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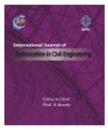

SA-EVPS ALGORITHM FOR DISCRETE SIZE OPTIMIZATION OF THE 582-BAR SPATIAL TRUSS STRUCTURE

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ABSTRACT

Metaheuristic algorithms have become increasingly popular in recent years as a method for determining the optimal design of structures. Nowadays, approximate optimization methods are widely used. This study utilized the Self Adaptive Enhanced Vibrating Particle System (SA-EVPS) algorithm as an approximate optimization method, since the EVPS algorithm requires experimental parameters. As a well-known and large-scale structure, the 582-bar spatial truss structure was analyzed using the finite element method, and optimization processes were implemented using MATLAB. In order to obtain weight optimization, the self-adaptive enhanced vibration particle system (SA-EVPS) is compared with the EVPS algorithm.

Keywords: Size optimization; Self-Adaptive algorithm; SA-EVPS algorithm; 582-bar spatial truss; discrete optimization problems.

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1. INTRODUCTION

A substantial community of researchers from many fields, particularly in engineering, has recently expressed interest in metaheuristic algorithms. In addition to their ability to obtain near-optimal solutions for any problem, including continuous and discrete problems, metaheuristic algorithms are practical optimization methods since they can easily be applied to a wide range of problems without gradient information. In order to provide more efficient answers in a reasonable amount of time, metaheuristic algorithms present methods that result in more efficient answers. Some of these methods include:

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Harmony Search (HS) [1], Coronavirus Herd Immunity Optimizer (CHIO) [2], Charged System Search Optimization [3], Su nFlower Optimization (SFO) algorithm [4], Tiki-Taka Algorithm (TTA) [5], Volleyball premier league algorithm [6], Simplified Dolphin Echolocation optimization (SDE) [7], Modified Dolphin Monitoring (MDM) [8], Artificial Algae Algorithm (AAA) [9], Harris hawks optimization [10], Lichtenberg algorithm [11], Water evaporation Optimization (WEO) [12], Sine Cosine Algorithm (SCA) [13], Water Strider Algorithm (WSA) [14], Water Wave Optimization (WWO) [15], and Lichtenberg Algorithm (LA) [16].

Metaheuristic Optimization Algorithms are developed to solve problems that are difficult to solve numerically. Nature is the most common source of inspiration for most of them. Exploration and exploitation are generally competing search mechanisms in Metaheuristic Optimization Algorithms. Exploration abilities should be balanced with exploration in order to produce a well-organized metaheuristic optimization algorithm [17]. Simple metaheuristic algorithms can be simulated, proposed, hybridized, or improved by computer scientists. As a result, other scientists can learn and apply metaheuristic algorithms quickly. A metaheuristic is flexible if it can be applied to different problems without requiring any special changes in its structure. Unlike other methods, metaheuristic algorithms tend to assume problems as black boxes. Metaheuristic algorithms consider only inputs and outputs of a system. Designers need only know how to represent their problems for metaheuristic algorithms. Most metaheuristic algorithms are not derivation-based. Metaheuristic algorithms optimize problems stochastically, unlike gradient-based optimization. To find the optimum, the optimization process starts with random solutions. Metaheuristic algorithms are highly appropriate for problems with expensive derivatives or unknowns. Metaheuristic algorithms are better than conventional optimization techniques at avoiding local optima. Metaheuristic algorithms are stochastic, thus avoiding local stagnation and searching the entire search space extensively.

Computer scientists can simulate, propose, hybridize, or improve simple metaheuristic algorithms. By utilizing metaheuristic algorithms, other scientists will be able to learn and apply them more quickly. The flexibility of a metaheuristic is determined by its ability to be applied to a variety of problems without requiring any special structural modifications. In contrast to other methods, metaheuristic algorithms tend to assume that problems are black boxes. There is no consideration of the inputs and outputs of a system in metaheuristic algorithms. A designer needs only be familiar with the way metaheuristic algorithms represent their problems. In order to determine the optimal solution, the optimization process begins with random solutions. Because metaheuristic algorithms are stochastic, they avoid local stagnation and search the entire search space thoroughly [17].

