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A comparative study of several bio-inspired algorithms in cost optimization of cellular beams

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Abstract. Castellated beams are commonly used in steel construction. This study will focus on castellated beams with circular-shaped openings, which are known as cellular beams. Cost optimization of cellular beams is needed to maintain cost efficiency. The optimization considers the selection of a root beam, the diameter of holes, and the total number of holes in the beam as the variables. Four metaheuristic algorithms are used to optimize the design, namely, the particle swarm optimization (PSO), differential evolution (DE), symbiotic organisms search (SOS), and artificial bee colony (ABC). A four-meter span beam with a 50 kN point live load in the middle of the beam and a 5 kN/m uniformly-distributed dead load are taken as the case study. The results indicate that the SOS algorithm yields the best optimization results in terms of the average, consistency, and convergence behavior with a 30 out of 30 success rates.

1. Introduction

A castellated beam is a modification of a root beam with open sections on its web. The castellated beam is made by unifying two parts of beams which are already cut in desired patterns on its web as shown in Figure 1. This modification has a higher capacity by increasing the beam's inertia, depth, and section modulus with no additional weight of the beam itself [1]. Castellated beams are commonly used for medium to long-span floor systems. By using castellated beams, the underfloor service ducts can be installed through the web opening without adding the floor height [2]. Normally, the openings provided for castellated beams are in hexagonal or circular shape [3]. The ones with circular-shaped openings are often called cellular beams. Cellular beams are made by cutting in a half circular pattern through the web twice [1]. Cellular beams are the modern version of castellated beams. Cellular beams could produce tapered beams with lower cost and more efficiently than castellated beams due to its geometry flexibility [1]. Therefore, this study focuses on cellular beams.

Cost efficiency in civil engineering is very important to be considered. The cost of a cellular beam is mostly affected by the area of the steel section, the diameter of holes, and the number of holes. To minimize the cost, optimization of those variables is needed. The cost optimization problem could be solved using a bio-inspired algorithm. Bio-inspired algorithms have shown better optimization results compared to the traditional one. Traditional optimization sometimes faces problems to find global optimum, while bio-inspired algorithms are more adaptive in finding global optimum [4]. However, every bio-inspired algorithm has its concepts and weaknesses. This paper will focus on comparing the performance of four bio-inspired algorithms, that is, the particle swarm optimization (PSO) [5], differential evolution (DE) [6], symbiotic organisms search (SOS) [7], and artificial bee colony (ABC) [8].



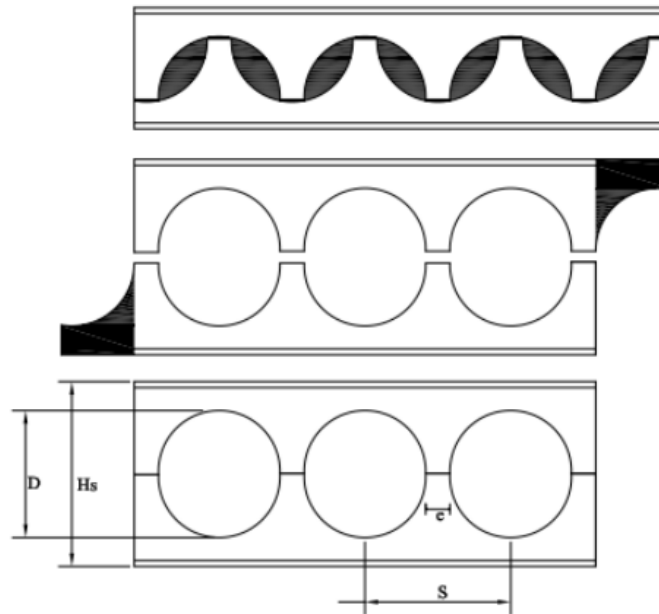


Figure 1. Cellular beams. Adapted from [9].

2. Review of bio-inspired algorithms

Bio-inspired algorithms are algorithms that are mostly based on animal behavior and Darwin's natural selection theory. This theory is used to find the fittest species which can survive in the environment. This paper specifically discuss algorithms that are inspired by the behavior of birds, bees, and ants [4].

