Research on building truss design based on particle swarm intelligence optimization algorithm

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Abstract Optimization methodologies are being utilized in various structural designing practices to solve size, shape and topology optimization problems. A heuristic Particle swarm optimization (HPSO) algorithm was anticipated in this article in order to address the size optimization problem of truss with stress and displacement constraints. This article contributes in improvisation in the truss structure design rationality while reducing the engineering cost by proposing the HPSO approach. Primarily, the basic principle of the original PSO algorithm is presented, then the compression factor is established to improve the PSO algorithm, and a reasonable parameter setting value is presented. To validate the performance of the proposed optimization approach, various experimental illustrations were performed. The results show that the convergence history of experimental illustration 2 and experimental illustration 3 is optimal. The experimental illustration 2 converges after about 150 iterations, however, the experimental illustration 3 is close to the optimal solution after about 500 iterations. Therefore, the PSO algorithm can successfully optimize the size design of truss structures, and the algorithm is also time efficient. The improved PSO algorithm has good convergence and stability, and can effectively optimize the size design of truss structures.

Keywords Particle swarm optimization algorithm · Truss structure · Compression factor · Heuristic particle swarm optimization · Engineering cost · Topology optimization problems

1 Introduction

The optimization of engineering structures provides a suitable frame structure for dealing with a variety of technical issues by combining the mechanical constraints along with optimization. Various engineering needs and parameters are involved in the computation of optimized structure for the establishment of a reasonable design scheme as per the engineering requirements [1]. The realization of modern optimization structures has become possible due to the advent in computer technology. There are several traditional structure optimization methods which have certain limitations like non-correspondence to the theoretical basis not achieving the best possible solutions. However, some of the methods incorporated the mathematical theory of learning, but are still unable to unveil the actual engineering structure problems. Thus, various researchers have proposed different optimization theories related to several intelligent algorithms that are based on the biological evolution and mimics natural survival [2–4]. The structure optimization plays a major role in improving the structure quality as well as design rationality along with the reduction in engineering cost [5–8]. For example, there are several applications of optimization algorithms in truss structures like application of artificial fish swarm algorithm, bee colony algorithm, firefly algorithm, etc. [9–11].
With the development in research and technology, intelligent optimization approaches are being employed in several fields for achieving size, shape and topology optimization [12]. One of the most commonly used metaheuristic approach is particle swarm optimization (PSO) that is dependent upon the social conduct of flock of birds. This is the most commonly used optimization methodology which has better global search capabilities and convergence. However, this methodology has certain drawback on their own, like, lack of local convergence and poor local search capabilities [13, 14]. However, several efforts have been made by the researchers for improvising the capabilities of PSO algorithm and advance its performance dynamically through adaptation. Several studies have applied the PSO algorithms for structural engineering problems and accelerated the PSO for finding the optimized design structures using numerical analysis.

The optimization design of truss structure belongs to the optimization design problem of building structure, which can be described as: how to arrange each bar in the truss to make the weight of the whole truss under the condition that the topology of the truss is fixed. It is the lightest and meets the requirements of structural strength and stability. At present, the intelligent algorithms with better performance for truss section optimization include heuristic particle swarm optimization (HPSO) algorithm, CMLPSA algorithm, harmony search (HS) algorithm and so on. Among them, the optimization time of HPSO method is long, while the optimization results of CMLPSA algorithm and HS algorithm are not guaranteed to completely meet the constraint conditions.

This article contributes in improvisation in the truss structure design rationality while reducing the engineering cost by proposing a Heuristic Particle Swarm Optimization (HPSO) approach. This article advances the constraint processing strategy of HPSO algorithm, which is further combined with another constraint processing method suitable for particle swarm optimization algorithm. This improved algorithm is applied to a truss structure section optimization design and a rationale design structure is obtained that is cost effective. The optimization results of the improved algorithm fully meet the constraints, and the optimization effect and stability are observed better than that of the HPSO algorithm. The program running time is nearly half of that of the HPSO algorithm which established the time-effective capabilities of the proposed methodology. This paper not only compares the optimal values of the improved algorithm and HPSO algorithm, but also gives its mean value and standard deviation [16].

The rest of this article is structured as: Literature review of various optimization algorithms is presented in Sect. 2. Section 3 presents various optimization research methods adopted in this work for truss structure optimization. The analysis of research results is presented in Sect. 4 followed by the concluding remarks in Sect. 5.