For a system with a single degree of freedom, the Vibrating Particle Systems (VPS) algorithm models viscous damping [18]. This algorithm examines the gradual movement of particles towards their equilibrium position. By modifying some parameters of the VPS algorithm, the EVPS algorithm was developed in order to improve the performance of VPS [19]. EVPS has been used to solve a variety of optimization problems, some of which are listed below:

Based on reliability, Hosseini *et al.* [20] developed a method of optimizing dome truss structures. In order to illustrate the process of Deterministic Design Optimization (DDO)

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and Random Binary Design Optimization (RBDO), they presented a flowchart. In addition, random variables are used to represent uncertain parameters in the evaluation of the reliability of the structure. Paknahad *et al*. presented a method for determining the practical parameters of the EVPS algorithm and developed a self-adaptive algorithm called SA-EVPS [21]. Kaveh *et al*. [22] applied the Modified Dolphin Monitoring (MDM) operator to the EVPS algorithm to evaluate three well-known steel frame structures. The study of Kaveh *et al*. [23] aimed to improve the EVPS algorithm by reducing the influence of regulatory parameters. As a result of a reduction in calculations associated with the former methods of damage detection, Kaveh et al have proposed a new objective function for detecting damages. The first phase of the process involves calculating natural frequencies, and the second phase involves evaluating mode shapes [24]. A reliability-based approach to designing concentric bracing layouts for 3D steel frames was developed by Haji Mazdarani et al. They used an objective function to reduce the total weight, and the layout of the braces was used as a variable in the optimization process [25]. As a result of nonlinear time history analysis, Kaveh *et al.* [26]. presented a new objective function for the optimal design of buckle-restrained braced frames (BRBFs) By using metaheuristic algorithms based on the displacement of nodes, Hosseini et al. calculated the reliability index of four transmission line towers and compared the results with Monte Carlo Simulations (MCS) Hosseini et al optimized two space trusses based on modulus of elasticity, yield stress, and cross-sectional uncertainties to increase response robustness and decrease weight [28]. Hosseini et al compared the reliability indices of Deterministic Design Optimization (DDO) and Reliability-Based Design Optimization (RBDO) for three large-scale dome trusses [29]. Kaveh and Rahami [30] used genetic algorithm and force method for optimal design.

In the EVPS algorithm, there are some practical parameters, containing α , p, w_1, w_2, *HMCR*, *PAR*, *Neighbor* and *Memory size*. According to the SA-EVPS algorithm, these parameters are set according to each problem. As a result, the SA-EVPS algorithm will be enhanced in terms of convergence speed and accuracy of the answer, as well as its ability to escape local optima. An optima. An evaluation of the SA-EVPS algor*i*thm was conducted using the 582-bar spatial truss structure as a well-known benchmark as well as a large scale structure, and the results will be compared with those of the EVPS algorithm.

The paper is organized as follows: Section one contains an introduction. A brief explanation of the EVPS and SA-EVPS algorithms is provided in the second section. The third section consists of the optimal design of the 582-bar spatial truss structure. In the final section of the paper, the conclusion is presented.

2. AN EXPLANATION OF THE EVPS AND SA-EVPS ALGORITHMS

The EVPS algorithm is an improved version of the VPS algorithm that had been presented in 2018 by Kaveh *et al*. [31]. This algorithm exhibits the following performance characteristics:

In the first stage, the allowable range of the initial population created by Eq. (1) should be considered.

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

where x_i^j is the *j*th variable of the *i*th particle; x_{max} and x_{min} are the upper and lower bounds of design variables in the search space, respectively. An additional parameter, called memory, maintains the number of memory sizes from the best positions achieved by the population. The effect of damping level on vibration is described by Eq. (2).

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

where *iter* is the current number of iterations; $iter_{max}$ is the total number of iterations and α is a parameter with a constant value; ±1 is used randomly. Finally, the new positions of the population are updated by Eq. (3).

