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Original Article

The Evolution of the Self-Adaptive Enhanced Vibrating Particle System (SA-EVPS) Algorithm for Optimizing Truss Structures

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Abstract - *Optimizing truss structures entails determining the most efficient arrangement and dimensions of members to fulfill specific goals, such as reducing weight and maximizing strength. Implementing the self-adaptive enhanced vibrating particle system (SA-EVPS) as a metaheuristic optimization technique for enhancing structural components in civil structures offers substantial potential for improving the efficiency and functionality of such components. This study presents a novel algorithm developed for optimizing the geometry and size of a 45-bar truss structure. Through extensive simulations and comparative analysis with seven recent metaheuristic algorithms, including the Whale Optimization Algorithm (WOA), the Marine Predators Algorithm (MPA), Sine Cosine Algorithm (SCA), Multi-Verse Optimizer (MVO), Moth-Flame Optimization (MFO), Grey Wolf Optimizer (GWO), and the Enhanced Vibrating Particle System (EVPS), the proposed algorithm demonstrates superior effectiveness in delivering enhanced structural performance by simultaneously optimizing member dimensions and structural geometry. The findings of this study indicate that the proposed SA-EVPS algorithm provides an effective and robust solution for improving the efficiency and reliability of structural optimization processes, with promising applicability to the optimization of a 45-bar truss structure. This advanced algorithm facilitates the identification of ideal geometries and member dimensions for structural components, considering factors such as load-bearing capacity and material optimization.*

Keywords - *Optimization, Metaheuristic algorithms, Self-Adaptive, SA-EVPS algorithm, Truss structures.*

1. Introduction

Metaheuristic algorithms represent a category of optimization techniques designed to address complex problems by identifying optimal solutions. These algorithms seek the best solution by exploring a broad search space (exploration) and concentrating on promising regions (exploitation) to avoid convergence in local optima [1-3]. Inspired by natural phenomena, these algorithms are recognized for their capacity to efficiently and effectively explore the solution space. Because of their capacity to attain nearly optimal solutions for various problems, both continuous and discrete, metaheuristic algorithms are realistic optimization approaches [4]. Metaheuristic algorithms and Artificial Intelligence (AI) methods connect within the broader context of optimization and problem-solving [5-7]. In the framework of AI, encompassing machine learning algorithms, neural networks, and evolutionary algorithms, there is a continual need for optimization. This optimization is necessary for tasks such as refining models, training weights, and adjusting parameters. On the other hand, metaheuristic algorithms offer a universal method for addressing sophisticated optimization problems, utilizing effective and heuristic exploration of solution spaces [8, 9]. A metaheuristic algorithm is considered adaptable when employed across diverse challenges without requiring specific modifications to its structure. In contrast to alternative methods, metaheuristic algorithms usually consider problems as black boxes, concentrating exclusively on the system's inputs and outputs [10]. Engineers only need to possess proficiency in representing their problems for metaheuristic algorithms, and unlike gradient-based optimization, the majority of metaheuristic algorithms do not rely on derivations; instead, they stochastically optimize problems. Metaheuristic algorithms excel in avoiding local optima, making them remarkably suitable for challenges with expensive derivatives or unknown factors [11]. These algorithms can be used to address a wide variety of challenges without the need for gradient information. This flexibility has led many researchers, particularly in the field of civil engineering, to employ these algorithms in diverse applications. Previous investigations have studied various traditional approaches, including linear and nonlinear programming, genetic algorithms, and other heuristic methods, for optimizing truss structures, focusing on minimizing weight, maximizing strength, and improving overall performance. [12-14]. Truss optimization has been significantly advanced with the incorporation of metaheuristic algorithms, including Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC), Cuckoo Search (CS), Tabu Search, Bat Algorithm (BA), Genetic Algorithms (GA), and Differential Evolution [15, 16]. These algorithms have effectively tackled the complicated and inherent complexity of truss optimization [17, 18].

The Vibrating Particle System (VPS) algorithm, derived from the concept of particle vibrations, has been utilized to address various optimization problems, notably in structural optimization [19, 20]. It has demonstrated effectiveness in exploring the search space and avoiding convergence local minima. Enhancements to the fundamental VPS algorithm have been implemented to improve its rate of convergence and precision. These enhancements consist of integrating the adaptive mechanisms of VPS with complementary optimization strategies. Self-adaptive algorithms have recently become increasingly recognized due to their capacity to adjust parameters dynamically throughout the optimization process, improving performance across various problems. Research has shown that self-adaptive approaches can contribute to more robust and effective optimization solutions [21-23]. Comparative studies of optimization algorithms for truss structure design have emphasized the strengths and shortcomings of each technique [24-26].

These studies frequently highlight the necessity of balancing the search for new solutions and improving current ones during the search process, resulting in the development of more advanced algorithms such as the SA-EVPS. For instance, Yue et al. [27] presented an approach that applies Particle Swarm Optimization (PSO) to identify damage in composite structures by optimizing target parameters. The population is assessed with a fitness function, and through iterative steps, the particle swarm converges on the damaged location. The study reveals that the suggested technique exhibits higher convergence speed and improved robustness compared with an imaging approach based on a genetic algorithm.

In a separate study, Wu et al. [28] presented an advanced artificial bee colony (ABC) algorithm that combines the finite element method with artificial neural networks. The study employs the concept of surrogate finite element methods integrated with Physics-Informed Neural Networks (PINNs) to tackle the geometrically nonlinear optimization challenge in a 10-bar truss structure considering size, shape, and topology. According to the study, employing metaheuristic algorithms can greatly accelerate the optimization process. In a related study, Jawad et al. [29] employed the ABC algorithm for truss structure optimization, focusing on factors such as displacement, stress, and buckling criteria. Nodal coordinates and cross-sectional areas were considered design parameters to optimize the shape and size of the truss structure. Their findings validated the algorithm’s proficiency, highlighting its superiority in achieving optimized weight, standard deviation, and efficiency in structural computations. The authors also utilized the Dragonfly Algorithm (DA), a recently developed optimization technique to enhance truss design within a discrete optimization framework [30]. They assessed the capability of this algorithm by comparing it with a range of different metaheuristic algorithms. The outcomes revealed that the DA surpasses other algorithms by achieving lighter structures, minimizing the need for structural analysis, and ensuring all necessary constraints are adequately met.

