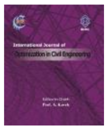
INTERNATIONAL JOURNAL OF OPTIMIZATION IN CIVIL ENGINEERING
Int. J. Optim. Civil Eng., 2025; 15(1):111-130



A SELF-ADAPTIVE ENHANCED VIBRATING PARTICLE SYSTEM ALGORITHM FOR STRUCTURAL OPTIMIZATION: APPLICATION TO ISCSO BENCHMARK PROBLEMS

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ABSTRACT

Structural optimization plays a crucial role in engineering design, aiming to minimize weight and cost while satisfying performance constraints. This research presents a novel Self-Adaptive Enhanced Vibrating Particle System (SA-EVPS) algorithm that automatically adjusts algorithm parameters to improve optimization performance. The algorithm is applied to two challenging examples from the International Student Competition in Structural Optimization (ISCSO) benchmark suite: the 314-member truss structure (ISCSO_2018) and the 345-member truss structure (ISCSO_2021). Results demonstrate that SA-EVPS achieves significantly better solutions compared to previous studies using the Exponential Big Bang-Big Crunch (EBB-BC) algorithm. For ISCSO_2018, SA-EVPS achieved a minimum weight of 16543.57 kg compared to 17934.3 kg for the best EBB-BC variant—a 7.75% improvement. Similarly, for ISCSO_2021, SA-EVPS achieved 4292.71 kg versus 4399.0 kg for the best EBB-BC variant—a 2.42% improvement. The proposed algorithm also demonstrates superior convergence behavior and solution consistency, with coefficients of variation of 3.13% and 1.21% for the two benchmark problems, compared to 12.5% and 2.4% for the best EBB-BC variant. These results highlight the effectiveness of the SA-EVPS algorithm for solving complex structural optimization problems and demonstrate its potential for engineering applications.

Keywords: Structural optimization; Metaheuristic algorithms; Self-adaptive parameters; Vibrating particle system; Truss structures; ISCSO benchmarks; Size optimization; Parameter tuning.

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Received: 10 February 2025; Accepted: 5 March 2025

1. INTRODUCTION

Structural optimization has emerged as a critical discipline in modern engineering design, driven by increasing demands for efficient, economical, and sustainable structures. The environmental and economic significance of structural optimization has gained greater recognition in recent years [1], as engineers and designers seek to minimize material usage while ensuring structural integrity and performance. This optimization approach is particularly valuable in the context of steel structures, where even marginal weight reductions can translate to substantial cost savings and reduced environmental impact.

Within the domain of structural optimization, truss systems have consistently served as ideal test cases. Their widespread practical applications in various engineering fields make them particularly relevant, but they also offer computational efficiency in providing conceptual designs for more complex structures [2]. Additionally, optimized truss instances effectively represent the complexities of challenging combinatorial optimization problems, making them excellent candidates for evaluating optimization algorithms across various disciplines including engineering optimization, applied mathematics, and computer science [3, 4].

Over the past several decades, researchers have developed numerous metaheuristic algorithms to address structural optimization challenges [5-10]. These algorithms, often inspired by natural phenomena, animal behavior, or evolutionary concepts, have demonstrated their effectiveness in finding near-optimal solutions within reasonable computational timeframes [11]. Among the most well-established methods are Genetic Algorithm (GA) [12], Particle Swarm Optimization (PSO) [13], Charged System Search (CSS) [14], Colliding Bodies Optimization (CBO) [15], and Big Bang-Big Crunch (BB-BC) [16].

More recent innovations include Teaching-Learning-Based Optimization (TLBO) [17], Water Wave Optimization (WWO) [18], Sine Cosine Algorithm (SCA) [19], League Championship Algorithm (LCA) [20], and Chemical Reaction Optimization (CRO) [21]. These algorithms offer distinct advantages in terms of exploration-exploitation balance, convergence behavior, and solution quality for different problem types [22-24].

Despite significant advances in algorithm development, benchmarking remains a critical challenge in the field. The performance evaluation of newly developed techniques has traditionally relied on conventional benchmark instances that have become increasingly unchallenging for contemporary algorithms [25]. As computational power and algorithm sophistication have increased, the differences in performance among modern algorithms on standard benchmarks have become marginal, making it difficult to identify truly superior methods [26, 27].

This situation has prompted calls for more challenging test examples that better reflect real-world design complexities [28, 29]. In a critical review of truss optimization with discrete variables spanning studies from 1968 to 2014, Stolpe [2] highlighted the urgent need for publicly available benchmark libraries to promote rigorous algorithm evaluation. This need has been partially addressed by the International Student Competition in

Structural Optimization (ISCSO), which provides a set of challenging benchmark problems that have been used to evaluate algorithm performance [30, 31].

Recent studies on these benchmark problems have demonstrated their challenging nature. Albert and Zhang [32] applied their SpartaPlex algorithm to ISCSO_2018 and ISCSO_2019 problems, finding that their solutions were still significantly heavier than the competition winners—by approximately 24% and 29%, respectively. Other researchers, including Etaati et al. [33], Dehkordi et al. [34], and Kaveh and Biabani Hamedani [35], have similarly reported difficulties in obtaining optimal solutions for ISCSO benchmark problems using various metaheuristic algorithms.

The Enhanced Vibrating Particle System (EVPS) algorithm is a relatively recent addition to the metaheuristic optimization landscape. Originally proposed as the Vibrating Particle System (VPS) algorithm by Kaveh and Ilchi Ghazaan [36], it draws inspiration from free vibration of single degree of freedom systems with viscous damping. The EVPS variant, introduced by Kaveh et al. [37], has shown promising results for structural optimization problems, including damage detection [38], reliability assessment [39], and optimal design of steel structures [40].

However, like many metaheuristic algorithms, EVPS performance relies heavily on proper parameter tuning. The algorithm includes multiple parameters such as α, p, w_1, w_2, HMCR, PAR, Neighbor, and Memory_size, which are traditionally determined experimentally or set to fixed default values. This dependence on appropriate parameter settings can limit algorithm efficiency and effectiveness when applied to new problem domains or specific challenging instances.

To address this limitation, this paper introduces a Self-Adaptive Enhanced Vibrating Particle System (SA-EVPS) algorithm [41-42], which automatically optimizes these parameters for each specific problem before conducting the main optimization process. This self-adaptive approach eliminates the need for manual parameter tuning and enhances the algorithm's ability to adapt to different problem characteristics.