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

where *OHB*, *GP*, and *BP* are determined independently for each of the variables, and *A* is defined as follows:

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

And we should have $\omega_1 + \omega_2 + \omega_3 = 1$ as defined in [31]. The coefficients ω_1, ω_2, and ω_3 are the relative importance for *OHB*, *GP*, and *BP*, respectively; *rand1*, *rand2*, and *rand3* are random numbers uniformly distributed in the [0, 1] range. The EVPS algorithm makes use of eight variables, including α, *p*, w_1, w_2, *HMCR*, *PAR*, *Neighbor*, and *Memory_size*, which are experimentally determined. In spite of the fact that these parameters are considered specific values by default in the EVPS algorithm, they are set as constants of 0.05, 0.2, 0.3, 0.3, 0.95, 0.1, 0.1 and 4, respectively. To implement the SA-EVPS algorithm, first all 8 parameters are optimized using the EVPS algorithm, and then the main optimization is conducted as illustrated in Fig. 1.

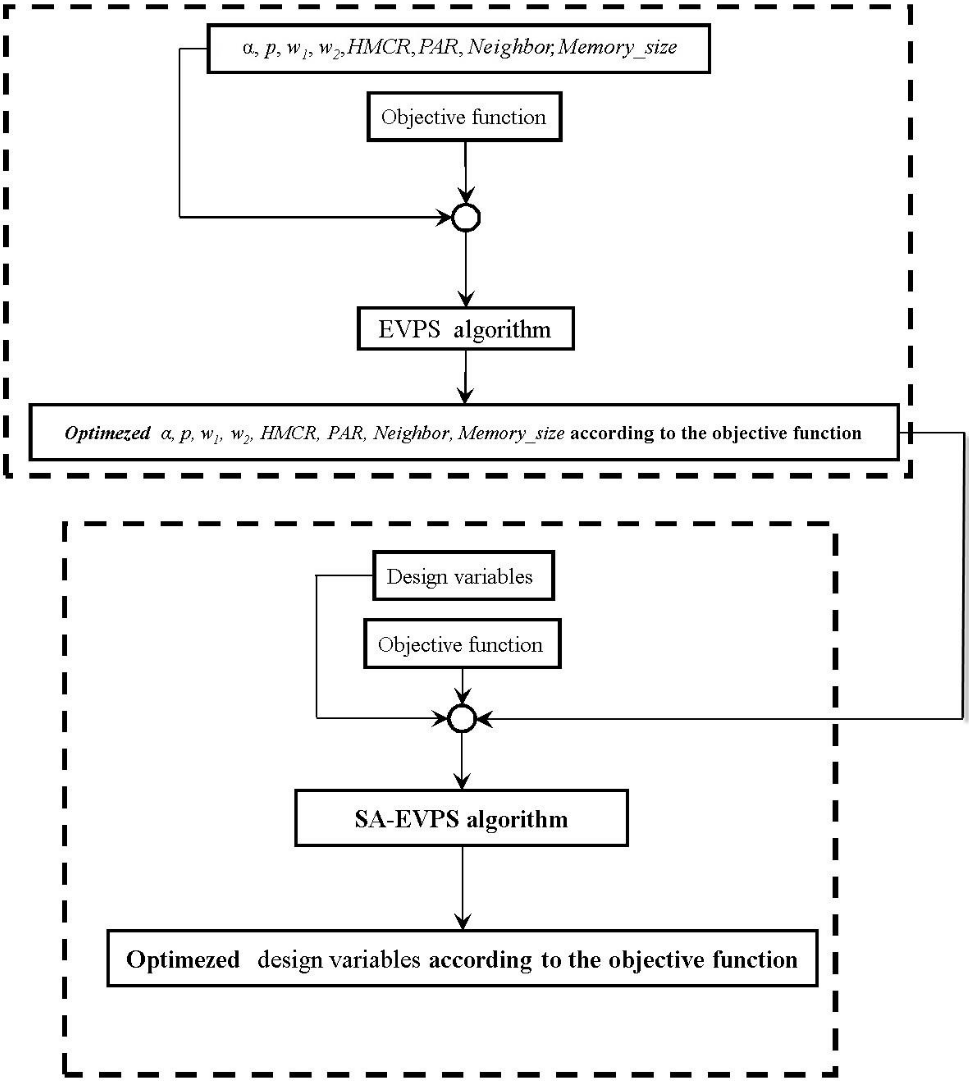

Figure 1. Schematic illustration of the SA-EVPS algorithm [25].

