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Research Paper

A Hybrid Particle Swarm Optimization and Genetic Algorithm for Truss Structures with Discrete Variables

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Abstract. A new hybrid algorithm of Particle Swarm Optimization and Genetic Algorithm (PSOGA) is presented to get the optimum design of truss structures with discrete design variables. The objective function chosen in this paper is the total weight of the truss structure, which depends on upper and lower bounds in the form of stress and displacement limits. The Particle Swarm Optimization basically modeled the social behavior of birds on the basis of the fact that Individual birds exchange information about their position, velocity, fitness, and on the basis that the behavior of the flock is then influenced to increase the probability of migration to other regions with high fitness. One of the problems of PSO is that it is easily trapped at the local point due to its non-uniform movement. The present study uses the mutation, random selection, and reproduction to reach the best genetic algorithm with the operators of natural genetics. Therefore, only identical chromosomes or particles can be converged. In other words, PSO and GA algorithm goes from one point in the search space to another point, interacting with each other. In this way, this helps them to find the optimum design by means of deterministic and probabilistic rules. The present study merged the two algorithms together in order to design several benchmark truss structures, and then the results of the new algorithm compared to those of other evolutionary optimization methods.

Keywords: Particle Swarm Optimization; Genetic Algorithm; Size optimization; Structural optimization; Discrete variables.

1. Introduction

During the last decades, the truss structural optimization has become one of the most important and challenging activity fields in structural engineering, and for this reason, it has received considerable attention. The structural weight is directly related to construction costs and economic issues. In fact, as the structure weight is decreased, the construction costs will be decreased. However, the fact is that the weight of the structure is directly related to strength, and therefore, there should be limitations in the optimization procedure. In general, these limitations are in the forms of stress and displacement. Therefore, one can easily have the optimum structures by using new meta-heuristic methods, given the constraints.

Recently, many new meta-heuristic algorithms have been developed for the optimization of truss structures, such as the Genetic Algorithm (GAs) model the process of natural evolution, which is developed by Rajeev and Krishnamoorthy [1-2], the Particle swarm optimization (PSO), which is inspired from the social behavior and the interaction between a flock of birds and a school of fish, which is proposed by Kennedy and Eberhart [3], the Harmony Search (HS), which is inspired from the behavior of musicians to find a better harmony, developed by Lee and Geem [4],

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the Ant Colony Optimization (ACO), which is an inspiration from the cooperative behavior of an ant colony, developed by Dorigo [5], the Charged System Search (CSS) [6], which uses the governing Coulomb law of electrostatics and the Newtonian laws of mechanics, the Big Bang-Big Crunch (BB-BC) [7-8], which uses the population averaging in a model of the evolution of the universe, the Artificial Bee Colony algorithm (ABC) [9], which is motivated by the intelligent behavior of honey bees, the spherical interpolation of objective function and constraints, which is used by Meshki and Joghataie [23], the Colliding bodies optimization (CBO) [24], the Vibrating Particles System (VPS) [25], the krill herd (KH) [26], the Whale Optimization Algorithm (WOA) [27], a hybrid Harmony Search [28], a hybrid algorithm based on TLBO [29] and TLBO [30], the force method and genetic algorithm [31], the water cycle, mine blast and the improved mine blast algorithms [32]. Because of their high potential for simulating optimization problems, these methods have been used in various fields of science. One of the advantages of such algorithms is that they do not require gradient information, and they possess better global search abilities, as compared to the conventional optimization algorithms.

In many cases, especially in structural engineering, most of the problems are defined as discrete problems. Therefore, it is important to introduce an effective algorithm which is able to perform the optimization process with discrete variables. The hybrid PSO and GA algorithm is one of the most efficient algorithms, which can be used in discrete optimization by applying new modifications in order to achieve the optimal solution. Once the particle's position is determined in the search space, the method proposed by the present study will move its value to the lowest optimal value near the discrete variable by means of some changes explained in section 2. Recently, many new algorithms have been developed, such as HPSO [10], HPSACO [11], and the improved GA [12], to achieve the optimum design of structures with discrete variables. However, these improved versions still cannot solve difficult problems. Considering the merit and demerit of PSO [3] and GA [1-2], the present study finds that a hybrid of these algorithms would improve their performance towards the optimum design.

2. Discrete Optimum Design Problem of Truss Structures

The present study tries to minimize the cross-sectional area of members, but the structural engineering, is faced with such limitations as the strength of each member and displacement for each connection. The objective function is chosen as the average weight of truss structure members. In this study, the optimal design is defined as:

$$\text{Find:} \quad A=[A_1, A_2, \ldots, A_n], \quad A \in D_i, D_i=\{d_{i,1}, d_{i,2}, \ldots, d_{i,r(i)}\}$$

$$\text{To Minimize:} \quad W=\sum_{e=1}^{N_m} \gamma_e . l_e . A_e \tag{1}$$

$$\text{Subject to:} \quad \sigma^l < \sigma_e < \sigma^u, \quad \delta^l < \delta_e < \delta^u$$

where w is the weight of truss, N_m is the number of members, γ_e is the unit weight of each member, l_e is the length of the individual member, and A_e is the cross-sectional area. This minimum design also has to satisfy the constraints on each member stress σ_e and displacement at each connection C.

The stress for each member σ_e is compared with the lower and upper bounds in Eq. (2) and the displacement for each connection to lower bound and upper bound Eq. (3).

$$\text{if} \quad \sigma^l < \sigma_e < \sigma^u \quad \text{then} \quad \varphi_\sigma^e = 0 \tag{2}$$

$$\text{if} \quad \sigma_e < \sigma^l \quad or \quad \sigma_e > \sigma^u \quad \text{then} \quad \varphi_\sigma^e = \left| \frac{\sigma_e - \sigma^{l,u}}{\sigma^{l,u}} \right| \tag{3}$$