The proposed SA-EVPS algorithm is applied to two challenging benchmark problems from the ISCSO suite: the 314-member truss structure (ISCSO_2018) and the 345-member truss structure (ISCSO_2021). These problems are particularly demanding due to their large number of design variables, complex constraints, and multimodal objective landscapes [43, 44].

The performance of SA-EVPS is compared with the Exponential Big Bang-Big Crunch (EBB-BC) algorithm, which has previously been applied to these benchmark problems with different population sizes [45]. The comparison includes not only the optimal solution quality but also convergence behavior, solution consistency, and computational efficiency.

The remainder of this paper is organized as follows. Section 2 introduces the SA-EVPS algorithm, providing a detailed explanation of its working mechanism and self-adaptive procedure. Section 3 describes the ISCSO benchmark problems used in this study, including their formulation, constraints, and design variables. Section 4 presents the optimization results and compares them with previous studies. Section 5 provides a discussion of the findings and their implications. Finally, Section 6 concludes the paper and suggests directions for future research.

2. SELF-ADAPTIVE ENHANCED VIBRATING PARTICLE SYSTEM ALGORITHM

2.1 Enhanced Vibrating Particle System (EVPS) Algorithm

The Enhanced Vibrating Particle System (EVPS) algorithm is a population-based metaheuristic method introduced by Kaveh et al. [37] as an improvement to the original Vibrating Particle System (VPS) algorithm [36]. The algorithm draws inspiration from the free vibration behavior of single degree of freedom systems with viscous damping, modeling the gradual movement of particles toward their equilibrium positions.

In the EVPS algorithm, each particle represents a candidate solution to the optimization problem. The population evolves through iterations, with particles moving toward promising regions of the search space under the influence of three types of equilibrium positions: the historically best position found by the entire population (HBP), a good position (GP) randomly selected from a memory that keeps track of the best positions achieved so far, and the best position in the current iteration (BP).

The algorithm begins by generating an initial population within the permissible range using Equation (1):

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

where x_i^j is the jth variable of the ith particle, and x_{min} and x_{max} are the lower and upper bounds of the design variables, respectively.

During each iteration, particles update their positions based on a damping level, which represents the influence of the current iteration on the search process. The damping level is calculated using Equation (2):

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

where $iter$ is the current iteration number, $iter_{max}$ is the maximum number of iterations, and α is a parameter with a constant value. The damping level controls the exploration-exploitation balance throughout the optimization process.

The new positions of the particles are then updated according to Equation (3):

$$x_i^j = \left\{ D \cdot A \cdot rand1 + OHB^j \quad (a)\; D \cdot A \cdot rand2 + GP^j \quad (b)\; D \cdot A \cdot rand3 + BP^j \quad (c) \right\} \tag{3}$$

where OHB, GP, and BP are determined independently for each variable, and A is defined as:

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

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

The coefficients ω_1, ω_2, and $\omega_3$represent the relative importance of OHB, GP, and BP, respectively, while $rand1$, $rand2$, and $rand3$are random numbers uniformly distributed in the range [0, 1].

In addition to these basic operations, EVPS incorporates a Harmony Memory Considering Rate (HMCR) and Pitch Adjusting Rate (PAR) from the Harmony Search algorithm to further enhance its search capabilities. The algorithm also utilizes a neighbor search mechanism and maintains a memory of best solutions.

While EVPS has demonstrated promising performance on various optimization problems, its efficiency depends on the proper setting of its parameters, which include α, p, w_1, w_2, HMCR, PAR, Neighbor, and Memory_size. Conventionally, these parameters are determined experimentally or set to default values (0.05, 0.2, 0.3, 0.3, 0.95, 0.1, 0.1, and 4, respectively).

2.2 Self-Adaptive Mechanism

The proposed Self-Adaptive Enhanced Vibrating Particle System (SA-EVPS) algorithm addresses the parameter tuning challenge by automatically optimizing the algorithm parameters for each specific problem. Rather than using fixed parameter values, SA-EVPS first employs the EVPS algorithm itself to optimize the eight parameters mentioned above, and then uses these optimized parameters for the main optimization process.

The self-adaptive procedure works as follows:

1. Define the problem to be optimized, including the objective function, constraints, and design variables.
2. Use the EVPS algorithm to optimize the eight parameters (α, p, w_1, w_2, HMCR, PAR, Neighbor, and Memory_size) with respect to the same objective function.
3. Use the optimized parameters in the main EVPS algorithm to solve the original optimization problem.

This approach ensures that the algorithm parameters are tailored to the specific characteristics of the problem at hand, potentially improving convergence speed, solution quality, and the algorithm's ability to escape local optima. The parameters optimized in step 2 are used directly in step 3 without further adjustment during the main optimization process.

Figure 1 illustrates the schematic framework of the SA-EVPS algorithm. The upper part shows the parameter optimization phase, where the eight EVPS parameters are optimized using the EVPS algorithm itself with default parameters. The lower part shows the main optimization phase, where the optimized parameters are used in the SA-EVPS algorithm to solve the original problem.

