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RESEARCH PAPER

Weight Optimization of Truss Structures by the Biogeography-Based Optimization Algorithms

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ABSTRACT: The fundamental concepts of biogeography-based optimization (BBO), a meta-heuristic algorithm, have been inspired by the geographical distribution of animals. This algorithm does not need a starting point, and performs a random search instead of a gradient-based search. In this article, for the first time, the weights of 2D and 3D trusses with specific geometries and different stress and displacement constraints have been optimized by using the BBO approach. Also, in this work, the numerical results achieved by other researchers through various optimization techniques have been compared with the results obtained from the Particle Swarm Optimization (PSO), Differential Evolution (DE) and BBO algorithms. It has been demonstrated that the search and exploration capability of the BBO algorithm is superior to that of the DE and PSO algorithms, and that it achieves better results than the other optimization techniques considered in this paper. This superiority is due to the excellent exploration capability of the BBO algorithm and the fact that it achieves a favorable optimal solution in the initial iteration.

Keywords: Biogeography-Based Optimization, Meta-Heuristic Algorithms, Weight Optimization.

1. Introduction

Different algorithms have been used in recent decades to solve various truss optimization problems. The truss optimization methods can be divided into three general categories: i) Optimization of truss size; ii) Optimization of truss shape and; iii) Optimization of truss topology

In the first method, the cross sectional area of truss elements is considered as the decision variable and the truss weight is usually the objective function. In the second approach, the coordinates of nodes constitute the decision variable, and in the third approach, the issue of concern is the locations of joints connecting the truss elements.

Some researchers have employed various meta-heuristic methods (GA, PSO, ACO algorithms, etc.) for the optimization of trusses (Arora, 2012). Simon (2008) introduced an optimization algorithm (BBO) based on the geographical distribution of living organisms for solving constrained and unconstrained optimization

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problems. The efficacy and superiority of the BBO algorithm was verified by comparing its results with those of the other algorithms including the genetic algorithm and the particle swarm optimization.

By employing the strain energy as the objective function, Nguyen and Lee (2015) were able to combine the size, shape and topology optimizations of truss structures. Artar (2016), Jalili and Hosseinzadeh (2015, 2018), Jalili et al. (2016) and Husseinzadeh Kashan et al. (2018) have conducted comparative studies on the optimal design of multi-element truss structures. Fedorik et al. (2015) have used the Finite Element method in the design optimization techniques for solving structural engineering problems. In a study by Massah and Ahmadi (2017), optimization techniques were employed to create a more regularized configuration and geometry for any structural plan by minimizing the types of elements considered in the design. Artar and Daloglu (2015) have investigated the optimal design of planar steel frames. Evolutionary algorithms have been widely used for engineering optimization. For instance, Khalkhali et al. (2014) applied the Genetic Algorithm to optimize the sandwich panels with corrugated cores. In another work, khalkhali et al. (2016) used the particle swarm optimization technique to optimize perforated square tubes. The PSO algorithm was also employed by Meshkat Razavi et al. (2015) for the optimization of tuned mass dampers and by Mousavian et al. (2015) for the optimal analysis of hydraulic systems.

In the present study, the BBO algorithm is used for the first time to optimize the weights of 2D and 3D trusses with specific geometries and with different stress and displacement constraints. It is demonstrated that the BBO algorithm is superior to the PSO and DE algorithms in searching the solution space and finding the optimal solutions. The software programs of "SAP2000" and "MASTAN2" are employed to evaluate the results obtained in this investigation and to verify their accuracy.

2. Structure Optimization Method

Some structure optimization problems can be classified as nonlinear programming problems (NLP). In truss optimization problems, the decision variables include the dimensions of the truss members' cross sections. In these problems, the objective function is the truss weight, and the decision variables must satisfy certain constraints (e.g., stress constraints, displacement constraints, etc.). A general structure optimization problem can be expressed as:

$$Minimize: f(x) = f(x_1, x_2, \dots, x_i), \quad i = 1, 2, \dots, n \tag{1}$$

$$Subject\ to:\ g_j(x) = g_j(x_1, x_2, \dots, x_j) \leq 0 \quad j = 1, 2, \dots, m \tag{2}$$

$$h_k(x) = h_k(x_1, x_2, \dots, x_k), \quad k = m+1, \dots, m+L \tag{3}$$

where $f(\boldsymbol{x})$: denotes the objective function (i.e., the truss weight), and $\boldsymbol{x}$: is the vector comprising the design variables. The number of decision variables and the number of inequality constraints ($g_j(\boldsymbol{x}) \leq 0$) are indicated by parameters n and m, respectively; and the number of equality constraints ($h_k(\boldsymbol{x}) = 0$) is represented by L.

3. The Considered Optimization Algorithms

In this study, the weights of some truss structures have been optimized by means of the Differential Evolution (DE), Particle Swarm Optimization (PSO) and Biogeography Based Optimization (BBO) algorithms, and the achieved results have been compared. These algorithms are introduced and described briefly in the following sections.

3.1. The Biogeography-Based Optimization (BBO) Algorithm

This algorithm has been inspired by the

natural world and it is based on the way animals migrate from a region or an island with lots of rivals to a less populated region with fewer rivals. Based on this algorithm, the more habitats a region has, the more suitable it is for living from a biological perspective and, thus, a higher fitness value it gets. In this algorithm, the optimization steps are implemented with the organisms migrating from the islands with higher fitness values to those with lower fitness values. The mathematical biogeography models express the way the organisms migrate and also indicate how a new organism emerges or becomes extinct. In this algorithm, the habitats with more suitable living conditions get a higher Habitat Suitability Index (HSI) than the other habitats. The ‘HSI’ in this case is equivalent to the fitness function or the objective function in the other algorithms; and the goal is to optimize the HSI value for each island or habitat. Also, the variables that define the habitability of a region are known as the Suitability Index Variables (SIVs). Hence, the SIVs are the independent parameters, while the HSI is the dependent parameter of a habitat (Massah and Ahmadi, 2017). The biogeography-based optimization algorithm runs through the following steps (Simon, 2008):

1) Initialize a set of solutions for the problem;
2) Compute a “fitness” (HSI) value for each solution;
3) Compute the values of S, λ and μ for each solution;
4) Modify the habitats (migration) based on the λ and μ values;
5) Perform mutation;
6) Implement typical elitism;
7) Go back to Step 2 if necessary.

3.2. The Particle Swarm Optimization (PSO) Algorithm

This algorithm was presented by Kennedy and Eberhart (1995). The development of the PSO algorithm is based on the social lives of fish and birds that live in schools and colonies and fulfill many of their basic needs, including the search for food, collectively and by using the swarm intelligence. In this algorithm, any particle in the search space is considered to be a solution to the optimization problem, and a group of particles is called a swarm. Depending on the quality of each particle’s response, a certain fitness value is assigned to that particle. This value is determined by means of a fitness function or an objective function. Each particle also has a velocity vector, which is updated (in every iteration) based on the particle’s experience, the experience of other particles, and the particle’s last speed.

