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Shape Optimization of Truss Structures for Displacement Constraints Using a Modified Particle Swarm Optimization (MPSO) Algorithm

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ABSTRACT

This paper presents a modified particle swarm optimization (MPSO) algorithm for the shape optimization of truss structures under displacement constraints. The proposed MPSO employs a multi-stage strategy, where the final solution of each stage is used to reinitialize the swarm in the next stage, improving convergence accuracy. A normal-based distribution is used for swarm regeneration, promoting effective exploration around the best solution found. Design variables are the nodal coordinates of the structures, and the total weight is considered as the objective function. Design constraints include limitations on nodal displacements, and some geometric constraints are also considered. The method is evaluated using four benchmark truss examples. Results show that MPSO reduces structural weight by 7% for the 13-bar truss, 5.7% for the 25-bar truss, and 2.2% for the 52-bar truss, compared to those reported in the literature, while also maintaining or improving displacement control. In the 37-bar planar truss, the algorithm marginally outperforms the existing result by reducing weight by 0.18%. These outcomes confirm that the proposed MPSO provides competitive or superior performance compared to reference methods in both efficiency and solution quality.

1. Introduction

Over recent years, substantial progress has been made in optimizing structures with linear elastic behavior. In many studies related to the optimal design of structures, instead of using classical mathematical methods, modern optimization algorithms have been used, and their performance is assessed. Natural processes often inspire modern optimization methods and offer key advantages, such as eliminating the need for derivative information and enhancing the ability to find global optima. Among these, a prominent class is metaheuristic algorithms, which have gained widespread attention for their effectiveness in tackling complex constrained optimization problems where traditional methods often fall short [1]. Metaheuristic algorithms are commonly categorized into three main groups, including evolutionary algorithms (e.g., genetic algorithm, differential evolution) [2, 3]; swarm intelligence methods (e.g., particle swarm optimization, ant colony optimization) [4-7]; and physics-inspired algorithms (e.g., simulated annealing) [8, 9].

Rajeev and Krishnamoorthy [10] modified the simple genetic algorithm introduced by Goldberg [11] for minimizing the structural weight as the objective function while the discrete area members of the structure were considered as the design variables. Wang et al. [12] made an effort to find the optimal shape of structures with displacement constraints. Lee and Geem [13] introduced a harmonic search algorithm (HS) for size optimization of truss structures under various loading conditions. Toğan and Daloğlu [14] introduced an adaptive approach in genetic algorithms (GA) in order to optimize three-dimensional truss structures. A modified genetic algorithm (MGA) was used by Salajegheh et al. [15] to optimize the space structures, in which the optimal size and shape design under various static loading conditions were studied. Limitations on stress, nodal displacement, and slenderness ratio were considered as design constraints, and structural weight was also selected as the objective function. Cheng [16] used a hybrid genetic

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algorithm for the optimal design of steel trusses of arched bridges, where the total structural weight was considered as the objective function. An enhanced charge system search (CSS) to determine the size and configuration optimum design of structures was introduced by Kaveh and Talatahari [17].

Particle swarm optimization (PSO), introduced by Kennedy and Eberhart [18], is a widely used metaheuristic known for its simplicity, fast convergence, and minimal parameter tuning. Its effectiveness has led to broad applications across disciplines, including structural engineering. Seyedpoor et al. [19] combined PSO with SPSA for truss size optimization, demonstrating improved efficiency in several benchmark problems. Luh and Lin [20] developed a two-stage PSO method for truss optimization, combining binary PSO for topology design and ARPSO for size and shape optimization. Their approach outperformed genetic algorithms and ant colony optimization in terms of structural weight, solution quality, and computational efficiency. The work of Gholizadeh [21] involved the formulation of a hybrid optimization technique for truss layout design, which integrates PSO alongside cellular automata (CA). This approach utilized a new CA-based PSO (CPSO) to improve particle paths, while constraints were addressed through a sequential unconstrained minimization technique (SUMT) paired with an exact penalty function. The findings indicated that SCPSO surpassed traditional PSO and other methods in reducing structural weight, speeding up convergence, and enhancing computational efficiency. Kaveh and Zolghadr [22] developed a democratic particle swarm optimization (DPSO) algorithm to address premature convergence in standard PSO, particularly in structural optimization problems with frequency constraints. The proposed DPSO introduces a democratic decision-making process where all eligible particles contribute to updating positions, enhancing exploration, and preventing local optima stagnation. Mortazavi and Toğan [23] introduced an integrated particle swarm optimizer (IPSO) for simultaneous size, shape, and topology optimization of truss structures. The algorithm employs a unified coding scheme within a ground structure framework to represent all design variables in a single solution vector. This integration allows for efficient exploration of the design space while satisfying structural constraints. Cao et al. [24] proposed an enhanced particle swarm optimization (EPSO) algorithm to improve the size and shape optimization of truss structures. EPSO integrates new movement rules and diversity-preserving mechanisms to prevent premature convergence and enhance global search ability. Tsiptsis et al. [25] Integrated isogeometric analysis (IGA) with PSO to improve structural shape optimization. By leveraging the smoothness and accuracy of NURBS-based IGA within the PSO framework, the method enhanced geometric representation and reduced numerical errors. Jafari et al. [26] proposed a hybrid optimization method integrating Particle Swarm Optimization (PSO) with cultural algorithm (CA) for truss structure design. In the proposed PSOC algorithm, the cultural space is used to guide particle movements, restrict variables within feasible ranges, and eliminate unnecessary analyses. By modifying the personal best term and applying a selective analysis strategy based on structural weight changes, the algorithm improves convergence speed and solution quality.

In this study, a modified version of the particle swarm optimization algorithm referred to as modified particle swarm optimization (MPSO) is introduced for the shape optimization of truss structures under displacement constraints. The proposed MPSO algorithm incorporates a multi-stage search strategy to improve convergence and solution accuracy. The method is validated using several benchmark truss examples, and numerical results indicate the effectiveness and robustness of MPSO in achieving optimized structural configurations.

2. PSO algorithm

The particle swarm optimization (PSO) algorithm was first introduced by Kennedy and Eberhart [18] in 1995. The algorithm has been inspired by the life of birds that live sociably and supply their needs together, such as searching for food. According to the algorithm, it has been assumed that the birds instinctively recognize their distance to the food while they are not aware of the food location. Furthermore, all the birds, by sharing their information, are aware of the location nearest to the food. In this algorithm, each bird can be considered as a potential solution called a particle, and the group of particles is called the swarm. Each particle has a fitness value that can be obtained by the objective function of the optimization problem. Accordingly, a bird that is closer to the food has the most merit. Each bird also has a velocity vector that indicates the movement direction and the size of the bird. During the optimization process, the location of a bird based on its personal experience and the experience of other birds is improved.

Numerically, the position of the ith particle at iteration $k + 1th$ is improved by Eq. 1. In this formula V_{k+1}^{i} is the modified velocity of the ith particle that can be obtained from Eq. 2 and Δt is a time step which may be calculated by Eq. 3. In many studies, the time step is assumed to be 1.

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

$$V_{k+1}^{i} = \rho_k V_{k}^{i} + c_1 r_1 \frac{(P_{k}^{i} - X_{k}^{i})}{\Delta t} + c_2 r_2 \frac{(P_{k}^{g} - X_{k}^{i})}{\Delta t} \tag{2}$$

$$\Delta t = \frac{1}{k_{max}} \tag{3}$$

where V_{k}^{i} is the velocity vector at iteration k, r_1 and r_2 are two random numbers between zero and one, P_{k}^{i} shows the best position of the i^{th} particle, and P_{k}^{g} is the best position of all particles until the k^{th} iteration in all groups. The c_1 and c_2 are called the trust and confidence parameters, ρ is a parameter called the inertia weight, and k_{max} stands for the maximum number of iterations.

Due to the importance of inertia weight in the PSO algorithm to reach the global solution, rather than considering a fixed value for ρ during the optimization process, it can be linearly varied from a maximum value ρ_{max} to a minimum value ρ_{min} as:

$$\rho_k = \rho_{max} - \frac{\rho_{max} - min}{k_{max} - 1}(k-1) \tag{4}$$

More information about the PSO algorithm can be found in research by Kennedy and Eberhart [18] and Seyedpoor et al. [27]. The PSO algorithm flowchart is shown in Fig. 1.