2.1. Particle swarm optimization (PSO)

In the year of 1995 PSO was introduced by Kennedy and Eberhart [5]. The behavior of a group of fish or birds while searching for food is the inspiration of PSO's concept. In that case, the behavior of each bird or fish will affect the overall group's behavior. In the beginning, the location of each particle will be generated randomly. In each iteration, every particle will move using the information of the velocity vector given in equation (1) and renews its location using equation (2):

$$v_i(t+1) = Wv_i(t) + r_1C_1(xP_{\text{best}}(t) - x_i(t)) + r_2C_2(xG_{\text{best}}(t) - x_i(t)) \quad (1)$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (2)$$

where $v_i(t+1)$ is the particle's velocity, W is the inertia weight, $v_i(t)$ is particle's initial velocity, r_1 is a random number between 0 and 1, C_1 is a cognitive parameter, r_2 is a random number between 0 and 1, C_2 is a social parameter, $xP_{\text{best}}(t)$ is the location of individual best, $x_i(t)$ is the particle's initial location, $xG_{\text{best}}(t)$ is the location of group best, and $x_i(t+1)$ is the particle's new location.

2.2. Differential evolution (DE)

Storn and Price [6] introduced DE around 1997. The DE has four phases, namely, initialization, differential mutation, crossover, and selection. The initial population in the DE comes by randomizing numbers between the lower and upper bounds in the initialization phase. The mutation is the second phase of the DE. This phase takes the difference of two random vectors, named $X_{r2,G}$ and $X_{r3,G}$, multiplied by F then added to a third vector $X_{r1,G}$ to become mutant vectors $V_{i(G+1)}$. The equation can be seen in equation (3) where F is taken between 0 and 2.

$$V_{i(G+1)} = X_{r1,G} + F(X_{r2,G} - X_{r3,G}) \quad (3)$$

The third phase is crossover. This phase generates a trial vector $U_{j,I,(G+1)}$ which is a new vector developed by combining the target vector with the mutant vector. If $rand_{j,i} \leq CR$ or $j = I_{rand}$, the mutant vectors $V_{j,I,(G+1)}$ will enter the trial population as shown in equation (4), otherwise the initial vector $X_{j,I,(G+1)}$ is the one that joins the trial population like shown in equation (5). $rand_{j,i}$ is taken between numbers 0 and 1 while I_{rand} is obtained by randomizing integer form (1, 2, ..., D).

$$U_{j,I,(G+1)} = V_{j,I,(G+1)} \quad (4)$$

$$U_{j,I,(G+1)} = X_{j,I,(G+1)} \quad (5)$$

The last phase is selection. This phase is looking for vectors that will join the next generation group by taking the better value between the trial and target vector.

2.3. Symbiotic organisms search (SOS)

The SOS algorithm was introduced in 2014 by Cheng and Prayogo [7]. It obtains its inspiration from three types of symbiotic interactions between living things, that is, mutualism, commensalism, and parasitism. In the phase of mutualism, organisms will interact in a mutually beneficial relationship to improve their independent quality. If the results of the new organisms are better, then the organisms will be renewed. The new organisms are created using equation (6) - (8):

$$newO_i = O_i + r_1 [O_{best} - O_{average} (1 + ro_1)] \quad (6)$$

$$newO_j = O_j + r_2 [O_{best} - O_{average} (1 + ro_2)] \quad (7)$$

$$O_{average} = \frac{O_i + O_j}{2} \quad (8)$$

where $newO_i$ is the new candidate for O_i , O_i is the i -organism in the ecosystem, r_1 and r_2 are random numbers between 0 and 1, ro_1 and ro_2 are rounded values of random numbers between 0 and 1, O_{best} is the global best organism, $newO_j$ is the new candidate for O_j , and O_j is the j -organism in the ecosystem.

In the commensalism phase, the organisms will interact in a relationship where one organism takes advantage while the other one is given neither advantage nor disadvantage. Organism O_i with the randomly chosen organism O_j . This phase will only modify organism O_i . The new organism is created from the formula shown in equation (9) where r_3 is a random number between -1 and 1:

$$newO_i = O_i + r_3 [O_{best} - O_j] \quad (9)$$

In the parasitism phase, one of the organisms will be harmed while the other one gains advantage. Organism O_i will produce an artificial parasite organism where its value will then be compared to organism O_j . If the value of organism O_j is worse, then organism O_j will be replaced.