3.3. The Differential Evolution (DE) Algorithm

The Differential Evolution (DE) algorithm introduced by Storn and Price (1997) has been explained in detail by Arunachalam (2008). This algorithm uses the mutation and natural selection operations as the main tool for conducting a search and directing it toward the prospective regions in the solution space. The major difference between GA and DE is that the former relies on crossover as a probabilistic mechanism for exchanging useful information among solutions to find better ones, while the latter uses mutation as the primary search mechanism.

4. Numerical Examples

The following examples show the higher accuracy, efficiency and execution speed of the “BBO” algorithm in the optimization of structures with respect to other considered methods.

4.1. A 10-Bar Planar Truss with 6 Nodes

The truss in Figure 1 has been numerically investigated by many researchers, including Ghasemi et al. (1997), Farshi and Ziazi (2010), Li et al. (2009) and others. The weight per unit volume of truss members is 0.1 lb/in^3 and their elastic modulus is 104 ksi (68947.54

MPa). The allowable stress for each element, whether in tension or compression, is ± 25 ksi (± 172.37 MPa), and each node's permitted displacement in any direction (x or y) is ± 2 in (± 5.08 cm). The weight of this truss with continuous variables is assessed with regards to P1 = 100 kips. The cross sections of all truss elements have a minimum area of 0.1 in^2 and maximum area of 35 in^2. The length 'a' in Figure 1 is equal to 360 in (9144 mm). Using the penalized technique, the objective function for this truss is obtained as:

$$f(A) = \left(\sum_{i=1}^{10} \rho_i L_i A_i\right) * (1 + \beta\vartheta)^{\alpha} \quad (4)$$

$$\vartheta = \sum_{j=2}^{3} max(0, g_j) \quad (5)$$

$$A = \{A_1, A_2, \ldots, A_{10}\} \quad (6)$$

$$g_1: \quad 0.1\, in^2 \leq Ai \leq 35\ in^2 \quad i = 1, 2, \ldots, 10 \quad (7)$$

$$g_2: \quad (\sigma_i/\sigma_{all}) - 1 \leq 0 \quad i = 1, 2, \ldots, 10 \quad (8)$$

$$g_3: \quad (\delta_j/\delta_{all}) - 1 \leq 0 \quad j = 1, 2, \ldots, 6 \quad (9)$$

After analyzing the problem and applying the constraints, the performance curves and data for the BBO algorithm are obtained and presented in Figure 2 and Table 1. By examining this figure and table, the efficiency of the BBO algorithm is confirmed. For example, in Figure 2, the BBO achieves a cost value of 5460 in iteration 50, while the PSO (which is a powerful algorithm) yields a value of 5780. It is also observed that even in the first 100 iterations, the BBO algorithm achieves a good approximation of the solution.

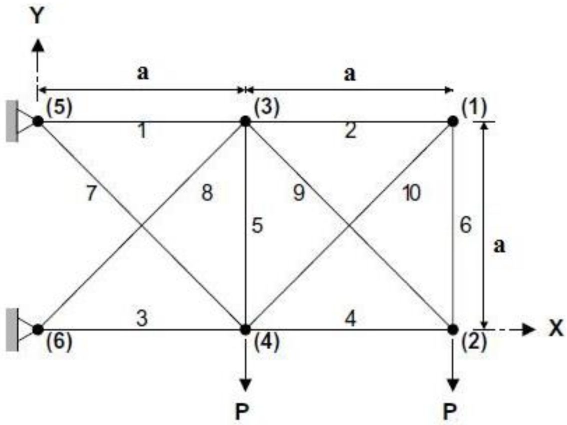

Fig. 1. The 10-bar 2D truss

Table 1. Comparison of different optimization schemes for the 10-bar 2D truss

Variables	**Schmit and Farshi (1974)**	**Schmit and Miura (1976)**	**Gellatly and Berke (1971)**	**Dobbs and Nelson (1976)**	**Rizzi (1976)**	**Khan et al. (1979)**	**This work**		
							DE	**PSO**	**BBO**
A1	33.43	30.67	31.35	30.5	30.73	30.98	30.68	30.78	30.42
A2	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
A3	24.26	23.76	20.03	23.93	23.93	24.17	23.08	23.37	23.14
A4	14.26	14.59	15.6	15.43	14.73	14.81	15.13	14.98	15.19
A5	0.1	0.1	0.14	0.1	0.1	0.1	0.1	0.1	0.1
A6	0.1	0.1	0.24	0.21	0.1	0.41	0.53	0.51	0.54
A7	8.39	8.58	8.35	7.65	8.54	7.547	7.49	7.53	7.46
A8	20.74	21.07	22.21	20.98	20.95	21.05	21.10	21.59	21.07
A9	19.69	20.96	22.06	21.82	21.84	20.94	21.49	20.84	21.64
A10	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
Weight (lb)	5089	5076.85	5112	5080	5076.66	5066.98	5061.18	5060.99	5060.76

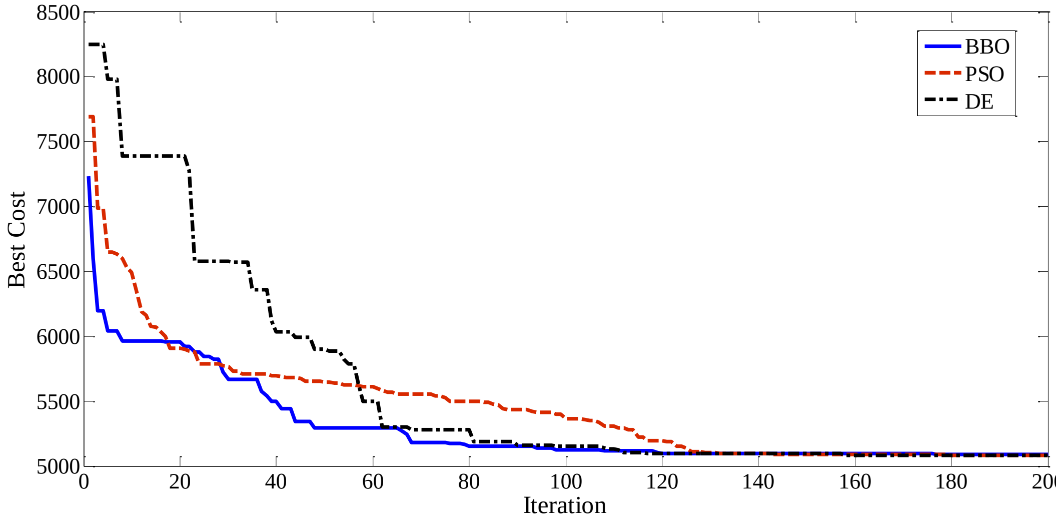

Fig. 2. The convergence of different algorithms to the optimal weight in the 10-bar 2D truss

4.2. A 17-Bar Planar Truss with 9 Nodes

Many researchers have investigated the 17-bar 2D truss shown in Figure 3, including Lee and Geem (2004) and Adeli and Kumar (1995). The material density and the elastic modulus of this system are 0.268 lb/in^3 and 30,000 ksi, respectively. The truss members undergo a maximum stress of ± 50 ksi, and the maximum displacement of truss nodes is considered to be ± 2.0 inches in both principal directions. A single vertical downward load of 100 kips is applied at node 9. No linking between design variables is considered, thus there are 17 independent design variables. The truss elements have a minimum cross-sectional area of 0.1 in^2. The results of this study and other analyses are compared in Figure 4 and Table 2.