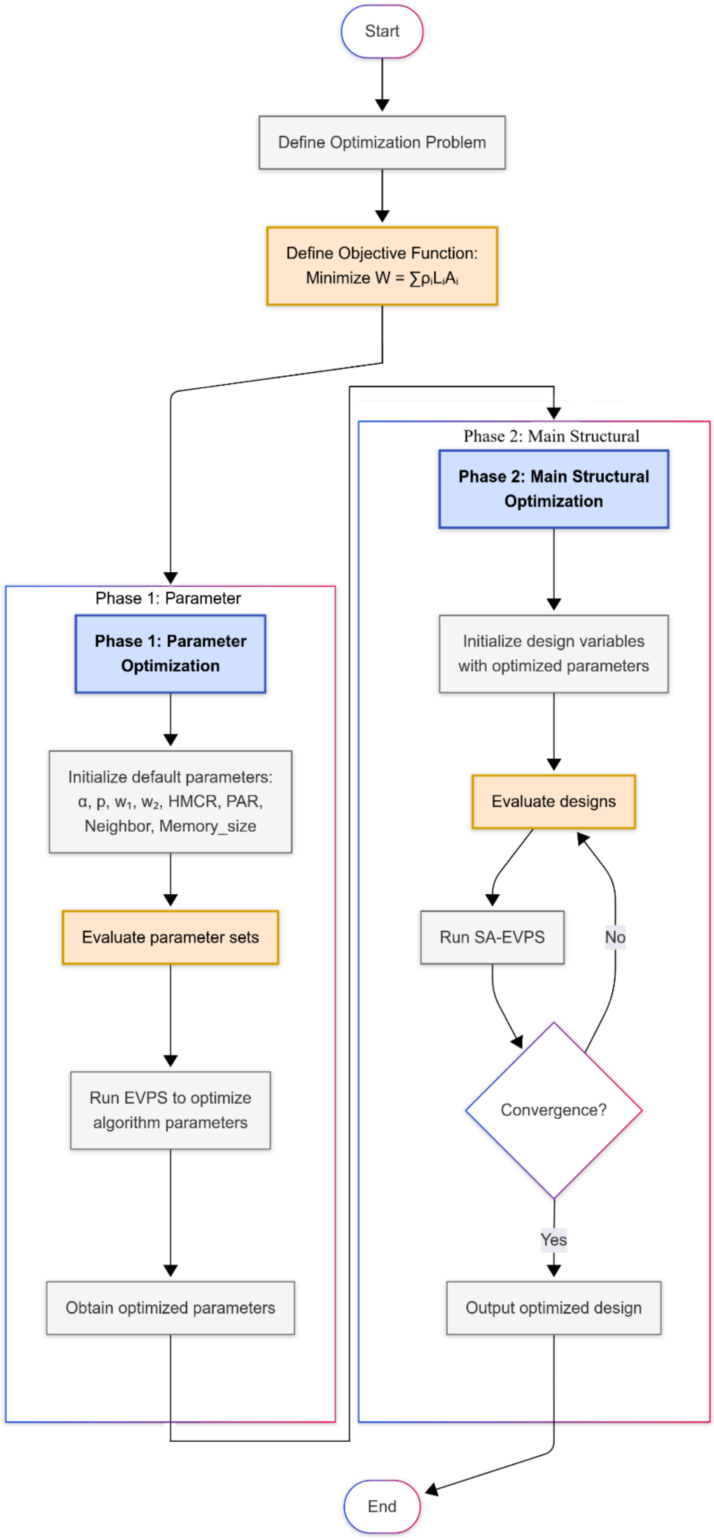


Figure 1: Schematic Framework of the SA-EVPS Algorithm Showing Parameter Optimization Phase and Main Optimization Phase

The SA-EVPS approach offers several advantages over the standard EVPS algorithm:

1. Eliminates the need for manual parameter tuning, which can be time-consuming and requires expert knowledge.
2. Adapts the algorithm parameters to the specific characteristics of each problem.
3. Potentially improves convergence speed and solution quality.
4. Enhances the algorithm's ability to escape local optima.

The computational overhead of the parameter optimization phase is justified by the improved performance of the main optimization process, particularly for complex problems where finding high-quality solutions is critical.

3. PROBLEM FORMULATION AND ISCSO BENCHMARK PROBLEMS

3.1 General Structural Optimization Problem Formulation

The general formulation of a single-objective truss optimization problem with respect to AISC-LRFD [46] can be expressed as follows:

Find a solution vector $X = [x_1.x_2.,,,.x_n]^T$ representing the design variables, such that the weight of the truss structure is minimized:

$$W = \sum_{i=1}^{N} \rho_i L_i A_i \tag{5}$$

where $W$is the net weight of the truss, ρ_i, L_i, and A_i are the unit weight, length, and cross-sectional area of the i-th member, respectively.

This weight minimization problem is subject to strength and displacement constraints. According to AISC-LRFD [46], the following relation must be satisfied for the strength requirement of each truss member:

$$\left[\frac{P_u}{\phi P_n}\right]_i - 1 \le 0 \tag{6}$$

where P_u and P_n are the required and nominal axial (tensile or compressive) strengths of the i-th truss member, respectively, and $\phi$is the resistance factor for axial strength, taken as 0.85 for compression and 0.9 for tension.

The nominal tensile strength of a truss member, based on yielding in the gross cross section, is computed as:

$$P_n = F_y A_g \tag{7}$$

where F_y is the member's specified yield stress and A_g is the gross cross section of the member.

For the nominal compressive strength of members with compact and/or non-compact elements, the limit state of flexural buckling is determined as:

$$P_n = F_{cr} A_g \tag{8}$$

where F_{cr} is the critical stress based on flexural buckling of the member, calculated as:

$$\text{For } \lambda_c = \frac{Kl}{r\pi}\sqrt{\frac{F_y}{E}} \le 1.5 : F_{cr} = (0.658^{\lambda_c^2})F_y \tag{9}$$

$$\text{For } \lambda_c = \frac{Kl}{r\pi}\sqrt{\frac{F_y}{E}} > 1.5 : F_{cr} = \left[\frac{0.877}{\lambda_c^2}\right]F_y \tag{10}$$

In the above equations, l is the laterally unbraced length of the member, K is the effective length factor, r is the governing radius of gyration about the buckling axis, and E is the modulus of elasticity.

For displacement constraints, the following criterion must be satisfied:

$$\frac{d_{j,k}}{(d_{j,k})_{all}} - 1 \le 0 \tag{11}$$

where $j = 1.2.,,,.N_j$ is the joint number, N_j is the total number of joints, and $d_{j.k}$ and $(d_{j.k})_{all}$ are the displacement computed in the k-th direction of the j-th joint and the corresponding maximum allowable value, respectively.

3.2 ISCSO_2018 Benchmark Problem

The ISCSO_2018 benchmark problem involves the optimization of a 314-member truss structure as shown in Figure 2. This structure has 328 design variables, including 314 sizing variables representing the cross-sectional areas of the truss members and 14 shape variables representing the z-coordinates of the top nodes (labeled Z1 to Z14 in Figure 2).

The truss is subject to two loading conditions:

1. Gravity loads applied to all nodes.
2. Lateral loads applied to specific nodes.

The constraints include stress limits for all members and displacement limits for all nodes. The allowable stress is 25 ksi for both tension and compression, and the allowable displacement is 0.25 inches in all directions. The material has a density of 0.1 lb/in³ and a modulus of elasticity of 10,000 ksi.