2.4. Artificial Bee Colony (ABC)

Karaboga and Basturk [8] in 2007 introduced a swarm-based metaheuristic algorithm called ABC. The intelligent behavior of honeybees when looking for food sources is the inspiration of this bio-inspired algorithm. ABC classified the bees into three groups, that is, employed bees which are connected to specific food sources, onlooker bees which choose a food source based on their observation on the dance of employed bees within the hive, and scout bees which look for food sources randomly.

In the initialization phase, the scout bees randomly discover food source locations. In the phase of employed bees, the bees exploit those food sources until they become exhausted. Employed bees whose food source location has been exhausted become scout bees who are looking for alternative food source

locations. The alternative food source location will be shared with the onlooker bees using equation (10):

$$newFood_i = Food_j + r_1 [Food_i - Food_j] \quad (10)$$

where $Food_i$ is the food source at i , r_1 is a random number between -1 and 1, $newFood_i$ is the modified food source at i after the onlooker bees' phase, and $Food_j$ is the food source at j chosen at random.

In the phase of the onlooker bees' group, the onlooker bees will use the probability provided by employed bees to choose the new location. In the scout bees' phase, the employed bees transform to scout bees and look for a new potential location to become an alternative in case the solution does not improve after a period of time. ABC optimization will stop the process if the number of iterations has obtained maximum iteration or the optimum value has been discovered.

3. Formulation of the cellular beam cost optimization problem

The main purpose of this study is to minimize the cost of cellular beams while considering all the constraints. When defining the cost of a cellular beam, a few factors such as the weight of the beam, cutting price, and welding price should be considered. The objective of the optimization is to obtain a vector is shown in equation (11):

$$\mathbf{x} = \{x_1 \quad x_2 \quad x_3\} \quad (11)$$

where x_1 is the selection of a root beam, x_2 is the diameter of hole (D_0), and x_3 is the total number of holes in the beam (NH). Variable x_1 affects the section area of the beam ($A_{initail}$). The cost of cellular beam is calculated using objective function shown in equation (12):

$$F_{\text{cost}} = \rho A_{\text{initail}} \left(L + \frac{S}{2} \right) P_1 + L_{\text{cut}} P_2 + L_{\text{weld}} P_3 \quad (12)$$

where ρ is the steel density, L is the span between two supports, S is the length from one hole's center to the other center, P_1 is the price of steel beam per unit weight, P_2 is the price of cutting per unit length, and P_3 is the price of welding per unit length. This paper uses dollars for all the price unit. L_{cut} is the length of cut steel, which is calculated using equation (13):

$$L_{\text{cut}} = \pi D_0 NH + 2e(NH + 1) + \frac{\pi D_0}{2} + e \quad (13)$$

while L_{weld} is the length of welded steel, which is calculated using equation (14):

$$L_{\text{weld}} = e(NH + 1) \quad (14)$$

where e is the clear distance between each hole (see Figure 1). The design should fulfil the following limitations (see Figure 2 and Figure 3) as shown in equation (15)-equation (26):