The stress penalty ϕ_σ^k for a truss design as follows:

$$\varphi_\sigma^k = \sum_{e=1}^{N_m} \varphi_\sigma^e \tag{4}$$

The formulation of deflection limitation in X, Y, and Z directions $\varphi_{\delta x}^c$, $\varphi_{\delta y}^c$, and $\varphi_{\delta z}^c$ total deflection penalty function is defined as:

$$\text{if} \quad \delta^l \le \delta_{c(x,y.z)} \le \delta^u \quad \text{then} \quad \varphi_{\delta(x,y,z)}^c = 0 \tag{5}$$

$$\text{if} \quad \delta_{c(x,y.z)} < \delta^l \quad \text{or} \quad \delta_{c(x,y.z)} > \delta^u \quad \varphi_{\delta(x,y,z)}^c = \left| \frac{\delta_{c(x,y.z)} - \delta^{l,u}}{\delta^{l,u}} \right| \tag{6}$$

$$\varphi_{\delta}^{k}=\sum_{c=1}^{N_m}[\varphi_{\delta x}^{c}+\varphi_{\delta y}^{c}+\varphi_{\delta z}^{c}] \tag{7}$$

The final penalty function ψ^k for truss composed of stress and deflection penalty as:

$$\psi^{k}=(1+\varphi_{\sigma}^{k}+\varphi_{\delta}^{k})^{\varepsilon} \tag{8}$$

where ε is a positive penalty coefficient. The value of penalized weight is defined as:

$$F^{k}=\psi^{k}.w^{k} \tag{9}$$

3. Review of Particle Swarm Optimization and Genetic Algorithm

3.1. Particle Swarm Optimization algorithm

The PSO algorithm is basically a continuous and population-based algorithm, and the population consists of members, with each being called particle. Each of these particles points to a special position of the search space, which updates its position based on speed and new gained information. Therefore, it moves toward the optimal solution by sharing the collected information with other particles. The initial position and velocity of particles use the upper and lower limits, and they are randomly determined. However, it improves the optimization process by repeating and sharing information in the next stage. This updating process is expressed as follows:

$$X_{i}^{k+1}=X_{i}^{k}+V_{i}^{k+1} \tag{10}$$

where V_i^{k+1} is a changing of velocity, and X_i^k is a current position.

The velocity consists of three contributing factors:

a) V_i^k is a velocity vector considered former attempts.

b) Moving towards the local best, P_i^k represents the best particle position.

c) Moving towards the global best, P_g^k is based on the publicized fitness.

Eq. (11) shows the mathematic relationship:

$$V_{i}^{k+1}=\omega V_{i}^{k}+c_{1}r_{1}(P_{i}^{k}-X_{i}^{k})+c_{2}r_{2}(P_{g}^{k}-X_{i}^{k}) \tag{11}$$

where ω is an inertia weight to control the influence of the previous velocity, r_1 and r_2 are two random numbers within the range [0,1], c_1 and c_2 are two acceleration constants, P_i^k is the best position of the i^{th} particle up to iteration K, and P_g^k is the best position among all particles in the swarm up to iteration [22]. P_i^k and P_g^k are defined in the Eq. (12). Figure 1 shows the scheme of PSO algorithm.

$$P_{i}^{k}=\begin{cases}P_{i}^{k} & f(X_{i}^{k})\geq f(P_{i}^{k-1})\\ X_{i}^{k} & f(X_{i}^{k})<f(P_{i}^{k-1})\end{cases} \tag{12}$$

$$P_{g}^{k}=\left\{P_{i}^{k}\mid f(P_{i}^{k})\min(f(P_{g}^{k-1})\,\&\,f(P_{l}^{k}),j=1,2,\ldots,M)\right\} \tag{13}$$

3.2. Genetic Algorithm

The GA is one of the most popular algorithms used in many types of research because of its ease of implementation and convenient concepts. The GA is inspired by the principles of genetics and evolution. This algorithm represents the design variables in the form of individualism and binary, with each of these candidates being called a chromosome. Moreover, the GA will encrypt the design parameters, and it will use the characteristic encryption to force the design variables to select only the values within the design scope. In the other hand, no solution has been allowed to violate the upper and lower bounds, because if this happens the objective function will not be run. The search process is started randomly from the population, and it evolves among successive generations. The GA uses three steps to propagate the population from one generation to another, and these steps are expressed as follows. Figure 2 shows the flow chart of the Genetic Algorithm.

Step 1: Selection; This operator follows the principle of proportional survival.

Step 2: Crossover; This operator imitates mating in bio-communities. The crossover operator passes the characteristics of good survival plans from the current population to another, which is better than the previous step.

Step 3: Mutation; The last operator is a mutation, which can promote diversity in demographic characteristics. This operator will search the entire search space and prevents the algorithm from being trapped at the local optimum.