Moving on, Gomes and Almeida [31] developed a robust inverse optimization approach utilizing a sunflower optimization algorithm for detecting damage in plate structures. In this approach, the process of evaluating damage involves minimizing an objective function that is influenced by the modal parameters of CFRP laminated structures. The results attained specify that this approach effectively recognizes the severity and location of fault in the composite plate. Additionally, the improved algorithm reveals superior proficiency and precision when compared to applied genetic algorithms. Diverse metaheuristic algorithms have been applied to produce more efficient solutions within an acceptable timeframe, tackling a range of complex challenges in civil engineering optimization. Some of these methods consist of Artificial Algae Algorithm [32, 33], Tabu Search [34], Fruit-Fly Optimization [35, 36], Harmony Search [37, 38], Arithmetic Optimization Algorithm [39], Sunflower Optimization (SFO) algorithm [40], Levy Flight Distribution (LFD) [41], Volleyball Premier League Algorithm [42], Beluga Whale Optimization [43], Harris Hawks Optimization [44], Sine Cosine Algorithm (SCA) [45], Political Optimizer (PO) algorithm [46], Bat Algorithm (BA) [47], and Lichtenberg Algorithm [48].

Additionally, Kaveh et al. [49] applied the Vibrating Particle Systems (VPS) algorithm to identify damage in truss structures, incorporating a model for viscous damping. This technique evaluates the movements of particles toward their stable position. To improve the performance of VPS, the authors presented the Enhanced Vibrating Particle System (EVPS) algorithm by modifying specific parameters. This Enhanced system has proven useful in addressing various optimization difficulties. As an example, Hosseini et al. [50] developed a method for improving the effectiveness of dome truss structures. The researchers used random parameters to represent Uncertain variables when evaluating the reliability of the structure. He and Cui [51] developed an innovative metaheuristic approach focused on optimizing the size and shape of truss structures. Their algorithm utilizes discrete variables for sizing and continuous variables for design. With the Medalist Learning Algorithm (MLA) implementation, their study achieved improved solutions for truss design optimization problems. Moreover, Kaveh et al. [52] employed the enhanced, modified dolphin operator in combination with the EVPS to evaluate three broadly recognized steel-framed structures. Furthermore, the authors concentrated on advancing the EVPS algorithm by minimizing the effect of adjusting parameters. In this research, to reduce the complexity of computation related to prior damage detection approaches, the authors introduced an innovative objective function. In their study, they calculated the modal parameters of the structure and presented a novel technique for optimizing frame structures utilizing time history analysis. This was attained through the application of metaheuristic algorithms that depend on node displacement. In addition, Haji Mazdarani et al. [53] established a reliability-based technique for designing 3D steel frames with concentric bracing. They used a function to minimize the total weight, with the bracing design serving as a variable in the optimization process.

In short, traditional metaheuristic algorithms utilized for optimization of truss structures often suffer from limitations such as slow convergence rate to local optima and difficulty in dealing with complex search spaces. Although the Vibrating Particle System (VPS) algorithm has exhibited potential to address these challenges, it still has limitations in flexibility, convergence speed and solution accuracy for complicated truss optimization problems. Therefore, a stronger, adaptable, reliable, and effective optimization algorithm is required to efficiently tackle the complexity of truss design problems. An enhanced Vibrating Particle System (VPS) algorithm, capable of self-adjusting its parameters, offers an efficient substitute. Hence, regardless of the current research efforts, there is still inadequate information and a need for further research on the evolution of the SA-EVPS algorithm for optimizing truss structures. This research seeks to overcome this gap by assessing the SA-EVPS algorithm to tackle these challenges. This study addressed the development of the SA-EVPS algorithm for geometry and sizing optimization of a 45-bar truss structure. The results of this investigation were compared with other optimization techniques, highlighting the algorithm's improved convergence rate and quality of the solutions.

2. Methods

This section presents the methodology of the SA-EVPS algorithm, an optimization method inspired by physical phenomena such as particle vibrations and developed with self-adaptive mechanisms. The EVPS algorithm represents an enhanced description of the VPS algorithm developed by Hamed Fathi et al. [55]. The algorithm's efficiency depends on the precise selection of the acceptable range for the initial population, as defined by Equation (1).

$$x_i^j = x_{min} + rand.(x_{max} - x_{min}) \tag{1}$$

Where x_i^j is the jth parameter of the ith particle, x_{max} and x_{min} are the maximum and minimum limits of design parameters within the search space, respectively.

Another variable, referred to as "memory," keeps track of the quantity of available memory capacities derived from the most optimal configurations attained by the samples. Equation (2) shows how the vibration is influenced by the damping level.

$$D = \left(\frac{iter}{iter_{max}}\right)^{-\alpha} \tag{2}$$

In this equation, iter represents the iteration count; $iter_{max}$ is the maximum cycles, and α is a fixed number. The quantity ±1 is arbitrarily employed. In addition, the population's new positions are adjusted using Equation (3).

$$x_i^j = \begin{cases} [D.A.rand1 + OHB^j] & (a) \\ [D.A.rand2 + GP^j] & (b) \\ [D.A.rand3 + BP^j] & (c) \end{cases} \tag{3}$$

OHB, GP, and BP are calculated individually for each variable, with A defined in the following manner as Equation (4).

$$A = \begin{cases} (\pm 1)\left(OHB^j - x_i^j\right) & (a) \\ (\pm 1)\left(GP^j - x_i^j\right) & (b) \\ (\pm 1)\left(BP^j - x_i^j\right) & (c) \end{cases} \tag{4}$$

$$\omega_1 + \omega_2 + \omega_3 = 1$$

The variables ω1, ω2, and ω3 denote the significance assigned to OHB, GP, and BP, respectively. Additionally, rand1, rand2, and rand3 represent arbitrary numbers evenly spread within the [0, 1] interval. Figure 1 provides a schematic representation of the SA-VPS algorithm. The EVPS algorithm incorporates eight parameters, namely p, ω1, ω2, ω3, HMCR, PAR, Neighbor, and Memory size, which are ascertained throughout experimentation. Although these parameters are initially set with specific values in the EVPS algorithm, they remain constant, taking on the values of 0.05, 0.2, 0.3, 0.3, 0.95, 0.1, 0.1, and 4, respectively. The EVPS parameters play an important role in controlling search accuracy, exploration and exploitation phases, convergence speed, and the overall behavior of the algorithm. Consequently, these parameters significantly affect the method's behavior. Before the primary optimization process, all eight parameters undergo optimization using the EVPS algorithm modified to the specific problem at hand. Subsequently, the main optimization is executed.