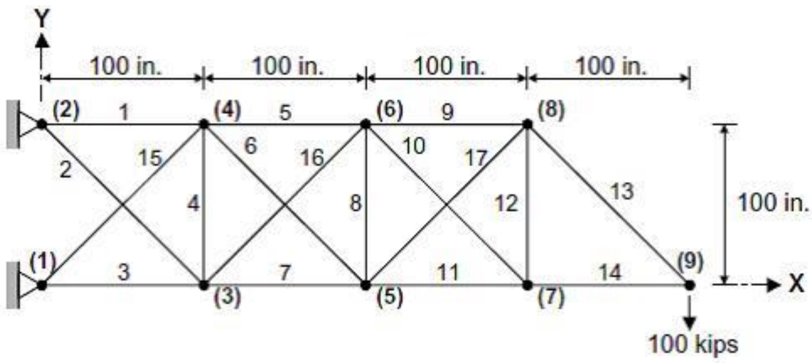

Fig. 3. The element and node numbering system for the 17-bar planar truss

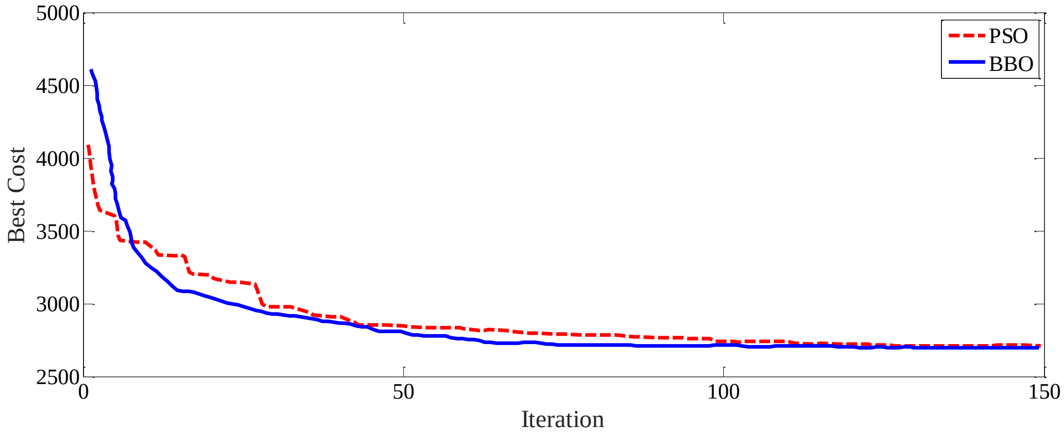

Fig. 4. The convergence of different algorithms to the optimal weight in the 17-bar planar truss

Table 2. Comparison of various optimization schemes for the 17-bar planar truss

Variables	Adeli and Kumar (1995)	Khot and Berke (1984)	This work	
			PSO	BBO
A1	16.03	15.93	16.05	15.94
A2	0.11	0.1	0.1	0.1
A3	12.18	12.07	12.07	12.09
A4	0.11	0.1	0.1	0.1
A5	8.42	8.07	8.08	8.04
A6	5.72	5.56	5.59	5.57
A7	11.33	11.93	11.88	11.92
A8	0.11	0.1	0.1	0.1
A9	7.30	7.95	7.86	7.94
A10	0.12	0.1	0.1	0.1
A11	4.05	4.06	4.11	4.05
A12	0.10	0.1	0.1	0.1
A13	5.61	5.66	5.70	5.66
A14	4.05	4	4.01	4.01
A15	5.15	5.56	5.50	5.56
A16	0.11	0.1	0.1	0.1
A17	5.29	5.58	5.53	5.58
Weight (lb)	2594.42	2581.89	2582.02	2581.89

4.3. A 72-bar space truss with 20 nodes

The 3D space truss displayed in Figure 5 has also been studied by several investigators, including Adeli and Cheng (1993), and Schmit and Farshi (1974). In this example, the weight per unit volume of truss members is 0.1 lb/in^3 and their elastic modulus is 10000 ksi. Two loading cases are applied to this space truss according to Table 3, and the optimization should be performed simultaneously for both of these loading cases.