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3. NUMERICAL EXAMPLE

Here, the EVPS and SA-EVPS algorithms are used to compare the benchmark structure, which is a 582-bar spatial truss structure. Each example is optimized using 30 independent runs. In all problems, the population size is 30. In the EVPS algorithm, p, w_1, w_2, *HMCR*, *PAR*, *Neighbor* and *Memory_size* are 0.05, 0.2, 0.3, 0.3, 0.95, 0.1, 0.1, and 4, respectively. As a point of clarification, EVPS and SA-EVPS both used 64 as the *population size*. Fig. 2 illustrates a schematic of a 582-bar tower truss with a height of 80 meters.

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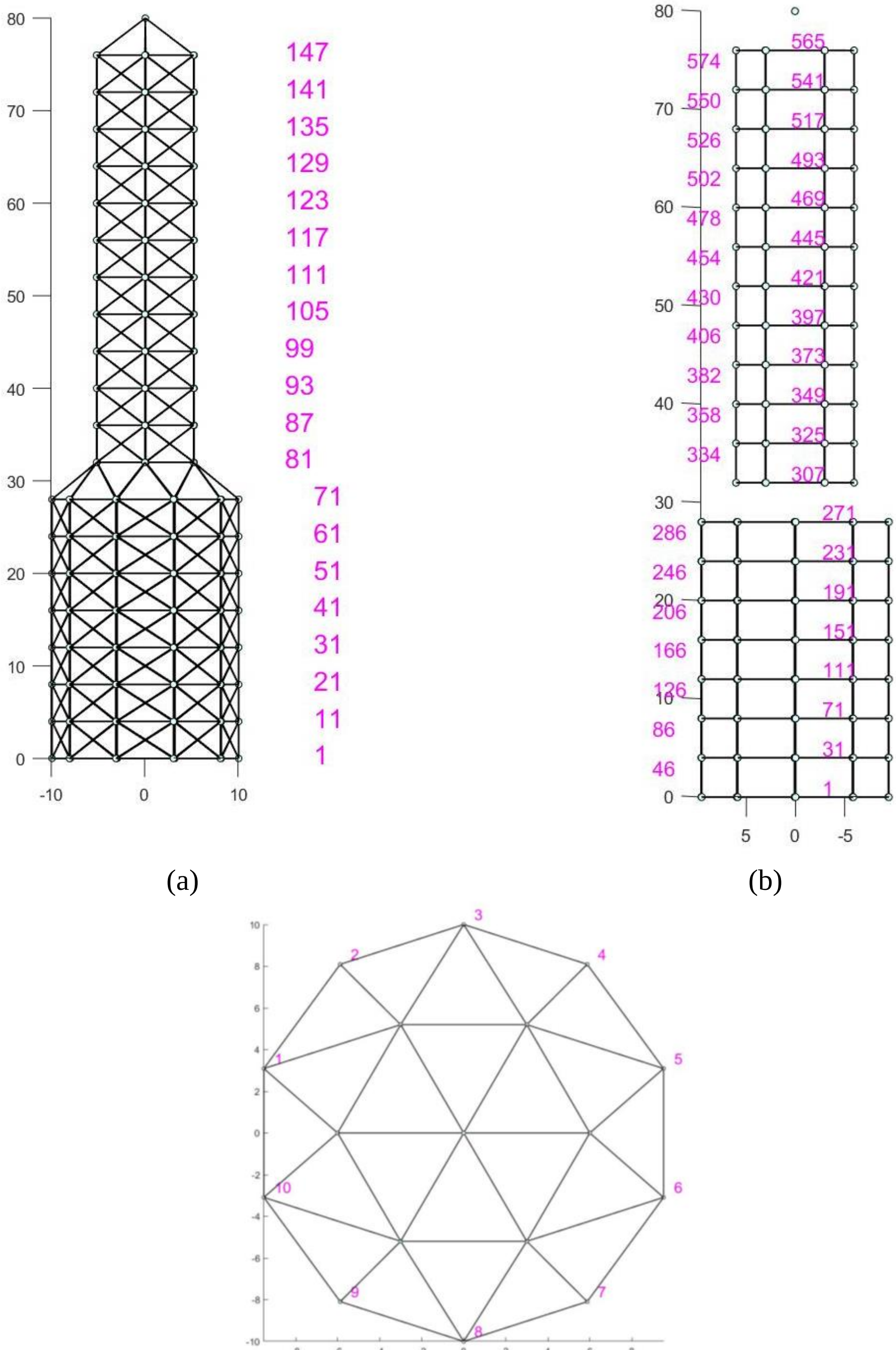

