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Comparison of meta-heuristic algorithms on the size and layout optimization of truss structures

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ABSTRACT

Truss structures constitute integral components of civil engineering projects, necessitating engineers to achieve optimal designs balancing material cost and structural capacity. Traditional gradient-based optimization methods often face challenges in nonlinear and non-convex optimization scenarios, leading to prolonged convergence times. Meta-heuristic algorithms present viable alternatives for optimizing the layout and dimensions of truss structures under such conditions. This study focuses on optimizing the sizes and configurations of three distinct planar benchmark truss structures using three different meta-heuristic optimization algorithms: Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Adaptive Geometry Estimation based MOEA (AGE-MOEA). The optimization results for the Planar 10-bar truss structure indicated that PSO slightly outperformed GA and AGE-MOEA by achieving the lowest weight of 5065.33 lb. For the 15-bar truss structure, GA achieved the lowest weight of 79.74 lb, demonstrating its effectiveness. In the case of the 18-bar truss structure, PSO again showed superior performance with the lowest weight of 4523.57 lb. Through comparative analysis of convergence rates and optimal solutions derived from these algorithms, this research evaluates their effectiveness in addressing the complexities of truss structural optimization. The findings suggest that while all three algorithms are effective, PSO often provides the most efficient solutions in terms of weight minimization for complex truss structures.

Keywords: Structural design, Truss optimization, Meta-heuristic algorithms

1 Introduction

Optimization of truss structures represents a well-established area of research encompassing various methodologies tailored to enhance structural efficiency. Optimization efforts typically fall within three primary categories: size optimization, which focuses on determining the optimal cross-sectional areas of structural members; shape optimization, aimed at identifying the optimal geometric coordinates of the structure; and topology optimization, which involves optimizing the layout or configuration of the structure [1]. Integrating optimization across these categories often yields superior results [2].

Meta-heuristic algorithms have emerged as preferred tools among researchers for optimizing benchmark truss structures. Unlike traditional gradient-based methods, meta-heuristic algorithms demonstrate advantages, particularly in scenarios where objective functions are highly nonlinear and multimodal, as commonly encountered in truss size and shape optimization problems [3]. Over the past decade, several

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meta-heuristic algorithms have gained prominence in this domain, including Particle Swarm Optimization (PSO) [4], Genetic Algorithm (GA) [5], Differential Evolution (DE) [6], Teaching Learning Based Optimization (TLBO) [7], Harmony Search (HS) [8], Firefly Algorithm (FA) [9], Colliding Bodies Optimization (CBO) [10], Symbiotic Organisms Search (SOS) [11], Big Bang - Big Crunch Optimization (BB-BC) [12], and Evolution Strategy (ES) [13].

Despite these advancements, optimizing truss structures remains a challenging task, particularly when considering both sizing and layout variables simultaneously. The distinct nature and differing magnitudes of these variables pose significant challenges in achieving optimal designs [14]. Evaluating the performance of meta-heuristic algorithms in this context is crucial, as these algorithms offer robust solutions by balancing global exploration of the search space with local exploitation of optimal solutions [15].

To address the complexities and gaps in existing literature, this paper focuses on comparing the performance of three widely adopted meta-heuristic algorithms applied to planar benchmark truss structures. By evaluating these algorithms under consistent parameters, this study aims to provide insights into their computational efficiency and optimization efficacy across diverse structural configurations.

The structure of this paper is organized as follows: Section 2 describes the optimization algorithms, including detailed formulations and pseudo-codes for the Genetic Algorithm, Particle Swarm Optimization, and Adaptive Geometry Estimation based MOEA (AGE-MOEA). Section 3 provides information about the planar benchmark truss structures used in this study, specifically the Planar 10-bar, Planar 15-bar, and Planar 18-bar Truss Structures. Section 4 presents the results of the optimization, examining each truss structure in detail. Section 5 offers a discussion of the findings, emphasizing the convergence behaviors and practical implications of each algorithm in real-world applications. Finally, Section 5 concludes the paper, summarizing the key contributions and potential areas for future research.

2 Optimization Algorithms

In this section, three distinct meta-heuristic optimization algorithms used for optimizing truss structures are presented. Multi-agent techniques are employed by these algorithms to improve the quality of solutions based on a defined cost function.