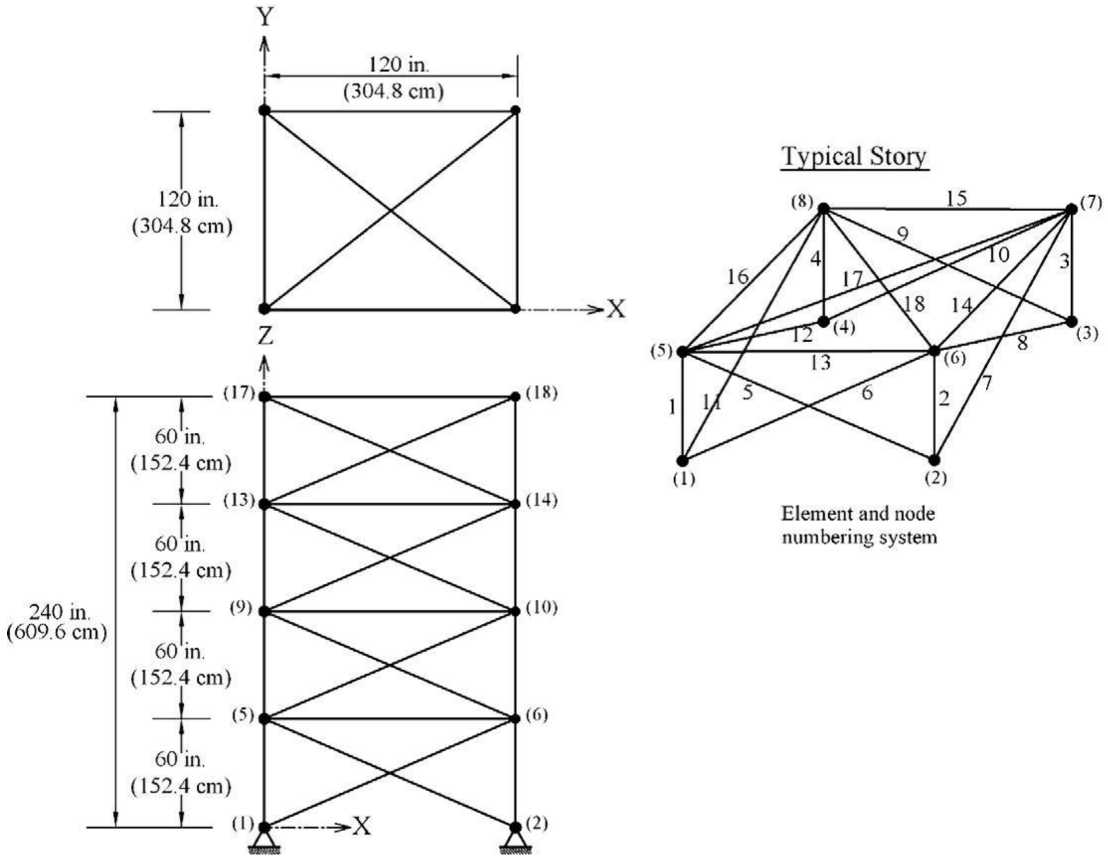

Fig. 5. The element and node numbering system for the 72-bar space truss

Table 3. Different loading conditions for the 72-bar space truss

Load case	Node No.	Px (kips)	Py (kips)	Pz (kips)
1	17	5	5	-5
2	17	0	0	-5
	18	0	0	-5
	19	0	0	-5
	20	0	0	-5

Another constraint considered in this problem is that the 3D truss must remain simultaneously symmetrical about the ‘x’ and ‘y’ axes. To this end, the similar truss elements have been grouped together (Table 4). The elements are subjected to stress limitations of ± 25 ksi, and the upper nodes of the truss (nodes 17-20) are allowed to move only 0.25 in. Also, a minimum area of 0.1 in^2 has been considered for the cross sections of truss members. The grouping of truss elements, for fulfilling the symmetry constraint, is shown in Table 4. The results pertaining to this and other studies are compared in Figure 6 and Table 5.

Table 4. Grouping the similar elements in the 72-bar space truss

Group IDs	Area of group elements
1	$A_1 \sim A_4$
2	$A_5 \sim A_{12}$
3	$A_{13} \sim A_{16}$
4	$A_{17} \sim A_{18}$
5	$A_{19} \sim A_{22}$
6	$A_{23} \sim A_{30}$
7	$A_{31} \sim A_{34}$
8	$A_{35} \sim A_{36}$
9	$A_{37} \sim A_{40}$
10	$A_{41} \sim A_{48}$
11	$A_{49} \sim A_{52}$
12	$A_{53} \sim A_{54}$
13	$A_{55} \sim A_{58}$
14	$A_{59} \sim A_{66}$
15	$A_{67} \sim A_{70}$
16	$A_{71} \sim A_{72}$

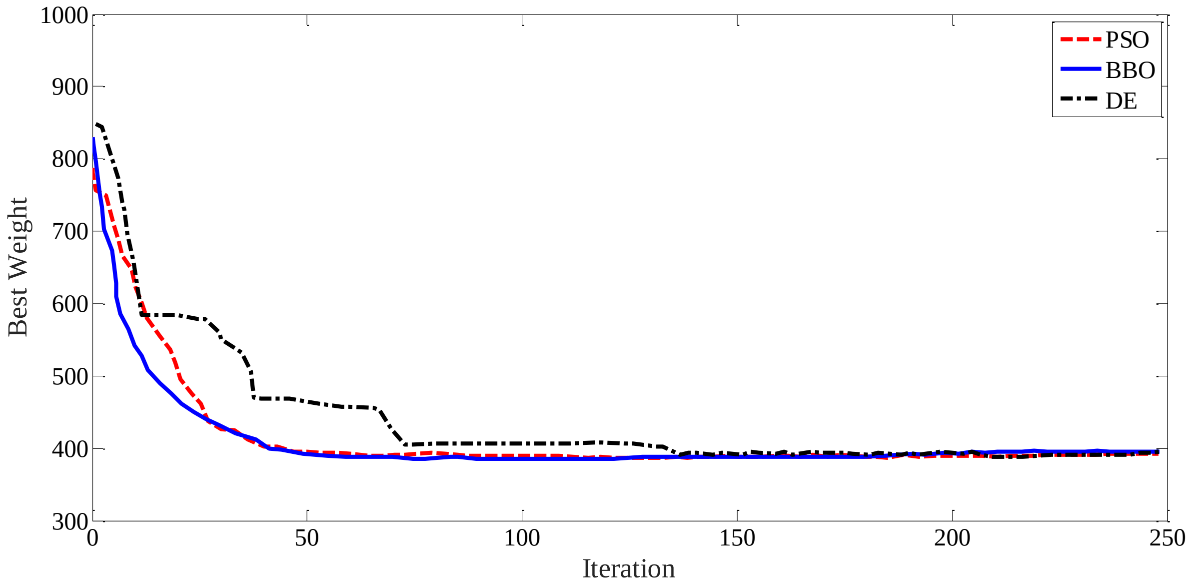

Fig. 6. The convergence of different algorithms to the optimal weight in the 72-bar space truss

Table 5. Comparison of various optimization schemes for the 72-bar space truss

Variables (in^2)	Schmit and Farshi (1974)	Gellatly and Berke (1971)	Khan et al. (1979)	Erbatur et al. (2000)	Kaveh and Talatahari (2009)	This work	
						PSO	BBO
A1 ~ A4	2.08	1.46	1.79	1.76	1.90	1.81	1.90
A5 ~ A12	0.50	0.52	0.52	0.51	0.52	0.51	0.51
A13 ~ A16	0.1	0.1	0.1	0.11	0.1	0.1	0.1
A17 ~ A18	0.1	0.1	0.1	0.16	0.1	0.1	0.1
A19 ~ A22	1.11	1.02	1.21	1.16	1.26	1.31	1.25
A23 ~ A30	0.58	0.54	0.52	0.59	0.50	0.51	0.51
A31 ~ A34	0.1	0.1	0.1	0.1	0.1	0.1	0.1
A35 ~ A36	0.1	0.1	0.1	0.1	0.1	0.1	0.1
A37 ~ A40	0.26	0.55	0.62	0.46	0.52	0.51	0.54
A41 ~ A48	0.55	0.61	0.52	0.53	0.52	0.53	0.52
A49 ~ A52	0.1	0.1	0.1	0.12	0.1	0.1	0.1
A53 ~ A54	0.15	0.1	0.2	0.177	0.1	0.1	0.1
A55 ~ A58	0.16	0.15	0.15	0.16	0.16	0.16	0.16
A59 ~ A66	0.59	0.77	0.57	0.54	0.54	0.54	0.54
A67 ~ A70	0.34	0.45	0.44	0.48	0.41	0.41	0.41
A71 ~ A72	0.61	0.34	0.52	0.52	0.58	0.59	0.57
Weight (lb)	388.63	395.97	381.72	385.76	379.66	379.83	379.64