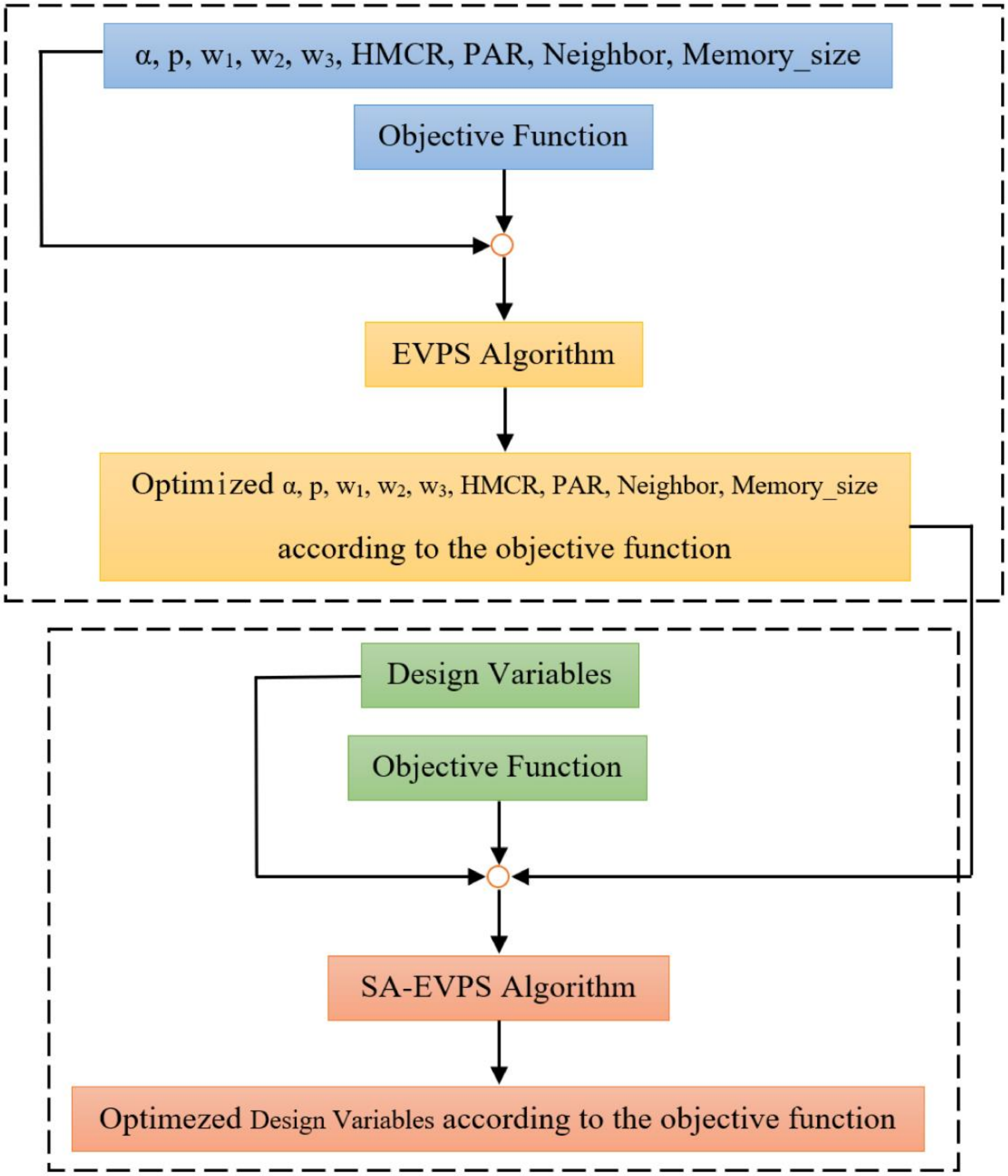

Fig. 1 Visual illustration of the SA-EVPS algorithm

3. Results and Discussions

This study involves the analysis of a 45-bar truss structure featuring a total span of 2000 inches and a depth of 200 inches under the influence of three downward forces. Figure 2 illustrates the geometry and configuration of this structure.

The structure experiences simultaneous application of three vertical loads. At nodes 15 and 19, two loads of P1 = 60 kips each are exerted, and at node 17, a load of P2 = 80 kips is imposed. Stress limits of 30 ksi, both in tension and compression, apply to all elements of the truss structure. This section considers the results from the shape and size optimization analysis of the 45-bar truss structure. These outcomes have been evaluated using various statistical criteria such as mean, best, worst, standard deviations, and medians. For assessing the effectiveness of the method, the SA-EVPS algorithm is compared to seven well-known methods such as the Marine Predators Algorithm (MPA), Whale Optimization Algorithm (WOA), Sine Cosine Algorithm (SCA), Multi-Verse Optimizer (MVO), and Enhanced Vibrating Particle System (EVPS). In this study, nodal displacement was constrained within ±2.0 inches in both horizontal and vertical directions. Figure 3 illustrates the nodal displacement of the 45-bar truss structure in both X and Y directions.