2.1 Genetic Algorithm

The Genetic Algorithm (GA) was selected due to its robustness and versatility in handling a wide array of optimization problems. GA starts with an initial population P_1 comprising randomly selected candidate solutions to the optimization problem. Iteratively, the algorithm progresses through the following steps until termination criteria are met :

1. **Initialization**: Initialize the population P_1.
2. **Iteration**: Increment the iteration counter t.
3. **Fitness Calculation**: Evaluate the fitness of each individual in P_t using the fitness function.
4. **Selection**: Select parents from P_t based on their fitness.
5. **Reproduction**: Generate offspring by applying crossover and mutation operations to the selected parents.
6. **Replacement**: Introduce new individuals into the population to maintain its size.
7. **Evaluation**: Evaluate the fitness of the new individuals.

8. **Update Population**: Update P_t to P_{t+1} and repeat until termination criteria are satisfied.

GA effectively combines selection, crossover, and mutation operations to iteratively improve the population's fitness and converge towards optimal solutions.

2.2 Particle Swarm Optimization

Particle Swarm Optimization (PSO), introduced by Kennedy and Eberhart [16] in 1995, was chosen for its simplicity and efficiency in handling continuous optimization problems. Each particle in the swarm maintains a position and velocity, influenced by the best solutions found locally and globally. The algorithm updates particle velocities and positions using the following equations (1) & (2):

The velocity of the particles is updated by,

$$V_d^i = \omega\, V_d^i + c_1 r_1 \left(P_d^i - X_d^i\right) + c_2 r_2 (G_d^i - X_d^i) \tag{1}$$

Position of the particles are updated by,

$$X_d^{(i)} = X_d^i + V_d^i \tag{2}$$

where $\mathbf{V}_d^i$ represents the velocity of the i-th particle in the d-th dimension, $\mathbf{X}_d^i$ denotes its position, $\mathbf{P}_d^i$ is the particle's personal best position, $\mathbf{G}_d^i$ is the globally (or locally) best solution found, ω is the inertia weight, c_1 and c_2 are acceleration coefficients, and r_1 and r_2 are random values.

PSO leverages swarm intelligence to iteratively converge towards optimal solutions by balancing exploration (through global best solutions) and exploitation (through personal best solutions).

2.3 Adaptive Geometry Estimation based MOEA (AGE-MOEA)

AGE-MOEA [17] is a recent addition to meta-heuristic algorithms, inspired by the NSGA-II structure but with enhancements in diversity preservation. AGE-MOEA was selected for its advanced capabilities in handling multi-objective optimization problems. The algorithm proceeds as followss:

- **Initialization:** Set the number of objectives M and population size N.
- **Population Generation:** Generate a random initial population P.
- **Iteration:** Iteratively perform the following steps until termination criteria are met:
  - Generate children Q from the current population P .
  - Perform fast non-dominated sorting (F) on $P \cup Q$.
  - Normalize the fronts (F).
  - Select individuals from these fronts based on their survival scores to maintain diversity and quality.
  - Update the population P with the selected individuals.

AGE-MOEA adapts the geometry of non-dominated solutions dynamically to enhance convergence and diversity simultaneously.

These algorithms represent diverse approaches to solving optimization problems, each offering unique advantages suited to different types of truss structure optimization challenges.

3 Planar Benchmark Structures

In this section, three planar benchmark truss structures that undergo size and shape optimization using the previously discussed meta-heuristic algorithms are detailed.

3.1 Planar 10-bar Truss Structure

The Planar 10-bar truss structure is a widely recognized benchmark in structural optimization research. It consists of 10 members interconnected by joints, forming a triangular configuration. For this study, the structure is subjected to a specific loading condition: a 100 kips (445.1 kN) force applied at nodes 2 and 4. The optimization task focuses exclusively on sizing the members to optimize structural performance while adhering to stress and displacement constraints.

Geometric Details:

- **Nodes and Members:** The truss comprises 6 nodes and 10 members.
- **Loading Condition:** A concentrated load of 100 kips is applied at nodes 2 and 4.
- **Objective:** Size optimization of member cross-sectional areas within predefined limits.
- **Constraints:** Upper and lower limits for member cross-sectional areas are set between 0.1 in² (0.645 cm²) and 35 in² (225.8 cm²).
- **Initial Configuration:** Figure 1 illustrates the initial geometry and loading configuration of the Planar 10-bar truss structure.