4.4. A 200-Bar Planar Truss with 77 Nodes

Researchers such as Lee and Geem (2004), Kaveh and Talatahari (2009), and Lamberti (2008) have employed different methods to optimize the size of the 200-bar 2D truss shown in Figure 7. The material density and the elastic modulus of truss members are 0.283 lb/in^2 and 30,000 ksi, respectively. The members of this truss are subjected to stress limitations of ±10 ksi. The other constraint of this problem is that the 2D truss must remain symmetric about the 'y' axis. To this end, the identical truss elements have been grouped together. The following loading conditions have been applied to the 200-member truss structure:

a) 1000 lbf in the positive x-direction at nodes: 1, 6, 15, 20, 29, 34, 43, 48, 57, 62 and 71;

b) 10000 lbf in the negative y-direction at nodes: 1, 2 , 3, 4, 5, 6, 8, 10, 12, 14, 15, 16, 17, 18, 19, 20, 22, 24, 26, 28, 29, 30, 31, 32, 33, 34, 36, 38, 40, 42, 43, 44, 45, 46, 47, 48, 50, 52, 54, 56, 58, 59, 60, 61, 62, 64, 66, 68, 70, 71, 72, 73, 74, 75;

c) The loading conditions (a) and (b) are simultaneously applied to the truss.

A minimum area of 0.1 in^2 has been considered for the cross sections of truss members. The grouping of the truss elements, for fulfilling the mentioned symmetry constraint, is illustrated in Table 6.

The convergence trends of the BBO and PSO algorithms are demonstrated in Figure 8. These performance curves indicate that the BBO algorithm achieves more uniform and faster convergence than the PSO algorithm. The BBO algorithm reaches an acceptable convergence after about 100 iterations, while it takes almost 350 iterations for the PSO to get to this level of convergence. This alone shows the more efficient searching capability of the BBO algorithm.

4.5. The 970-Bar Space Truss

In this example, the 970-bar space truss shown in Figures 9-11 is investigated. The weight per unit volume and the elastic modulus of truss members are 7850 kg/m^3 and 210 GPa, respectively. The allowable stress for each element, whether in tension or compression, is 150 MPa (≈ 0.6 Fy). A displacement of 20 cm (height/500) is allowed for each structure node in any direction (x, y or z). The truss elements have a minimum cross sectional area of 20 cm^2 and a maximum area of 1000 cm^2.

In order to add to the complexity of this example problem, a large exploration limitation has been considered to better demonstrate the exploration and searching capability of the BBO algorithm. This space truss is composed of 251 nodes and 37 member groups, which are considered as design variables. The tower is assumed to be symmetric about both the 'x' and 'y' axes; therefore, the same cross-sectional area is used for the vertical, horizontal, and inclined members at every two stories.