3. Modified particle swarm optimization (MPSO) algorithm

The MPSO algorithm is a modified form of the PSO algorithm. The main body of the MPSO algorithm consists of the PSO. According to the algorithm, instead of implementing the PSO algorithm at once, it is run in several stages so that the final solution of each stage is used to create an initial swarm for the next optimization stage. In the first stage of the optimization, an initial swarm is randomly generated within the allowable space of design variables. In the next stage, the swarm is produced by a normal distribution around the solution obtained from the previous stage according to Eq. 5, and the PSO program is called again. This process is repeated until a satisfactory convergence is achieved in solving the optimization problem.

$$X^i = X_{MPSO}\{1 + randn(i,j)\}_{nv\times 1} Covx, \quad i = 1,\dots,np, \;\; j = 1,\dots,nv \tag{5}$$

where the randn (i, j) is a function that will generate a random quantity with a normal distribution, and *Covx* is the variation coefficient of the random variable. Also, *np* and *nv* are the total number of particles and design variables in optimization.

The MPSO algorithm flowchart is shown in Fig. 2.

4. The optimal design problem

In this study, the capabilities of the MPSO algorithm for solving the shape optimization of truss structures are studied. The truss optimization problem under displacement constraints is examined, and the optimal design problem can be expressed as:

$$\begin{aligned} &\text{Find} &&: X = \{x_1, x_2, \dots, x_{nv}\}^T \\ &\text{Minimize} &&: W(X) \\ &\text{Subject to} &&: g_q(X) \le , \;\; q = 1,\dots,m \\ & && \;\; X^1 \le X \le X^u \end{aligned} \tag{6}$$

where X is a design variable vector with *nv* unknowns, $W(X)$ represents an objective function that should be minimized, and g_q is the *qth* constraint from *m* inequality constraints. Also, X^l and X^u represent the lower and upper bounds of the design variable vector, respectively.

4.1. The design variables

In optimization of truss structures, the nodal coordinates of joints are considered as the design variable vector that can be expressed as:

$$X = \{x_1, y_1, z_1, \dots, x_i, y_i, z_i, \dots, x_{nj}, y_{nj}, z_{nj}\}^T \tag{7}$$

where x_i, y_i, *and* z_i are the *x*, *y*, and *z* coordinates of joint *i* of the structure, and *nj* is the total number of joints in the truss.

4.2. The objective function

The total weight of the truss structure is considered as the objective function, which can be defined as follows:

$$W(X) = \sum_{n=1}^{ng} a_n \sum_{i=1}^{nm} \gamma_i l_i(X) \tag{8}$$

where γ_i and l_i are the specific weight and length of the *ith* member of the structure, respectively; *nm* is the total number of members in group *n* having the sectional area a_n, and *ng* is the total number of area groups in the structure.

4.3. Design constraints

Design constraints include some restrictions on nodal displacements and a number of geometric ones. Nodal displacement constraints can be given by Eq. 9.

$$g_{dj}(X) = \frac{|\delta_j|}{|\delta_{ju}|} - 1 \le 0 \quad j = 1,\dots,nj \tag{9}$$

where δ_j is the nodal displacement of node *j*; δ_{ju} is the allowable displacement of node *j*, and *nj* is the total number of displacement constraints.

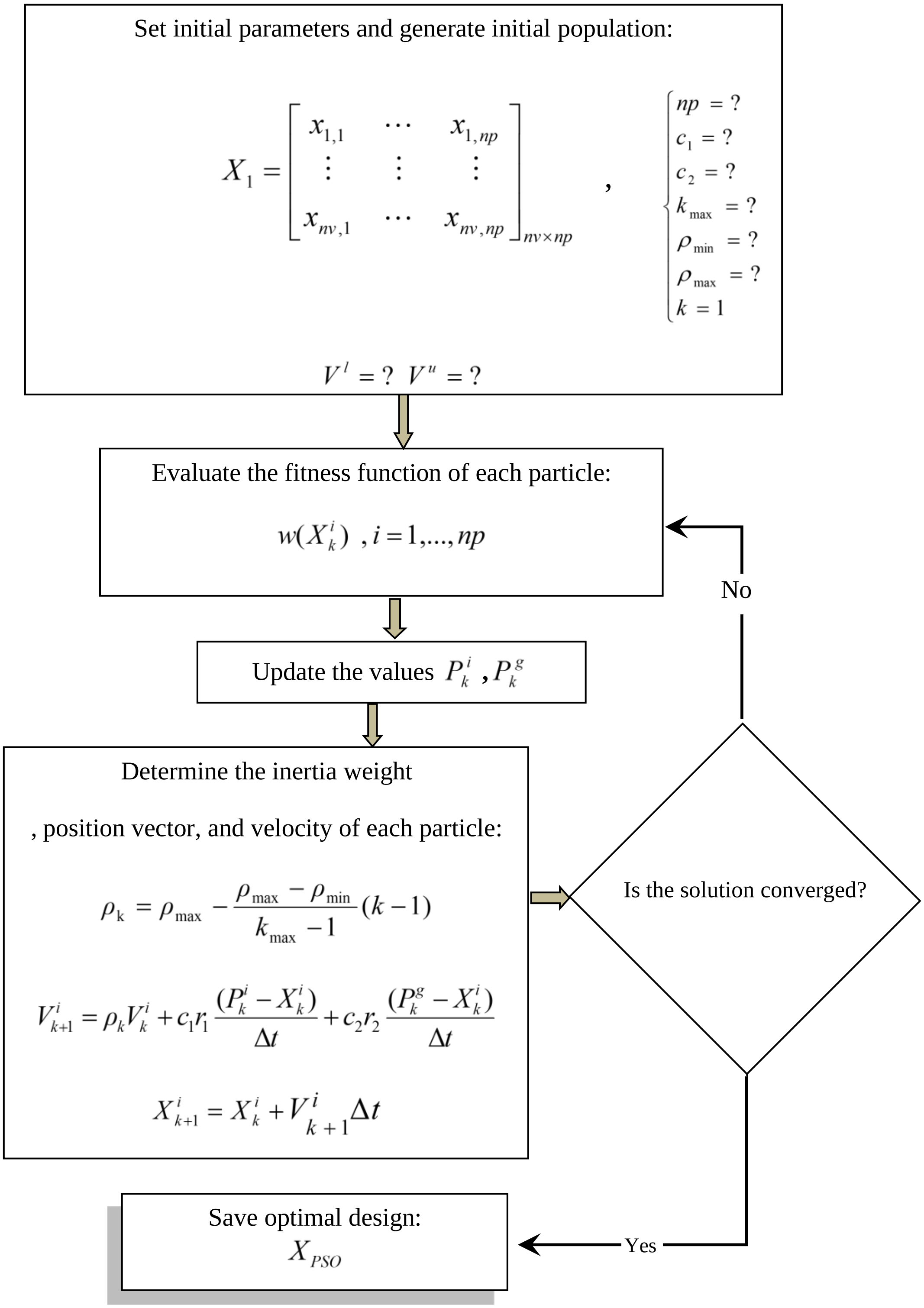

Fig. 1. PSO algorithm flowchart.

In this study, a fitness function (quasi-objective function) is defined by Eq. 10:

$$Z(X, r_p) = W(X)\left\{1 + r_p \sum_{q=1}^{m}\left[max\left(0, g_q(X)\right)\right]^2\right\} \tag{10}$$

where Z is the fitness function and r_p is a penalty multiplier.

5. Numerical examples

In order to assess the performance of the proposed method, four standard test examples are selected from the literature. The examples consist of a 13-bar planar truss, a 25-bar space truss, a 52-bar space truss, and a 37-bar planar truss, respectively. The input parameters of the MPSO algorithm for all the test examples are given in Table 1.