$$g_1 = S - 1.6D_0 \leq 0 \quad (15)$$

$$g_2 = 1.08D_0 - S \leq 0 \quad (16)$$

$$g_3 = H_s - 1.75D_0 \leq 0 \quad (17)$$

$$g_4 = 1.25D_0 - H_s \leq 0 \quad (18)$$

$$g_5 = M_u - M_p \leq 0 \quad (19)$$

$$g_6 = V_{\text{hmax}} - P_{\text{vh}} \leq 0 \quad (20)$$

$$g_7 = V_{\text{omax}} - P_{vy} \leq 0 \tag{21}$$

$$g_8 = V_{\text{supmax}} - P_v \leq 0 \tag{22}$$

$$g_9 = M_{\text{aamax}} - M_{\text{wmax}} \leq 0 \tag{23}$$

$$g_{10} = \frac{P_0}{P_u} + \frac{M}{M_p} - 1 \leq 0 \tag{24}$$

$$g_{11} = V_{\text{tee}} - 0.5P_{vy} \leq 0 \tag{25}$$

$$g_{12} = Y_{\text{max}} - \frac{L}{360} \leq 0 \tag{26}$$

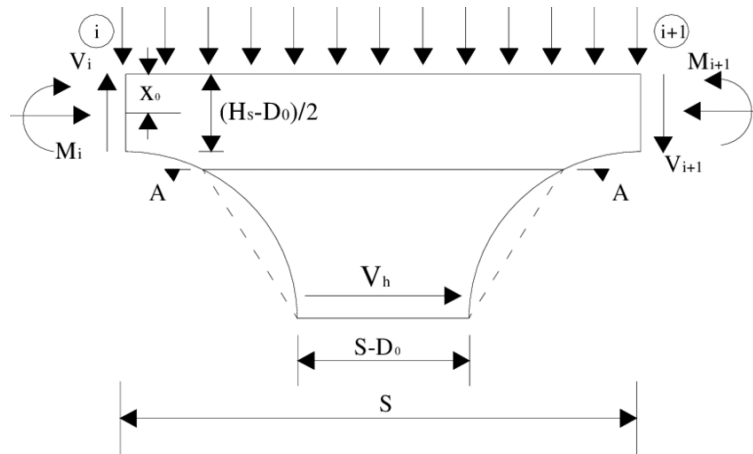


Figure 2. Horizontal shear in cellular beam. Adapted from [9].

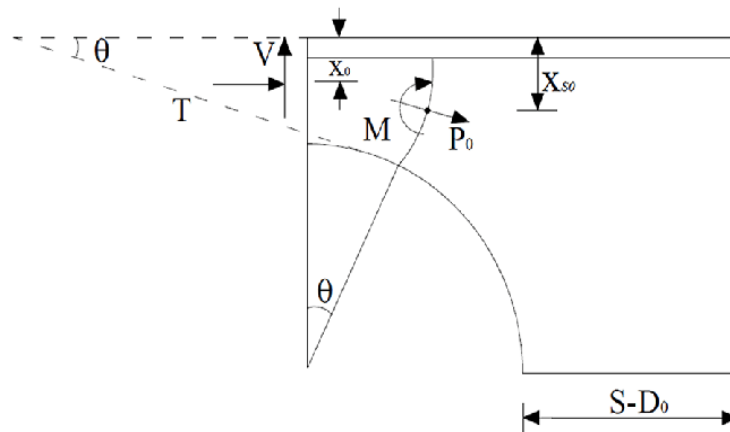


Figure 3. Olander's curved beam approach. Adapted from [9].

where:

H_s is the total height of the cellular beam,

M_u is the maximum moment,

M_p is cellular beam's plastic moment capacity,

V_{hmax} is maximum horizontal shear,

P_{vh} is the total horizontal shear capacity of tee section,
 V_{omax} is maximum shear at the opening,
 P_{vy} is the total vertical shear capacity of tee section,
 V_{supmax} is the maximum shear at support,
 P_v is total shear capacity of tee section,
 M_{aamax} is the maximum moment at A-A section as shown in Figure 2,
 M_{wmax} is the maximum permitted web post moment,
 P_o and M are the internal forces on the web as shown in Figure 3,
 P_u and M_p is the tee's section axial and moment capacity at an angle θ as shown in Figure 3,
 V_{tee} is the vertical shear on the tee at $\theta = 0^\circ$ of web opening, and
 Y_{max} is the maximum deflection of the cellular beam.

4. Cellular beam cost optimization procedures

The PSO, DE, SOS, and ABC algorithms were coded in MATLAB R2019a. Optimization runs were executed on a laptop with a 3.18 GHz Intel Core I5-7200U processor and 8GB of RAM memory. The algorithms search an optimal selection of a root beam, the diameters of holes, and the total number of holes in the beam. The program will run until it reaches the maximum iteration set.

Whenever the solution violates the constraints, \$1000 penalty is added to the objective function. This study uses 50 populations and 30 repetitions for each to examine the algorithms' consistency. This study considers the difference of function evaluation in each algorithm. Therefore, the number of iterations is taken as 200 iterations for PSO, ABC, and DE, while SOS uses 50 iterations as it has 4 function evaluations. The parameters for each algorithm are shown in Table 1.

Table 1. Parameter Setting of the Algorithms.