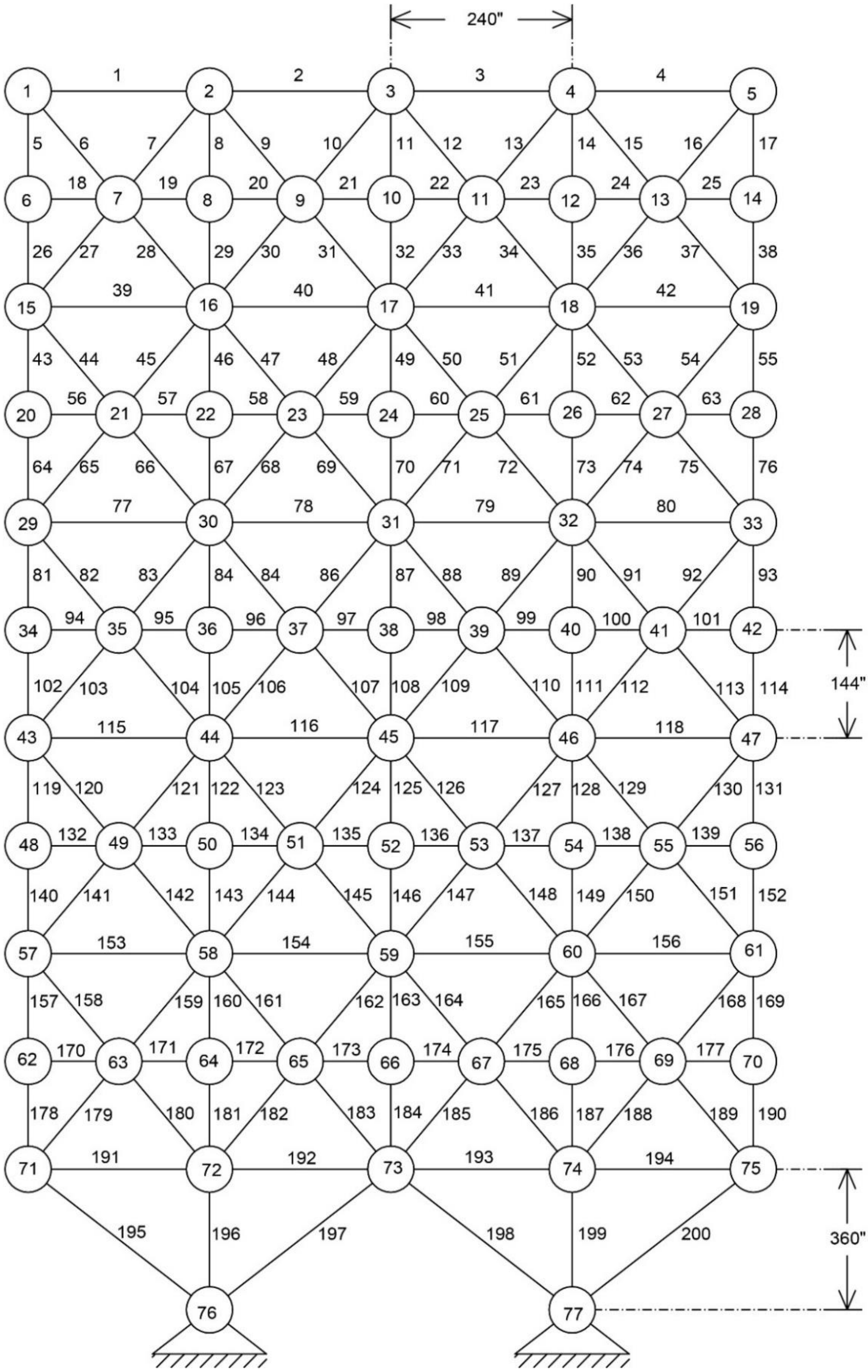

Fig. 7. The element and node numbering system for the 200-bar planar truss

Table 6. Grouping the similar elements in the 200-bar planar truss

Group IDs	Member IDs
1	1,2,3,4
2	5,8,11,14,17
3	19,20,21,22,23,24
4	18,25,56,63,94,101,132,139,170,177
5	26,29,32,35,38
6	6,7,9,10,12,13,15,16,27,28,30,31,33,34,36,37
7	39,40,41,42
8	43,46,49,52,55
9	57,58,59,60,61,62
10	64,67,70,73,76
11	44,45,47,48,50,51,53,54,65,66,68,69,71,72,74,75
12	77,78,79,80
13	81,84,87,90,93
14	95,96,97,98,99,100
15	102,105,108,111,114
16	82,83,85,86,88,89,91,92,103,104,106,107,109,110,112,113
17	115,116,117,118
18	119,122,125,128,131
19	133,134,135,136,137,000
20	140,143,146,149,152
21	120,121,123,124,126,127,129,130,141,142,144,145,147,148,150,151
22	153,154,155,156
23	157,160,163,166,169
24	171,172,173,174,175,176
25	178,181,184,187,190
26	158,159,161,162,164,165,167,168,179,180,182,183,185,186,188,189
27	191,192,193,194
28	195,197,198,200
29	196,199

Table 7. Comparison of various optimization schemes for the 200-bar planar truss

Variables (in^2)	Farshi and Ziazi (2010)	Rahami et al. (2011)	This work
A1	0.15	0.15	0.14
A2	0.95	0.94	0.95
A3	0.10	0.11	0.12
A4	0.10	0.11	0.10
A5	1.95	1.95	1.91
A6	0.30	0.30	0.30
A7	0.10	0.10	0.12
A8	3.11	3.11	3.06
A9	0.10	0.11	0.12
A10	4.11	4.11	4.06
A11	0.40	0.40	0.43
A12	0.19	0.20	0.16
A13	5.43	5.42	5.37
A14	0.10	0.10	0.10
A15	6.43	6.43	6.33
A16	0.58	0.58	0.57
A17	0.13	0.13	0.13
A18	7.97	7.98	7.84
A19	0.10	0.10	0.10
A20	8.97	8.96	8.84
A21	0.71	0.70	0.62
A22	0.42	0.43	0.88
A23	10.87	10.86	10.93
A24	0.10	0.10	0.10
A25	11.87	11.86	11.90
A26	1.04	1.03	1.32
A27	6.69	6.68	5.37
A28	10.81	10.82	9.95
A29	13.84	13.83	14.15
Weight (lb)	25456.57	25449.27	24958.02

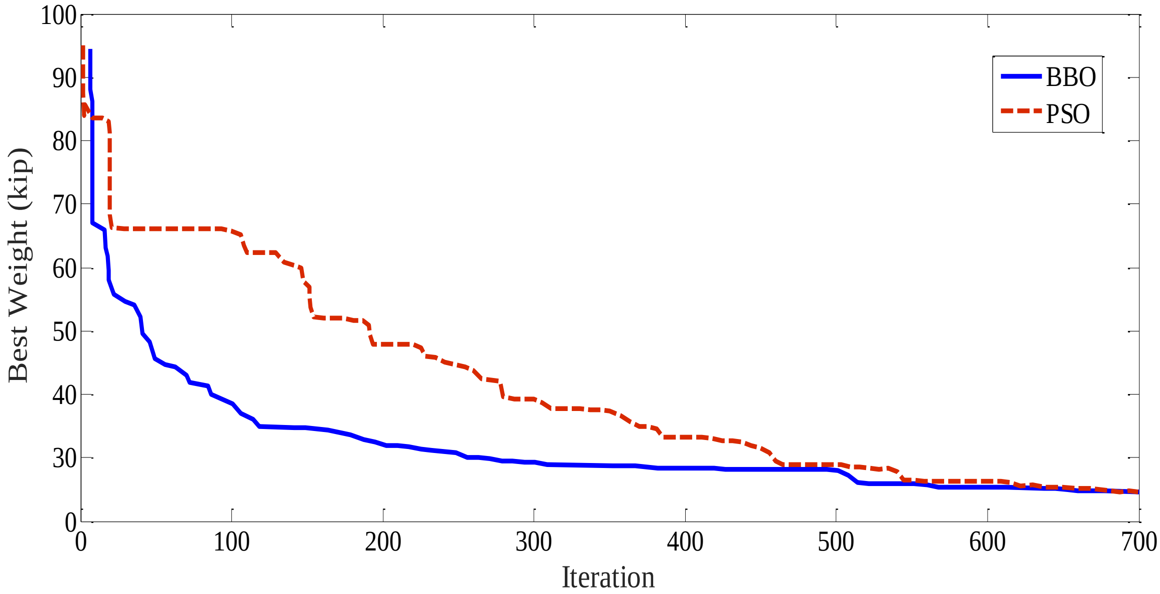

Fig. 8. The convergence of different algorithms to the optimal weight in the 200-bar planar truss

A vertical load of 50 KN in the downward z direction and horizontal loads of 10 KN in both the 'x' and 'y' directions are applied to all the free nodes of the tower structure. To show the superiority of the BBO algorithm over the PSO algorithm, it was necessary to apply equal and similar conditions to both algorithms. Therefore, a total population of 50 and a maximum number of 1000 iterations have been considered for this simulation. The results obtained for both algorithms are illustrated and compared in Figure 1 and Table 8.

The allowable and the existing displacements and stresses obtained for the 970-bar truss structure by the BBO and PSO algorithms are compared in Figures 13-15. The maximum amount of displacement permitted for the truss nodes in the 'x', 'y' or 'z' directions is 20 cm, and the maximum allowable stress is 150 MPa. It should be mentioned that there is only a marginal difference between the analysis results of the SAP2000, MASTAN2 and MATLAB software programs.

