. Conclusion is presented in section 5.

2. FORMULATION OF OPTIMIZATION PROBLEM

Optimization algorithms are utilized to maximize or minimize one/some objective functions under some specific limitations. These algorithms can be classified as multi-objective and mono-objective. In most of optimization problems, we deal with multi-objective functions; but for simplification, we have considered this problem as mono-objective and the penalty function approach has been used for handling the constraints. The mono-objective optimization problem can be stated as follows:

Find

$X = [x_1 . x_2 . \dots . x_n]$

To minimize

$Mer(X)$ (1) (1)

Subjected to

$g_j\,(X) \leq 0$, j=1,2,…,m

$x_{imin} \leq x_i \leq x_{imax}$

where X is the vector of all design variables with n unknowns; Mer(X) is the objective functions; g_j is the jth constraint from m inequality constraints. Also, x_{imin} and x_{imax} are the lower and upper bounds of design variable vector, respectively. the merit (or pseudo objective) function which should be minimized is defined as:

$$\mathrm{Mer(X)} = \mathrm{F(X)} \times \mathrm{f}_{penalty}\ \mathrm{(X)} = \mathrm{F(X)} \times \left(1 + \gamma \times \sum_{k=1}^{m} \max\big(0.\mathrm{g(X)}\big)\right) \quad (2)$$

where Mer(X) is the merit function; F(X) is the objective function; γ is penalty parameter and $f_{penalty}$(X) is the penalty function.

3. MOUTH BROODING FISH ALGORITHM

In the sea, many underwater creatures have strategies to protect themselves from harm, such as camouflage, not all have methods for protecting their young, too. Mouth brooders, however, are well-known for their ability to take care and protect their offspring, largely due to a very unusual technique. Mouth brooders protect their young by using their mouths as a shelter.

The way the mouth brooding fish (MBF) life cycle processes, has inspired the MBF algorithm. this algorithm has 5 controlling parameters which the user determines. These parameters are the number of population of cichlids (nFish), mother's source point (SP), the amount of dispersion (Dis), the probability of dispersion (Pdis), and mother's source point damping (SPdamp). the most important base of a MBF algorithm, is how cichlids surround their mother or in other words move around her, and the impacts of nature on their movements. The flowchart of the MBF is shown in Fig. 1 and the steps involved are given as follows:

- The main movements
- The additional movements
- Crossover
- Shark attack

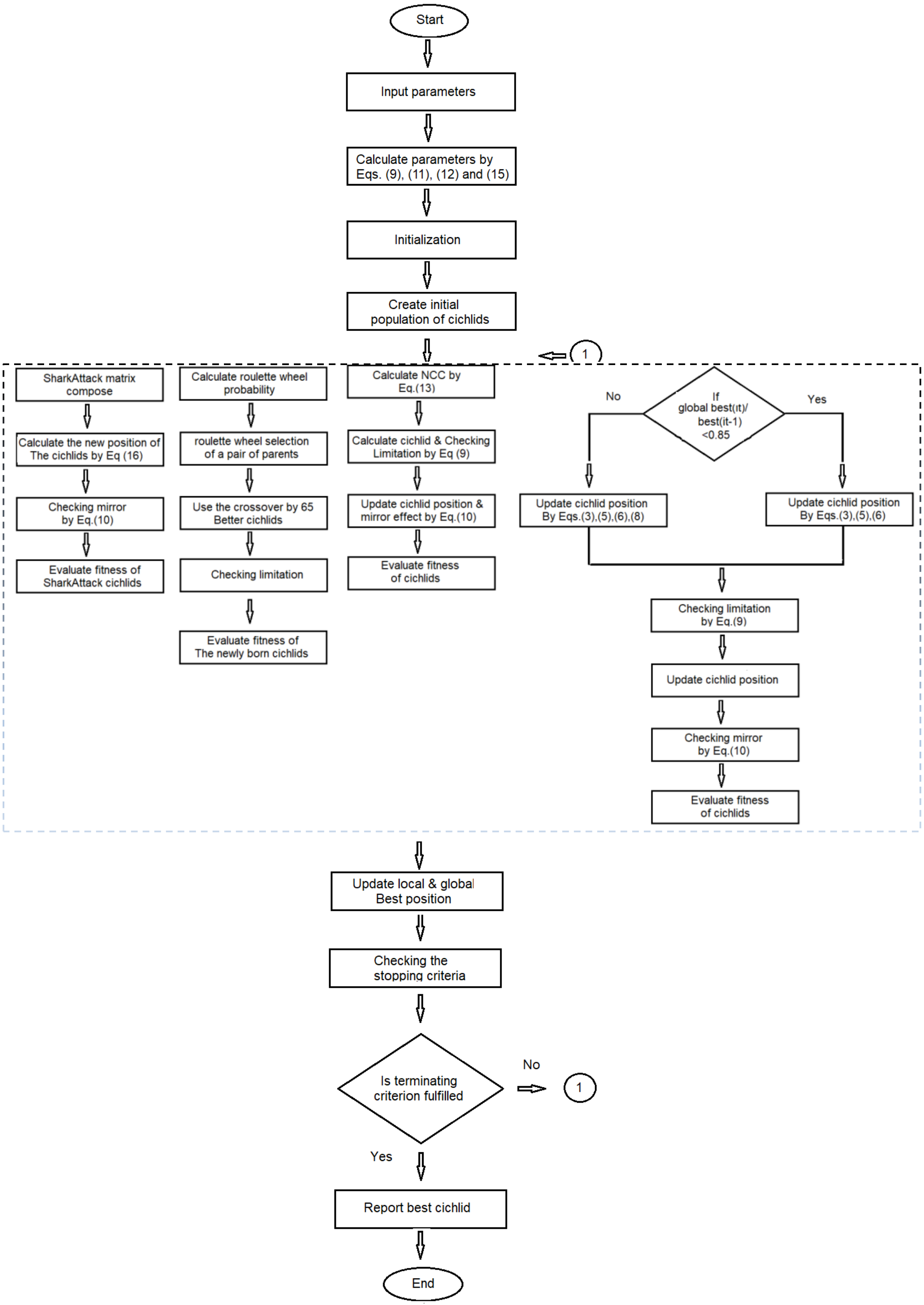

Figure 1. Flowchart of the MBF algorithm

3.1 The main movements

The main movements of each cichlid are calculated as follows:

$$\mathrm{A}_{sp} = \mathrm{SP} \times \mathrm{Cichlids} \cdot \mathrm{Movements} \tag{3}$$

where SP is the mother’s source point and Cichlids.Movements is the last movements of cichlids.

$$\mathrm{SP} = \mathrm{SP} \times \mathrm{SPdamp} \tag{4}$$

where SP is mother’s source point that changes for the next iteration and SPdamp is mother’s source point damp and varies between 0.85 and 0.95.

$$\mathrm{A}_{lb} = \mathrm{Dis} \times (\mathrm{Cichlids} \cdot \mathrm{Best} - \mathrm{Cichlids} \cdot \mathrm{Position}) \tag{5}$$

where Cichlids.Best is the best position that the cichlid gets through the past iterations and Cichlids.Position is the current position of the same cichlid. Dis is the am ount of dispersion that is one of the controlling parameters which is selected by the user and could increase or decrease the effect of this movement.

$$\mathrm{A}_{gb} = \mathrm{Dis} \times (\mathrm{Global} \cdot \mathrm{Best} - \mathrm{Cichlids} \cdot \mathrm{Position}) \tag{6}$$

where Global.Best is the best position found of all cichlids colony through passed iterations and Cichlids.Position is the current position for each cichlid.

$$\mathrm{NewN} \cdot \mathrm{F} \cdot \mathrm{P} = 10 \times \mathrm{SP} \times \mathrm{NatureForce} \cdot \mathrm{Position(SelectedCells)} \tag{7}$$

where NatureForce.Position(SelectedCells) is the selected cell from 60 percent difference cells of best position of last and current generation.

$$\mathrm{A}_{nf} = \mathrm{Dis} \times (\mathrm{NewN} \cdot \mathrm{F} \cdot \mathrm{P} - \mathrm{NatureForce} \cdot \mathrm{Position}) \tag{8}$$

where natureForce.Position is the best position of cichlids of the last iteration.

According to the main movements, each child can move no more than the additional surrounding dispersion positive or the additional surrounding dispersion negative (ASDP or ASDN).

The two parameters mentioned above are defined as:

$$\mathrm{ASDP} = 0.1 \times (\mathrm{VarMax} - \mathrm{VarMin})\,.\,\mathrm{ASDN} = -\mathrm{ASDP} \tag{9}$$

where VarMin and VarMax are the minimum and maximum limits of the problems variation respectively.

After that, we find a new position for cichlids if we add the calculated movements of cichlids to their current position. Now if their current position is out of the search space area, new movement is added by using the mirror effect (i.e. by negativing the movement changing the direction of movement) and it is defined as follows:

$$\mathrm{Cichlids} \cdot \mathrm{Movements} = -\,\mathrm{Cichlids} \cdot \mathrm{Movements} \tag{10}$$

where Cichlids.Movements is the movements of cichlids before and after of mirror effects. Each position of cichlids is also checked with search space limits (VarMin and VarMax) therefore no cichlids have left the search space area.