The cross-sectional areas can vary between 0.1 in² and 4.0 in². The shape variables (Z1 to Z14) can vary within specified ranges to maintain the overall structural form while allowing for optimization of the geometry.

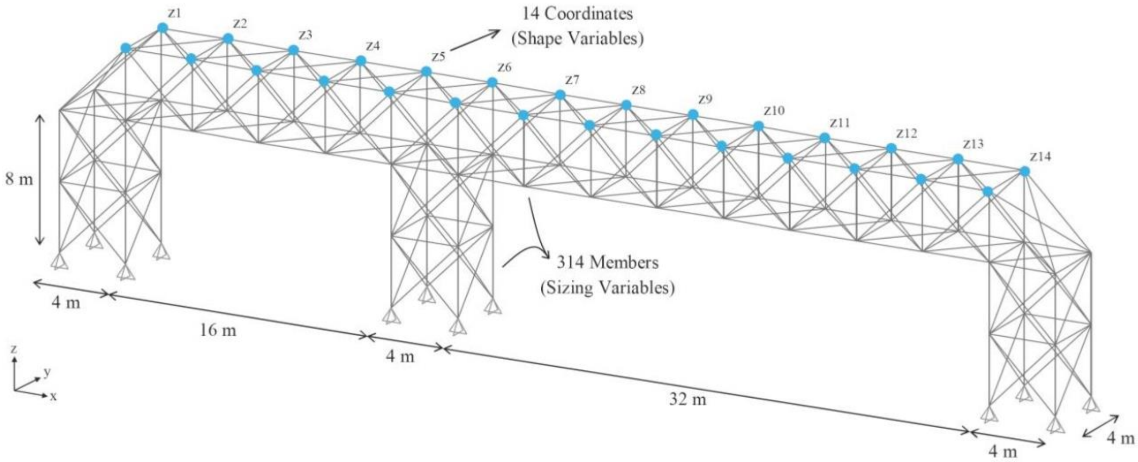


Figure 2: Geometry of the 314-Member Truss Structure (ISCSO_2018 Benchmark Problem)

3.3 ISCSO_2021 Benchmark Problem

The ISCSO_2021 [31] benchmark problem involves the optimization of a 345-member dome truss structure as shown in Figure 3. This structure has 345 design variables, all of which are sizing variables representing the cross-sectional areas of the truss members.

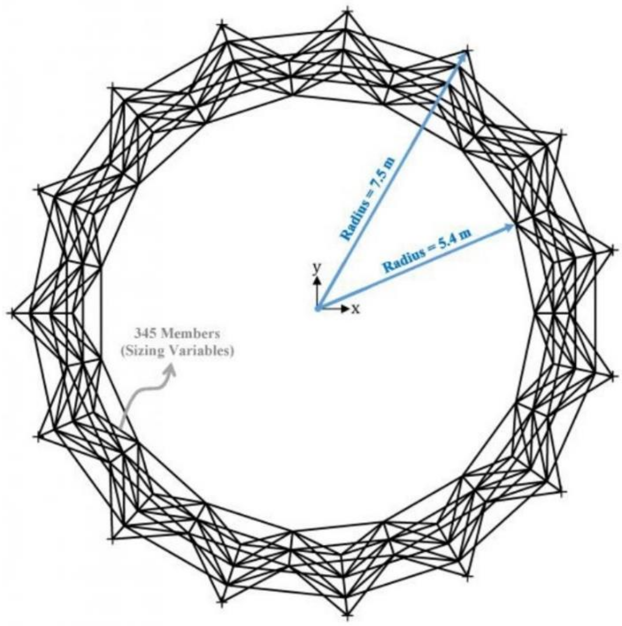


Figure 3: Geometry of the 345-Member Dome Truss Structure (ISCSO_2021 Benchmark Problem)

The dome has a height of 1.9 m and a radius of 5.4 m. It is supported at the perimeter nodes, and loads are applied at all unsupported nodes. The constraints include stress limits for all members and displacement limits for all nodes. The material properties and allowable stress and displacement values are similar to those used in the ISCSO_2018 problem.

The cross-sectional areas can vary between 0.1 in^2 and 4.0 in^2. The dome structure presents a different type of optimization challenge compared to the ISCSO_2018 problem, with a focus solely on sizing optimization rather than combined sizing and shape optimization.

4. RESULTS AND DISCUSSION

4.1 Implementation Details

This study used two key metrics to evaluate algorithm performance. The "ISCSO winner solution" represents the best structural weight achieved by the winning team in the ISCSO competition, serving as a global benchmark for solution quality. The "Normalized solution quality" is calculated as the ratio of the ISCSO winner weight to the algorithm's best weight (ISCSO winner weight / algorithm best weight). This normalization yields values between 0 and 1, where higher values indicate solutions closer to the competition winner's result.

The SA-EVPS algorithm was implemented and tested on the ISCSO_2018 and ISCSO_2021 benchmark problems. For comparison, results from three variants of the Exponential Big Bang-Big Crunch (EBB-BC) algorithm with different population sizes—denoted as EBB-BC(25), EBB-BC(50), and EBB-BC(100)—were considered. These results were obtained from previous studies [31].

For all algorithms, a population size of 20 and a maximum of 1000 iterations were used, resulting in a total of 200,000 function evaluations for each run. Thirty independent runs were conducted for each algorithm to ensure statistical significance of the results.

For the SA-EVPS algorithm, the eight parameters (α, p, w_1, w_2, HMCR, PAR, Neighbor, and Memory_size) were first optimized using the EVPS algorithm with default parameters, and then these optimized parameters were used for the main optimization process.

4.2 Results for ISCSO_2018

Table 1 presents the optimization results for the ISCSO_2018 benchmark problem, comparing the performance of the SA-EVPS algorithm with the three variants of the EBB-BC algorithm.

As shown in Table 1, the SA-EVPS algorithm achieved a best weight of 16543.57 kg, which is 7.75% lighter than the best result obtained by EBB-BC(50) (17934.3 kg), 11.72% lighter than EBB-BC(100) (18704.7 kg), and 12.50% lighter than EBB-BC(25) (18906.3 kg). This represents a significant improvement over the existing methods.