2 Literature review

Swarm intelligence algorithm (Swarm Intelligence Algorithm) belong to the new advanced heuristic algorithm, in 90 began to grow in the 20th century, there have been a mimic natural biological group behavior structure stochastic optimization algorithm. Typical methods mainly include the proposed ACO and PSO. Ant Colony Algorithm is a type of colony intelligence algorithm proposed by Dorigo in the 1990 s and designed according to the principle of ant foraging. It is also the earliest form of ant colony algorithm. In the process of foraging, many ants have the behavior of setting and following trails [17]. The agent secretes a chemical pheromone from the route of the nest in the food source area, and other foragers will follow the pheromone path to search for food resources. Its principle is a system of positive feedback mechanism, which converges to the optimal path through constant updating of pheromones [18]. Therefore, ant colony algorithm is also a reinforcement learning method based on Monte Carlo. PSO is an intelligent simulation optimization process based on the foraging conduct of birds proposed by Kennedy and Eberhart in 1995. Due to its unpretentious concept and easy implementation, the algorithm has been rapidly developed in just a few years, and many improved particle swarm optimization algorithms have emerged. Baskar proposed his own collaborative PSO algorithm, and improved the particle swarm optimization by optimizing different dimensions of multiple particle swarm and collaborative optimization. Higashi proposed the self-mutation PSO algorithm, and enhanced its global search capability by introducing mutation operator to jump out of the attraction of local extreme point [19]. The multi-phasepso proposed by Al-Kazemi is that the individuals searching for the selected part of the particle population are constantly moving in the direction of global optimization, while the other individuals are constantly moving in the opposite direction, thus expanding the spatial scope of the search. Shelokar heterozygous PSO algorithm and ACO algorithm. Kao heterozygosity genetic algorithm and PSO algorithm. Brits applies PSO to search for multiple optimal values [20, 21]. Kiranyaz proposed a multidimensional space search method for PSO. Based on genetic algorithm and PSO, Cui Guangzhao proposed an improved PSO. Yu Xuejing set the sensitive particles and response threshold, and proposed the dynamic particle swarm optimization algorithm. Since Schmit combined mathematical programming theory with finite element method for solving the minimum weight design problem of elastic structures
under various loading conditions, the new idea of structural optimization design quickly attracted the attention of structural design engineers. In the past few years, the structural optimization has become one of the hot research directions in structural engineering [22].

For truss structure, given the structure form, material, layout topology and shape, optimizing each member of the section size to make the structure the lightest or the most economical is called size optimization. The design variable in dimension optimization is the cross-sectional area of the member. For the optimal design of discrete variable structure, the algorithm usually determines the efficiency of calculation and the quality of results [23]. In the arena of structural optimization, traditional optimization algorithms, such as Optimization Criterion (OC) and Mathematical Programming (MP), have been widely used in the past decades. OC method is more effective for optimization problems with single constraints, it is easy to get iterative formula, and the convergence speed is fast. However, for optimization problems with multiple constraints, OC method is difficult to determine whether the constraints are effective or not. Different kinds of constraints, variables, objective functions and so on, are required for deriving different optimization criteria, so the generality is poor. The MP method can attain the global optimal solution of convex optimization and non-convex optimization problems [24]. It is a precise solution method and can be directly applied to continuous variable structure optimization. However, when MP is used to optimize large-scale structural systems, there are many times of structural reanalysis, which requires a large amount of storage space, a large amount of computation, and the algorithm is poor in generality. Any parameter change may cause the failure of the algorithm. Therefore, it is only suitable for the optimization of components, but not for the optimization of large structural systems. Recently, heuristic algorithms like GA and simulated annealing algorithm (SA) have emerged in the field of engineering structure optimization design [25]. GA has no requirement for continuous differentiability of the optimization model, and it can search the global optimum solution, so it has been widely used. However, GA mainly has some disadvantages, such as the difficulty in determining the population-size, cross-over, mutation rate, time-consuming, etc. However, when SA is used for structural optimization design, there are many times of structural reanalysis, large calculations, low efficacy and problematic determination of control parameters [26, 27].