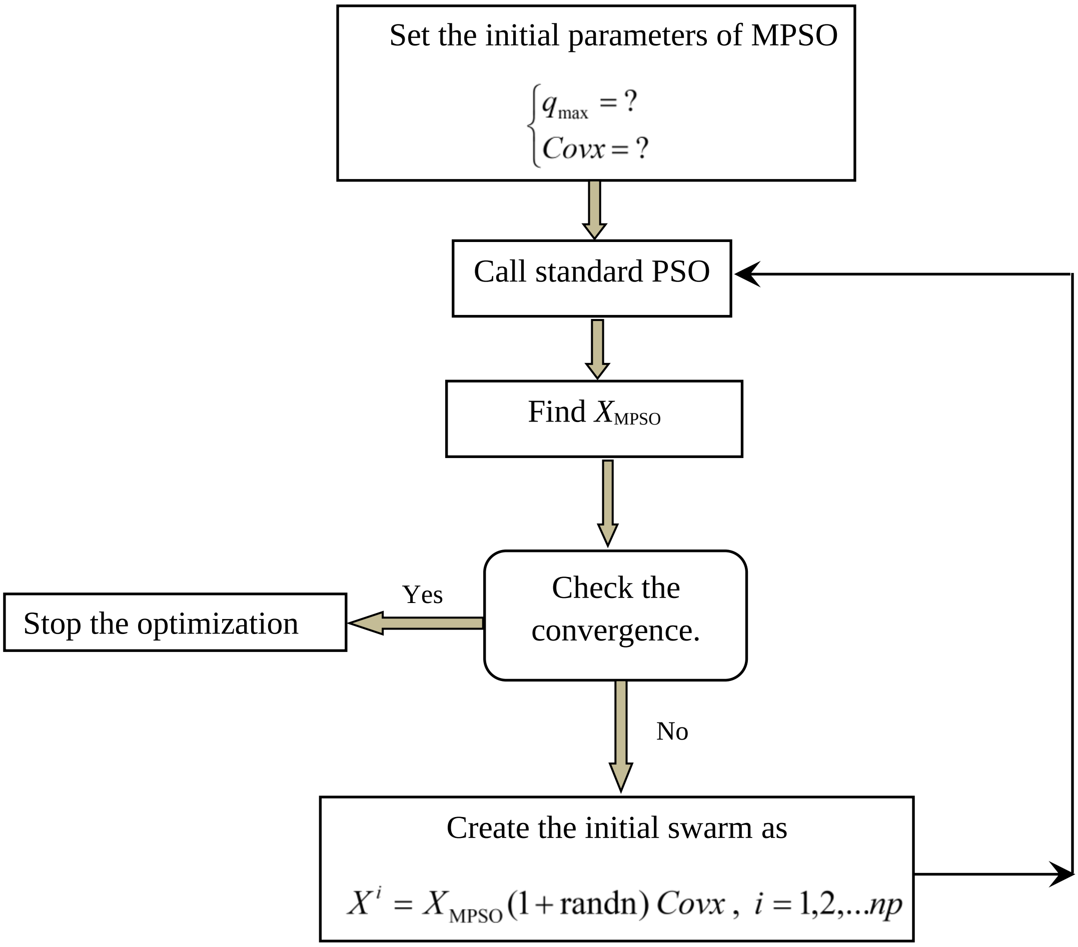

Fig. 2. MPSO algorithm flowchart.

Table 1. Initial parameters of the MPSO algorithm.

Parameters	Describtiom	Value
c_1	Cognitive parameter	2.00
c_2	Social parameter	2.00
ρ_{min}	Minimum of inertia weight	0.01
ρ_{max}	Maximum of inertia weight	0.90
np	Swarm size for examples 1–4, respectively	10, 10, 30, 20
k_{max}	Maximum number of PSO iterations for examples 1–4, respectively	40, 40, 60, 60
q_{max}	Maximum number of MPSO iterations for examples 1–4, respectively	5, 6, 5, 6
$Covx$	Variation coefficient	0.015

5.1. Thirteen-bar planar truss

The first example is a 13-bar planar truss, as shown in Fig. 3. The optimum shape design of the structure has been made by Wang et al. [12] under nodal displacement constraints. The structure is subjected to the vertical load of 200 kN at node 1. The maximum vertical displacement of nodes should be smaller than or equal to 1.168 mm. Young's modulus is $E = 2.1 \times 10^{11}$Pa, and the material density is 7800 kg/m^3. The cross-sectional area of all bars is equal to A = 10 cm^2. For shape optimization, nodes 3 and 7 in the horizontal direction and nodes 4, 5, and 6 in the vertical direction are allowed to move. During the optimization process, the structural symmetry must be maintained. So, with respect to the symmetry shape of the structure, the positions of nodes 5, 6, and 7 must be considered as the design variables.

Before the optimization, the structural weight was 71.4 kg. When the vertical load of 200 kN is applied at node 1, the vertical displacement of the node reaches 4.805 mm. Wang et al. [12], could reach the total weight of the truss from 71.4 kg to 78.6 kg, while the nodal displacement decreased from 4.805 mm to 1.168 mm. In this study, to demonstrate the performance of the MPSO, the structure is optimized, and the results are compared with those reported by Wang et al. [12] in Table 2.

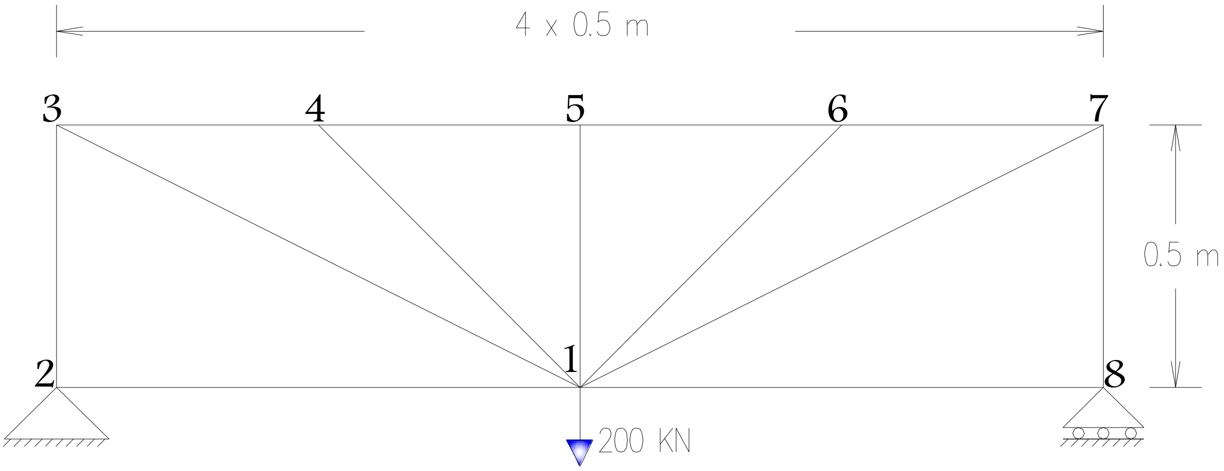

Fig. 3. Thirteen-bar planar truss.

As given in the table, the optimum weight obtained by MPSO is 73.068 kg, while the vertical displacement of node 1 is 1.168 mm. It can be concluded that the structure weight is reduced by 7% when compared with those obtained by Wang et al. [12]. The optimum shape of the structure obtained by MPSO is shown in Fig. 4.

Table 2. Optimal design comparison for the 13-bar planar truss.

Design variables(m)	Initial coordinates	Optimum coordinates [12]	Optimum coordinates MPSO
y_5	0.5	1.008	0.8911
y_6	0.5	0.867	0.745
x_7	1.0	0.848	0.756
Weight (kg)	71.40	78.6	73.068
δ_{max} (mm)	4.805	1.168	1.168