PSO	DE	SOS	ABC
$n = 50$	$n = 50$	$n = 50$	$n = 50$
$c_1 = 1$	$F = 0.2 - 0.8$		$n_{Onlooker} = 50$
$c_2 = 1$	$p_{CR} = 0.2$		$L = 90$
$w = 0.9$			$a = 1$

Note: n = population size/ecosystem size/colony size; c_1 = cognitive coefficient; c_2 = social coefficient; w = inertia weight; F = scaling factor; p_{CR} = crossover probability; $n_{Onlooker}$ = number of onlooker bees; L = trial limit; a = acceleration coefficient upper bound

The results from four algorithms were then analysed to compare their performance using statistical analysis, such as the median, the average, and the standard deviation. The optimization process flow chart of the cellular beam is shown in Figure 4.

5. Test Problems and Results

A four-meter span beam with simply supported idealization as shown in Figure 5 is selected for problem example [1, 9]. The problem example is taken from several previous studies as the benchmark to compare the results. The beam is loaded with a 50 kN point live load at the center of the beam and a 5 kN/m uniformly-distributed dead load including the cellular beam's weight. The steel used for design is Grade 50 and has the modulus elasticity of 205 kN/mm². The steel weight density is 78.5 kN/m³. P_1 , P_2 , and P_3 is taken as \$0.85, \$0.3, and \$1 respectively.

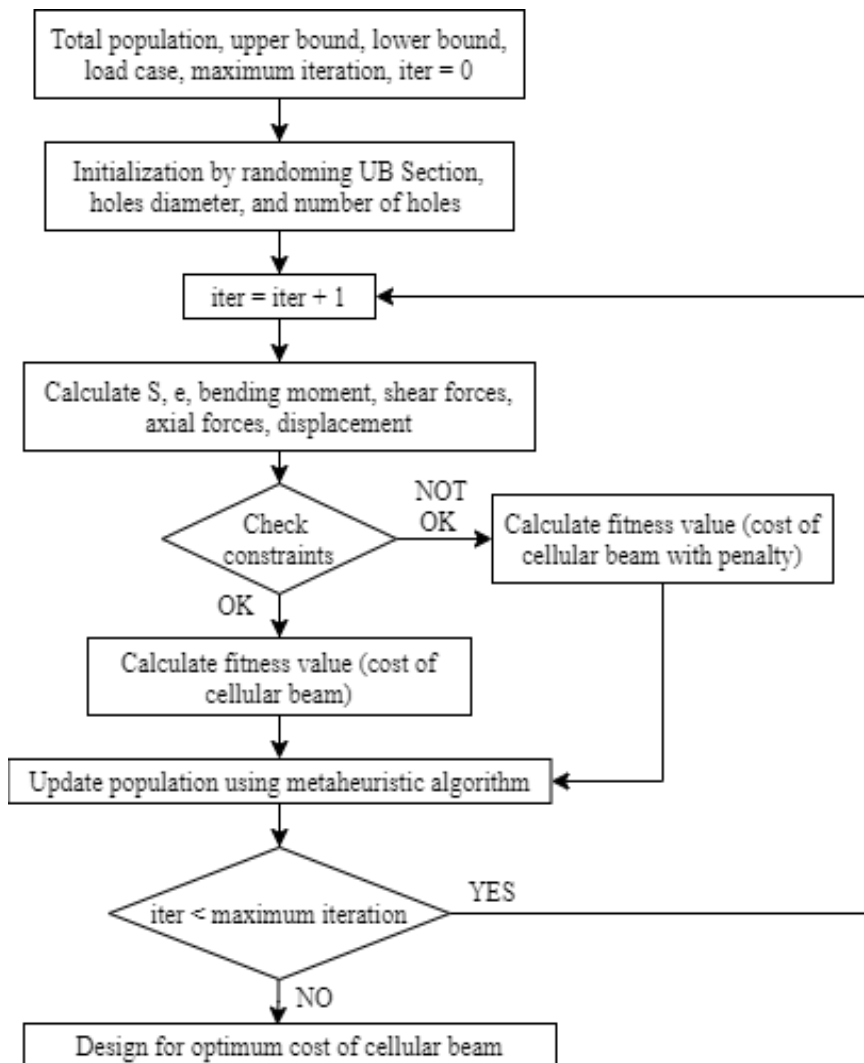


Figure 4. Flow chart for cost optimization of cellular beam.