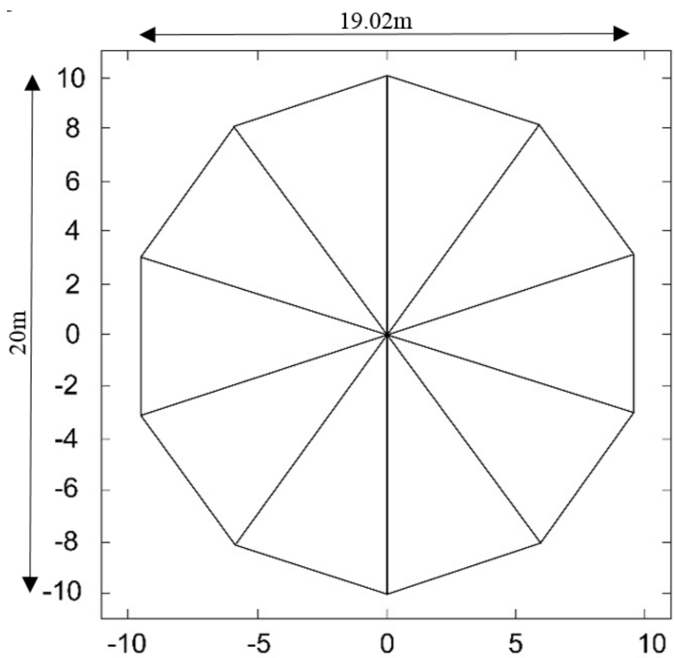

Fig. 9. The plan view of the 970-bar space truss

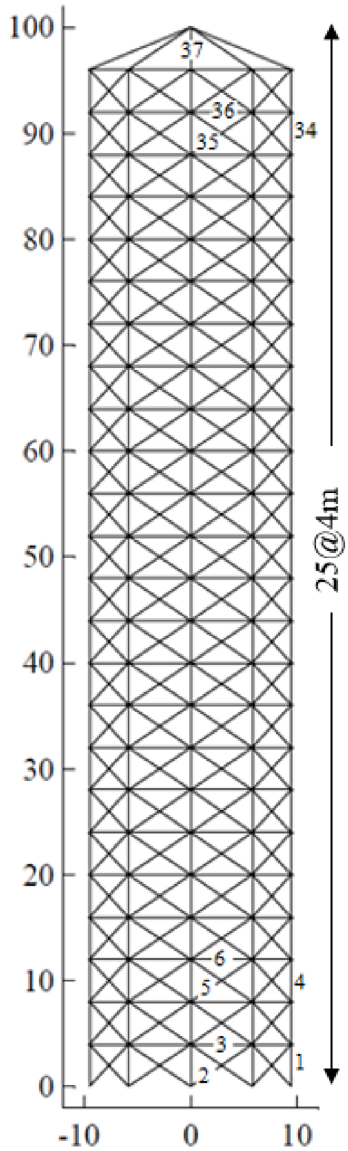

Fig. 10. The lateral view of the 970-bar space truss

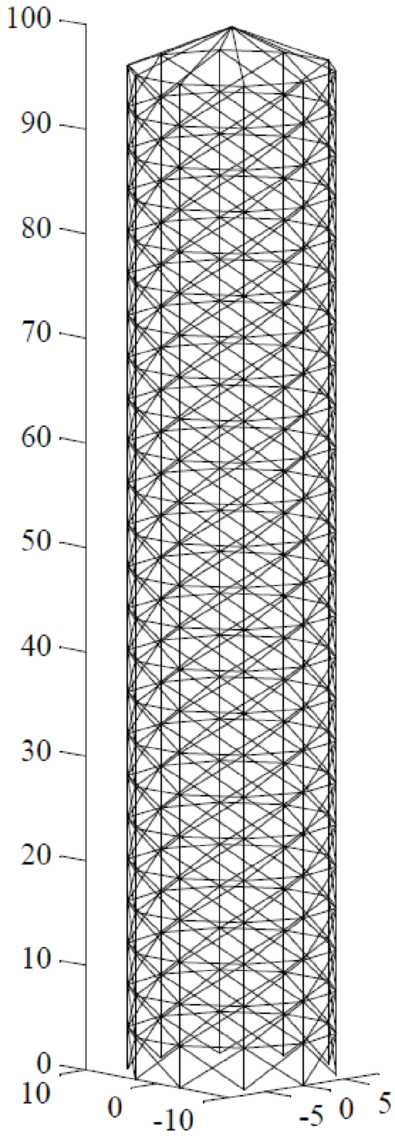

Fig. 11. The 3D view of the 970-bar space truss

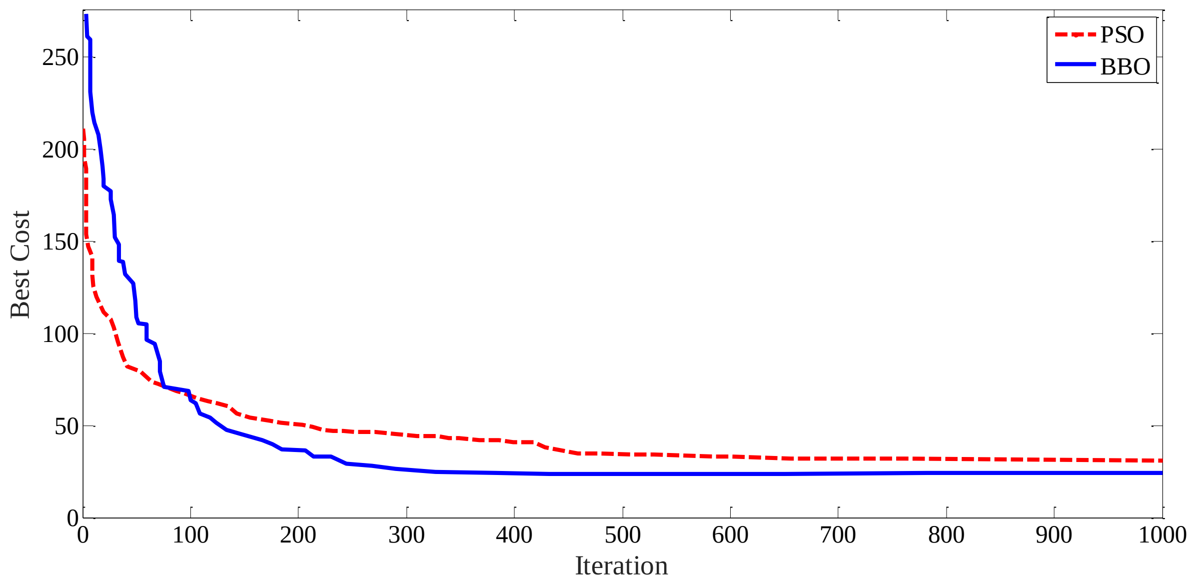

Fig. 12. The convergence of different algorithms to the optimal weight in the 970-bar space truss

Table 8. Comparison of various optimization schemes for the 970-bar space truss

Variables (cm^2)	PSO	BBO
A_1	321.94	323.82
A_2	30.51	29.10
A_3	20.24	20.06
A_4	253.58	273.59
A_5	25.82	27.29
A_6	20.00	20.08
A_7	251.19	235.14
A_8	28.18	24.98
A_9	20.26	20.00
A_{10}	345.60	197.44
A_{11}	20.88	23.83
A_{12}	20.00	20.01
A_{13}	148.04	168.55
A_{14}	20.10	22.67
A_{15}	20.00	20.05
A_{16}	149.92	131.51
A_{17}	20.09	20.86
A_{18}	20.20	20.07
A_{19}	93.70	103.86
A_{20}	20.08	20.47
A_{21}	20.00	20.18
A_{22}	70.10	87.82
A_{23}	20.22	20.09
A_{24}	20.00	20.02
A_{25}	54.42	56.26
A_{26}	20.00	20.23
A_{27}	476.27	20.00
A_{28}	41.58	39.47
A_{29}	20.00	20.12
A_{30}	20.00	20.00
A_{31}	20.00	20.00
A_{32}	20.08	20.09
A_{33}	60.42	20.01
A_{34}	20.44	20.70
A_{35}	20.00	20.00
A_{36}	20.00	20.00
A_{37}	20.38	20.17
Volume (m^3)	31.33	24.40
Weight (ton)	245.94	191.52
σ_{max} (MPa)	149.54	146.92
Δ_{max} (cm)	19.75	20.00