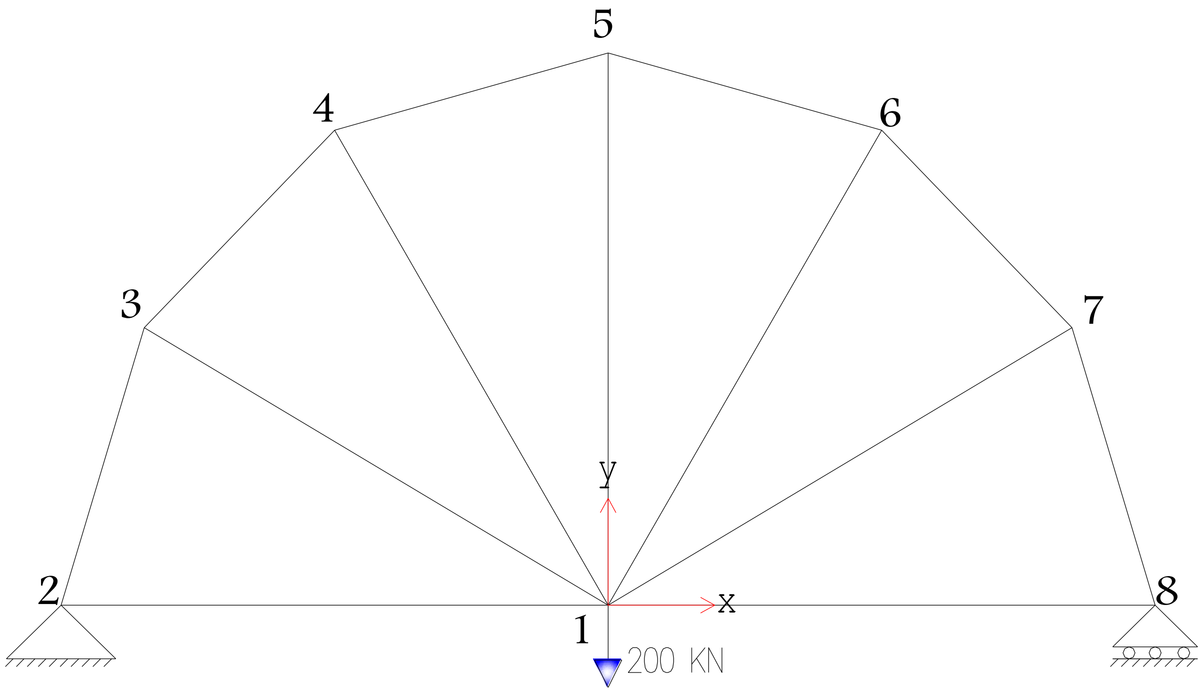

Fig. 4. Shape optimization of 13-bar planar truss obtained by MPSO.

The convergence history of optimization is shown in Fig. 5, where the objective function is represented in terms of the optimization stage. As can be seen, in each stage of optimization, the objective function increases to satisfy the displacement constraint. Fig. 6 shows the vertical displacement of node 1 in terms of the optimization stage.

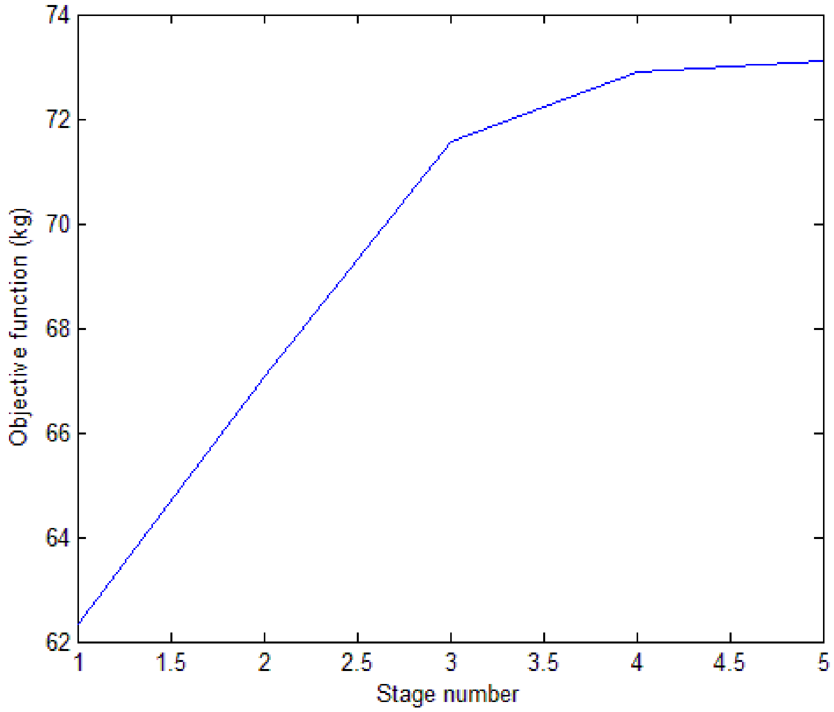

Fig. 5. The convergence history of MPSO for the 13-bar planar truss.

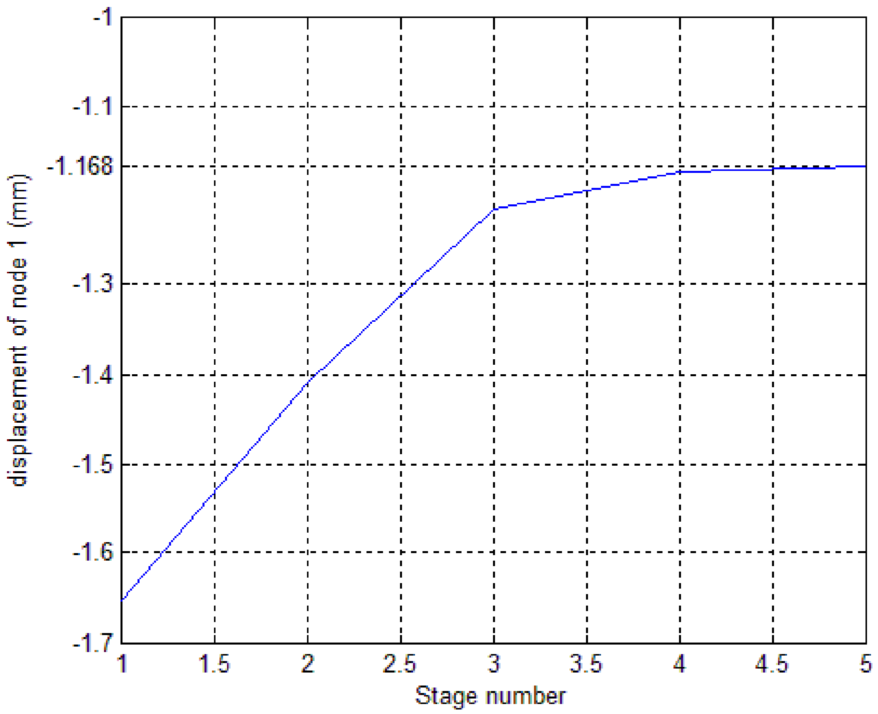

Fig. 6. Displacement variations of node 1 of the 13-bar planar truss for the MPSO algorithm.

5.2. Twenty-five-bar space truss

The shape optimization of a 25-bar space truss shown in Fig. 7 is considered as the second example [12]. The modulus of elasticity is $E = 6.89 \times 10^{10}$ Pa and mass density is $\rho = 2768$ kg/m^3. The structure is subjected to two separate loading conditions as given in Table 3. Design constraints are considered to limit the vertical displacement of nodes to 8.89 mm. During the optimization process, the fully symmetric structure should be preserved. Therefore, nodes 4 and 8 are allowed to move along the x, y, z, and x, y axes, respectively, and the optimal design problem has four shape variables. In this example, the member areas are divided into two groups as listed in Table 4. The initial design variables of the truss, the best solution achieved by MPSO, and that reported by Wang et al. [12] are given in Table 5.

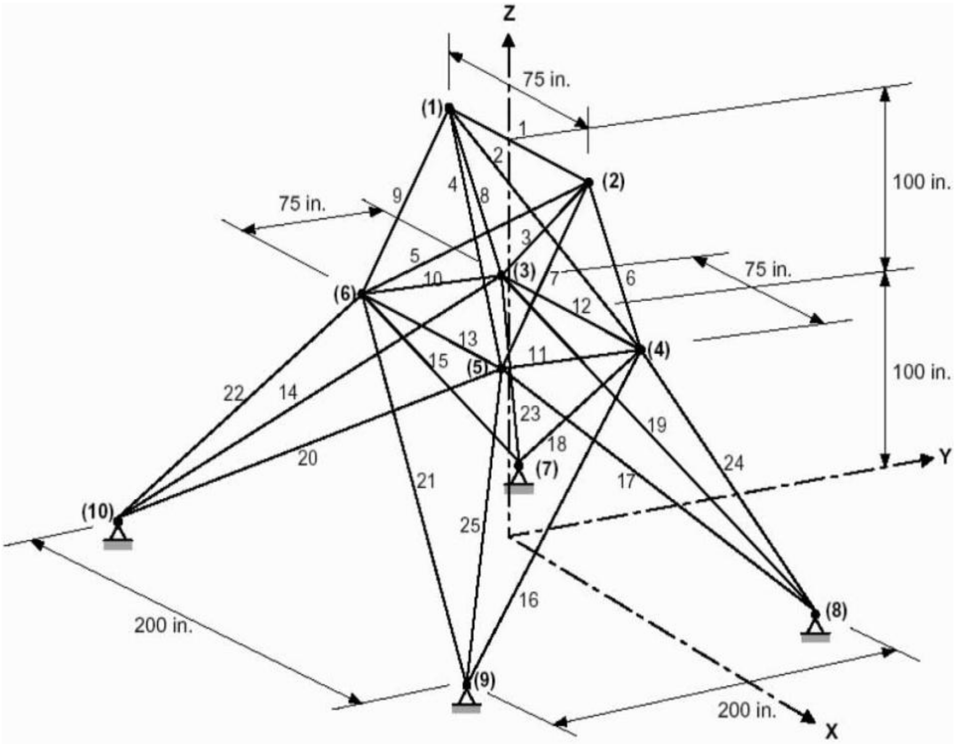

Fig. 7. The 25-bar space truss.