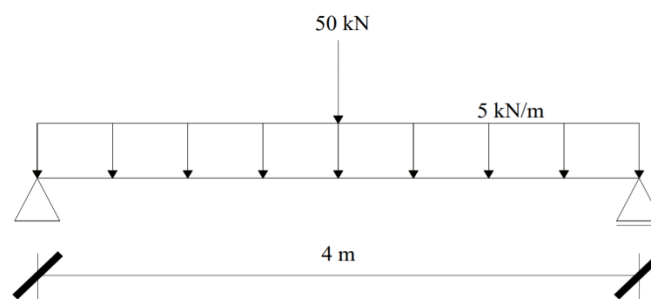


Figure 5. Simply supported 4-m span beam.

To solve the problem, three variables, that are, the selection of a root beam, the diameter of holes, and the total number of holes in the beam need to be randomized. The first variable is selected from a data set that is composed of 89 Universal Beam (UB) sections from 254 x 102 x 28 to 914 x 419 x 388. The diameter of holes and the total number of holes is taken between 180 mm to 600 mm and 2 to 39 holes, respectively [1].

Table 2 shows that the four algorithms could find the optimal cost, that is \$91.562, from 30 times of run in the program. The table also contains the median result of four algorithms, the statistical analysis from 30 repetitions, and the average of computational time. The success rate is counted based on the results with no constraints violated. The DE, SOS, and ABC have a 100% success rate while the PSO has only about 86%. The table shows that the SOS has the smallest standard deviation among other algorithms. It shows that the SOS has the best consistency compared to the DE, ABC, and PSO. This convergence behavior can be seen clearly through the convergence graph shown in Figure 6. The convergence graph is drawn from the best fitness from each function evaluation on the 15th trials for ABC, SOS, and DE while PSO is taken on the 12th trials. The graph only presents up to 5000th function evaluation, since there is no improvement on the cost optimization afterward. The DE is the first algorithm that found the optimal cost, followed by the SOS. On the other hand, ABC and PSO are not able to find optimal cost. Figure 7 shows the iteration process from the initialization to the final design, which in this paper PSO algorithm is taken as an example.

Table 2. Optimizations results from 4 algorithms.

Variables	PSO	DE	SOS	ABC
x_1	85	85	85	85
x_2	249	249	249	249
x_3	14	14	14	14
Best (\$)	91.562	91.562	91.562	91.562
Average (\$)	97.633	92.939	91.562	92.371
Worst (\$)	103.577	123.564	91.562	94.060
Stdev (\$)	6.070	5.841	0	0.644
Median (\$)	98.399	91.562	91.562	92.235
Success Rate	26/30	30/30	30/30	30/30
Average Time (s)	0.2754	0.4651	0.2445	1.0150

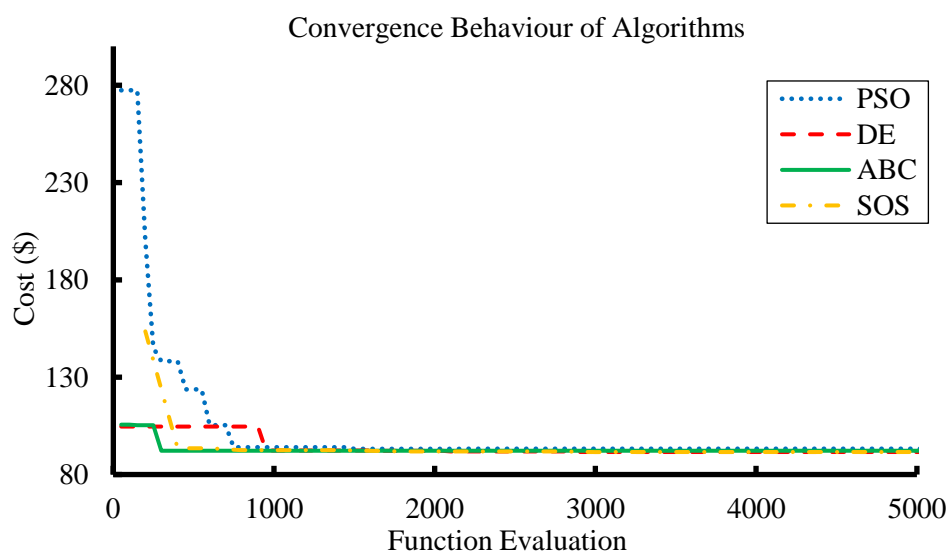


Figure 6. Convergence behaviour of PSO, DE, ABC, and SOS algorithms.

