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Dual Target Optimization of Two-Dimensional Truss Using Cost Efficiency and Structural Reliability Sufficiency

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ABSTRACT

The main contribution of this study is to open a discussion regarding the structural optimization associated with the cost efficiency and structural reliability sufficiency consideration. To do so, several various optimization approaches are investigated to deliberate both cost and reliability concerns. Particularly, particle swarm optimization is highlighted as a reliable optimization approach. Accordingly, an illustrative example is rendered to compare the feasibility of the considered optimization approaches. The feasibility of the investigated approaches is evaluated using the cost and reliability analysis. For the considered example, it was observed that the PSO optimization algorithm has multiple advantages such as easy realization, fast convergence, and promising performance in nonlinear performance optimization. The PSO optimization algorithm can be successfully applied in various fields of civil engineering. This popularity is due to the understandable performance of the PSO as well as its simplicity. In this paper, first, the literature on the subject has been described by two-dimensional truss analysis using the finite element method and optimized using the PSO particle swarm algorithm. A comparison of the results with this reference indicates the accuracy of this particle swarm algorithm in truss optimization. Indeed, this study ignites two main insights in structural optimizations assessment. The first illustration is related to how to establish a framework for structural system reliability analysis associated with the different degrees of indeterminacies. And the second illustration is related to making a decision problem concerning the structural optimization while both cost and reliability metric are two main parameters for the construction point of the view.

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1. Introduction

Swarm intelligence (SI) is the collective behavior of decentralized systems consisting of many individuals who coordinate their activities using self-organization [1]. The SI systems are inspired by biological systems that are usually composed of a population of simple agents interacting with each other and globally with their environment. Ant colonies [2], bird flocks [3,4], honey bee colonies [5,6], and fish schools [7,8] are examples of natural SI systems. Based on the systems, several optimization algorithms such as ant colony, artificial honey bee colony, and particle swarm optimization (PSO) algorithms have been developed. PSO is a computational method based on a powerful population that is capable of solving the problem using the population of candidate solutions. To improve the candidate solution, PSO frequently moves the candidates using simple mathematical equations in a search space [9]. Since the introduction by Kennedy and Eberhart (1995) [10] and Eberhart and Kennedy (1995) [11], the PSO algorithm has been successfully used in various fields of civil engineering.

The optimization methods and algorithms are divided into two categories: exact algorithms and approximate algorithms. Exact algorithms can accurately find the optimal solution, but they do not work in hard optimization problems, and the solving time in these problems increases exponentially. Approximate algorithms can find good (quasi-optimal) solutions to difficult optimization problems in the short solving time. Approximate algorithms are also divided into two categories: heuristic and meta-heuristic algorithms. The two major problems with heuristic algorithms are (1) falling in local optima, and (2) inability to be applied to different problems. The meta-heuristic algorithms have been proposed to solve the problems of heuristic algorithms. The meta-heuristic algorithms are one of the approximate optimization algorithms that have the mechanism to exit local optima and can be used in a wide range of problems. In recent decades, various categories of this type of algorithm have been developed. Over the past few years, PSO has been widely used in various aspects of geotechnical engineering such as slope stability analysis, pile and foundation engineering, rock and soil mechanics, tunneling, and underground space design [12].

2. Particle swarm optimization algorithm

In many optimization problems, especially the big ones, choosing the best solution through the global search, though not being impossible, is very difficult. The goal of the optimization problem is to reduce the search time. Heuristic methods are good solutions for finding the optimal solution, but they do not guarantee to find the optimal solution. Today, however, as the problems become bigger, the popularity of heuristic and meta-heuristic methods has considerably grown.

Particle swarm optimization (PSO) is one of the meta-heuristic optimization techniques that work based on the population. The original idea for the method was first proposed in 1995 by Kennedy and Eberhart [10] which was inspired by the collective behavior of fish and birds for finding the food. A group of birds and fish look for food in random space, and there is only one piece of food, and none of the birds knows the location of the food and only knows the distance to the food. One of the best strategies is to follow a bird that is closest to the food. This view is the main strategy of the algorithm.