Table 3. Loading cases for the 25-bar space truss.

Node	Load case 1 (kN)			Load case 2 (kN)		
	Px (kN)	Py (kN)	Pz (kN)	Px (kN)	Py (kN)	Pz (kN)
1	4.4482	44.482	-22.241	0.0	88.964	-22.241
2	0.0	44.482	-22.241	0.0	-88.964	-22.241
3	2.2241	0.0	0.0	0.0	0.0	0.0
6	2.2241	0.0	0.0	0.0	0.0	0.0

Table 4. Member area grouping for the 25-bar space truss.

Group number	Truss elements	Area (cm^2)
1	A_1-A_9	4
2	A_{10}–A_{25}	5

Table 5. Optimal design comparison for the 25-bar space truss.

Design variables (m)	Initial coordinates	Optimum coordinates [12]	Optimum coordinates MPSO
X_4	0.952	0.608	0.3814
Y_4	0.952	1.957	1.8767
Z_4	2.54	2.756	3.0475
X_8	2.54	1.575	1.2948
Y_8	2.54	3.020	2.4490
Weight (Kg)	109.00	114.40	107.84
δ_{max} (mm)	29.60	8.89	8.89

The initial structure weighs 109.0 kg, leading to a displacement of 29.60 mm for node 1. Wang et al. [12] reached the structural weight from 109.0 kg to 114.40 kg, while the nodal displacement of the joint changed from 29.6 mm to 8.89 mm. In fact, after optimization, the structural weight increased by 4.95% and the displacement decreased by 70%.

The MPSO could achieve a weight of 107.84 kg and nodal displacement of 8.89 mm. Compared with the primary shape of the structure, nodal displacement 70% reduced and the structural weight 1.06% reduced. Compared to the solution of Wang et al. [12], the displacement does not change, but the structural weight 5.7% reduced. The optimal shape of the structure is shown in Fig. 8. According to the results given in Table 5, reaching a reasonable configuration for the structure, the performance of the MPSO method can be realized.

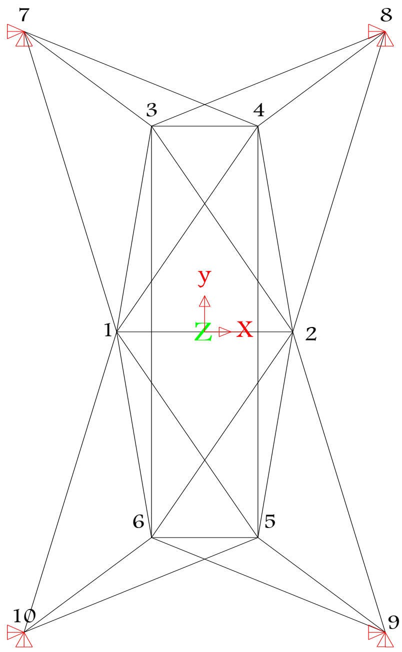

Fig. 8. Optimal design of 25-bar space truss obtained by the MPSO algorithm.

The convergence history of the optimization process for the 25-bar space truss is shown in Fig. 9. Fig. 10 also shows the maximum displacement of the truss nodes for two load cases in terms of optimization stage.

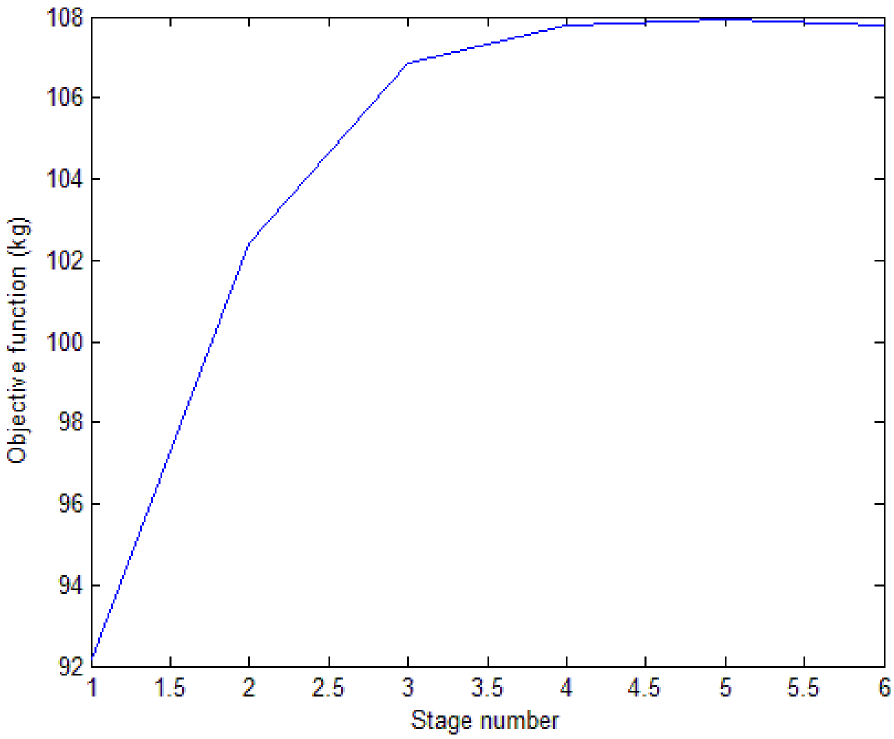

Fig. 9. Convergence history of MPSO for 25-bar space truss.

5.3. Fifty-two-bar dome structure

The third example is a 52-bar dome structure, as shown in Fig. 11 [12]. The structure is under four load cases given in Table 6. The modulus of elasticity and mass density of the structure are considered $E = 2.1 \times 10^{11}$Pa and ρ=7850 kg/m^3, respectively. Displacement of node 1 along the z axis is limited to 10 mm. During the optimization process, the axial symmetry for the dome structure should be preserved. Thus, the x and z coordinates of nodes 1, 2, and 6 are considered as design variables, and the optimization problem has six design variables related to the shape of the structure. In this example, the cross-section of all members is assumed to be 10 cm^2.