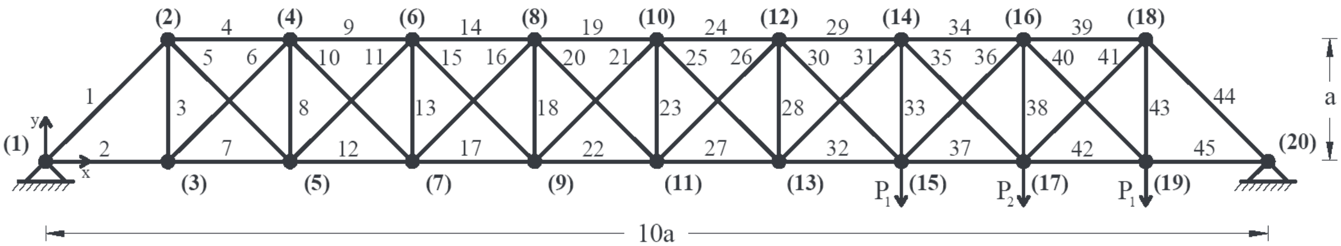

Fig. 2 Geometry and configuration of a planar 45-bar truss structure

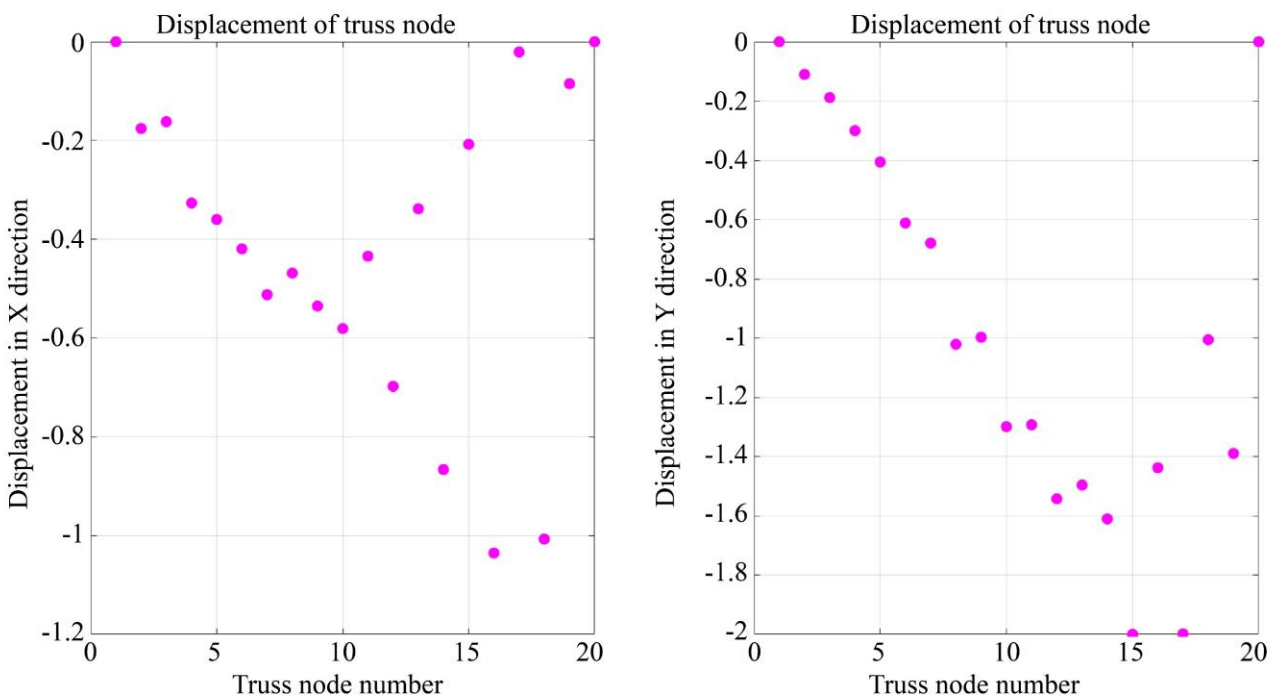

Fig. 3 Displacement of nodes in the X and Y directions for the 45-bar truss structure

As illustrated in Figure 3, the largest displacements along the X and Y directions are equal to -1.0354 and -2 inches, respectively. The material's density used was 0.283 lb/in^3, and the elastic modulus measured 30,000 ksi. The challenge involves 45 sizing variables corresponding to the cross-sectional areas of truss elements and 9 shape parameters representing the vertical coordinates (i.e., y-coordinates) of nodes 2, 4, 6, 8, 10, 12, 14, 16, and 18. Consequently, there are 54 design variables in total. A limitation is placed on the shape variables, allowing only discrete integer values.

The minimum and maximum limits for the shape variables are 100 inches and 1400 inches, respectively. As for the sizing variables, selecting cross-sectional areas for members (A1 to A45) must fall within the range of 0.1 to 15 in^2, with increments of 0.1 in^2. The optimization techniques considered in this research are coded using MATLAB software. The results for the best, mean, and worst optimum weight of the 45-bar truss structure are presented in Table 1. As presented in Table 1, all the models achieved for the truss structure satisfy the designated design constraints. Nevertheless, the SA-EVPS algorithm has produced the most advantageous optimal weights. Convergence curves in the optimization of truss structures demonstrate the development of objective functions, such as minimizing weight or maximizing stiffness during the iterations of an optimization algorithm. These curves are crucial for the effectiveness of the optimization procedure. The convergence curve shows the rate at which the optimization algorithm approaches a solution. A steeper initial slope indicates faster convergence, while a gentler incline indicates slower progress. Figure 4 shows the convergence curves of the present study and competing algorithms in optimizing the 45-bar truss. As shown in Figure 4, the EVPS and SA-EVPS algorithms have demonstrated exceptional design outcomes characterized by favorable relative convergence rates. The ranking of each optimization algorithm based on the Friedman test is demonstrated in Table 2. This table shows the best weight and the mean weight of 30 independent runs obtained by EVPS and seven different optimization algorithms. SA-EVPS algorithm has achieved better results than all algorithms, according to the Friedman test.