In this method, each bird has a possible solution in the problem space called a particle. Each particle has a fitness value that is calculated by the problem. The particle that is closest to the solution has the highest fitness. This algorithm has a continuous nature and has been proven to be efficient in numerous applications [13].

This algorithm is one of the population-based parallel search algorithms that start with a group of random solutions (particles) and then continues to search for finding the optimal solution in the problem space by updating the position of the particles. Each particle is denoted in the multidimensional mode (depending on the type of problem) by two vectors Xid and Vid, which represent the position and velocity in dimension d of particle i, respectively. At each stage of the population movement, the position of each particle is updated by two best values. The first value is the best experience ever gained by a particle and is represented by p_best. The second value is the best experience gained among all the particles and is shown by g_best. In each iteration, after finding these two values, the algorithm updates the new velocity and position of the particle-based on Equations (1) and (2).

$$v_{id}(t+1) = w.v_{id}(t) + c_1.rand_1\left(p\_best_{id}(t) - x_{id}(t)\right) + c_2.rand_2\left(g\_best_{id}(t) - x_{id}(t)\right) \quad (1)$$

$$\mathrm{x_{id}(t+1) = x_{id}(t) + v_{id}(t+1)} \quad (2)$$

In Equation (1), w is the inertia weight factor, which is usually in the range [0-1]. C1 and C2 are the learning or acceleration factors, which are selected in the range [0-2], which, in most cases, are set to 1.49 or 2. rand1 and rand2 are also two random numbers in the range [0-1]. Also, the final value of each particle's velocity to prevent algorithm divergence is limited to one range.

$v_{id} \in [-v_{max} \ .v_{max}]$ is the termination condition of the convergence algorithm to a certain extent or to stop after a certain number of iterations. Equation (2) also updates the current position vector of the particle according to its new velocity.

The right side of Equation (1) consists of three parts; the first part is a factor of the current velocity of the particle, the second part is used for changing the velocity and rotation of the particle towards the best personal experience, and the third part is used for changing the velocity and rotation of the particle towards the best group experience.

The optimization of the particle swarm without the first part of Equation (1) will be a process in which the search space is gradually reduced and the local search is formed around the best particle. In contrast, the first part of Equation (1) will cause the particles to move in their normal direction to reach the wall of the search area and perform some sort of global search. By combining the two factors, it was attempted to strike a balance between local and global search. To better strike such balance, w was first proposed in [14], which specifies the movement factor in the global search. The parameters c1 and c2 also specify the movement factor in local search.