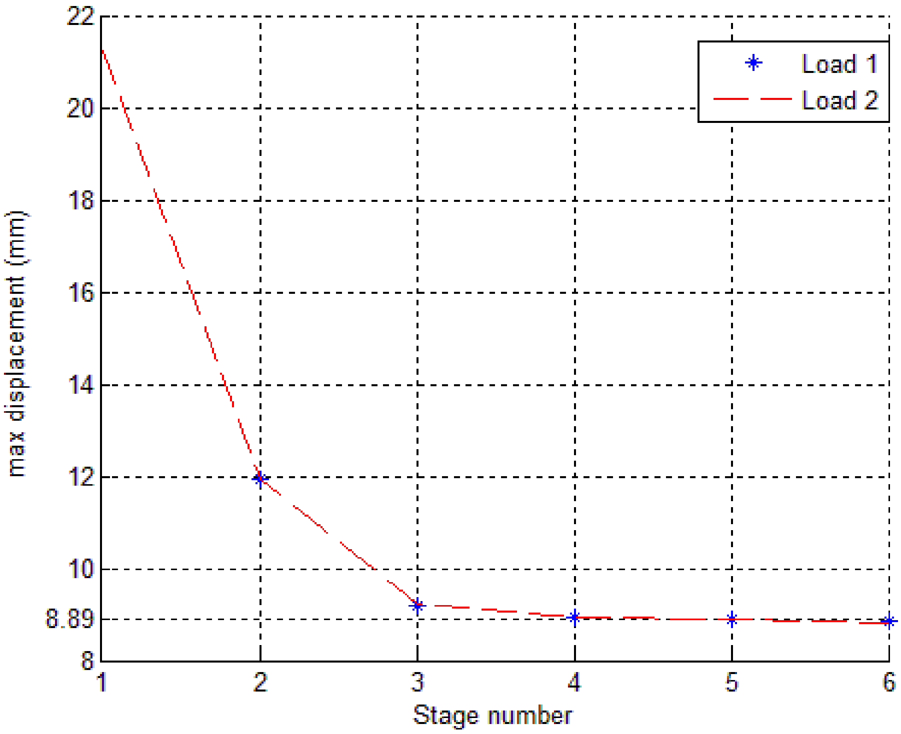

Fig. 10. Maximum displacement variations of the 25-bar space truss for two load cases.

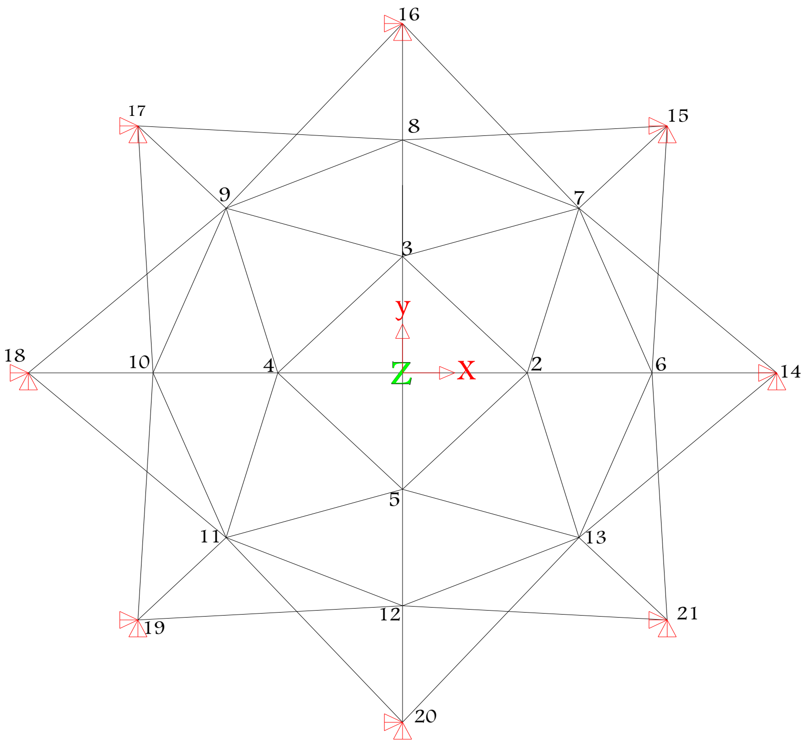

Fig. 11. Fifty-two-bar dome structure.

Table 6. Load cases for the dome structure.

Load cases	Node	P_z (kN)
1	1	300
2	1-13	300
3	1	150
	4-5	100
4	1	150
	2-4	70

The initial values of design variables, the best solution obtained by MPSO, and that reported by Wang et al. [12] are compared in Table 7.

Table 7. Optimal design comparison for the 52-bar dome structure.

Design variables (m)	Initial coordinates	Optimum coordinates [12]	Optimum coordinates MPSO
X_1	0.00	0.00	0.00
Z_1	9.25	9.62	8.3230
X_2	5.00	2.10	1.5666
Z_2	8.22	7.41	6.8363
X_6	10.0	7.21	5.5000
Z_6	5.14	4.08	4.3386
Weight (kg)	3459.2	3174.80	3104.50
δ_{max} (mm)	63.04	10	10

The initial structure weighs 3459.2 kg, leading to a maximum displacement of 63.04 mm for node 1. Wang et al. [12] reached the structural weight from 3459.2 kg to 3174.8 kg, so that the weight and maximum displacement of the structure 8.2% and 84%, respectively, were reduced. The MPSO achieved a weight of 3104.5 kg, leading to 1 cm for node 1. The displacement and weight 84% and 10.3 % have been reduced compared to the original shape. Compared with the solution of Wang et al. [12], structural weight 2.2% reduced. The optimum shape of the structure and the convergence history of optimization are shown in Figs. 12 and 13, respectively. Fig.14. shows displacement variations of node 1 for different load cases of the 52-bar space structure.

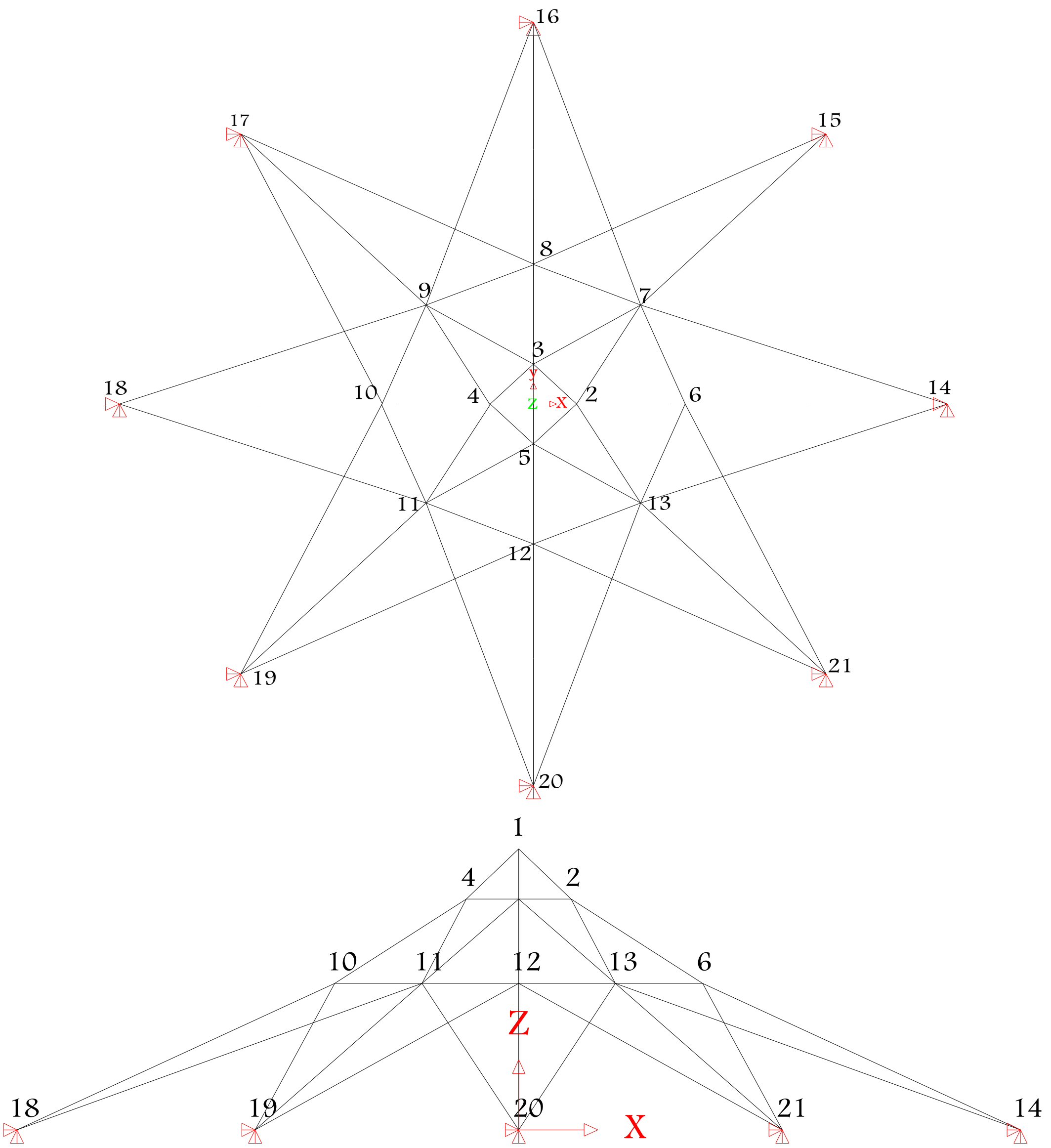

Fig. 12. Optimum configuration of the dome structure.