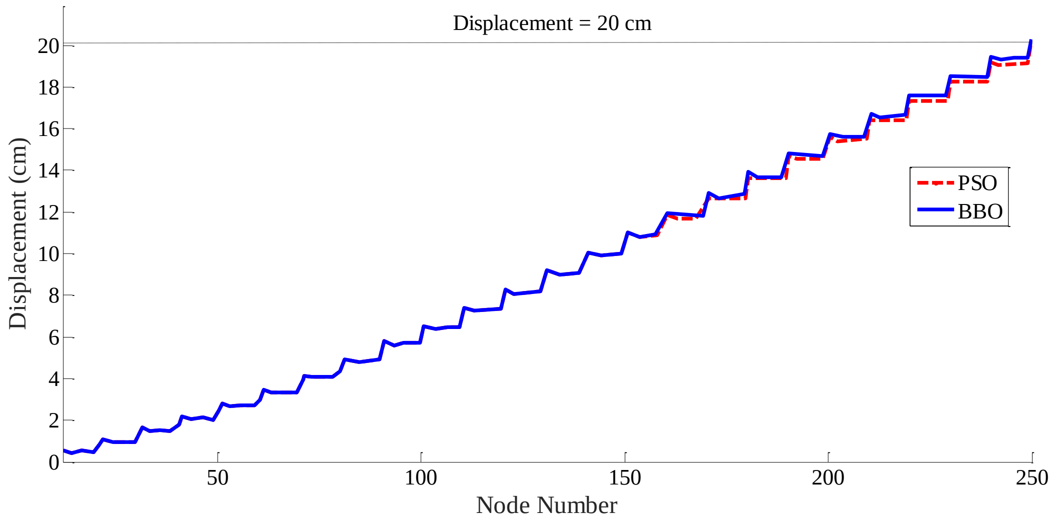

Fig. 13. Comparing the allowable and the existing displacements in the x or y direction obtained by the BBO and PSO algorithms

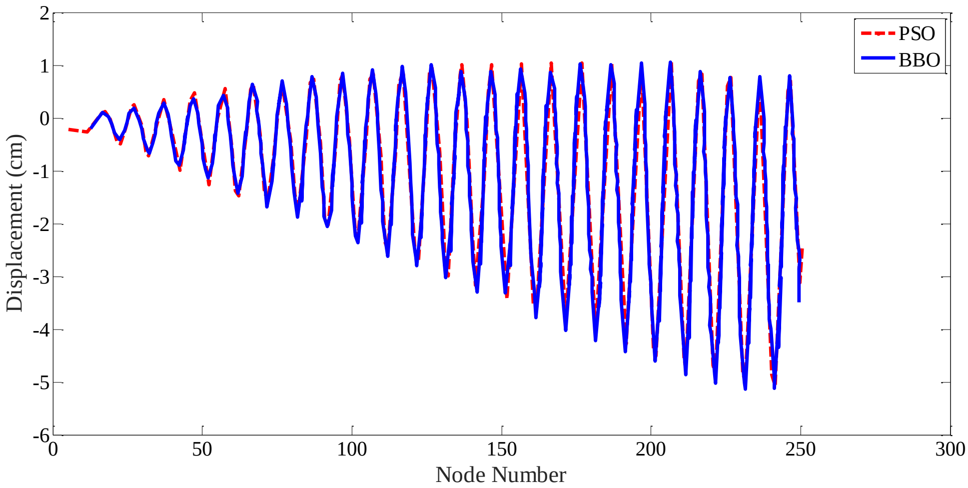

Fig. 14. Comparing the allowable and the existing displacements in the z direction obtained by the BBO and PSO algorithms

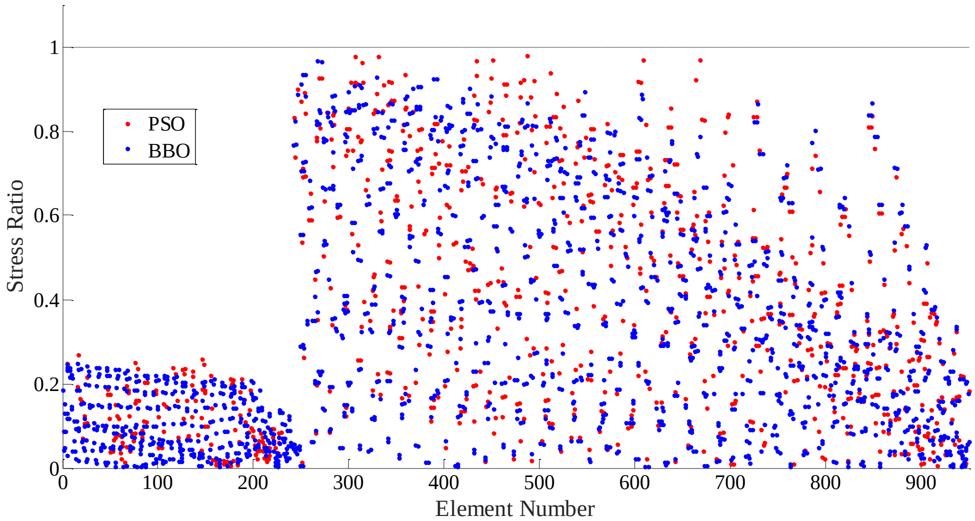

Fig. 15. Comparing the allowable and the existing stress ratios obtained by the BBO and PSO algorithms

5. Conclusions

In this article, the biogeography-based optimization algorithm, which is based on the geographical distribution of animals in their natural habitats, has been used for the weight optimization of 2D and 3D trusses with continuous decision variables. Of course, the use of this algorithm is not limited to continuous variables or truss structures, and it can be easily applied to frames, plates, and other structures with discrete or continuous variables. Based on the results obtained from the analysis of benchmark problems in this paper, it is concluded that the BBO algorithm is ranked among the effective optimization algorithms. Moreover, because of using the solutions of the preceding steps at each current step, and also using the mutation operator by the BBO algorithm, the probability of its getting trapped in local minima and maxima is greatly reduced and the algorithm achieves a high rate of convergence. Also, in view of the results presented in the given figures and tables, this algorithm has a good search and exploration capability and achieves a favorable optimal solution in the initial iterations. All the results obtained in this investigation have been evaluated by means of software programs such as “SAP2000” and “MASTAN2”, and their accuracy has been verified. The results obtained by the BBO algorithm are superior to those of the other optimization techniques considered in this paper.

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