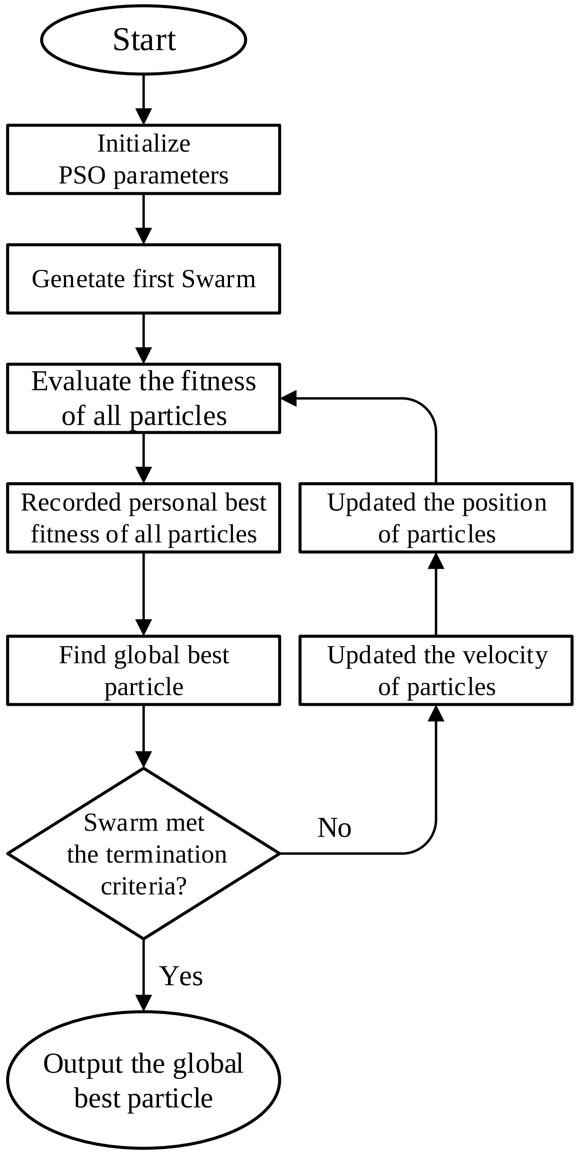

Fig. 1. PSO flowchart [15].

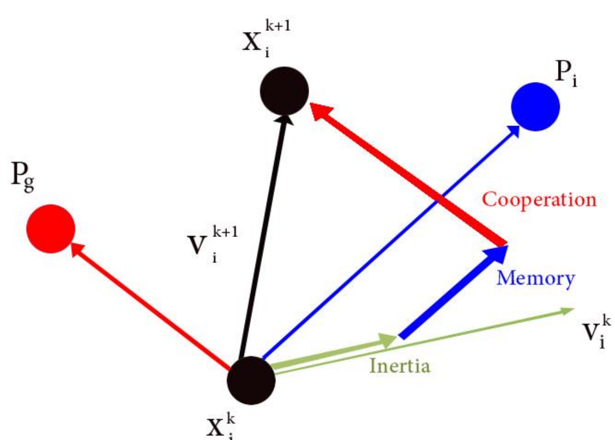

Fig. 2. Movement of a particle in PSO.

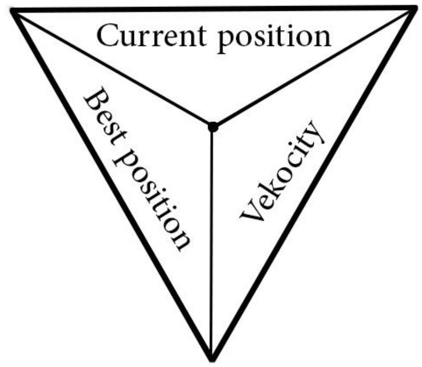

Fig. 3. Schematic structure of particle in PSO [16].

2.1. PSO algorithm in unconstrained problems

The unconstrained PSO algorithm can be expressed as the figure below.

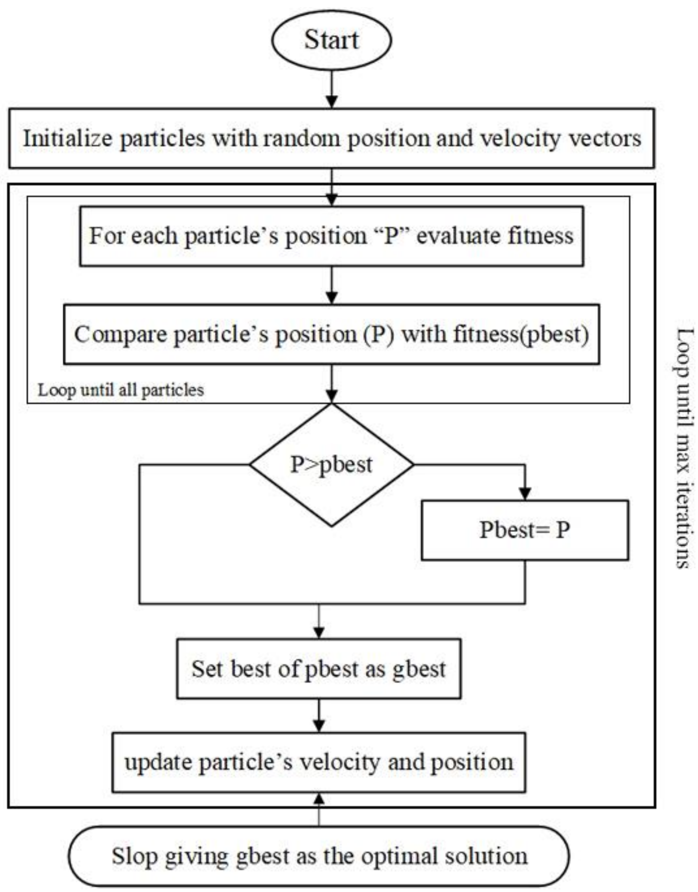

Fig. 4. Flowchart of particle swarm optimization algorithm in unconstrained problems [13].