PSO algorithm is a swarm intelligence algorithm based on stochastic optimization technology proposed by Kennedy and Eberhart under the stimulation of the social conduct of birds and fish. PSO shares many characteristics with GA, for example, the system is adjusted with a randomly distributed population, and the optimal solution is found by updating the evolutionary generation. Unlike GA, PSO has no evolutionary operators like cross-over and mutation. In the PSO algorithm, the possible solution called particle follows the current optimal particle to fly in the solution space, and each particle has an adaptive value and a velocity obtained according to the best experience of the group to adjust its flight direction in the multi-dimensional solution space to discover the global optimal solution [28]. Compared with traditional optimization algorithms and other evolutionary algorithms, PSO has some unique advantages: First, PSO has memory function, and each particle retains the optimal solution it has experienced; Secondly, in PSO, there are constructive operators among particles, that is, the information between particles is shared among the population. Third, the principle of PSO is simple, only a few parameters need to be adjusted, and it is easy to implement in the algorithm. As a novel evolutionary algorithm, PSO is getting more and more attention and application due to its simplicity, easy execution and fast convergence. In structural engineering, there are few literatures on PSO based on actual structural system optimization [29].

The innovation point of this paper: this paper applies PSO algorithm to the size optimization of truss structures, and evaluates the effect of using PSO algorithm to optimize the size of truss structures by solving typical illustrations and comparing with the results of relevant literatures.

3 Research methods

3.1 Particle swarm optimization algorithm

Particle Swarm Optimization (PSO) process was initially anticipated by Kennedy and Eberhart in 1995, which originated from the simulation of foraging conduct for the birds. The algorithm is described as follows: the group in the PSO algorithm is called the particle swarm, and the individuals in the swarm are called particles. In a D-dimensional search space, there are n elements. In the kTH iteration, the position of the ith particle is Xki Rd, and its historical optimal position is PKI. All PKI (I = 1, 2, ..., n) is Pkg, and the flight velocity of the particle is VKI ε Rd [30][31]. The initial position and velocity of the element is randomly generated. In the k + 1 iteration, the flight speed and position of each particle are calculated according to Eqs. (1) and (2):

\[ V_{i}^{k+1} = wV_{i}^{k} + c_{1}r_{1}(P_{i}^{k} - X_{i}^{k}) + c_{2}r_{2}(P_{g}^{k} - X_{i}^{k}) \]  

(1)

\[ X_{i}^{k+1} = X_{i}^{k} + V_{i}^{k+1} \]  

(2)
Where, \( c_1 \) and \( c_2 \) are positive constants, called learning factors or acceleration factors, and \( r_1 \) and \( r_2 \) are consistently distributed random numbers between [0,1]. \( \Omega \) is the inertial weight coefficient, which the researchers have added later to control the search step size of the algorithm. In each iteration, the flight speed is limited within the interval \([-V_{\text{max}}, V_{\text{max}}]\). Each element in the particle swarm starts from the initial position and velocity and carries out iterative calculation according to Eqs. (1) and (2) until the termination condition of the algorithm is met[32]. Many scholars have improved the PSO algorithm. Some of the researchers proposed the passive swarm particle swarm optimization algorithm (PSOPC) that adds a term to the original PSO algorithm to describe the passive clustering phenomenon. Formula depicted in Eq. (1) is improved to the formula in Eq. (3):

\[
V_{i}^{k+1} = \omega V_{i}^{k} + c_1 r_1 (P_{i}^{k} - X_{i}^{k}) + c_2 r_2 (P_{g}^{k} - X_{i}^{k}) + c_3 r_3 (R_{k}^{q} - X_{i}^{k})
\]

In the formula, \( A=[A_1, A_2, \ldots, A_n]^{T} \) is the interface design variable, \( n \) is the number of bars after connecting the section design variable, \( W \) is the structure weight, \( L_i, A_i \) and \( \rho_i \) are the length, section area and density of the \( i \)th group of bars, \( g_{j}^{A}(A, X) \) and \( g_{j}^{I}(A, X) \) are stress constraints and displacement constraints, respectively. \( [\sigma_i] \) and \( [\epsilon_i] \) are the allowable stress values of the \( i \)th group of bars and the most adverse stress values under various working conditions respectively. \([u_j] \) and \([u_j] \) are the allowable displacement values on the given direction \( I \) of a specific node \( j \) and the most adverse displacement values under various working conditions respectively. \( K \) is the total quantity of bars, \( m \) is the total nodes, \( ND \) is the constraint dimension of node displacement. \( A_{\text{min}} \) and \( A_{\text{max}} \) are the constraints of section size. \( M \) is a predefined large number; \( \lambda \) is a penalty function factor. The structural design variables meet the constraint conditions, \( \lambda = 0 \), otherwise \( \lambda = 1 \).