Table 1. Weight results of optimizing the 45-Bar truss structure (lb)

Statistics Tool	MPA	WOA	SCA	MVO	MFO	GWO	EVPS	Present Study
Mean	7237.49859	19052.3032	43796.5235	16014.123	17914.47	5839.84602	4910.37363	4814.92601
Best	6415.80364	12362.8406	34239.1057	11046.2183	5517.92055	5167.95654	4499.1858	4205.93002
Worst	8413.4653	31620.5867	63457.6809	20237.8398	34238.9602	7053.19251	5566.75091	5810.11732
Std	469.678158	4118.14371	7016.27398	2419.16541	6749.263	473.348275	314.821469	411.325128
Median	7180.64285	18782.1296	42485.416	15596.8047	16579.6329	5752.00992	4841.24801	4818.02925

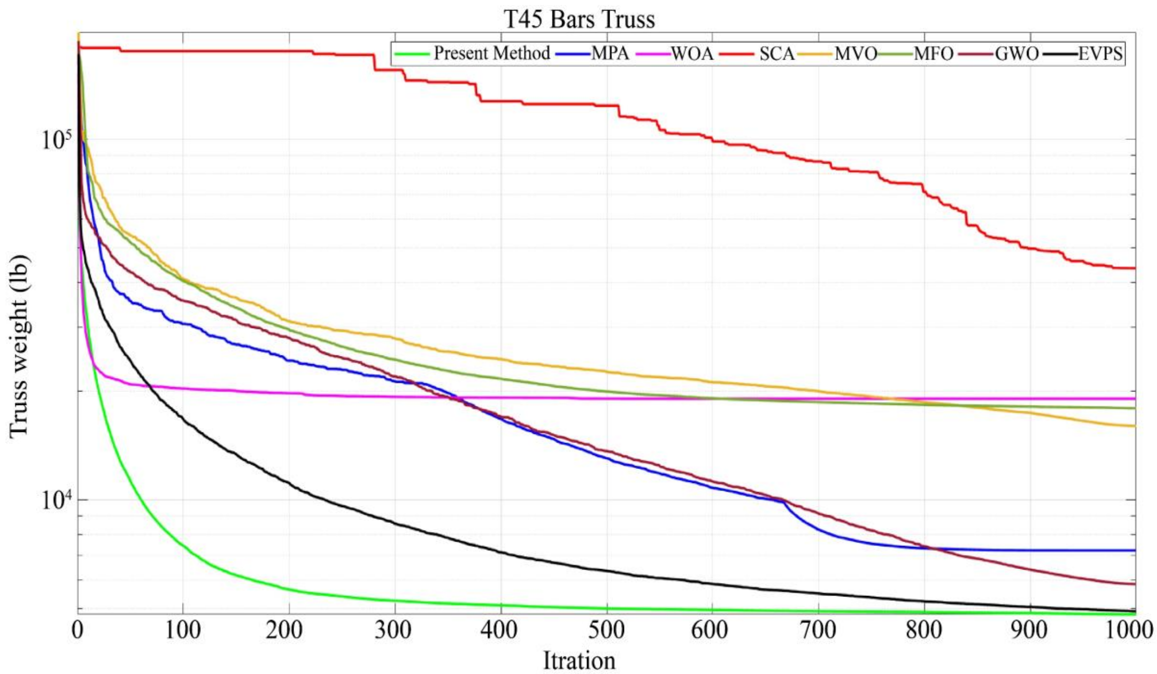

Fig. 4 Convergence curves of optimizing the 45-Bar Truss Structure

Table 2. Ranking of each algorithm based on the friedman test

Statistic Tool	MPA	WOA	SCA	MVO	MFO	GWO	EVPS	Present study
Best Rank	4	6.4333	8	5.6	5.9	3	1.6	1.4667
Mean Rank	3.7667	4.4333	8	6.6333	6	4.1667	2	1
Overall Best	4	7	8	5	6	3	2	1
Overall Mean	3	5	8	7	6	4	2	1

In the optimization process, 30 independent runs are conducted for each example, with a consistent population size of 30 in all problems. In the EVPS algorithm α, p, ω1, ω2, PAR, HMCR, memory size, and Neighbor are 0.05, 0.2, 0.3, 0.3, 0.1, 0.95, 4, and 0.1, respectively. The optimized geometry of the 45-bar truss, achieved through the SA-EVPS algorithm, is illustrated in Figure 5. This figure illustrates that the optimized geometry of the 45-bar truss, attained through the SA-EVPS algorithm, represents the most efficient set of dimensions achieved through an iterative procedure, meeting specific performance objectives such as minimizing weight or maximizing stiffness. The optimum outcomes for section areas and elevation results of each optimization technique are presented in Tables 3 and 4. These tables include the numerical outcomes demonstrating the performance of different algorithms.

Table 3. Section results of optimized the 45-bar truss structure in^2 (Cross sectional area)

Section	This study area in^2	EVPS area in^2	GWO area in^2	MFO area in^2	MVO area in^2	SCA area in^2	WOA area in^2	MPA area in^2
A1	2.9	3	3.1	3.2	6.3	5.1	3.9	3.2
A2	1	1	1.7	2.5	2.6	10.5	2.4	1.9
A3	0.4	0.7	1.1	1.5	3.6	4.9	5	3.6
A4	2.8	3	3.4	4	3.5	6.7	8.2	3.2