2.2. PSO algorithm in constrained problems [13]

In the constrained problems, the particles should satisfy the constraint, which is the case with the truss problems.

Particle swarm optimization algorithm in constrained problems:

```
For each particle {
    Do {
        Initialize particle
    } While particle is in the feasible apace (i.e. it satisfies all the constraints)
}
Do {
    For each particle {
        Calculate fitness value
        If the fitness value is better than the best fitness value (pBest)
        in history AND the particle is in the feasible space, set current
        value as the new pBest
    }
    Choose the particle with the best fitness value of all the particles as
    the gBest
    For each particle {
        Calculate particle velocity according to equation (a)
        Update particle position according to equation (b)
    }
} While maximum iterations or minimum error criteria is not attained
```

3. Truss analysis using finite element method

Trusses include two-force members, and the external forces are only applied to the nodes.

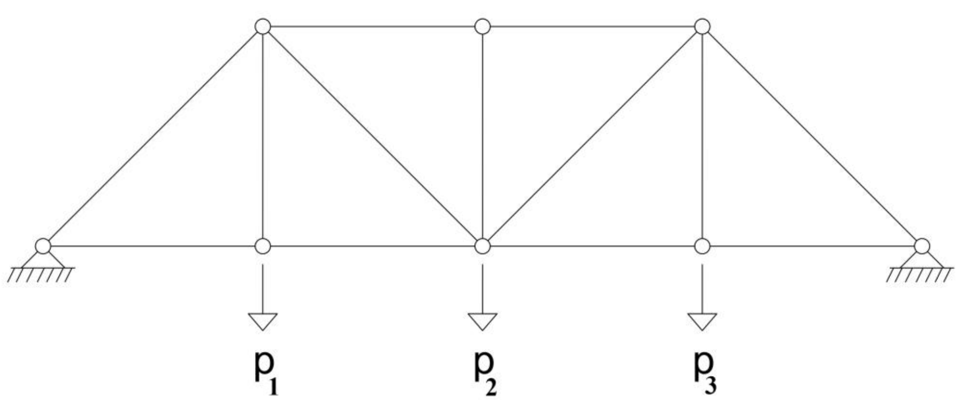

Fig. 5. Two-dimensional truss.

3.1. Local and global coordinates

Figure 6 shows a truss member and the equations for transforming two local and global coordinates are derived:

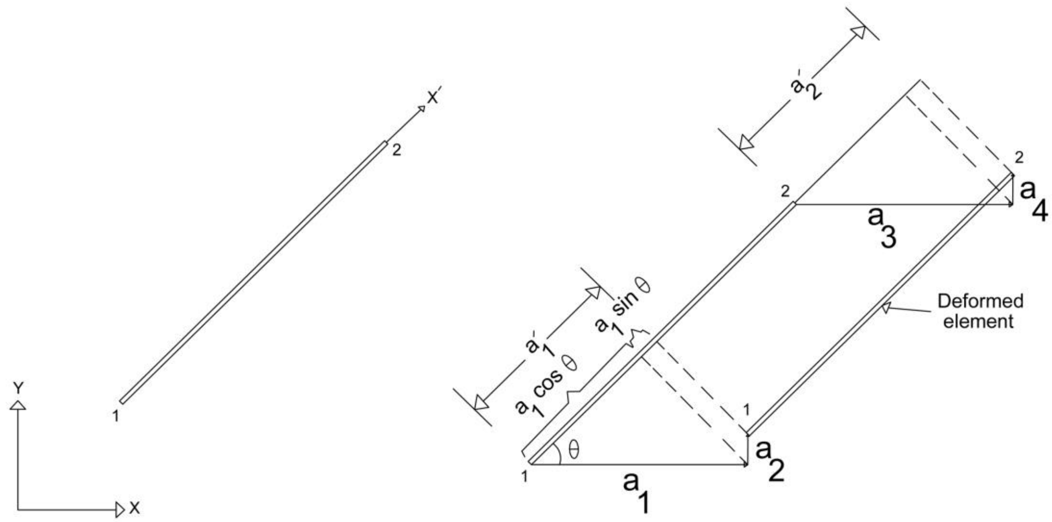

Fig. 6. A member of truss and equations for transforming two local and global coordinates.

Local coordinate system

$$q' = [q'_1 \,.\, q'_2]^T \tag{3}$$

Global coordinate system

$$Q = [Q_1 . Q_2 . \dots . Q_N]^T \tag{4}$$

The relationship between q and q' is as follows:

$$q'_1 = q_1 \cos\theta + q_2 \sin\theta \tag{5}$$

$$q'_2 = q_3 \cos\theta + q_4 \sin\theta \tag{6}$$

$$q' = Lq \tag{7}$$

Transformation matrix

$$L = \begin{bmatrix} l & m & 0 & 0 \\ 0 & 0 & l & m \end{bmatrix} \tag{8}$$

Calculation of m and l

$$l = \cos\theta = \frac{x_2 - x_1}{l_e} \tag{9}$$

$$m = \cos\varphi = \sin\theta = \frac{y_2 - y_1}{l_e} \tag{10}$$

$$l_e = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \tag{11}$$

Element stiffness matrix

Element stiffness matrix in the local coordinate system

$$k' = \frac{E_e A_e}{l_e} \begin{bmatrix} 1 & -1 \\ -1 & 1 \end{bmatrix} \tag{12}$$

Element stiffness matrix in the global coordinate system

The formula to calculate the strain energy in the local coordinates can be expressed as follows:

$$\mathrm{U_e} = \frac{1}{2} \mathrm{q'^T k' q'} \tag{13}$$

$$q' = Lq \rightarrow U_e = \frac{1}{2} q^T [L^T k' L] \mathrm{q} \tag{14}$$

The formula for calculating the strain energy in the global coordinates is as follows:

$$\mathrm{U_e} = \frac{1}{2} \mathrm{q^T k q} \tag{15}$$

Element stiffness matrix in the global coordinate system

$$\mathrm{k = L^T k' L} \tag{16}$$

$$\mathrm{L} = \begin{bmatrix} \mathrm{l} & \mathrm{m} & 0 & 0 \\ 0 & 0 & \mathrm{l} & \mathrm{m} \end{bmatrix} \rightarrow \tag{17}$$

$$k = \frac{E_e A_e}{l_e} \begin{bmatrix} l^2 & lm & -l^2 & -lm \\ lm & m^2 & -lm & -m^2 \\ -l^2 & -lm & l^2 & lm \\ -lm & -m^2 & lm & m^2 \end{bmatrix} \tag{18}$$

The stiffness matrices of the elements combine to form the stiffness matrix of the structure.

Stress calculations

$$\sigma = E_e \varepsilon = E_e B q' \tag{19}$$

$$\sigma = \frac{E_e}{l_e} [-1 \quad 1] \begin{Bmatrix} q'_1 \\ q'_2 \end{Bmatrix} = E_e \frac{q'_2 - q'_1}{l_e} \tag{20}$$

$$q' = Lq \rightarrow \sigma = \frac{E_e}{l_e} [-1 \quad 1] Lq \tag{21}$$

$$L = \begin{bmatrix} l & m & 0 & 0 \\ 0 & 0 & l & m \end{bmatrix} \rightarrow \tag{22}$$

$$\sigma = \frac{E_e}{l_e} [-l \quad -m \quad l \quad m] \tag{23}$$

4. Numerical example of single-objective truss optimization

4.1. Particle swarm optimization

In the example of the optimization of a conventional truss [17], which was analyzed by various methods so far, it is optimized by particle swarm optimization (PSO) algorithm method and the final result is compared with other methods. For this purpose, the total number of particles is considered to be 60, and the constant values of w, c_1, and c_2 are selected as 0.5, 1.5, and 1.5, respectively. The algorithm code is written in the MATLAB software and the structure is analyzed using the stiffness matrix (finite element) method.