3.2 The additional movements

The mother can keep as many cichlids as its mouth capacity allows and the remaining members, which have to face up with challenges in nature, are named left out cichlids.

The number of left out cichlids is calculated as follows:

$$\mathrm{nm} = 0.04 \times \mathrm{nFish} \times SP^{-0.431} \tag{11}$$

where nFish is the population size of cichlids and SP is the mother’s source point and nm is the number of left out cichlids. These left out cichlids in order to survive from danger have to move further from the main movement that for this movement MBF algorithm uses another controlling parameter named probability of dispersion (Pdis) and it is between 0 and 1.

The number of cells for the chosen left out cichlids is calculated as follows:

$$\mathrm{NCC} = [\mathrm{nVar} \times \mathrm{Pdis}] \tag{12}$$

where NCC is the number of the cells that are to be changed. Left out cichlids have the second part of a movement, therefore, the limitation of movement is multiply by 4 as follows:

$$\mathrm{UASDP} = 4 \times \mathrm{ASDP} \,.\, \mathrm{UASDN} = -\mathrm{UASDP} \tag{13}$$

where UASDP and UASDN are the ultra-additional surrounding dispersion positive and negative limits for the left out cichlids movements.

The second part of movement is calculated as follows:

$$\mathrm{LeftCichlids} \cdot \mathrm{Position} = \mathrm{UASDP} \pm \mathrm{Cichlids} \cdot \mathrm{P(SelectedCells)} \tag{14}$$

where Cichlids.P(SelectedCells) are the randomly selected cells of cichlids by the number of NCC and LeftCichlids.Position is the new position of left out cichlids after the second part of movements.

3.3 Crossover

Mouth brooding fish allows its best cichlids to marry; thus, in the MBF algorithm by using a probability distribution or Roulette Wheel selection, we select one pairs of parents from each cichlid. The single point crossover by the probability of crossover of 65 percent of the better parent and 35 percent of another parent is conducted to generate the new fish. These newly born cichlids that have new position, take the place of their parents and their movement would be zero. Before evaluating the newly born fish with fitness function we should check that the new position for the generated children is in the search space area.

3.4 Shark attack

The number of cichlids for shark attack (effects of danger on cichlids) movements is calculated as follows:

$$\mathrm{nshark} = 0.04 \times \mathrm{nFish} \tag{15}$$

where nshark is the number of cichlids that is chosen for shark attack effect.

Shark attack affects 4 percent of cichlids population on position and movements as follows:

$$\mathrm{Cichlids \cdot NewPosition} = \mathrm{SharkAttack} \times \mathrm{Cichlids \cdot Position} \tag{16}$$

where SharkAttack is the matrix that holds the number of cells and how many times they have changed and Cichlids.Position is the randomly selected cichlids from 4 percent population.

4. NUMERICAL EXAMPLE

In this section the efficiency of the MBF algorithm, is studied through one structure example taken from the optimization literature. In this example the performance of this algorithm is studied for cost optimization of reinforced concrete one-way ribbed slabs.

This example is independently optimized 30 times. A comparison study of the obtained results is performed for the considered example.

In a reinforced concrete one-way ribbed slab optimization problem, the aim is to minimize the cost of the structure while satisfying some constraints. The six discrete design variables selected for modeling of the ribbed slab are shown in Fig. 2. These include the thickness of the top slab (X1), the rib spacing (X2), the rib width at the lower end (X3), the rib width at the top end (X4), the bar diameter (X5), and the rib depth (X6).

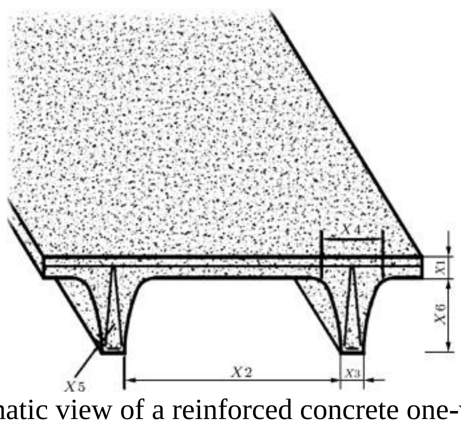

Figure 2. Schematic view of a reinforced concrete one-way ribbed slab

4.1 Optimum design process

Typical design of the ribbed slabs consists of two phases:
- Selecting random values for the variables and checking the dimensions according to the ACI 318.08 standard[15].
- Calculating the required reinforcement and checking the strength.