A5	0.1	0.2	1.1	0.3	4.1	5.5	4	0.8
A6	0.6	0.7	1.2	1.4	0.3	4	6	0.8
A7	0.8	0.6	0.5	0.5	8.1	12.9	6.5	3
A8	0.2	0.4	1.1	2.3	2.2	4.7	7.7	1.3
A9	3.3	3.1	3.8	3.3	3.9	4.8	3.3	3
A10	0.2	0.2	0.3	0.6	4.5	13.4	3.5	0.4
A11	0.2	0.3	0.8	0.8	0.8	8.7	1.9	0.7
A12	0.4	0.8	0.4	0.4	1.2	6.7	0.4	0.6
A13	0.1	0.1	1.3	0.9	2	12.3	1.4	1.3
A14	3.3	3.3	4.3	3.2	4.3	7.4	4.2	3.5
A15	0.2	0.3	0.7	0.4	0.7	5	0.8	0.7
A16	0.2	0.5	0.5	0.6	2.7	11	1.5	0.5
A17	0.2	0.4	0.6	0.5	3.8	4.1	4.4	0.5
A18	0.1	0.2	0.2	0.3	3.9	12.6	2.1	0.3
A19	3.9	3.8	3.4	4.5	6.7	4.5	12.6	5.2
A20	0.2	0.3	0.2	0.2	1.4	0.7	1.4	0.5
A21	0.1	0.3	0.6	0.9	3.1	1.9	0.9	0.2
A22	0.1	0.1	0.3	0.6	1.3	9.7	1.8	2.1
A23	0.1	0.1	0.5	1	0.3	7.9	8.4	0.8
A24	3.6	3.9	3.6	4	7.3	6.2	8.7	4.2
A25	0.2	0.5	0.1	0.1	4.2	9	4.5	1.7
A26	0.2	0.3	0.2	0.8	2.6	1.4	3.4	0.7
A27	0.1	0.2	1.1	1	2.5	10	2	0.6
A28	0.1	0.1	0.5	0.6	1.5	2.4	1.4	0.5
A29	4.6	4.4	4.3	4.1	9.8	7.6	5.6	5.8
A30	1.7	1.5	1.3	1.3	1.9	3.8	2.3	1.9
A31	0.1	0.3	0.3	0.5	1.3	1.9	0.4	0.5
A32	0.1	0.5	1	0.5	11.3	4	9.6	1.5
A33	0.8	0.9	0.8	0.9	0.9	8.9	1.3	1.2
A34	4.8	4.2	5.4	4.3	8.2	6.4	8	6.8
A35	0.2	0.2	0.8	0.9	0.9	6.5	2	1
A36	0.3	0.4	0.4	0.4	3.5	13	3.6	2
A37	0.7	1.1	1	0.8	4.4	7.4	4.5	1.1
A38	1.8	1.7	1.4	1.5	1.1	8	2.4	0.9
A39	4.9	5.2	5.1	5.5	7.6	7.4	10.4	6.3
A40	0.1	0.3	0.3	0.3	0.5	13.9	4.4	0.6
A41	1.3	1.3	1.3	1.9	2.4	10.9	2.5	2.1
A42	0.3	0.3	0.3	0.5	2.6	6.3	0.9	0.5
A43	2	1.9	2.1	2	2.6	10.2	4.7	2
A44	6.5	6.5	6.5	6.5	7.8	10.5	7.8	6.8
A45	0.3	0.4	0.4	0.5	1.2	11.5	3.7	0.7

Table 4. Elevation results of optimized the 45-bar truss structure in^2 (Vertical coordinates)

Elevation Variable	This Study in^2	EVPS in^2	GWO in^2	MFO in^2	MVO in^2	SCA in^2	WOA in^2	MPA in^2
Y1	104	113	111	113	153	399	155	122
Y2	188	197	194	185	177	448	149	202
Y3	263	271	274	280	271	473	266	271
Y4	334	345	344	340	258	490	297	318
Y5	406	407	399	408	326	593	283	384
Y6	474	469	464	469	402	543	361	434
Y7	464	462	475	473	385	632	378	438
Y8	427	426	427	426	325	341	318	405
Y9	297	296	294	289	230	297	199	297

One of the primary reasons for the SA-EVPS algorithm's improved performance compared to current optimization techniques lies in its self-adaptive process. Traditional metaheuristic algorithms, such as Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO) and Genetic Algorithms (GA), depend significantly on pre-set parameters that they initially set or manually modify during the optimization process. This can negatively impact their performance, especially in tackling challenging problems like truss structure optimization, where the search domain is significant and nonlinear. The comparison of deformations in both the original and optimized truss structures provides valuable insights into how optimization has impacted the structural response. Displacement in members of the 45-bar truss is shown in Figure 6. As shown in Figure 6, the optimized truss structure exhibits lower deformations than the original, indicating that the optimization process has effectively improved structural performance by redistributing loads or adjusting member sizes. In this study, the optimized truss met the design criteria for deformation limits and indicated a successful outcome. This is remarkably important in the area of structural engineering, where providing safety and serviceability standards is crucial.

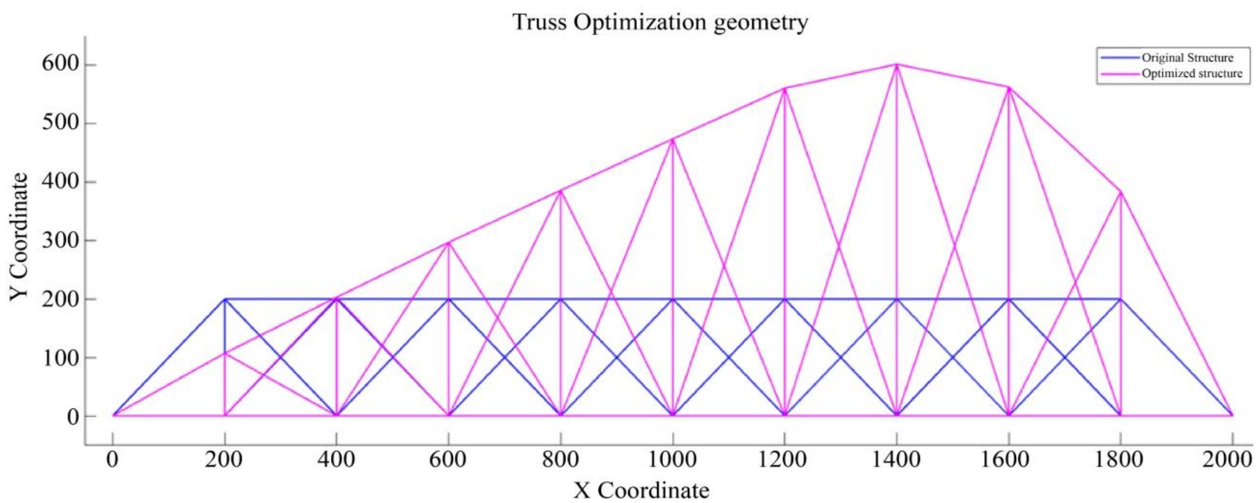

Fig. 5 Comparison of the original and optimized geometry of the 45-bar truss structure