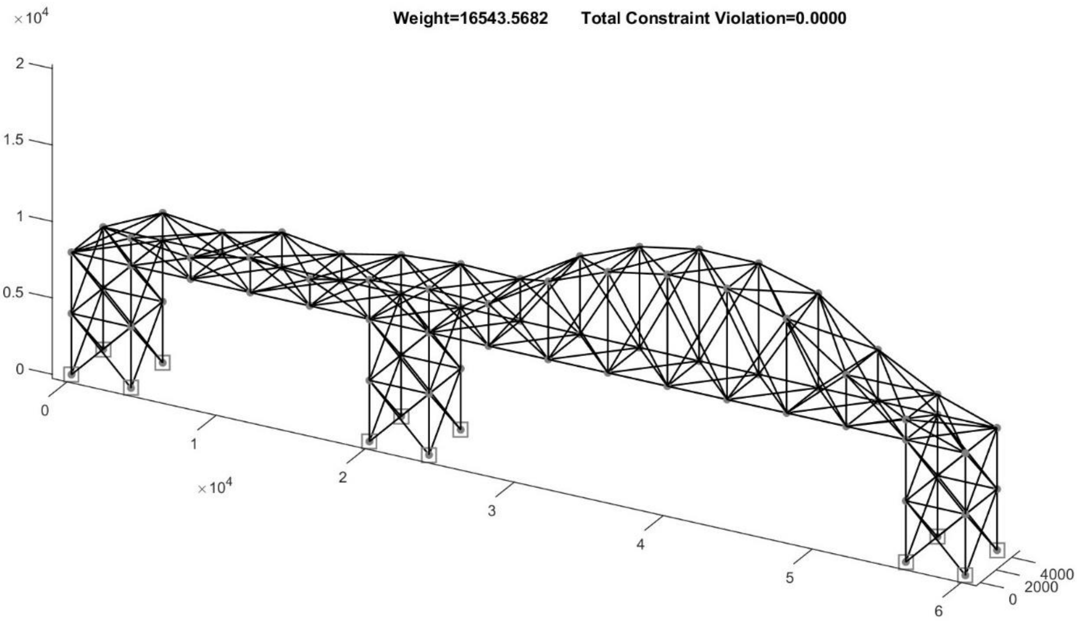
Moreover, the SA-EVPS algorithm demonstrated superior consistency across the 30 independent runs. The coefficient of variation for SA-EVPS was only 3.13%, compared to 12.7%, 12.5%, and 11.8% for EBB-BC(50), EBB-BC(100), and EBB-BC(25), respectively. This indicates that SA-EVPS not only finds better solutions but also does so more reliably.

The worst weight obtained by SA-EVPS (18604.89 kg) was still considerably lighter than the worst weights obtained by the EBB-BC variants, which ranged from 27459.5 kg to 30630.3 kg. This further demonstrates the robustness of the SA-EVPS algorithm.

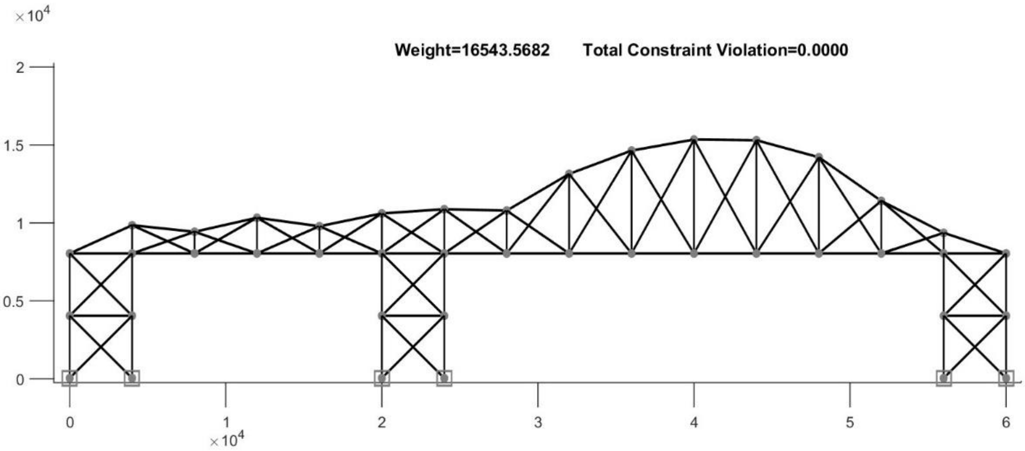
Table 1: Comparison of Optimization Results for the 314-Member ISCSO_2018 Truss Structure Between SA-EVPS and EBB-BC Variants

Run no.	**ISCSO (2018) [31]**			**Current study**
	EBB-BC(25)[31]	**EBB-BC(50) [31]**	**EBB-BC(100)[31]**	
1	21916.0	19101.9	28816.6	16875.69
2	21783.2	26245.1	21258.3	17995.13
3	22161.8	18700.3	22676.0	16794.04
4	22342.8	22041.6	20486.7	17391.34
5	23957.8	19567.5	22394.2	18236.43
6	23723.6	19886.0	21044.1	16900.00
7	19671.2	17934.3	19121.6	17961.01
8	20467.3	18960.8	20647.9	17246.51
9	26649.8	18423.2	19080.7	18186.28
10	22685.8	18528.9	21363.8	18150.59
11	26355.4	22833.0	21786.7	18303.43
12	19413.7	23237.2	24848.1	17500.50
13	24492.4	21361.3	19963.0	16543.57
14	25383.6	23122.6	19548.0	16693.72
15	18906.3	19229.4	19366.8	17537.07
16	19750.6	25896.2	30630.3	18227.37
17	24646.2	18567.4	18704.7	17883.55
18	20942.3	24130.7	22321.3	16891.81
19	28408.1	21491.4	22829.3	17669.89
20	23564.5	17989.5	22166.0	17935.90
21	21257.8	27459.5	19391.2	18397.21
22	27707.3	21225.1	20452.5	17991.64
23	20052.8	18824.9	22703.6	17599.88
24	27349.4	19533.5	24191.8	18604.89
25	23153.9	21187.9	20186.9	17873.97
26	22018.0	20246.9	19970.6	17046.35
27	21379.6	25238.6	20031.3	17914.63
28	24073.4	18830.2	20669.3	17571.68
29	23033.9	20933.7	19267.8	17678.12
30	28202.8	19692.0	21655.7	18119.39
Best weight (kg)	18906.3	17934.3	18704.7	16543.57
Worst weight	28408.1	27459.5	30630.3	18604.89
Mean weight	23181.7	21014.0	21585.8	17657.39
Standard deviation	2726.9	2664.3	2699.1	552.80
Coefficient of variation (%)	11.8	12.7	12.5	3.13
No. analyses	200000	200000	200000	200000
***ISCSO winner solution (kg) [31]**	14425.097	14425.097	14425.097	14425.097
Normaliz solution quality	0.76	0.80	0.77	0.87