### 3.3 Optimization program of truss size based on PSO algorithm

The steps of truss size optimization based on PSO algorithm are discussed in the following points:

1. Set program parameters, initialize design variables and particle speed;
2. Determine whether the design variable meets the limit constraint and whether the particle velocity meets the limit of the velocity, and limit the design variable in the design space;
3. Conduct structural analysis to calculate the value of structural behavior variables corresponding to the design variables represented by different particles, such as stress of each bar and joint displacement;
4. Calculate the suitability of each and every element, and add a very large constant penalty \( M \) to the particle that does not meet the constraint conditions;
5. For each of the elements, compare its suitability with the suitability of the experienced finest position \( P_i \) and if it is improved, consider it as the present best position;
6. For each particle, its suitability is compared with the fitness of the finest position \( P_i \) experienced globally. If it is improved, it will be regarded as the current global finest position;
7. According to the velocity update equation and position update equation, the velocity and position of the particle are updated;
8. Determined whether the preset condition has been reached, if so, it will end, otherwise return 2).

Flow chart of truss structure optimization based on PSO algorithm (Fig. 1).
4 Result analysis and discussion

The experimental illustration is performed in this research and the PSO parameters were selected as follows: PS = 40, $\chi = 0.729$, MaxIt = 1000, C1 = C2 = 2.05. Figure 2 shows a 10-bar truss structure with the same material for each bar, $\rho = 2768$Kg/m3, elastic modulus $E = 68,950$ MPa, allowable stress $\sigma = 172.3$ MPa, load $P = 444.5$kN, $L = 9.144$ m. The lower limit of the design variable is $64.5 \times 10^{-5}$m$^2$, the upper limit is $0.0258$m$^2$, and the displacement constraint of each node is 50.8mm.

Under the same constraint conditions, the structure was optimized randomly for 20 times, and the best and worst results were selected to compare with the results of other
literatures (see Table 1). Experimental illustration 225-bar space truss (single working condition) is considered for research analysis.

Table 1 Comparison of optimization results of 10-bar plane truss

| Bar | PSO best | PSO worst | The literature [17] | The literature [16] | The literature [18] | The literature [29] | The literature [19] |
|-----|----------|-----------|---------------------|---------------------|---------------------|---------------------|---------------------|
| 1   | 19833.21 | 20403.65  | 16599.966           | 21568.989           | 20180.604           | 19936.73            | 17870.48            |
| 2   | 64.516   | 64.516    | 70.322              | 64.516              | 64.516              | 64.516              | 86.516              |
| 3   | 14906.12 | 15170.68  | 16032.226           | 15651.581           | 15903.194           | 15190.29            | 14899.13            |
| 4   | 9840.824 | 9867.087  | 10548.366           | 9199.981            | 9929.012            | 9651.594            | 10012.95            |
| 5   | 64.516   | 64.516    | 68.386              | 64.516              | 64.516              | 64.516              | 64.516              |
| 6   | 351.162  | 348.845   | 70.322              | 64.516              | 64.516              | 64.516              | 944.901             |
| 7   | 4810.161 | 4756.416  | 5612.892            | 5411.602            | 5096.764            | 4910.313            | 4994.7              |
| 8   | 13492.24 | 13064.31  | 13812.875           | 13380.618           | 13890.294           | 13725.78            | 14855.13            |
| 9   | 64.516   | 64.516    | 78.709              | 64.516              | 64.516              | 64.516              | 64.516              |
| 10  | 13856.43 | 13770.38  | 14387.068           | 12703.200           | 12303.2             | 13,649              | 13798.68            |
| The Average weight | 2293.925 | 2295.344 | 2311.386 | 2308.370 | 2291.587 | 2299.48 | 2317.37 |

The unit of weight column is kg, and the unit of other items is mm²

Figure 3 shows a 25-bar space truss with stress constraints of \([-275.8, 275.8]\) MPa, \(E = 68,950\) MPa, \(\rho = 2678\) kg/m³, and the maximum vertical displacements of the first and second joints cannot exceed \(D_{\text{max}} = 8.889\) mm and \(L = 635\) mm. The node load is shown in Table 2, and the bar grouping is shown in Table 3.