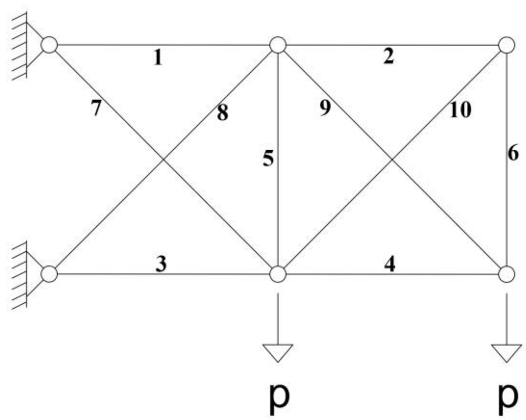

Fig. 7. 10-bar truss from [17].

Table 1
Parameters related to Fig. 7.

Parameter	Value	Unit
E	10^4	ksi
ρ	0.1	lbm/in^3
σ_{allow}	25000	psi
d_{max}	2	in
L	360	in
P	100	kip

Consider the 10-bar truss in Figure 1 which was studied to compare and verify the algorithm. The purpose of the problem is to minimize the weight of the structure f(x):

$$f(x) = \sum_{n=1}^{10} (\rho\, A_i\, L_i) \tag{24}$$

x is the solution to the problem, A_i is the cross-sectional area of bar i, L_i is the length of bar i, and ρ is the weight density:

$$\rho = 0.10\ {}^{Ib}/_{in^3}\ (2770\ {}^{kg}/_{m^3}) \tag{25}$$

The elastic modulus $E = 1 \times 10^4\ ksi\ (6.89 \times 10^4\ Mpa)$ and downward external force $100\ kips\ (445.374\ KN)$ are applied to nodes 2 and 4.

The truss constraints are:

$$\sigma_i \leq \sigma_{all} \quad i = 1{:}\,10 \tag{26}$$

$$u_i \leq u_a \tag{27}$$

where σi is the stress in bar i and σ_{all} is the maximum allowable stress for all bars, u_i is the displacement of each node (horizontal and vertical), and u_a is the maximum allowable displacement for all nodes.

$$u_a = 2\ in\ (50.8\ mm) \tag{28}$$

$$\sigma_{all} = \pm 25\ Ksi\ \ (172.25\ Mpa) \tag{29}$$

This problem is optimized using the PSO algorithm, and the results are summarized in Table 2; To compare with the results of Table 3, the problem is optimized twice (the cross-sectional area of the bars is considered in two different ranges):

Table 2
Results from the optimization of 10-bar truss size using PSO algorithm method, first run.

$0.1 \leq A_i\,(in^2) \leq 33.5$, Iteration: 50											
Method	**Weight (lb)**	**A1**	**A2**	**A3**	**A4**	**A5**	**A6**	**A7**	**A8**	**A9**	**A10**
PSO (obtained Results)	**5187.4**	**31.18**	**0.1**	**26.16**	**16.80**	**0.1**	**0.1**	**7.28**	**20.85**	**21.03**	**0.1**

Table 3
Results from the optimization of 10-bar truss size using PSO algorithm method, second run.

$1.62 \leq A_i\,(in^2) \leq 33.5$, Iteration: 50											
Method	**Weight (lb)**	**A1**	**A2**	**A3**	**A4**	**A5**	**A6**	**A7**	**A8**	**A9**	**A10**
PSO (obtained Results)	**5636.2**	**32.2**	**1.62**	**25.89**	**17.08**	**1.62**	**1.62**	**8.37**	**22.56**	**21.52**	**1.62**

Table 4
Results from the optimization of 10-bar truss size from [17].