Figure 4-(a) shows the three-dimensional view of the optimized structure obtained using SA-EVPS for the ISCSO_2018 problem, while Figure 4-(b) presents the two-dimensional view. The optimized structure satisfies all stress and displacement constraints.



(a)



(b)

Figures 4: Optimized 314-Member Truss Structure (ISCSO_2018) Using SA-EVPS: (a) 3D View and (b) 2D View

Figure 5 illustrates the convergence behavior of the SA-EVPS algorithm. The convergence curve shows that SA-EVPS achieves faster convergence and reaches a better final solution than all EBB-BC variants. This improved convergence behavior can be attributed to the self-adaptive parameter tuning mechanism, which tailors the algorithm parameters to the specific characteristics of the problem.

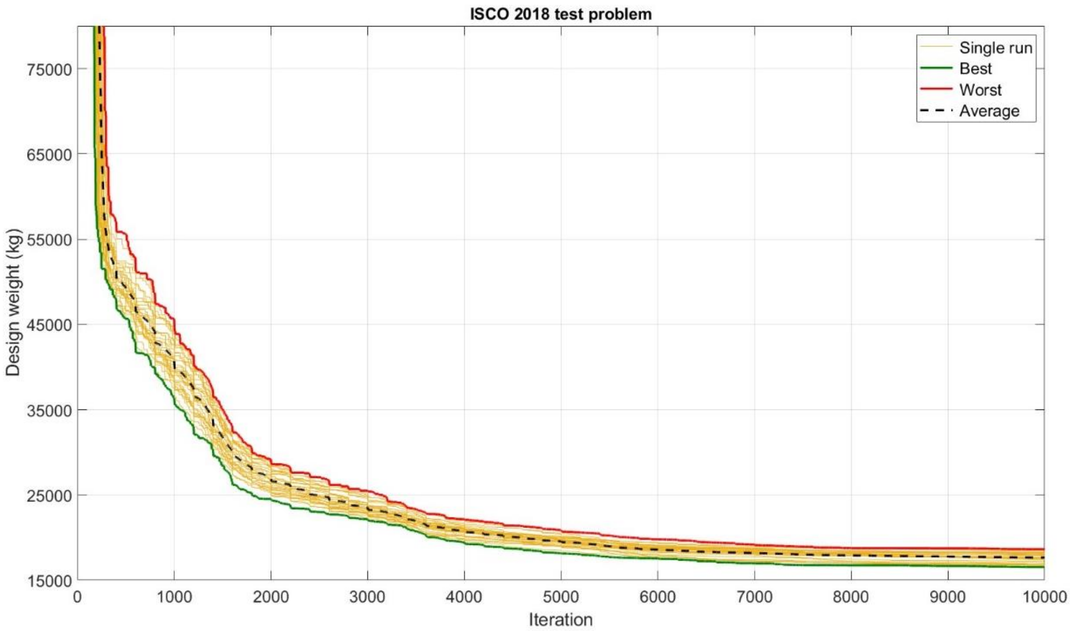


Figure 5: Convergence History of the SA-EVPS Algorithm for the ISCSO_2018 Problem

Figure 5 illustrates the convergence behavior of the SA-EVPS algorithm for the ISCSO_2018 problem. The convergence curve shows steady improvement in the objective function value, with rapid initial convergence followed by more gradual refinement in later iterations. This efficient convergence behavior can be attributed to the self-adaptive parameter tuning mechanism, which tailors the algorithm parameters to the specific characteristics of the problem.

4.3 Results for ISCSO_2021

Table 2 presents the optimization results for the ISCSO_2021 benchmark problem [31], comparing the performance of the SA-EVPS algorithm with the three variants of the EBB-BC algorithm.

For the ISCSO_2021 problem, the SA-EVPS algorithm achieved a best weight of 4292.71 kg, which is 2.42% lighter than the best result obtained by EBB-BC(100) (4399.0 kg), 2.77% lighter than EBB-BC(50) (4415.2 kg), and 5.03% lighter than EBB-BC(25) (4520.0 kg). While the improvement is more modest than for ISCSO_2018, it still represents a significant enhancement in solution quality.

The consistency of the SA-EVPS algorithm was also superior for this problem. The coefficient of variation for SA-EVPS was only 1.21%, compared to 2.4%, 2.4%, and 4.2% for EBB-BC(100), EBB-BC(50), and EBB-BC(25), respectively. This indicates that the algorithm's self-adaptive mechanism effectively tunes the parameters for different problem types.

Figure 6 shows the convergence curve for the SA-EVPS algorithm applied to the ISCSO_2021 problem. Similar to the ISCSO_2018 case, the algorithm demonstrates effective convergence behavior, with significant improvements in the early iterations followed by fine-tuning in later stages.