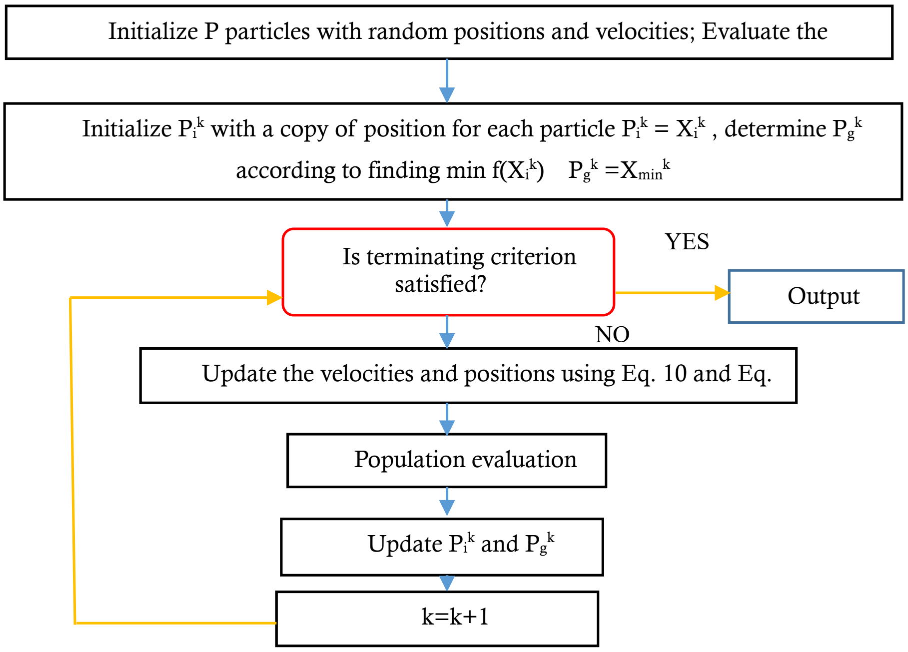

Fig. 1. The flow chart of PSO

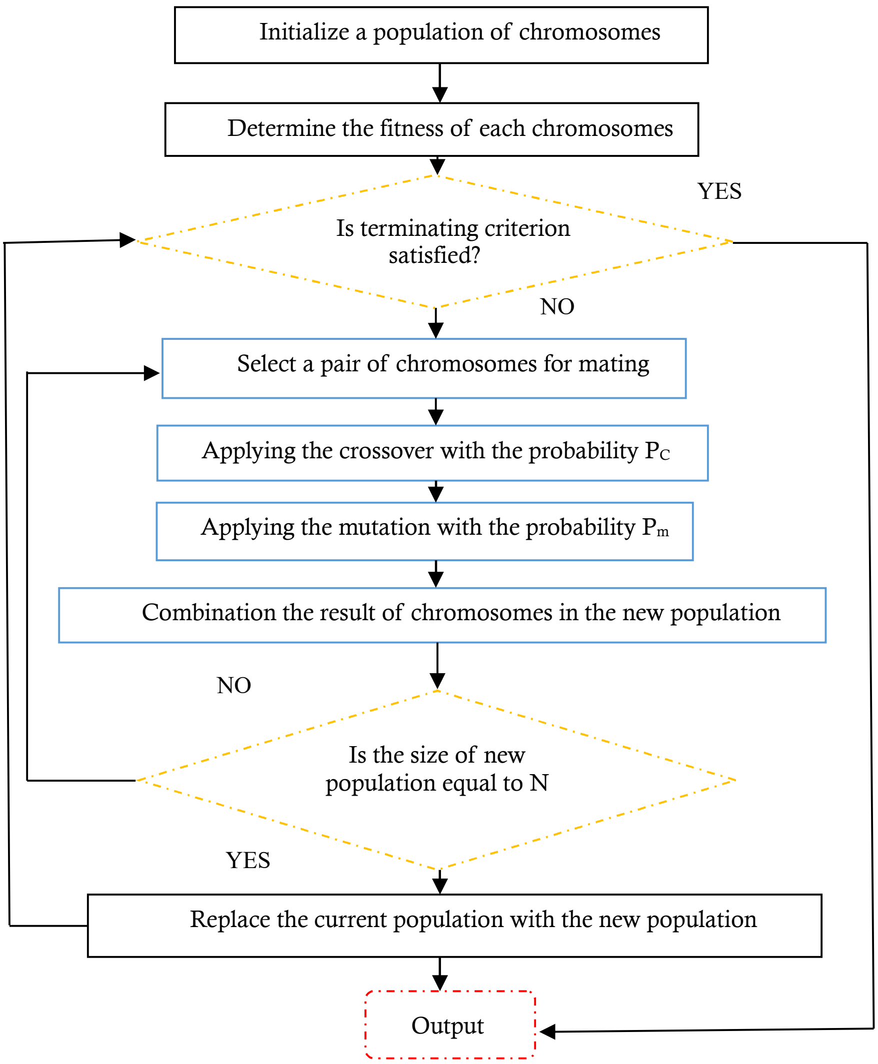

Fig. 2. The flow chart of the Genetic algorithm

4. A Discrete Hybrid PSO and GA Algorithm

Rajeev and Krishnamoorthy [1] improved the Genetic Algorithm for discrete truss optimization. Kaveh and Talatahari [21] improved a particle swarm ant colony optimization for truss structures with discrete variables on the basis of the primary continuous PSO and ACO algorithm. However, the two mentioned algorithms have some difficulty in solving the problems with large search space. After recognizing their merits and demerits, therefore, they merged to form a professional hybridized algorithm. One of the main disadvantages of the PSO algorithm is that it has a high speed of convergence. Compared to other meta-heuristic methods, it causes some difficulty to find the optimal solution in the optimization problems with large search space. In fact, it is unable to explore all the unknown parts of the search space, because of the high rate of convergence. This problem makes it possible to trap at the local optimal which is between the best global and the best local position. The reason is that particles are sharing duplicated information, and this causes the particles to be unable to explore the entire search space.

Particles move in each direction between the maximum and minimum velocities, and they cannot go over these bounds. If the velocities violate the V_{max}, then it is limited to V_{max}, this would increase the rate of convergence. Most of the stochastic algorithms have problem-dependent performance. This dependency usually results from the parameter setting in each algorithm. The other reason is that particles are sharing duplicated information. In general, one cannot use the same parameter setting to solve all optimization problems.

PSO and GA algorithms have many similarities that complement each other. For example, they are both stochastic and population-based, in the sense that they first randomly generate a population and then use a fitness value to evaluate the population. This process continues in each run until the best answer is obtained.

During the past, many discrete PSO and GA algorithms have been employed on the basis of conventional PSO and GA algorithms or their relevant principles to solve the optimization-related problems. Given the experiences, the present study finds that the PSO algorithm will be easily trapped at the local search. The increased inertia weight can increase the speed of exploration, and this will lead to trap in the local optimum. In order to solve the problem, therefore, the GA algorithm was employed in the present study.

The present study proposes a new discrete algorithm called a hybrid Particle Swarm Optimization and Genetic Algorithm for truss structures with discrete variables. The framework of this new algorithm is shown in Figure 3. In fact, since the optimization based on discrete variables is very difficult, many different methods have been introduced for discrete optimization to improve the problem. For this reason, the new function was used in this study to round the values of continuous variables to the nearest discrete variable.

$$X_i^{k+1} = fix(X_i^k + V_i^{k+1}) \tag{14}$$

The hybrid optimization procedure in accordance with the following steps is as:

Step 1: Initialize P particles with random positions and velocities, and then evaluate the population; k=0.
Step 2: If the convergence criteria are applied, stop and display the best individual; otherwise, proceed to step 3.
Step 3: Find the best one and ignore others.
Step 4: Perform the conventional Particle Swarm Optimization.
Step 5: Use the operators of GA in order to improve the Particle Swarm Optimization.
Step 6: Form a new population, and then, go to step 2 in order to examine the last terminating criterion.