Under the same constraint conditions, the structure was optimized randomly for three times, and the convergence curve was shown in Fig. 4. The optimization results were

![25-bar space truss](image_url)
compared with those in other literatures, as shown in Table 4.

The 372 bar space truss (multiple working conditions) is calculated for the research analysis. Figure 5 is a 4-story 72-bar space truss structure, which is divided into 16 groups. The constraint conditions are as follows: the maximum displacement of 1–16 nodes along X and Y cannot exceed 6.35mm, and the maximum allowable stress $[-172.375, 172.375]$ MPa. Table 5 shows the position and magnitude of load action under the two different working conditions, and Table 6 shows the section grouping.

Under the same constraint conditions, the structure was optimized randomly for 6 times. The convergence curve of the optimization process is revealed in Fig. 6, and the comparison between the optimization results and those in other literatures is shown in Table 7.

### 4.1 Discussion

In the above three experimental illustrations, under the premise of constant PSO parameter selection and the same constraint conditions, the structure was optimized randomly for several times respectively. The optimal and worst values of the optimization results were listed in Tables 1, 4 and 7, and the optimization results of relevant literature were also given in the table. By comparing the data in the above table, it can be depicted that the optimized results of the PSO algorithm proposed in this article are all superior to the results of the literature. Figures 4 and 6 respectively show the convergence history of experimental illustration 2 and experimental illustration 3. The experimental illustration 2 basically converges after about

| Group no. | Bar |
|-----------|-----|
| $A_{11}$  | 1   |
| $A_{32}$  | 2   |
| $A_{43}$  | 3   |
| $A_{54}$  | 4   |
| $A_{65}$  | 5   |
| $A_{76}$  | 6   |
| $A_{87}$  | 7   |
| $A_{88}$  | 8   |

### Table 2 Load table

| Node number | FX/kN | FY/kN   | FZ/kN   |
|-------------|-------|---------|---------|
| 1           | 4.458 | 44.485  | – 22.241|
| 2           | 0.00  | 44.485  | – 22.241|
| 3           | 22.241| 0.00    | 0.00    |
| 6           | 22.241| 0.00    | 0.00    |

### Table 3 Grouping of rod members

| Group no. | Bar |
|-----------|-----|
| $A_{11}$  | 1   |
| $A_{32}$  | 2   |
| $A_{43}$  | 3   |
| $A_{54}$  | 4   |
| $A_{65}$  | 5   |
| $A_{76}$  | 6   |
| $A_{87}$  | 7   |
| $A_{88}$  | 8   |

Fig. 4 Convergence curve of PSO algorithm for optimal design of 25-bar space truss in single working condition
150 iterations, while experimental illustration 3 approaches the optimal solution after about 500 iterations. Therefore, the PSO algorithm can successfully optimize the size design of truss structures, and the algorithm is effective.

**Table 4** Comparison of optimization results of 25-bar space trusses

| Bar | PSO best | PSO worst | The literature [16] | The literature [20] | The literature [30] | The literature [21] |
|-----|----------|-----------|---------------------|---------------------|---------------------|---------------------|
| 1   | 64.516   | 65.7      | 6.4516              | 64.516              | 64.516              | 64.516              |
| 2   | 228.5    | 242.9     | 1281.933            | 774.192             | 1225.804            | 322.58             |
| 3   | 2237.6   | 2278.4    | 1931.609            | 2064.512            | 1677.416            | 2193.544           |
| 4   | 64.516   | 65.2      | 6.4516              | 64.516              | 64.516              | 64.516              |
| 5   | 1227.9   | 1245.5    | 6.4516              | 709.676             | 64.516              | 967.74             |
| 6   | 506.9    | 501.5     | 441.2894            | 580.644             | 516.128             | 580.644            |
| 7   | 83.9     | 91.2      | 1081.933            | 258.064             | 1354.836            | 387.096            |
| 8   | 2575.7   | 2524.3    | 1717.416            | 2193.544            | 1677.416            | 2193.544           |

The average weight: 216.339 kg, 216.463 kg, 247.284 kg, 223.987 kg, 255.345 kg, 220.581 kg