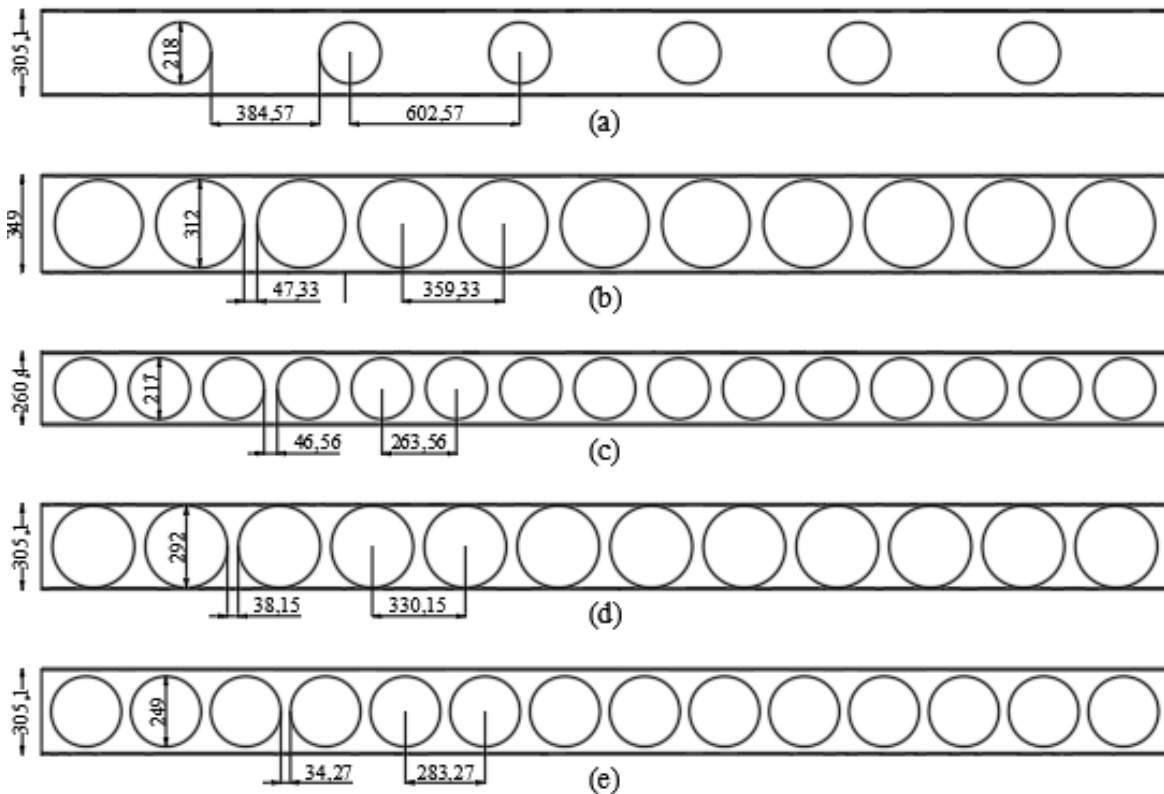


Figure 7. PSO results for: (a) initial design, (b) 1st iteration, (c) 3rd iteration, (d) 13th iteration, (e) final design.

6. Conclusions

This paper compares four algorithms, that is, the SOS, ABC, DE, and PSO to optimize the cost of a cellular beam using a case study. The optimization takes UB sections, hole diameter, and the total number of holes into considerations. Using 200 numbers of iterations, the optimal cost is \$91.5622. Comparing all the results, PSO performed worst in this case with a success rate of 26 out of 30. On the other hand, SOS performs consistently in all 30 independent runs. The SOS also gives the best average, consistency, and convergence behavior. Therefore, the SOS is the most suitable algorithm to optimize the cost of cellular beam.

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