(a) (b)

(c)

Figure 2. Illustration of the 582-bar spatial truss from three view

According to the symmetry of the tower around the x-axis and y-axis, the 582 members are grouped into 32 independent size variables. At all nodes of the tower, lateral loads of 5.0

kN are applied in both x and y directions and vertical loads of -30 kN are applied in the z-direction. Size variables are determined by selecting 137 economical steel sections from a list of W-shape profiles based on their area and radii of gyration. 39.74 cm^2 and 1387.09 cm^2 are taken as the lower and upper bounds of the size variables. According to ASD-AISC [32], the members are subject to stress limitations. In addition, nodal displacements should not exceed 8.0 cm or 3.15 in. in any direction. According to the ASD-AISC design code provisions [32], the maximum slenderness ratio for tension members is 300, and it is recommended to be 200 for compression members. The parameters of the SA-EVPS algorithm that are self-adaptive (optimized) can be found in Table 1. In Table 2, the results obtained by EVPS and SA-EVPS algorithms are presented. In comparison with the EVPS algorithm, the SA-EVPS algorithm achieves better results in the best, worst, average, and standard deviation (STD) of answers. Fig.3 (a) illustrates the demand to capacity of stress ratios (DCR) of all elements of the 582-bar spatial truss structure. Fig. 3 (b) shows the deformed shape (a hundredfold) of the 582-bar spatial truss structure resulting from the SA-EVPS algorithm, in comparison to the original 582-bar spatial truss. Fig. 4 shows the convergence diagrams for EVPS and SA-EVPS algorithms for 30 independent runs.

Table 1: SA-EVPS algorithm parameters that are self-adaptive (optimized) for 582-bar spatial truss

	Parameter	Value
1	α	0.12091
2	p	0
3	w_1	0.42038
4	w_2	0.19072
5	HMCR	0.99836
6	PAR	0.28643
7	Neighbor	0
8	Memory_size	2

Table 2: Evaluation of EVPS and SA-EVPS results for the 72-bar spatial truss

Element Group	Optimal cross-sectional areas		Element Group	Optimal cross-sectional areas	
	EVPS	SA-EVPS		EVPS	SA-EVPS
1	W8X21	W8X21	17	W21X62	W12X65
2	W14X74	W14X74	18	W8X24	W8X24
3	W8X24	W8X24	19	W8X21	W8X21
4	W10X60	W14X61	20	W8X40	W14X43
5	W8X24	W8X24	21	W8X24	W8X24
6	W8X21	W8X21	22	W8X21	W8X21
7	W10X49	W10X49	23	W6X25	W8X24
8	W8X24	W8X24	24	W8X24	W8X24
9	W8X21	W8X21	25	W8X21	W8X21
10	W8X48	W12X45	26	W12X22	W8X21
11	W8X24	W8X24	27	W8X24	W8X24
12	W8X67	W12X72	28	W8X21	W8X21