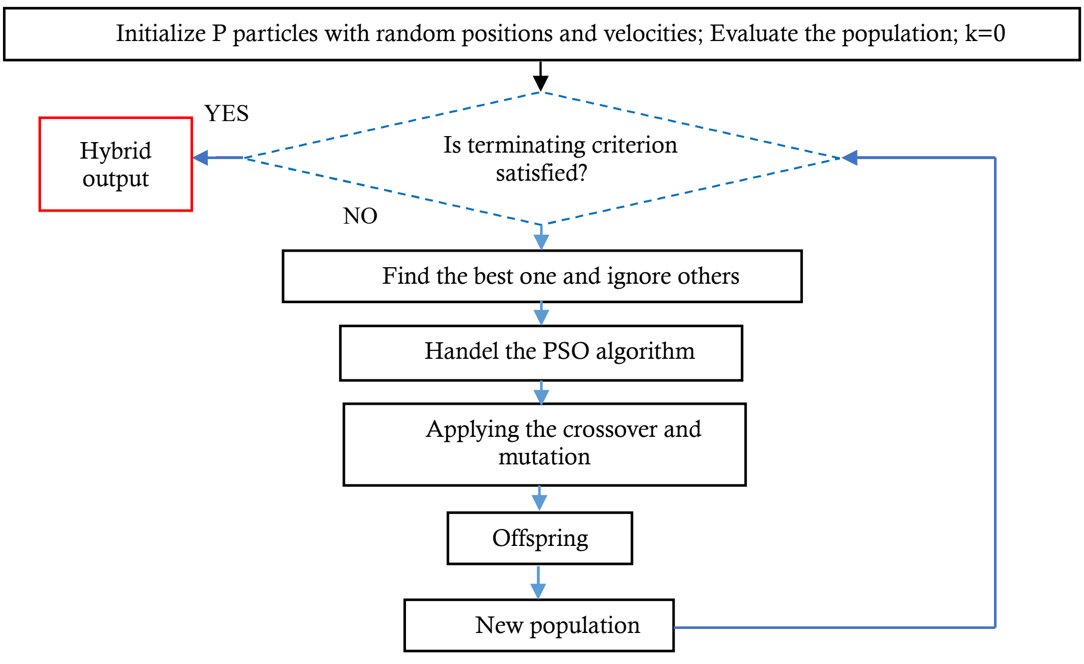

Fig. 3. The flow chart of the Hybrid PSO and GA

5. Numerical Examples

In this section, some truss structures with discrete variables are presented; 25-bar spatial truss with 8 design variables, 10-bar truss with 10 design variables, 52-bar truss with 12 design variables, 72-bar spatial truss with 16 design variables. In all examples, the results of hybrid PSO and GA are compared to other meta-heuristic algorithms.

5.1. Twenty-five bar spatial truss

The topology of a 25-bar spatial truss is shown in Figure 4. In this example, the structure is subjected to a single load case of Table 1. The members are subjected to the allowable stress limitation of ±40ksi. All connections are subjected to the allowable displacements ±0.35in. There are 8 groups of discrete design variables with a range of 0.1 - 3.4 in^2, with 0.1 in^2, which listed in Table 2. Unit weight 0.1 *lb*/in^3, modulus of elasticity is 107 psi.

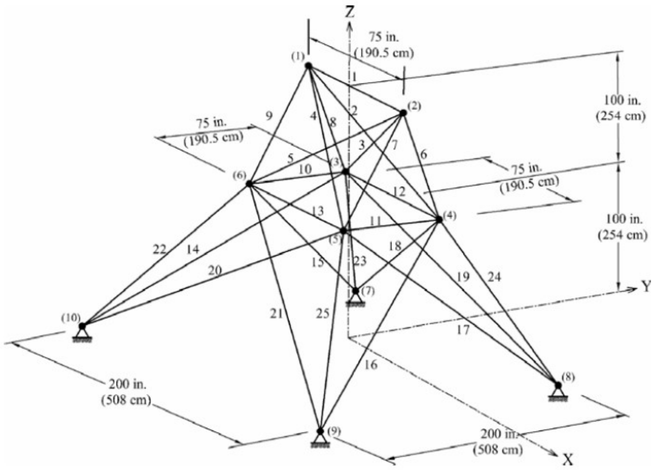

Fig. 4. Topology of the 25-bar spatial truss

Table 1. Loading conditions for the 25-bar space

Case	Node	P_x (kips)	P_y (kips)	P_z (kips)
1	1	1.0	-10.0	-10.0
	2	0.0	-10.0	-10.0
	3	0.5	0.0	0.0
	6	0.6	0.0	0.0

Note: 1 in^2 = 6.452 cm^2 ; 1 *lb* = 4.45 N

Table 2. Elements information

Group of elements							
1	2	3	4	5	6	7	8
1(1,2)	2:(1,4)	6:(2,4)	10(6.3)	12:(3,4)	14:(3,10)	18:(4,7)	22:(6,10)
	3:(2.3)	7:(2,5)	11:(5,4)	13:(6,5)	15:(6,7)	19:(3,8)	23:(3,7)
	4:(1,5)	8:(1,3)			16:(4,9)	20:(5,10)	24:(4,8)
	5:(2,6)	9:(1,6)			17:(5,8)	21:(6,9)	25:(5,9)