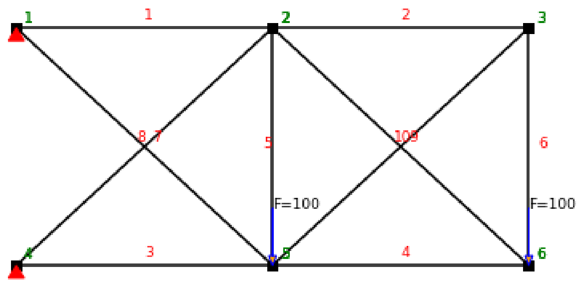

Figure 1. *Ten bar structure*

3.2 Planar 10-bar Truss Structure

The Planar 15-bar truss structure is more complex, featuring 15 members and 8 nodes arranged in a geometrically intricate pattern. This structure is designed to test optimization algorithms across a broader spectrum of member sizes and layouts.

Geometric Details:

- **Nodes and Members:** The truss comprises 8 nodes and 15 members.
- **Loading Condition:** A load of 10 kips (44.5 kN) is applied at node 8.

- **Material Properties:** Members are made from a material with a density of 0.1 lb/in³ (2767.99 kg/m³).
- **Constraints:** Members are constrained by stress limits of 25 ksi (172.369 MPa) in compression and tension.
- **Objective:** Optimization includes both sizing member cross-sectional areas and adjusting the layout of nodes to optimize structural efficiency.
- **Initial Configuration:** Figure 2 depicts the initial geometry of the Planar 15-bar truss structure.

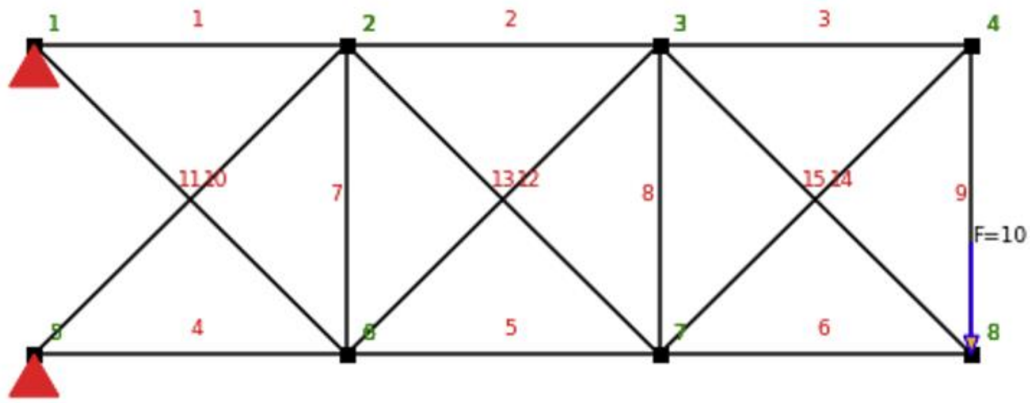

Figure 2. *Fifteen bar structure*

3.3 Planar 18-bar Truss Structure

The Planar 18-bar truss structure is the most complex of the three benchmarks, comprising 18 members categorized into 4 groups based on their cross-sectional areas. This structure also incorporates variability in the coordinates of lower chords, presenting a multi-objective optimization challenge.

Geometric Details:

- **Nodes and Members:** The truss features 10 nodes and 18 members**.**
- **Cross-sectional Area Groups:** Members are grouped into 4 categories based on their cross-sectional areas.
- **Lower Chord Coordinates:** The coordinates of the lower chords are variable, adding complexity to the optimization task.
- **Objective:** Optimization aims to find the optimal distribution of member sizes within each group and adjust the lower chord coordinates to enhance structural robustness and efficiency.
- **Initial Configuration:** Figure 3 illustrates the initial geometric configuration of the Planar 18-bar truss structure.

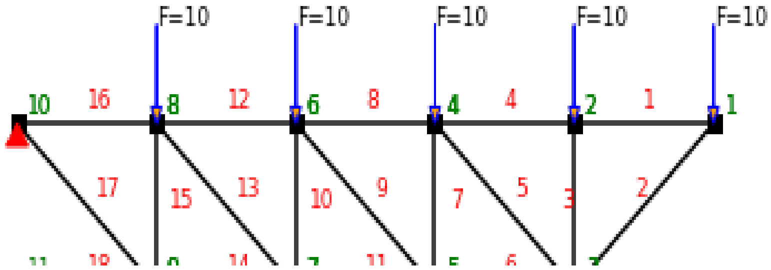

Figure 3. *Eighteen bar structure*

These benchmark structures are selected to represent varying levels of complexity in truss design optimization, enabling a comprehensive evaluation of the meta-heuristic algorithms' performance in tackling size and shape optimization challenges in structural engineering. The subsequent sections will analyze and compare the optimization results obtained for each structure using the selected algorithms.