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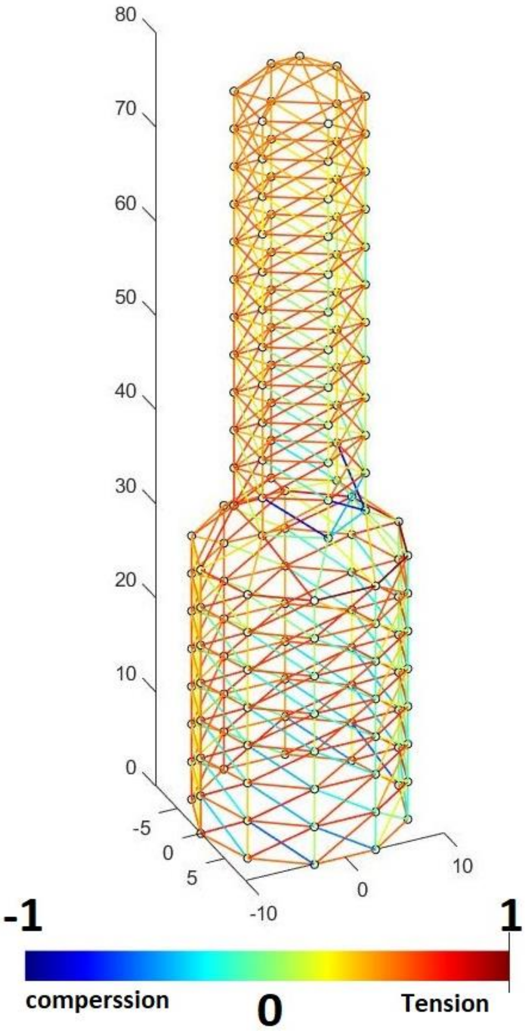
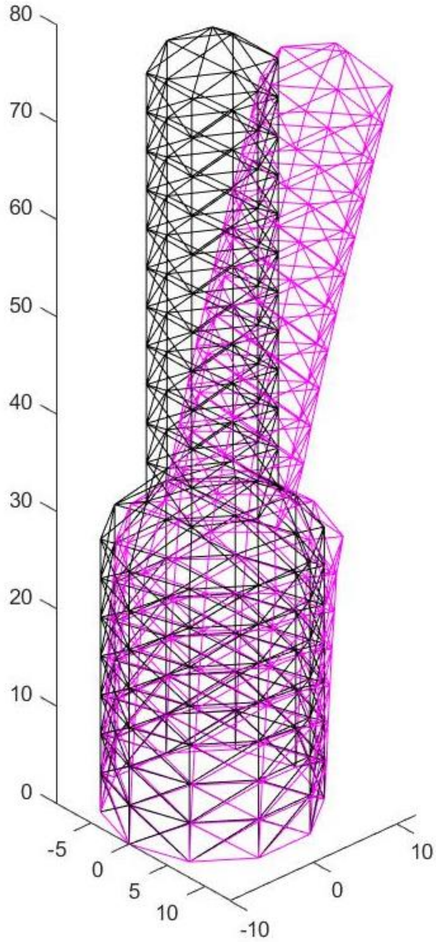
13	W12X79	W12X79	29	W8X21	W8X21
14	W8X48	W10X49	30	W8X24	W8X24
15	W10X88	W12X79	31	W8X21	W8X24
16	W8X24	W8X24	32	W8X24	W8X21

	EVPS	SA-EVPS
Best weight (m^3)	21.0761927	21.05647922
Worst weight (m^3)	21.26676063	21.12315966
Average weight(m^3)	21.11430829	21.07340576
STD	0.039286787	0.014263105



(a)



(b)

Figure 3. (a) The demand to capacity of stress ratios (DCR) of all elements of the 582-bar spatial truss structure, and (b) The deformed shape (a hundredfold) of the 582-bar spatial truss structure resulting from the SA-EVPS algorithm, in comparison to the original 582-bar spatial truss