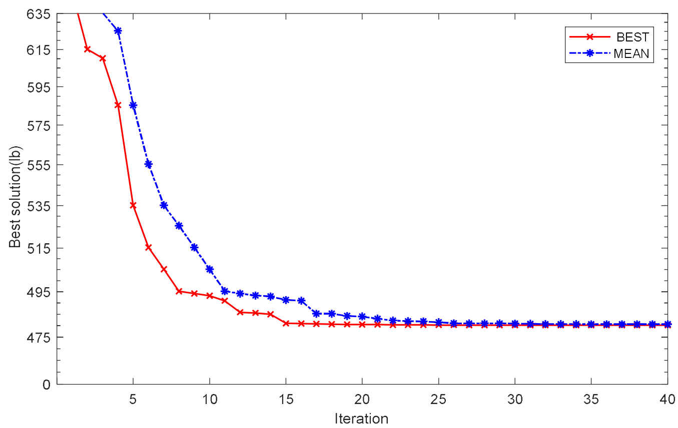

Fig. 5. The convergence history of 25-bar spatial truss

The results of the hybrid PSO and GA and other meta-heuristic algorithm are listed in Table 3. As one can see, the best weight designed by the hybrid PSO and GA is 482.25 *lb* after 100 iterations and 1,200 searches. The best weight designed by GA standard [1] is 546.01 *lb* with 800 searches, which more than hybrid PSO and GA algorithm also they did not report any information about standard deviation and number of iterations. The best weight of GA [2] algorithm is 485.05 *lb* with 15,000 searches, also it did not report any information about standard deviation. The best weight of ACO [13] algorithm is 484.85 *lb* after 100 iterations and 7,700 searches and with standard deviation 4.71 *lb*. The best weight of BB-BC [14] is 484.85 *lb* after 100 iterations and 6,670 searches, with standard deviation 0.62 *lb*. The TLBO [15] algorithm achieved the best weight 484.85 *lb* after 100 iterations and 4,910 searches which 24% more than Hybrid PSO and GA algorithm with standard deviation 0.17 *lb*. The best weight designed by IPSO [33] is 484.85lb, which is more than a new algorithm, and it did not report number of iterations.

However, the result of the hybrid PSO and GA is better than those of other meta-heuristic algorithms. The average weight of the hybrid PSO and GAs is 483.10 *lb* with standard deviation 0.25 *lb*. Also the hybrid PSO and GA require fewer iterations for convergence. Figure 5 shows the convergence history of the hybrid PSO and GA algorithm for the 25-bar spatial truss.

Table 3. Performance comparison for 25-bar spatial truss with Discrete variables

Variables		Cross-sectional area (in^2)						
Element group	Members	GA Rajeev and Krishnamoorthy [1]	GA Cao [2]	ACO Camp and Bichon [13]	BB–BC [14]	TLBO [15]	IPSO [33]	This work
1	1	0.10	0.10	0.10	0.10	0.10	0.10	0.10
2	2,3,4,5	1.80	0.50	0.30	0.30	0.30	0.30	0.50
3	6,7,8,9	2.30	3.40	3.40	3.40	3.40	3.40	2.30
4	10,11	0.20	0.10	0.10	0.10	0.10	0.10	0.10
5	12,13	0.10	1.90	2.10	2.10	2.10	2.10	1.50
6	14,15,16,17	0.80	0.90	1.00	1.00	1.00	1.00	0.70
7	18,19,20,21	1.80	0.50	0.50	0.50	0.50	0.50	0.90
8	22,23,24,25	3.00	3.40	3.40	3.40	3.40	3.40	3.10
Weight (*lb*)		546.01	485.05	484.85	484.85	484.85	484.85	482.25
W_{avg} (*lb*)		-	-	486.46	485.20	484.91	484.85	483.10
W_{stdv} (*lb*)		-	-	4.71	0.62	0.17	0	0.25
$N_{analysis}$		800	15,000	7,700	6,670	4,910	620	1,200

Note: 1 in^2 = 6.452 cm^2 ; 1 *lb* = 4.45 N

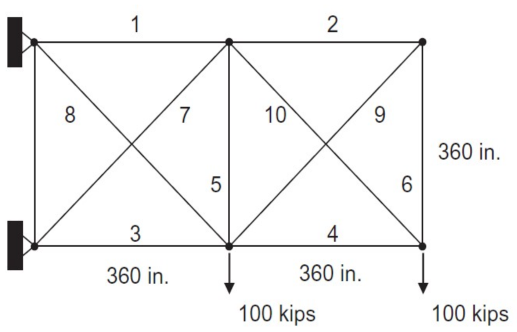

Fig. 6. Topology of 10-bar planar truss

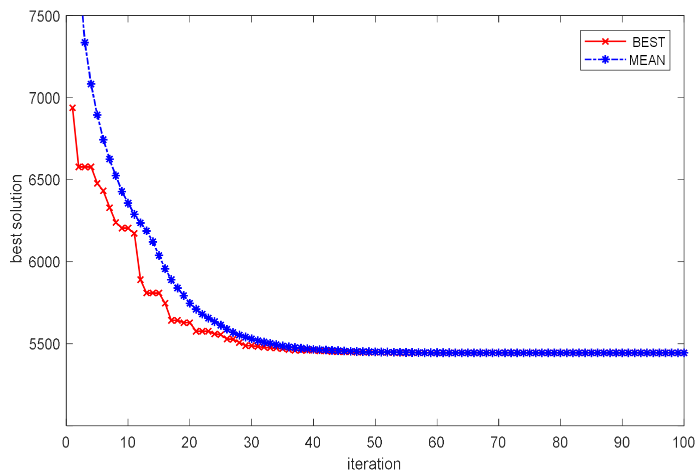

Fig. 7. The convergence history of 10-bar truss

Table 4. Performance comparison for 10-bar truss with Discrete variables

Variables		Cross-sectional area(in^2)						
Element group	Members	GA Mahfouz [16]	ACO Camp and Bichon [13]	BB–BC [14]	GA Barbosa et al. [17]	TLBO [15]	IPSO [33]	This work
1	1	33.50	33.50	33.50	33.50	33.50	33.50	33.50
2	2	1.62	1.62	1.62	1.62	1.62	1.62	1.62
3	3	22.90	22.90	22.90	22.90	22.90	22.90	22.00
4	4	14.20	14.20	14.20	14.20	14.20	15.50	13.90
5	5	1.62	1.62	1.62	1.62	1.62	1.62	1.62
6	6	1.62	1.62	1.62	1.62	1.62	1.62	1.62
7	7	22.90	22.90	22.90	22.90	22.90	7.97	22.00
8	8	7.97	7.97	7.97	7.97	7.97	22.00	7.97
9	9	1.62	1.62	1.62	1.62	1.62	22.00	1.62
10	10	22.00	22.00	22.00	22.00	22.00	1.62	22.00
Weight (*lb*)		5,490.74	5,490.74	5,490.74	5,490.74	5,490.74	5491.70	5,485.23
W_{avg} (*lb*)		-	5,510.52	5,494.17	5,534.98	5,503.21	5496.33	5,486.98
W_{stdv} (*lb*)		-	23.19	12.42	-	20.33	5.75	16.30
$N_{analysis}$		8,000	10,000	8,694	200,000	5,183	2480	5,000