Table 2. Comparison of Optimization Results for the 345-Member ISCSO_2021 Dome Truss Structure Between SA-EVPS and EBB-BC Variants

Run no.	**ISCSO (2021) [31]**			**Current study**
	EBB-BC(25) [31]	**EBB-BC(50) [31]**	**EBB-BC(100) [31]**	
1	4772.5	4716.9	4540.1	4413.69
2	4898.0	4607.6	4537.0	4336.07
3	4945.0	4536.7	4542.6	4400.41
4	4773.8	4649.8	4399.0	4309.47
5	4808.5	4753.6	4483.0	4348.69
6	4849.2	4544.8	4472.6	4421.85
7	4755.5	4795.6	4611.9	4362.24
8	4599.0	4556.4	4542.4	4432.14
9	4520.0	4690.2	4783.9	4384.03
10	5051.3	4521.9	4578.9	4310.18
11	4676.4	4714.2	4593.8	4372.34
12	4627.6	4503.0	4570.6	4375.80
13	4603.9	4632.0	4636.0	4339.10
14	4845.9	4736.4	4595.0	4478.80
15	4626.1	4545.1	4704.4	4393.07
16	4832.1	4553.0	4658.8	4433.10
17	4696.0	4758.0	4420.9	4416.24
18	5630.8	4587.7	4565.4	4292.71
19	4871.4	4800.0	4481.4	4414.82
20	4979.9	4608.9	4434.2	4318.82
21	4796.5	4656.3	4519.5	4463.99
22	4721.2	4810.9	4852.6	4378.54
23	5067.7	4482.0	4641.5	4352.22
24	4829.6	4415.2	4491.4	4300.69
25	4910.0	4753.0	4693.2	4298.71
26	4661.9	4634.2	4615.7	4443.76
27	4806.1	4457.5	4405.6	4453.23
28	4890.3	4629.3	4564.7	4366.50
29	4688.7	4452.0	4502.6	4390.28
30	4823.1	4519.2	4738.1	4462.38
Best weight (kg)	4520.0	4415.2	4399.0	4292.71
Worst weight	5630.8	4810.9	4852.6	4478.80
Mean weight	4818.6	4620.7	4572.6	4382.13
Standard deviation	203.0	113.1	109.6	53.10
Coefficient of variation (%)	4.2	2.4	2.4	1.21
No. analyses	200000	200000	200000	200000
***ISCSO winner solution (kg) [31]**	3977.261	3977.261	3977.261	3977.261
Normalized solution quality	0.88	0.90	0.90	0.93

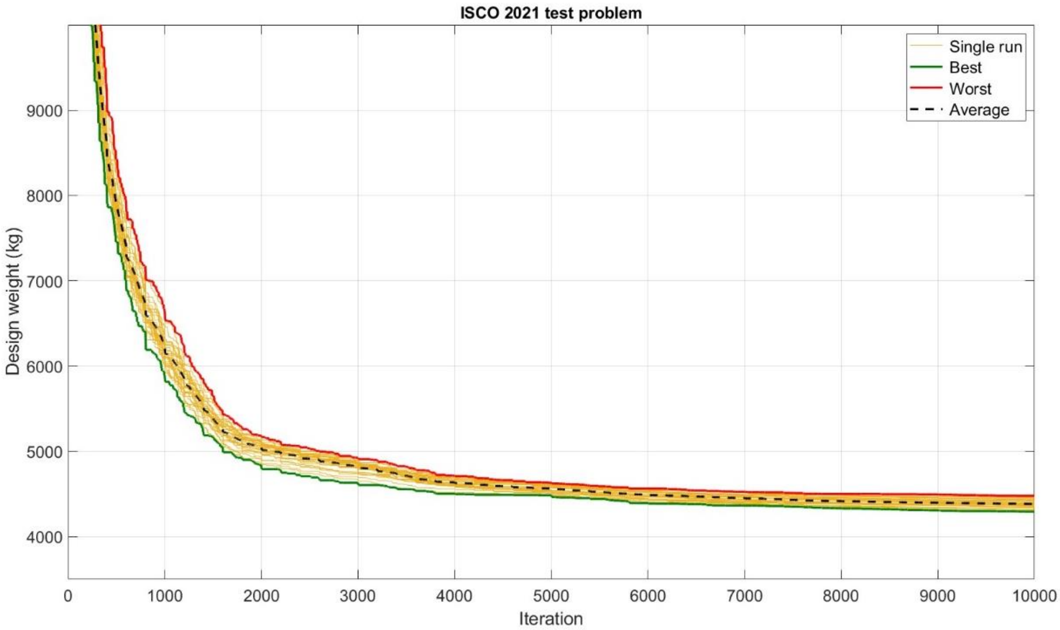


Figure 6: Convergence History of the SA-EVPS Algorithm for the ISCSO_2021 Problem

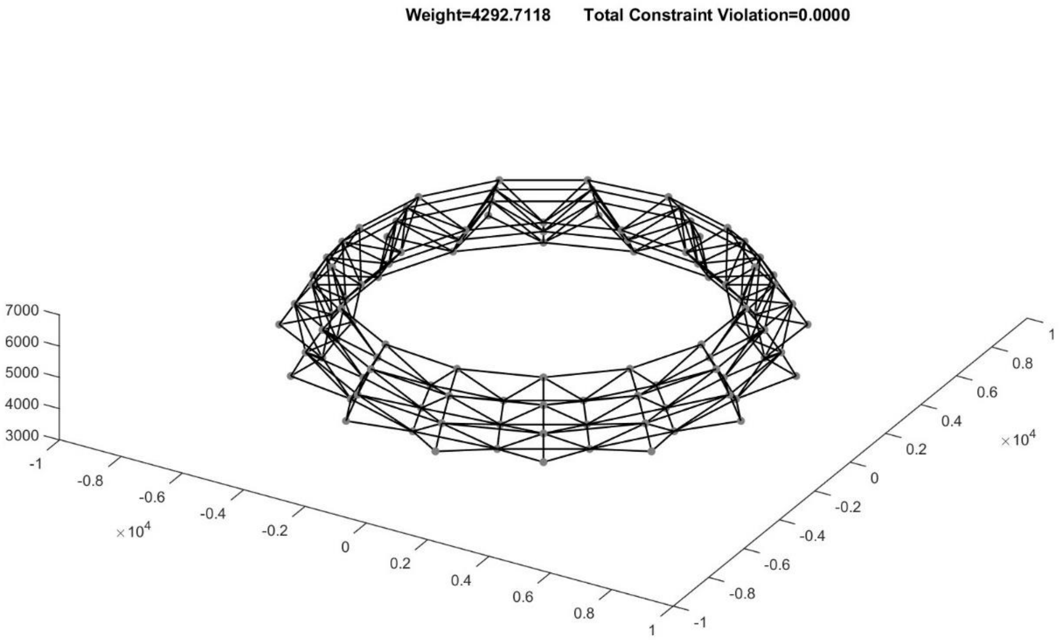


Figure 7: Optimized 345-Member Dome Truss Structure (ISCSO_2021) Using SA-EVPS

Compared to the winner solution of ISCSO_2021 (3977.261 kg), the SA-EVPS result (4292.71 kg) is 7.93% heavier. However, it represents a notable improvement over previous metaheuristic approaches, with a normalized solution quality of 0.93 (compared to 0.90 for the best EBB-BC variants).