Method	**Weight (lb)**	**A1 (in^2)**	**A2 (in^2)**	**A3 (in^2)**	**A4 (in^2)**	**A5 (in^2)**	**A6 (in^2)**	**A7 (in^2)**	**A8 (in^2)**	**A9 (in^2)**	**A10 (in^2)**
OPTDYN	5472.00	25.70	0.10	25.11	19.39	0.10	0.10	15.40	20.32	20.74	1.14
CONMIN	5563.00	25.20	1.89	24.87	15.83	0.10	1.75	16.67	19.73	20.98	2.51
GENETIC	5620.08	33.50	1.62	22.00	15.50	1.62	1.80	14.20	19.90	19.90	2.62
Rajeev	5613.84	33.50	1.62	22.00	15.50	1.62	1.62	14.20	19.90	19.90	2.62
M-3	5719.00	25.84	3.07	26.42	12.77	0.10	3.43	19.34	19.17	18.76	4.42
M-5	5725.00	25.83	2.88	26.45	12.75	0.10	3.77	19.37	19.18	18.77	4.38
GRP-UI	5727.00	24.78	4.17	24.78	14.45	0.10	4.17	17.46	19.26	19.27	5.26
SUMT	5932.00	30.69	2.37	31.62	11.66	0.10	3.71	21.71	20.90	13.97	3.26
LINRM	6249.00	21.57	10.98	22.08	14.95	0.10	10.98	18.91	18.42	18.40	13.51

The comparison of the obtained results with [17] confirms the PSO algorithm used in this research for the truss optimization.

4.2. Structural reliability analysis

In this section, the reliability level of the truss system is determined to evaluate the difference between the available optimization approaches. The reliability analysis process is established based on the provided framework by Ghasemi and Nowak [18,19]. To do so, two types of the limit state functions based on the ultimate limit state function (ULSF).

$$\text{ULSF: } g_u = \sigma_y - \frac{P}{A} \tag{30}$$

where g_u and g_s stand as the ultimate and service limit state functions, respectively. P is the element's load; A represents the optimum value of the element's cross-section. Tables 5 shows the reliability indices of each truss element, corresponding to the considered optimization approaches. It is worth mentioning that the reliability index is simply taken from FORM methods as shown in the following equation [20].

$$\beta_e = \frac{R_n.\lambda_R - Q_n \lambda_Q}{\sqrt{\sigma_R^2 + \sigma_Q^2}} \tag{31}$$

where R_n and Q_n are the nominal value of the structural resistance (nominal value of $\sigma_y$for USLF and nominal value of $\alpha L$for SLSF) and nominal value of loads. $\lambda_R$and $\lambda_Q$denote the bias factor (mean over nominal value) of resistance and load. Also, $\sigma_R$and $\sigma_Q$are the standard deviation of the resistance and load. The statistical parameter of both resistance and load can be taken from Ghasemi and Lee [21].

Table 5
Reliability indices of each element corresponding to the given optimization approaches concerning ULSF.

Method	Weight (lb)	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10
OPTDYN	5472.00	8.48	-9.10	5.12	8.62	-9.6	-9.10	2.68	10	8.15	-2.44
CONMIN	5563.00	8.45	-3.18	5.08	9.57	-8.39	-3.65	3.18	10	9.55	-3.56
GENETIC	5620.08	8.85	3.34	4.45	8.14	-3.42	3.96	2.15	10	7.94	4.13
Rajeev	5613.84	8.85	3.46	4.45	8.12	-3.47	3.46	2.15	10	7.92	4.24
M-3	5719.00	8.49	-0.47	5.37	9.68	-7.30	0.31	4.06	10	9.69	-0.34
M-5	5725.00	8.49	-0.92	5.37	9.68	-7.30	0.98	4.07	10	9.69	-0.41
GRP-UI	5727.00	8.42	1.53	5.06	9.77	-6.71	1.53	3.46	10	9.75	0.74
SUMT	5932.00	8.75	-2.08	6.14	9.58	-7.77	1.04	4.69	10	9.50	-2.27
LINRM	6249.00	8.17	6.44	4.47	9.91	-2.13	6.44	3.93	10	9.89	5.89
PSO	5636.20	8.80	4.64	5.27	8.19	-3.85	4.64	-1.53	10	7.95	2.59