Note: 1 in^2 = 6.452 cm^2 ; 1 *lb* = 4.45 N

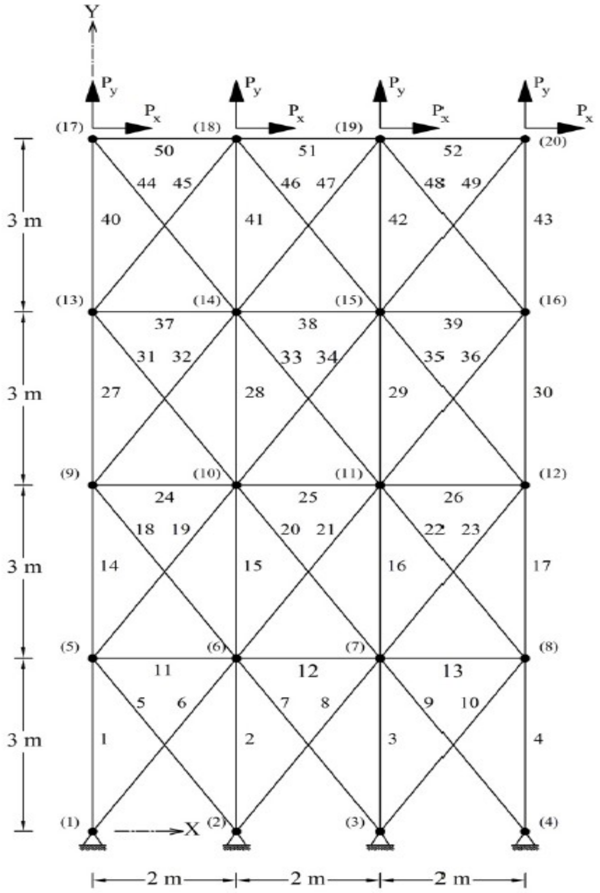

Fig. 8. Topology of 52-bar planar truss

Table 5. The available cross-section areas of the AISC code

NO	in²	mm	NO	in²	mm
1	0.111	71.613	33	3.840	2477.414
2	0.141	90.968	34	3.870	2496.796
3	0.196	126.451	35	3.880	2503.221
4	0.250	161.290	36	4.180	2696.769
5	0.307	198.064	37	4.220	2722.575
6	0.391	252.258	38	4.490	2896.768
7	0.442	285.161	39	4.590	2961.284
8	0.563	363.225	40	4.800	3096.768
9	0.602	388.386	41	4.970	3206.445
10	0.766	494.193	42	5.120	3303.219
11	0.785	506.451	43	5.740	3703.218
12	0.994	641.289	44	7.220	4658.055
13	1.000	645.160	45	7.970	5141.925
14	1.228	792.256	46	8.530	5503.215
15	1.266	816.773	47	9.300	5999.988
16	1.457	393.998	48	10.850	6999.986
17	1.563	1008.385	49	11.500	7419.430
18	1.620	1045.159	50	13500	8709.660
19	1.800	1161.288	51	13.900	8967.724
20	1.990	1283.868	52	14.200	9161.272
21	2.130	1374.191	53	15.500	9999.980
22	2.380	1535.481	54	16.000	10322.560
23	2.620	1690.319	55	16.900	10903.204
24	2.630	1696.771	56	18.800	12129.008
25	2.880	1858.061	57	19.900	12838.684
26	2.930	1890.319	58	22.000	14193.520
27	2.090	1993.544	59	22.900	14774.164
28	1.130	729.031	60	24.500	15806.420
29	3.380	2180.641	61	26.500	17096.740
30	3.470	2238.705	62	28.000	18064.480
31	3.550	2290.318	63	30.000	19354.800
32	3.630	2341.931	64	33.500	21612.860

Table 6. Performance comparison for 52-bar truss with discrete variables

Variables		Cross-sectional area(mm²)						
Element group	Members	Wu and Chow GA [18]	Lee and Geem HS [19]	Li et al. [20]			DHPSAC [21]	This work
				PSO	PSOPC	HPSO		
1	01-4	4658.055	4658.055	4658.055	5999.988	4658.055	4658.055	4658.055
2	05-10	1161.288	1161.288	1374.190	1008.380	1161.288	1161.288	1161.288
3	13-10	645.160	506.451	1858.060	2696.380	363.225	494.193	285.161
4	14-17	3303.219	3303.219	3206.440	3206.440	3303.219	3303.219	3303.219
5	18-23	1045.159	940.000	1283.870	1161.290	940.000	1008.385	1045.159
6	24-26	494.193	494.193	252.260	729.030	494.193	285.161	363.225
7	27-30	2477.414	2290.318	3303.220	2238.710	2238.705	2290.318	2477.414
8	31-36	1045.159	1008.385	1045.160	1008.380	1008.385	1008.385	1045.160
9	37-39	285.161	2290.318	126.450	494.190	388.386	388.386	161.290
10	40-43	1696.771	1535.481	2341.930	1283.870	1283.868	1283.868	1283.868
11	44-49	1045.159	1045.159	1008.380	1161.290	1161.288	1161.288	1161.288
12	50-52	641.289	506.451	1045.160	494.190	729.256	506.451	506.451
Weight(kg)		1970.142	1906.76	2230.16	2146.63	1905.49	1904.83	1901.35

Note: 1 in² = 6.452 cm² ; 1 *lb* = 4.45 N

5.2. Ten-bar truss

The topology of a 10-bar truss is shows in Figure 6. 41 discrete values are used for cross-sectional areas (1.62, 1.80, 1.99, 2.13, 2.38 ,2.62 ,2.88, 2.93, 3.09, 3.13, 3.38, 3.47, 3.55, 3.63, 3.84, 3.87, 3.88, 4.18, 4.22, 4.49, 4.59, 4.8, 4.97, 5.12, 5.74, 7.22, 7.97, 11.5, 13.5, 13.9, 14.2, 15.5, 16, 16.9, 18.8, 19.9, 22, 22.9, 26.5, 30 and 33.5 in²). All notes in X and Y directions are subject to the allowable displacements ±2.00in. There are 10 of discrete design variables, unit weight 0.1 *lb*/in³, modulus of elasticity is 10^7 psi.