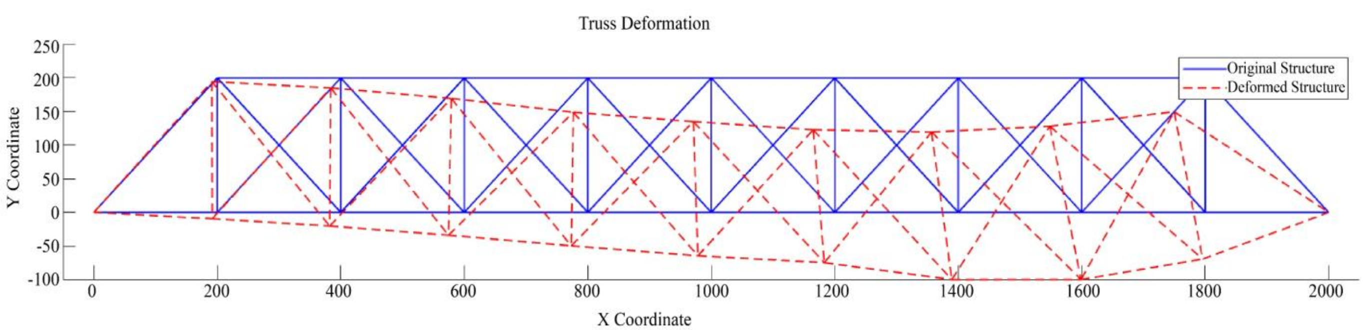

Fig. 6 Comparison of deformation between the original and optimized structure

Comparing stress levels at each node between the original and optimized truss structures offers significant information about how the optimization procedure has impacted the overall structural performance. In Figure 7, the narrow range between the highest and lowest stress ratios highlights the outstanding capability of the suggested technique for optimizing the design of the 45-bar truss structure. The figure shows that stress levels at nodes in the optimized truss structure are lower than in the original, indicating that the optimization has successfully decreased extreme stress among nodes. This signifies that the optimization procedure has improved the load-carrying capacity of the truss, leading to a more efficient distribution of forces throughout the structure. From Figures 6 and 7, the obtained results satisfy all the limitations of stress and displacement described for the problem. The stress ratio is typically calculated as the ratio of the actual stress to the allowable stress for each element.

Figure 8 illustrates the stress ratio of each element corresponding to the best design of SA-EVPS. According to Figure 8, a reduction in stress ratios for some members in the optimized truss indicates an overall improvement in structural efficiency, suggesting that the optimization procedure has led to a more balanced distribution of forces. The highest magnitude of the stress ratio of elements is 100% for this structure.