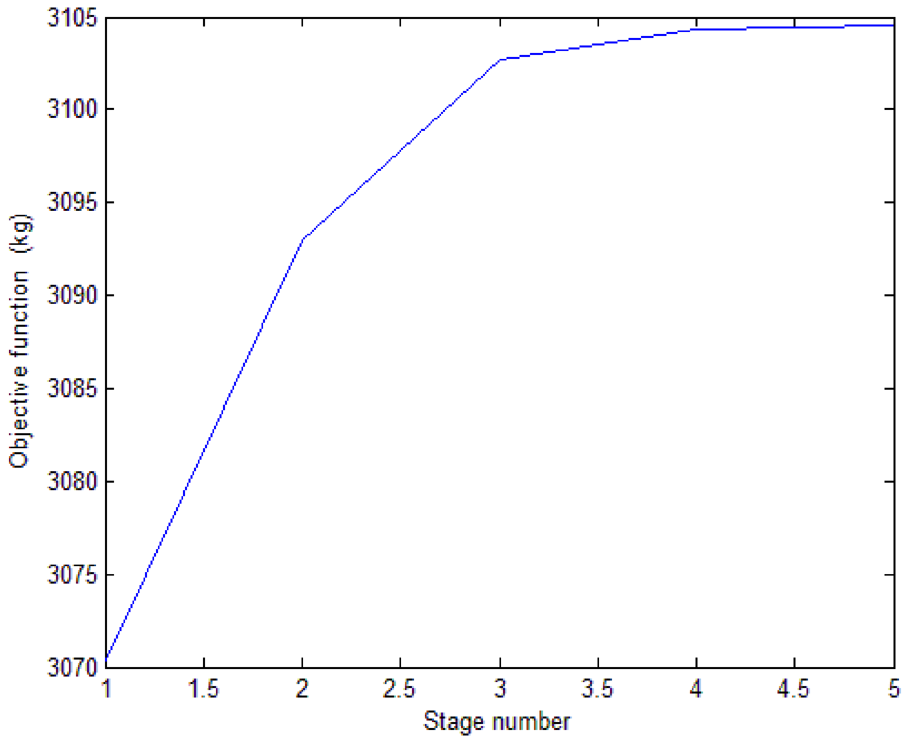

Fig. 13. The convergence history of MPSO for a 52-bar space structure.

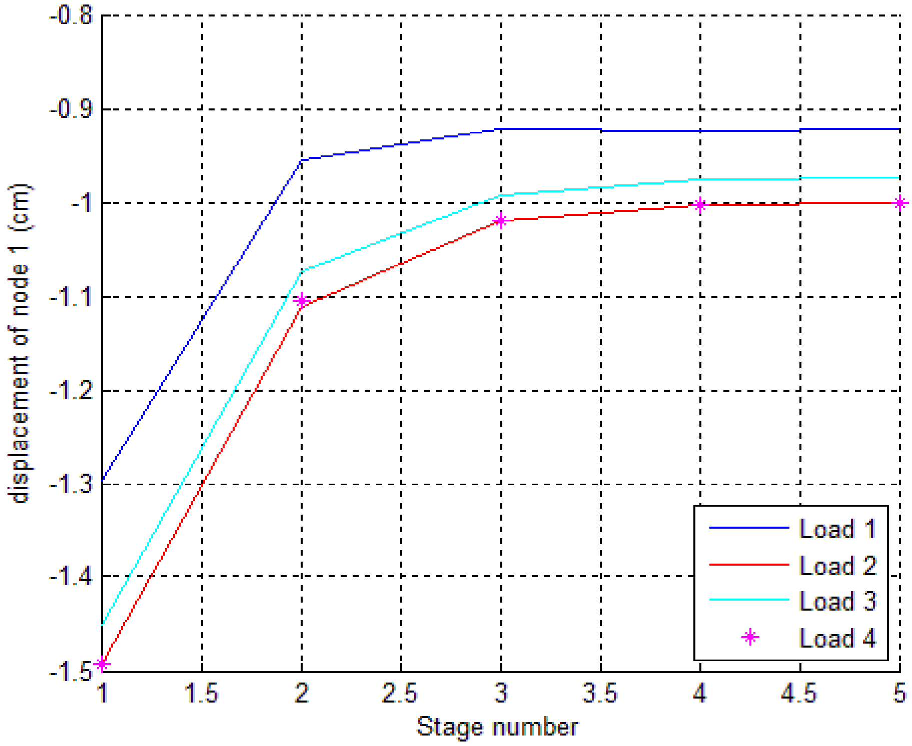

Fig. 14. Displacement variations of node 1 for different load cases of the 52-bar space structure.

5.4. Thirty-seven-bar planar truss

The last example is related to the optimization of the structure of a bridge, a 37-bar-planar truss as shown in Fig. 15. The truss structure is under two load cases given in Table 8. The modulus of elasticity is $E = 2.1 \times 10^{11}$Paand mass density is ρ=7800 kg/m^3. Vertical displacement of nodes 8 and 10 is limited to 10 mm. Bottom nodes of the bridge structure are kept constant, and top nodes are allowed to move along the y-axis. During the optimization process, the fully symmetric structures should be preserved. Thus, the y coordinates of nodes 3, 5, 7, 9, and 11 are considered here as the design variables. As shown in Fig. 15, the truss members are divided into two groups. Bottom members have a sectional area of 40cm^2, and the other members have a sectional area of 5cm^2. The initial values of design variables, the best solution obtained by MPSO, and the solution of Wang et al. [12] are given in Table 9.

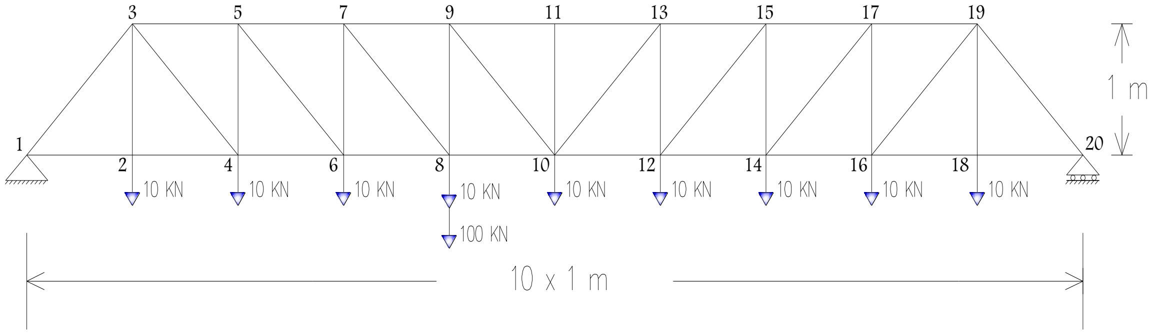

Fig. 15. Thirty-seven-bar bridge truss.

Table 8. Loading conditions for the 37-bar planar truss.

Load cases	P_y (kN)	Nodes
1	-10.0	2-4-6-8-10-12-14-16-18
2	-100	8

Table 9. Optimal design comparison for the 37-bar planar truss.

Design variables (m)	Initial coordinates	Optimum coordinates [12]	Optimum coordinates MPSO
Y_3	1.00	1.042	1.086
Y_5	1.00	1.646	1.6373
Y_7	1.00	2.172	2.1804
Y_9	1.00	2.449	2.4216
Y_{11}	1.00	2.544	2.4539
Weight (kg)	433.5	489.06	488.73
δ_{max} (mm)	32	10	10

The initial weight of the truss is 433.5 kg, leading to a maximum displacement of 32 mm at node 8. Wang et al. [12] reached the weight from 433.5 kg to 489.6 kg with 10 mm for nodal displacements. Indeed, the weight of the structures 13% increased while the displacement 69% reduced. In this study, the MPSO reached a weight of 488.73 kg while the maximum displacement of nodes reached 10 mm. It can be observed that the structural weight, 0.18% has decreased when compared with that obtained by Wang et al. [12].