The results of the hybrid PSO and GA and other meta-heuristic algorithm are listed in Table 4. The best-optimized weight of 10-bar truss designed by the hybrid PSO and GA is 5,485.23 *lb* after 100 iterations and 5,000 searches. The best weight designed by the rest of meta-heuristic algorithms such as Mahfouz [16], Camp and Bichon [13], BB–BC [14], Barbosa et al [17], and TLBO [15] is 5,490.74 *lb*, after 100 iterations which more than Hybrid PSO and GA algorithm.

The best weight designed by IPSO is 5491.70 *lb* after 1000 iterations, which is more than the new algorithm. However, the result of the hybrid PSO and GA in both weight and searches are better than those of other meta-heuristic algorithms. While the average weight of the hybrid PSO and GAs is 5,486.98 *lb* with standard deviation 16.30 *lb* also the hybrid PSO and GA require fewer iterations for convergence. Figure 7 shows the convergence history of the hybrid PSO and GA algorithm for the 10-bar truss.

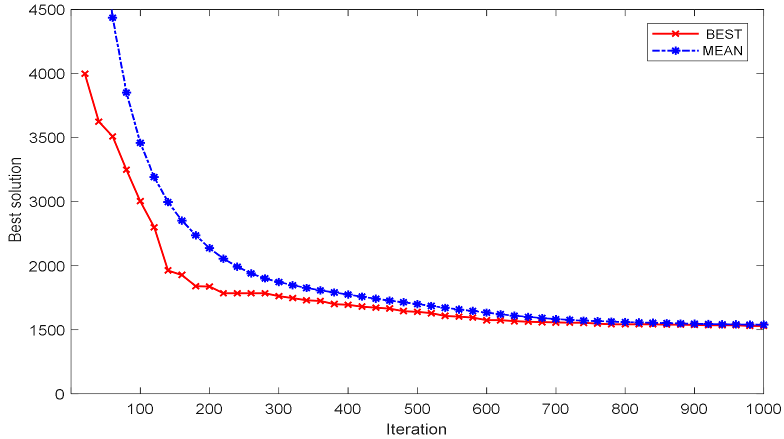

Fig. 9. The convergence history of 52-bar truss

5.3. Fifty-Two bar planar truss

Figure 8 displays the geometry of 52-bar planar. This truss structure has been size optimized using other methods by Wu and Chow [18], Lee and Geem [19], Li et al [20], Kaveh and Talatahari [21]. There are 12 groups of design variables: (1) A1 _ A4, (2) A5 _ A10, (3) A11 _ A13, (4) A14 _ A17, (5) A18 _ A23, (6) A24 _ A26, (7) A27 _ A30, (8) A31 _ A36, (9) A37 _ A39, (10) A40 _ A43, (11) A44 _ A49, (12) A50 _ A52. The modulus of elasticity 2.05×10^5 MP, the members are subject to the allowable stress limits of ±180MP, the unit weight of the material is 36.13×10^{-6} *lb*/in^3, the structure is subject to the load, P_x = 100 KN and P_y=200 KN. The discrete variables are chosen from Table 5.

The results of the hybrid PSO and GA and other meta-heuristic algorithm are listed in Table 6. As you see the best weight of 52-bar truss designed by the hybrid PSO and GA is 1901.35kg with 250 iterations and 5,000 searches. The standard deviation and average weight of hybrid PSO and GA are 2.35kg and 1903.75kg. HPSO [20] designed the best weight 1905.49kg after 2000 iterations, the best weight designed by DHPSACO [21] is 1904.83kg with 212 iterations and 5300 searches, which more than Hybrid PSO and GA algorithm. However, the result of the hybrid PSO and GA is better than other Meta-heuristic algorithms. Also, they did not report any information about standard deviation and average weight. Figure 9 shows the convergence history of the hybrid PSO and GA algorithm for the 52-bar truss.

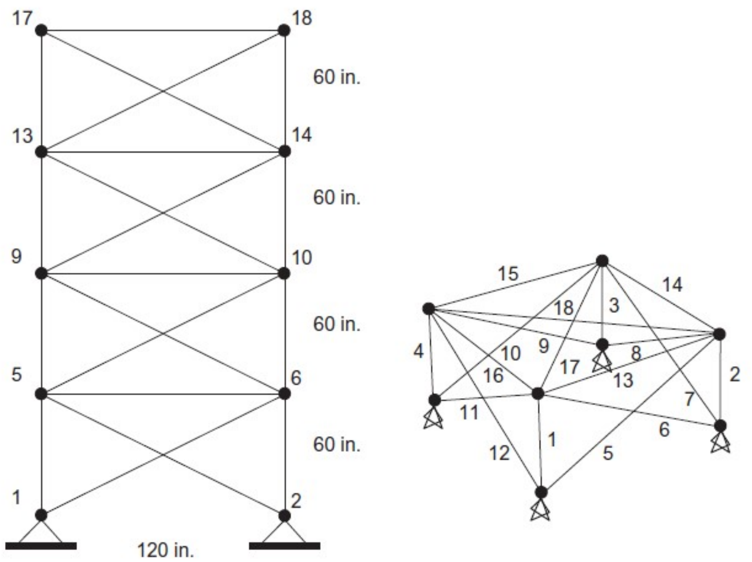

Fig. 10. Geometry and elements definition of 72-bar truss. (a) dimension and node numbering; (b) the pattern of element numbering.