The unit of weight column is kg, and the unit of other items is mm²

**Table 5** Load condition and node load table

| Load condition | Node number | FX/kN  | FY/kN  | FZ/kN |
|----------------|-------------|--------|--------|-------|
| 1              | 1           | 22,250 | 22,250 | -22,250 |
| 2              | 1           | 0      | 0      | -22,250 |
| 2              | 2           | 0      | 0      | -22,250 |
| 2              | 3           | 0      | 0      | -22,250 |
| 2              | 4           | 0      | 0      | -22,250 |

**Table 6** Grouping table of rod members

| Group no. | Bar |
|-----------|-----|
| A11       | 1 2 3 4 |
| A12       | 5 6 7 8 9 10 11 12 |
| A13       | 13 14 15 16 |
| A14       | 17 18 |
| A15       | 19 20 21 22 |
| A16       | 23 24 25 26 27 28 29 30 |
| A17       | 31 32 33 34 |
| A18       | 35 36 |
| A19       | 37 38 39 40 |
| A110      | 41 42 43 44 45 46 47 48 |
| A111      | 49 50 51 52 |
| A112      | 53 54 |
| A113      | 55 56 57 58 |
| A114      | 59 60 61 62 63 64 65 66 |
| A115      | 67 68 69 70 |
| A116      | 71 72 |

Fig. 5 72-bar space truss
Fig. 6 Convergence curve of PSO algorithm for optimal design of 72-bar space truss under multiple working conditions

Table 7 Comparison of optimization results of 72-bar space trusses

| Bar | PSO best | PSO worst | The literature [30] | The literature [20] | The literature [17] | The literature [16] |
|-----|----------|-----------|---------------------|---------------------|---------------------|---------------------|
| 1   | 100.74   | 101.9     | 103.871             | 100.000             | 102.258             | 101.355             |
| 2   | 360.28   | 342.29    | 359.354             | 345.161             | 382.967             | 345.548             |
| 3   | 269.20   | 271.92    | 243.225             | 309.677             | 220.258             | 264.258             |
| 4   | 367.69   | 361.63    | 326.451             | 335.483             | 391.999             | 367.290             |
| 5   | 342.92   | 326.06    | 394.193             | 296.774             | 170.516             | 326.903             |
| 6   | 336.70   | 340.12    | 343.225             | 341.935             | 353.548             | 335.483             |
| 7   | 64.516   | 64.516    | 64.516              | 77.419              | 64.516              | 64.516              |
| 8   | 64.516   | 70.659    | 64.516              | 106.451             | 97.355              | 64.516              |
| 9   | 870.23   | 811.16    | 803.869             | 745.160             | 713.999             | 825.869             |
| 10  | 318.26   | 326.04    | 338.064             | 377.419             | 373.741             | 332.128             |
| 11  | 64.516   | 64.516    | 64.516              | 64.516              | 64.516              | 64.516              |
| 12  | 64.516   | 64.516    | 64.516              | 64.516              | 64.516              | 64.516              |
| 13  | 1188.0   | 1235.3    | 1172.90             | 1132.256            | 1340.901            | 1224.062            |
| 14  | 325.44   | 337.48    | 338.06              | 325.806             | 324.774             | 332.774             |
| 15  | 64.516   | 64.933    | 64.516              | 67.741              | 64.516              | 64.516              |
| 16  | 64.516   | 64.471    | 64.516              | 100.000             | 64.516              | 64.516              |

The average weight

| The average weight | 172.44 | 172.48 | 172.91 | 174.98 | 176.28 | 172.21 |

The unit of weight column is kg, and the unit of other items is mm²
5 Conclusions

In this article, an improvised heuristic particle swarm optimization (HPSO) algorithm is proposed that improves the constraint processing strategy of the conventional HPSO method. The proposed methodology addresses the optimization problem of truss with stress and displacement constraints and improves the design rationality while reducing the engineering cost. The optimal performance of the proposed optimization approach is validated using various experimental illustrations and the improved algorithm runs faster than the original algorithm and has better overall optimization effect and stability. The experimental evaluation established the time-effective capabilities of the proposed methodology, as the program running time is nearly half of that of conventional HPSO algorithm. The observation made reveals that the proposed and improvised PSO algorithm can successfully optimize the size design of truss structures, and provides an effective optimization solution. The improved algorithm is further applicable to other constrained optimization problems, which provides a new choice for solving constrained optimization problems. The future scope of this work will be considering the other topological and shape constrains for optimization problem in building truss structure.

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Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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