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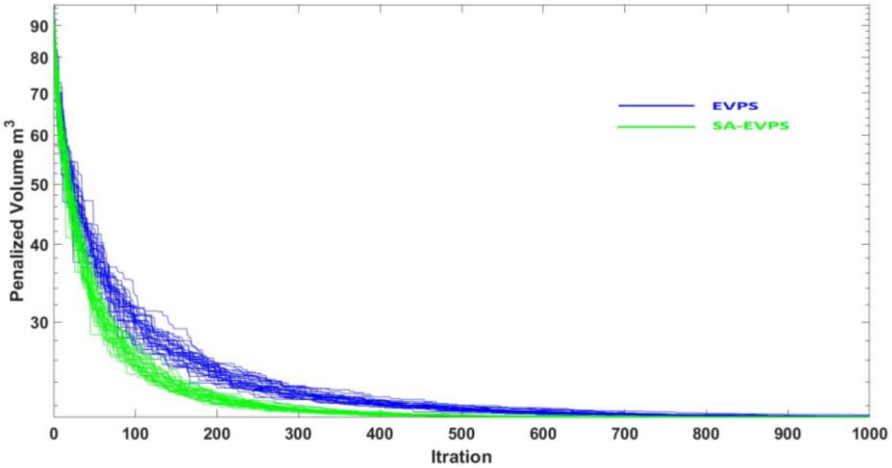
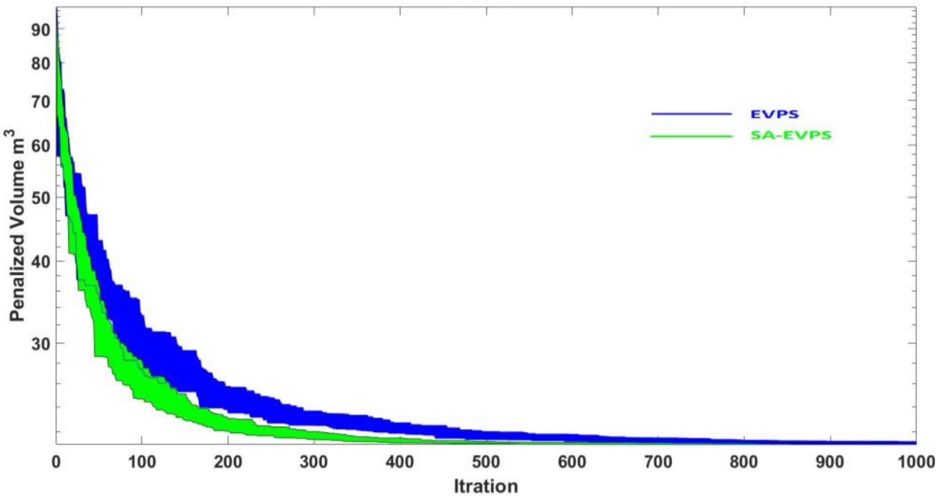


(a)



(b)

Figure 4. Convergence curves for the spatial 582-bar spatial truss of 30 independent runs for EVPS and SA-EVPS. (a) graph in linear form, (b) graph in Solid form

4. CONCLUSION

There have been many optimization problems that have been solved successfully using the EVPS algorithm, but this algorithm, as with many metaheuristic algorithms, includes parameters such as α , *p*, w_1, w_2, *HMCR*, *PAR*, *Neighbor* and *Memory_size* that are directly determined. As these parameters are very effective in determining the optimal answer for some problems, the SA-EVPS algorithm automatically adjusts these parameters to improve the quality of the answers. The 582-bar spatial truss structure, a well-known and large-scale problem, was examined using both EVPS and SA-EVPS algorithms. Both algorithms were presented, and the optimal design of the SA-EVPS algorithm was also graphically illustrated for greater clarity. This study found that the SA-EVPS algorithm achieved better results than

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the EVPS algorithm in terms of best and worst designs, average and standard deviation (STD), as well as convergence speed and solution quality. As a final recommendation, the SA-EVPS algorithm may be used for other engineering problems as well

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