Table 7. Multiple loading for the 72-bar truss

Case	Node	P_x (kips)	P_y (kips)	P_z (kips)
1	17	0.0	0.0	-5.0
	18	0.0	0.0	-5.0
	19	0.0	0.0	-5.0
	20	0.0	0.0	-5.0
2	17	5.0	5.0	-5.0

Note: 1 in^2 = 6.452 cm^2 ; 1 *lb* = 4.45 N

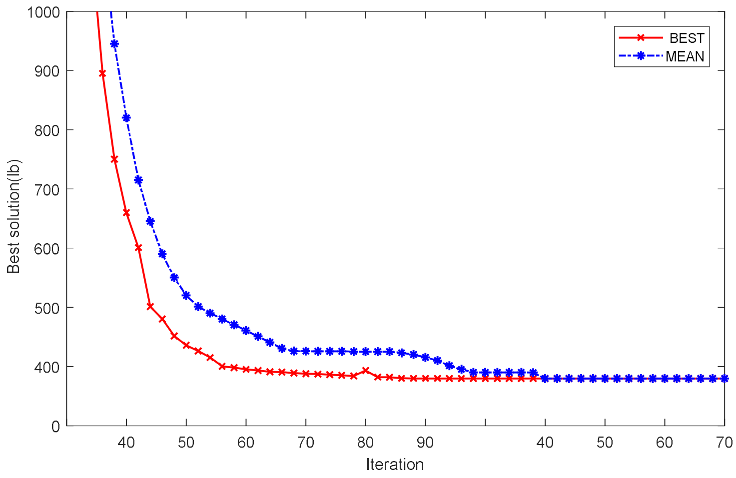

Fig 11. The convergence history of 72-bar spatial truss

Table 8. Performance comparison for 72-bar spatial truss with discrete design variables

Variables		Cross-sectional area(mm²)							
Element group	Members	Wu and Chow GA [18]	Lee and Geem HS [19]	Li et al. [20]			DHPSACO [21]	IPSO [33]	This work
				PSO	PSOPC	HPSO			
1	01-4	1.5	1.9	2.6	3.0	2.1	1.9	2.0	1.9
2	05-12	0.7	0.5	1.5	1.4	0.6	0.5	0.5	0.5
3	13-16	0.1	0.1	0.3	0.2	0.1	0.1	0.1	0.1
4	17-18	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
5	19-22	1.3	1.4	2.1	2.7	1.4	1.3	1.3	1.3
6	23-30	0.5	0.6	1.5	1.9	0.5	0.5	0.5	0.5
7	31-34	0.2	0.1	0.6	0.7	0.1	0.1	0.1	0.1
8	35-36	0.1	0.1	0.3	0.8	0.1	0.1	0.1	0.1
9	37-40	0.5	0.6	2.2	1.4	0.5	0.6	0.5	0.5
10	41-48	0.5	0.5	1.9	1.2	0.5	0.5	0.5	0.5
11	49-52	0.1	0.1	0.2	0.8	0.1	0.1	0.1	0.1
12	53-54	0.2	0.1	0.9	0.1	0.1	0.1	0.1	0.1
13	55-58	0.2	0.2	0.4	0.4	0.2	0.2	0.2	0.2
14	59-66	0.5	0.5	1.9	1.9	0.5	0.6	0.6	0.5
15	67-70	0.5	0.4	0.7	0.9	0.3	0.4	0.4	0.3
16	71-72	0.7	0.6	1.6	1.3	0.7	0.6	0.6	0.6
Weight (*lb*)		400.66	387.94	1089.88	1069.79	388.94	385.54	385.54	383.54

5.4. Seventy-two bar spatial truss

Figure 10 shows the geometry and more details of the 72-bar truss. The structure is subjected to multiple loading listed in Table 7. The modulus of elasticity is 1e7 psi. The unit weight of the material is 0.1 *lb*/in^3. The members are subjected to the allowable stress limits of ±25ksi, and the maximum displacement of each node is ±0.25 in through X, Y, and Z direction. There are 16 groups of design variables with a minimum 0.1in^2 and maximum 3.0 in^2: (1) A1 _ A4. (2) A5 _ A12, (3) A13 _ A16, (4) A17 _ A18, (5) A19 _ A22, (6) A23 _ A30, (7) A31 _ A34, (8) A35 _ A36, (9) A37 _ A40, (10) A41 _ A48, (11) A49 _ A52, (12) A53 _ A54, (13) A55 _ A58, (14) A59 _ A66, (15) A67 _ A70, (16) A71 _ A72. A set of discrete variables are as: {0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0, 1.1, 1.2, 1.3, 1.4, 1.5, 1.6, 1.7, 1.8, 1.9, 2.0, 2.1, 2.2, 2.3, 2.4, 2.5, 2.6, 2.7, 2.8, 2.9, 3.0, 3.1, 3.2} (in:2)
The results of the meta-heuristic algorithms are listed in Table 8. The best weight of hybrid PSO and GA is 383.54 *lb* with 250 iterations and 5250 searches, The standard deviation and average weight of hybrid PSO and GA are 1.29 *lb* and 385.23 *lb*, Wu and Chow [18] best weight is 400.66 *lb*. The best weight of the Lee and Geem [19] is 387.94 *lb*. HPSO [20] designed the best weight 388.94 *lb* after 1000 iterations and 50000 searches, and the best weight of the DHPSACO [21] is 385.54 *lb* with 213 iterations and 5330 searches, which is more than hybrid PSO and GA algorithm. They did not report any information about standard deviation and average weight. The best weight of the IPSO [33] is 385.54 *lb* and the standard deviation and average weight are 0.62 *lb* and 387.11 *lb*. Figure 11 shows the convergence history of the hybrid PSO and GA algorithm for the 72-bar spatial truss.

6. Conclusion

The present study has developed a hybrid PSO and GA for the optimal design of trusses. During the last decades, PSO and GA algorithms have shown an outstanding performance and have been widely used in different sciences. The PSO and GA algorithms are very similar in their optimization process. For example, they are both population-based, in the sense that they enhance the search process for the optimal design by sharing information among the group members. One of the PSO weaknesses is that it is trapped at the local optimum. To remove this problem, the GA algorithm was used not only to enhance the global exploration but also to help achieve the optimal design. To demonstrate the good performance of this new algorithm, several truss structures were optimized, and then the results of this new algorithm were compared to those of the most popular meta-heuristic algorithms. The results indicated that the new algorithm developed the performance.

Conflict of Interest

The authors declared no potential conflicts of interest with respect to the research, authorship and publication of this article.

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