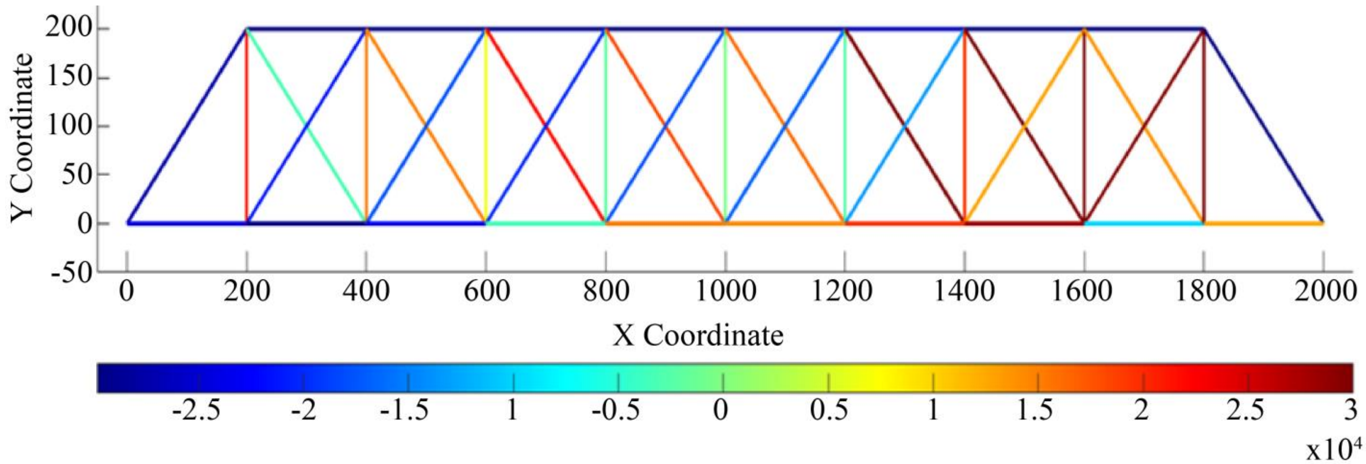

Fig. 7 Stress distribution in the members of optimized truss

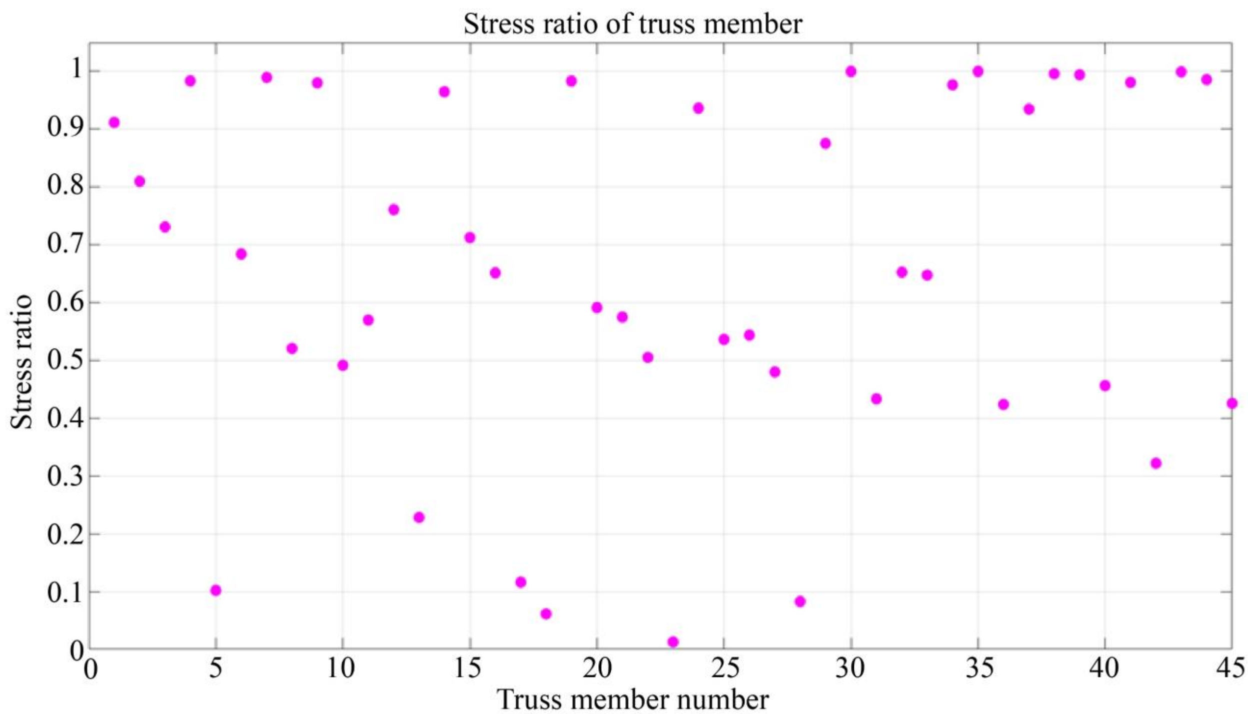

Fig. 8 Stress ratio among members in the 45-bar truss structure

In the construction sector, the SA-EVPS algorithm can offer a more effective way to design truss structures and other structural elements, reducing material expenses by finding optimized designs that need fewer resources or are easier to construct. Optimized truss structures can enhance load distribution and general stability, which is significant for safety in some important structures such as bridges and buildings. Applying the SA-EVPS algorithm can anticipate potential weak points in structures and minimize the risk of damage. To evaluate the real-world application for this research, it's significant to compare the SA-EVPS algorithm with other reputable optimization algorithms. SA-EVPS can be contrasted with a genetic algorithm (GA) frequently applied for structural optimization. In real-world applications, genetic algorithms are regularly utilized to optimize structural designs, but SA-EVPS could provide benefits by converging more rapidly and enhancing capability in complex designs more efficiently [54]. Particle Swarm Optimization (PSO) is another algorithm widely applied in structural optimization. Both SA-EVPS and PSO are population-based, but SA-EVPS, with its self-adaptive nature, could propose more optimal stability between exploration and exploitation [55]. Real-world engineering challenges usually include large-scale optimization, so trying SA-EVPS on structures with a lot of members could show its strength. It is worth mentioning that although SA-EVPS is self-adaptive, it still relies on initial parameters and scalability issues in large truss structures. Inappropriate parameter settings can reduce the convergence rate, increase the risk of rapid convergence to a local optimum and cause non-optimal results. Its applicability is restricted due to a lack of validation in various real-world problems. Similar to other metaheuristic approaches, it is probabilistic and can become trapped in local optima.

4. Conclusion

This study presented an efficient methodology for optimizing the design optimization of a 45-bar truss structure through the application of the SA-EVPS algorithm. Furthermore, a comparative investigation is conducted, evaluating the performance against seven recently developed metaheuristic algorithms. The optimized configuration of the 45-bar truss, achieved with the SA-EVPS algorithm, signifies the most productive arrangement of dimensions derived from an iterative process, reaching defined targets such as weight minimization or maximizing structural rigidity. According to the results of this study, the optimized truss structure exhibits enhanced structural functioning by redistributing loads or adjusting member dimensions efficiently. Furthermore, stress levels at the joints in the optimized truss structure demonstrate that the optimization procedure has effectively reduced overstressing among the joints. The Friedman test, assessing the ranking of each optimization algorithm in accordance with both the best weight and the mean weight across 30 independent runs, exposed that the SA-EVPS algorithm surpassed other algorithms in this research. Remarkably, the SA-EVPS algorithm demonstrated a superior capability for preventing local optima compared to alternative optimization methods. Additionally, it exhibited greater accuracy relative to other algorithms, considering aspects such as optimal and least efficient designs, average and standard deviation, convergence speed, and solution fitness. This innovative algorithm holds significant potential to play a crucial role in determining optimal dimensions for structural elements by considering factors like load-bearing capacity and material efficiency. By integrating self-adaptive features and enhancing the behaviour of vibrating particles, the algorithm demonstrates exceptional capabilities in determining the design space and identifying optimal configurations for the truss structure. Although the SA-EVPS algorithm is self-adaptive, its effectiveness may depend on the initial parameter selections, possibly resulting in suboptimal outcomes. It may also encounter challenges with scalability when used in large truss structures due to the increased difficulty of the search space. Furthermore, its performance has not been extensively evaluated across diverse real-world design cases, which limits its broader applicability. As with many metaheuristic algorithms, SA-EVPS is probabilistic and does not guarantee finding the global optimum, leaving it vulnerable to getting stuck in local optima in complex structures. Future work developing the SA-EVPS algorithm for optimizing truss structures could emphasize covering the algorithm for multiobjective optimization, allowing for the simultaneous consideration of multiple criteria such as weight, cost and structural integrity. Combining hybrid methods with other optimization methods, advancing computational proficiency for different structures, and integrating real-world restrictions could develop the algorithm's applicability.

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