4.2 Objective function

The objective function of concrete ribbed slab optimization includes the costs associated with concrete and steel material as well as concreting and erecting the reinforcement. The optimal design of the concrete ribbed slab is determined by the minimum of these costs. This can be achieved by determining the optimal values for decision variables X1 to X6. The objective function can be expressed as follows:

$$\mathrm{Q} = \mathrm{Vconc} \times (\mathrm{C1} + \mathrm{C2}) + \mathrm{Wsteel} \times (\mathrm{C3} + \mathrm{C4}) \tag{17}$$

By considering $\bar{Q} = \mathrm{Q}/(\mathrm{C1} + \mathrm{C2})$ we have:
Minimized

$$\bar{Q} = [\mathrm{Vconc} + \mathrm{Wsteel}((\mathrm{C3} + \mathrm{C4})/(\mathrm{C1} + \mathrm{C2}))]/\mathrm{br} \tag{18}$$

where V_{conc} and W_{steel} are the volume of concrete and the weight of the reinforcement steel in the unit length (m3/m, kg/m), respectively; C1 and C3 are the costs of concrete and steel ($/kg for steel and $/m3 for concrete), respectively; C2 and C4 are the costs of concreting and erecting the reinforcement, respectively. br is the center-to-center distance of the ribs. Based on reviews and the cost estimation performed, a value of 0.04 for the coefficient $C(C = ((C3 + C4)/(C1 + C2))$ was obtained.

4.3 Design constraints

The formulation of the design problem is carried out according to the provisions provided in [16-18].

Flexural Constraint

The flexural constraint can be described in the following form:

$$M_u/(\emptyset_b M_n) \leq 1 \tag{19}$$

where M_u and M_n are the ultimate design moment and the nominal bending moment, respectively.

Shear Constraint

The shear constraint is presented in the following form:

$$V_u/(\emptyset_v V_n) \leq 1 \tag{20}$$

where V_u and V_n are the ultimate factored shear force and the nominal shear strength of the concrete, respectively. The concrete should carry the total shear because no stirrup is used in the slab. The shear strength V_c provided by the concrete for the ribs may be taken to be 10% greater than that of the beams. This is mainly due to the interaction between the slab and the closely spaced ribs.

Serviceability Constraints

The serviceability constraints are presented in terms of the limits on the steel reinforcement ratio and the bar spacing. The steel reinforcement ratio should satisfy the following constraint:

$$\rho \leq \rho_{max} = 0.75\rho_b \tag{21}$$

The minimum shrinkage steel ratio, $\rho_{\min}$, in the slab is 0.002 for slabs in which bars of grade 40 or 50 are utilized and 0.0018 for slabs in which deformed bars of grade 60 are used. The bar spacing should satisfy the following constraints:

- The minimum clear spacing between parallel bars in a layer, d_b, should not be less than 25 mm.
- The maximum spacing between the bars ≤ 5 times the rib thickness ≤ 450 mm (18 in.).

Deflection Constraints

The thickness of the top slab should not be less than 1/12 of the clear span between the ribs or 50 mm (2 in.). Based on the ACI code a minimum slab thickness h_{min} of L/16, L/18.5, L/21, or L/8 is required, depending on the support conditions. Here, L is the effective span length of the slab.

Other Constraints

The ribs should not be less than 100 mm in width, and should have a depth of no more than 3.5 times the minimum width of the rib. Clear spacing between the ribs should not exceed 750 mm. A limit on the maximum spacing of the ribs is required because of the special provisions permitting higher shear strengths and lower concrete protection for the reinforcement of these relatively small repetitive members.

4.4 Design

A minimizing problem of a one-way reinforced concrete ribbed slab simply supported at both ends is considered in this paper in order to examine the effectiveness of the above mentioned methods.

The general data for the example is provided in Table 3. The clear concrete cover is 20 mm. The design variables are shown in Table 4. The results of the optimum design are provided in Table 5 and Convergence curve of the MBF algorithm is shown in Fig. 3.

Table 5 compares the results of the optimum design for the one-way reinforced concrete ribbed slab attained by the Harmony Search, Colliding Bodies Optimization, Charged System Search, enhanced charged system search, Democratic Particle Swarm Optimization and Standard Particle Swarm Optimization algorithms. It should be noted that the weight obtained by MBF is much less than the weight obtained by the other algorithms.