As can be seen in Figure 7 and based on the load distribution analysis, elements A1, A4, A8 and A9 do not contributed to carry the applied loads. Also, since the truss has a two degree of indeterminists, we let two of the elements to exceed the allowable stress at a joint in such a way that elimination of those element cannot lead to the system instability. A5 to fail due to the high amount of applied tension. Therefore, in this illustrative example, elimination of two elements out of A5, A7, and A10 is permissible. Accordingly, GENETIC, Rajeev, GRP-UI, LINRM, and PSO are the only options which are resulting from a acceptable reliability indices greater than zero. Accordingly, a minimal reliability index of A2, A3, and A6 will be a dominant reliability index of a considered method.

Table 6
System reliability indices comparison.

Method	Weight (lb)	β
GENETIC	5620.08	3.34
Rajeev	5613.84	3.46
GRP-UI	5727.00	1.53
LINRM	6249.00	4.47
PSO	5636.20	4.64

As tabulated in Table 6. the highest reliability index is related to the PSO method. Although the second reliable approach is LINRM, the assigned cross-sections with correspondence to this method is the heaviest and the expensive option.

5. Result and discussion

In computational science, molecule swarm optimization (PSO) could be a computational method that optimizes an issue by iteratively attempting to make strides a candidate arrangement with respect to a given degree of quality. It understands an issue by having a populace of candidate arrangements, here named particles, and moving these particles around within the search-space concurring to basic numerical formulae over the particle's position and speed. Each particle's movement is affected by its local best-known position but is additionally guided toward the leading known positions within the search-space, which are overhauled as a way better positions are found by other particles. This is often anticipated to move the swarm toward the finest arrangements.

PSO may be a metaheuristic because it makes few or no suspicions approximately the issue being optimized and can look very large spaces of candidate arrangements. Be that as it may, metaheuristics such as PSO don't ensure an ideal arrangement is ever found. Moreover, PSO does not utilize the slope of the issue being optimized, which implies PSO does not require that the optimization issue be differentiable as is required by classic optimization strategies such as slope plunge and quasi-newton strategies.

PSO has to been connected to multi-objective issues, in which the objective work comparison takes Pareto dominance into consideration when moving the PSO particles and non-dominated arrangements are put away to inexact the Pareto front. Multi-swarm optimization could be a variation of particle swarm optimization (PSO) based on the utilize of numerous sub-swarms rather than one (standard) swarm. The common approach in multi-swarm optimization is that each sub-swarm centers on a particular locale whereas a particular enhancement strategy chooses where and when to dispatch the sub-swarms. The multi-swarm system is particularly fitted for the optimization of multi-modal issues, where numerous (local) optima exist.

6. Conclusions

In this paper, a two-dimensional truss was analyzed with the finite element method and optimized using the PSO algorithm and then, the optimization results were compared with those of [17]. The analysis of comparisons suggests that the PSO algorithm leads to better results in terms of the higher convergence rate. Comparing the results with this reference shows confirms the PSO algorithm in this paper for truss optimization. It seems that the PSO algorithm (bird algorithm) is a good choice for the optimization of trusses and has an acceptably high rate of convergence. This method is dependent on the values of ω, c_1, and c_2, and the values suggested in this paper can be used as the initial data. The number of particles (birds) is also important in this algorithm, but it is less important than the above factors and can be considered from 40 to 70.

By the way, this problem opens two main question in structural optimizations. The first question is to how establish a framework to determine the reliability index of a system associated with the different degree of indeterminacies? And the second question is how to make a decision of optimization approach selection with consideration of both cost and reliability? The methodologies of addressing the responses to the above-mentioned questions are expected to be conducted in future studies. This, this paper attempts to shed more light to address the concern of the system reliability with various possible redundancy and target reliability selection associated with cost and reliability.

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