4 Results

In this section, the optimization results for each benchmark truss structure are presented and discussed using the GA, PSO, and AGE-MOEA. The algorithms were configured with hyperparameters to ensure comparable computational times in finding the optimal solutions.

4.1 Results of 10-bar Truss Structure

The optimization results for the Planar 10-bar truss structure are summarized in Table 1. This structure focuses on size optimization of its 10 members under a specific loading condition, with the goal of minimizing weight while meeting structural constraints.

Table 1. *Optimization results for ten bar structure*

Design Variable (in^2)	**(GA)**	**(PSO)**	**(AGE-MOEA)**
A1	30.830	30.203	29.838
A2	0.13	0.107	0.108
A3	23.315	24.721	22.705
A4	13.058	14.99	15.13
A5	0.12	0.146	0.108
A6	0.134	0.595	0.54
A7	8.672	7.31	7.575
A8	21.124	20.7	21.981
A9	22.35	21.398	21.491
A10	0.147	0.143	0.109
Weight (lb)	**5092.68**	**5065.33**	**5065.47**

The optimization results for the 10-bar truss structure indicate that all three algorithms—GA, PSO, and AGE-MOEA—achieved similar results in terms of the design variables (A1 to A10) and the overall weight of the structure. PSO slightly outperformed GA and AGE-MOEA by achieving the lowest weight of 5065.33 lb, compared to 5092.68 lb and 5065.47 lb for GA and AGE-MOEA, respectively. This outcome suggests that PSO was more effective in finding a configuration that minimized the structural weight while satisfying the specified constraints.

4.2 Results of 15-bar Truss Structure

The optimization results for the Planar 15-bar truss structure, detailed in Table 2, involve optimizing both member sizes and node coordinates under multiple loading conditions.

Table 2. *Optimization results for fifteen bar structure*

Design Variable (in^2)	**(GA)**	**(PSO)**	**(AGE-MOEA)**
A1	1.174	0.954	0.954
A2	0.954	0.954	0.954
A3	0.287	0.27	0.44
A4	1.081	1.081	1.081
A5	0.539	0.954	0.954
A6	0.141	0.27	0.141
A7	0.111	0.111	0.111
A8	0.22	0.111	0.111
A9	0.44	0.22	0.539
A10	0.111	0.44	0.347
A11	0.27	0.347	0.27
A12	0.22	0.22	0.141
A13	0.539	0.174	0.287
A14	0.141	0.287	0.141
A15	0.287	0.287	0.44
X2	100.044	105.437	123.77
X3	250.688	220	220
Y2	123.314	118	126.285
Y3	105.479	115.437	124.798
Y4	51.255	78.449	58.486
Y6	15.431	-16.778	7.11
Y7	-13.34	2.369	18.118
Y8	51.493	38.216	58.479
Weight (lb)	**79.74**	**83.94**	**80.61**

For the 15-bar truss structure, the optimization results show that GA achieved the lowest weight of 79.74 lb, indicating its effectiveness in minimizing the structural weight while meeting the design constraints. PSO and AGE-MOEA also performed competitively, with weights of 83.94 lb and 80.61 lb, respectively. The adjustments in design variables (A1 to A15) and node coordinates (X2, X3, Y2, Y3, etc.) illustrate the optimization process's capability to find optimal configurations that balance structural stability and weight optimization.

4.3 Results of 18-bar Truss Structure

The optimization results for the Planar 18-bar truss structure, presented in Table 3, involve optimizing member sizes and node coordinates across 18 members and multiple load conditions.

Table 3. *Optimization results for eighteen bar structure*

Design Variable (in^2)	**(GA)**	**(PSO)**	**(AGE-MOEA)**
A1	13.0	15.25	13.25
A2	14.25	13.5	12.75
A3	8.5	8.25	8.0
A4	16.0	3.5	13.5
X3	899.876	857.988	837.494
Y3	180.946	157.01	102.089
X5	611.868	554.32	608.825
Y5	101.312	136.516	30.363
X7	441.472	413.865	425.098
Y7	41.997	116.4	52.308
X9	177.891	199.119	205.231
Y9	-18.369	62.774	3.485
Weight (lb)	**5702.134**	**4523.57**	**5424.542**

For the 18-bar truss structure, PSO achieved the lowest weight of 4523.57 lb, indicating its superior performance in optimizing the structural design for minimal weight. GA and AGE-MOEA also provided competitive results with weights of 5702.134 lb and 5424.542 lb, respectively. The adjustments in member sizes (A1 to A4) and node coordinates (X3, Y3, X5, Y5, etc.) demonstrate the algorithms' capability to handle complex optimization tasks involving multiple design variables and constraints effectively.