Number of agent and iteration in this example are 30 and 200, respectively Investigation of the convergence curve in Fig. 3 shows that downfall of the curve, in initial steps, demonstrates the power of the method in exploration. This occurs in the first 10 iterations. Then, a local search is started and, in 25 iterations, the minimum solution is found.

Table 3: General data

f_y	420 Mpa
f_c'	28 Mpa
DL	0.78 kN/m^2
LL	4 kN/m^2
L	6 m
Cover	20 mm
Ws	78.5 kN/m3
Wc	24 kN/m3

Table 4: Design variables

Slab thickness (cm)	5, 7.5, 10
Rib spacing (cm)	40, 42.5, 45,…, 72.5, 75
Rib width at lower end (cm)	10, 12.5,…, 22.5, 25
Rib Width at toper end (cm)	10, 12.5,…, 27.5, 30
Bar diameter (cm)	1, 1.2, 1.4, 1.6, 1.8, 2
Rib depth (cm)	15, 17.5,…, 72.5, 75

Table 5: Results of the optimization

Algorithm	Slab thickness (cm)	Rib spacing (cm)	Rib width at lower end (cm)	Rib Width at toper end (cm)	Bar diameter (cm)	Rib depth (cm)	Weight ($/m2)	Number of analyses
HS[16]	5	60	10	10	1.4	35	1.3626	6000
PSO[17]	5	60	17.5	17.5	1.4	32.5	1.3184	6000
CBO[17]	7.5	67.5	10	10	1.4	30	1.2927	6000
DPSO[17]	7.5	67.5	10	10	1.4	30	1.2927	6000
ECSS [18]*	5	59	10	10	1.6	15	N/A	N/A
CSS[18]*	5	57	10	10	1.6	15	N/A	N/A
Present study(MBF)	5	60	10	10	1.4	25	1.1953	6000
*f_c'=21								

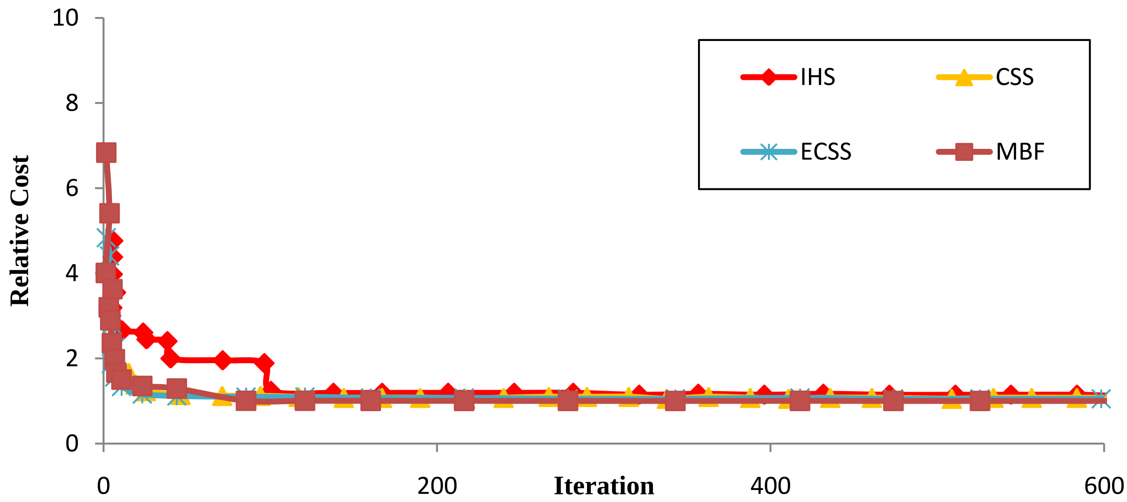

Figure 3. Convergence curves of the MBF, IHS[18], CSS[18] and ECSS[18] algorithms for RC One-Way Ribbed Slabs

5. CONCLUSIONS

In this article, the mouth brooding fish algorithm is utilized for structural cost optimization of a reinforced concrete one-way ribbed slab. This algorithm consists of three modules:

- A design module that performs the design of the ribbed slab.
- A cost module that computes the total cost of the ribbed slab.
- An optimization module that searches for optimal design alternatives.

The main objective of this paper is to study the convergence curve of this method for a concrete ribbed slab and compare the obtained values with results of harmony search, colliding bodies optimization, particle swarm optimization, democratic particle swarm optimization, charged system search and enhanced charged system search.

Based on the presented numerical example, the results obtained show that MBF method is powerful and efficient approaches for finding the optimum solution to structural optimization problems. This meta-heuristic algorithm can be used in many other engineering design problems to decrease the construction costs.

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