The optimum shape of the structure is shown in Fig. 16. The convergence history of optimization is depicted in Fig. 17. All the results demonstrate the efficiency of the proposed MPSO for shape optimization of truss structures.

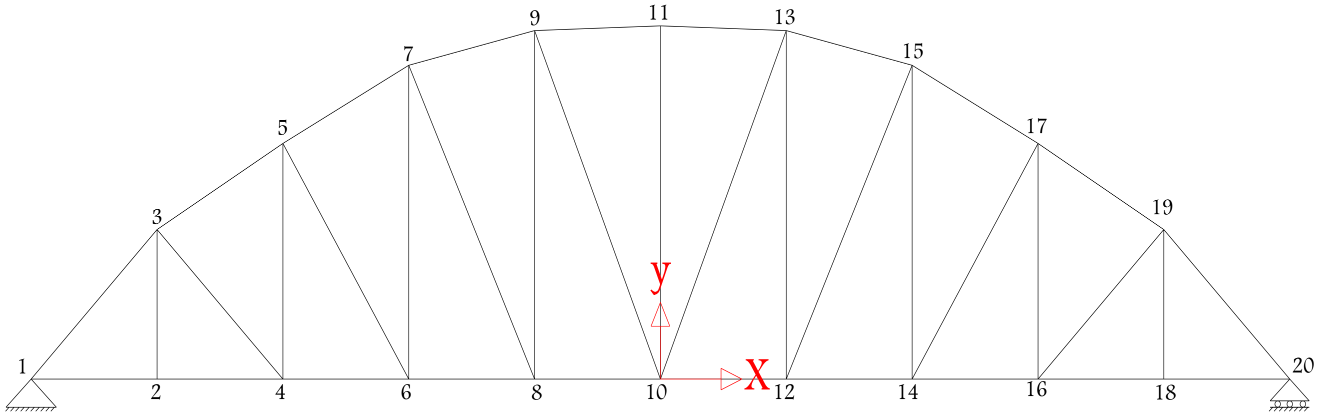

Fig. 16. Optimum configuration of simply supported bridge.

Fig.18. shows the vertical displacement variations of nodes 8 and 10 for two load cases of a 37-bar space structure for the MPSO algorithm, where the maximum displacement at node 8 and critical loading is loading 2.

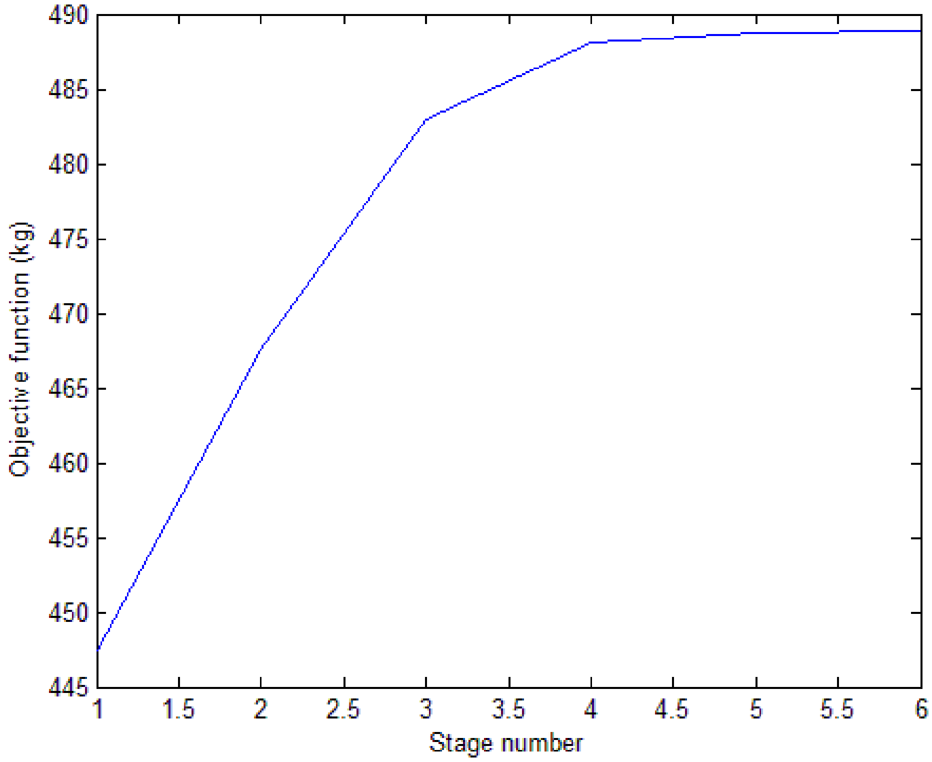

Fig. 17. The convergence history of MPSO for the 37-bar planner truss.

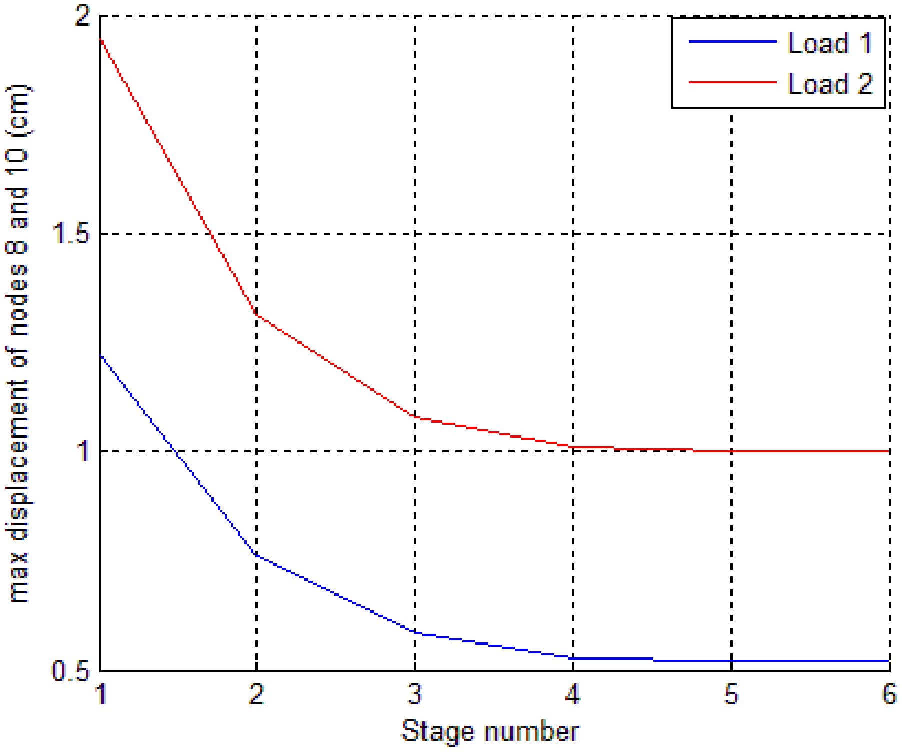

Fig. 18. Maximum displacement variation of nodes for two load cases of a 52-bar space structure.

6. Conclusion

In this study, a Modified Particle Swarm Optimization (MPSO) algorithm was developed for the shape optimization of truss structures under displacement constraints. The proposed method incorporates a multi-stage search strategy in which the final solution of each stage guides the initial population of the next, effectively improving convergence precision and reducing randomness. To evaluate the performance of the MPSO, four standard benchmark problems were investigated, including planar and spatial truss structures. The results demonstrate that the proposed MPSO achieves competitive or improved solutions in terms of structural weight reduction while satisfying displacement constraints, when compared with existing methods reported in the literature. In all examples, the MPSO not only attained feasible designs with lower structural weights but also showed a stable convergence trend with reduced computational effort. Overall, the MPSO algorithm proves to be an efficient and robust tool for solving shape optimization problems in truss structures, with strong potential for broader applications in structural engineering problems involving complex design constraints.

Statements & Declarations

Author contributions

Seyed Mohammad Seyedpoor: Conceptualization, Methodology, Supervision, Writing - Original Draft.

Morteza Pendashteh: Investigation, Visualization, Validation, Resources, Formal analysis.

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Data availability

The data presented in this study will be available on interested request from the corresponding author.

Declarations

The authors declare no conflict of interes.

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