5 Discussion

This study aimed to compare the performance of three meta-heuristic algorithms—GA, PSO, and AGE-MOEA on three distinct benchmark truss structures. Each algorithm was allotted 15 minutes to find the optimal solution, with all successfully converging to feasible solutions within this time frame.

The 10-bar truss structure was primarily optimized for weight reduction under specific loading conditions. Here, both PSO and AGE-MOEA achieved comparable results, yielding an optimal weight of approximately 5065 lbs. In contrast, GA performed slightly worse with a weight of 5092.68 lbs. This suggests that PSO and AGE-MOEA were more effective in minimizing weight by optimizing member sizes.

Moving to the 15-bar truss structure, which required optimization of member sizes and node coordinates under various loading conditions, GA emerged as the top performer with a weight of 79.74 lbs. PSO and AGE-MOEA achieved weights of 83.94 lbs and 80.61 lbs, respectively. GA's success in this scenario indicates its ability to handle the complexity of optimizing both structural dimensions and node placements effectively.

The 18-bar truss structure posed additional challenges due to its increased complexity. PSO demonstrated superior performance by achieving a weight of 4523.57 lbs, significantly lower than GA's 5702.134 lbs and AGE-MOEA's 5424.542 lbs. This highlights PSO's strength in finding configurations that minimize weight while meeting all design constraints effectively.

Table 4 summarizes the optimization results across all benchmark structures, showing the function values (weights) obtained by each algorithm. The results indicate varying performances of GA, PSO, and AGE-MOEA across different benchmark structures, with PSO often delivering competitive or superior results in weight optimization.

Table 4. *Comparison of the optimization results*

Algorithm / **Benchmark Structures**	**(GA)**	**(PSO)**	**(AGE-MOEA)**
10-bar	5702.134	5065.33	5065.47
15-bar	79.74	83.94	80.61
18-bar	5702.134	4523.57	5424.542

These findings underscore the importance of selecting the appropriate meta-heuristic algorithm based on the specific characteristics and complexities of the optimization problem. Future research could explore hybrid approaches or further parameter tuning to enhance the efficiency and robustness of optimization algorithms across a broader range of structural configurations.

In conclusion, this study compared the performance of GA, PSO, and AGE-MOEA on three benchmark truss structures: the 10-bar, 15-bar, and 18-bar trusses. The primary objective was to optimize these structures for minimal weight while ensuring structural integrity under specific loading conditions. Each algorithm was given 15 minutes to converge to an optimal solution, successfully achieving feasible designs within this time frame. The results revealed varying performances across the benchmark structures.

PSO consistently demonstrated competitive performance, often achieving optimal weights that were lower compared to GA and AGE-MOEA. The superior performance of PSO can be attributed to its effective balance between exploration and exploitation, facilitated by the velocity and position update mechanisms. These mechanisms enable PSO to efficiently search the solution space and converge towards global optima, reducing structural weight effectively. Specifically, PSO outperformed in optimizing the 18-bar truss structure, highlighting its effectiveness in handling complex configurations and reducing structural weight effectively.

However, GA showcased exceptional performance in optimizing the 15-bar truss structure, where it achieved the lowest weight among the algorithms tested. This indicates GA's capability in managing both member sizing and node placement complexities, essential for optimizing such intricate structural designs. Despite their successes, each algorithm exhibited limitations. GA, while effective in some scenarios, struggled with achieving competitive results in the 10-bar truss structure compared to PSO and AGE-MOEA. AGE-MOEA, while generally competitive, showed mixed performance across different structures, indicating sensitivity to problem complexity and configuration.

The relevance of this research lies in its contribution to understanding the strengths and limitations of meta-heuristic algorithms in truss optimization, crucial for engineering design processes. By identifying algorithmic strengths and weaknesses across diverse structural configurations, engineers can make informed decisions when selecting optimization tools for specific design challenges. Moving forward, further research could explore hybrid approaches combining the strengths of different algorithms or refine parameter settings to enhance performance across a wider range of structural complexities. Additionally, exploring the applicability of these algorithms to other types of engineering structures beyond trusses could broaden their practical utility in civil engineering and beyond.

In conclusion, this study underscores the importance of algorithm selection tailored to specific structural optimization tasks, aiming for efficient and effective designs that meet engineering requirements while optimizing performance metrics such as weight and structural integrity.

Authors' Contributions

All authors have contributed equally to the conception, design, execution, and analysis of the research, as well as the drafting and revision of the manuscript.

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