4.4 Comparison and Discussion

Figure 8 presents a comparison of the normalized solution quality for the SA-EVPS algorithm and the three EBB-BC variants across both benchmark problems. The normalized solution quality is calculated by dividing the weight of the ISCSO winner solution by the weight of the algorithm's best solution. A higher value indicates a better solution.

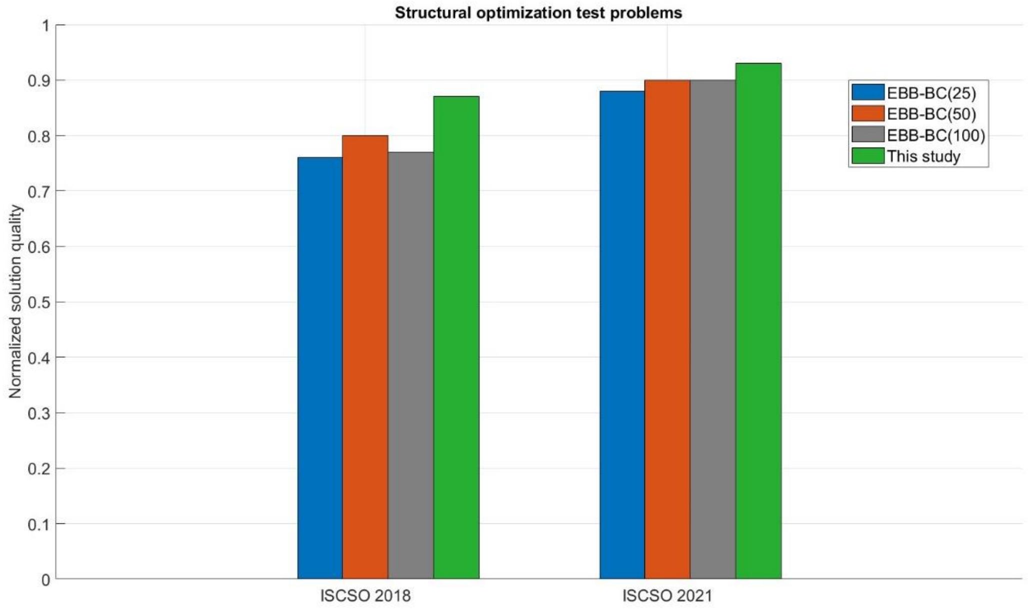


Figure 8: Comparison of Normalized Solution Quality Between SA-EVPS and EBB-BC Variants for ISCSO Benchmark Problems

As shown in Figure 8, the SA-EVPS algorithm consistently achieves better normalized solution quality than all EBB-BC variants for both benchmark problems. This demonstrates the effectiveness of the self-adaptive parameter tuning mechanism in enhancing the algorithm's performance across different problem types.

The improved performance of SA-EVPS can be attributed to several factors:

1. The self-adaptive parameter tuning mechanism eliminates the need for manual parameter tuning and adapts the algorithm parameters to the specific characteristics of each problem.
2. The optimized parameters enhance the algorithm's ability to balance exploration and exploitation, leading to more effective search behavior.
3. The improved search strategy allows the algorithm to escape local optima more effectively, resulting in better final solutions.
4. The combination of self-adaptive parameters and the EVPS algorithm's inherent strengths creates a powerful optimization tool that can handle complex structural optimization problems.

The results also indicate that the SA-EVPS algorithm is more effective for the ISCSO_2018 problem (which involves both sizing and shape optimization) than for the ISCSO_2021 problem (which involves only sizing optimization). This suggests that the algorithm's adaptive capabilities are particularly valuable for problems with mixed types of design variables and more complex solution spaces.

It is worth noting that while SA-EVPS significantly outperforms the EBB-BC variants, it still does not match the solutions obtained by the winners of the ISCSO competition. This indicates that there remains room for further improvement in metaheuristic algorithms for structural optimization, possibly through hybridization with other techniques or the incorporation of problem-specific knowledge.

5. CONCLUSION

This paper introduced a Self-Adaptive Enhanced Vibrating Particle System (SA-EVPS) algorithm for structural optimization problems. The algorithm addresses the parameter tuning challenge by automatically optimizing algorithm parameters for each specific problem, eliminating the need for manual tuning and enhancing the algorithm's adaptive capabilities.

The proposed SA-EVPS algorithm was applied to two challenging benchmark problems from the International Student Competition in Structural Optimization (ISCSO): the 314-member truss structure (ISCSO_2018) and the 345-member dome truss structure (ISCSO_2021). Its performance was compared with three variants of the Exponential Big Bang-Big Crunch (EBB-BC) algorithm.

The main findings and contributions of this study can be summarized as follows:

1. The SA-EVPS algorithm achieved significant improvements in solution quality compared to the EBB-BC variants, with weight reductions of 7.75% for ISCSO_2018 and 2.42% for ISCSO_2021.
2. The algorithm demonstrated superior consistency across multiple independent runs, with coefficients of variation of 3.13% and 1.21% for ISCSO_2018 and ISCSO_2021, respectively, compared to 11.8-12.7% and 2.4-4.2% for the EBB-BC variants.
3. The convergence behavior of SA-EVPS was faster and more efficient than that of the EBB-BC variants, highlighting the effectiveness of the self-adaptive parameter tuning mechanism.
4. The normalized solution quality of SA-EVPS was higher than all EBB-BC variants for both benchmark problems, indicating its superior overall performance.

These results demonstrate that the self-adaptive approach to parameter tuning can significantly enhance the performance of metaheuristic algorithms for structural optimization. By automatically adapting algorithm parameters to the specific characteristics of each problem, SA-EVPS achieves better solution quality, faster convergence, and improved consistency compared to algorithms with fixed parameters.

Future research directions include:

1. Extending the SA-EVPS algorithm to handle multi-objective optimization problems, where multiple competing objectives must be optimized simultaneously.
2. Incorporating additional adaptation mechanisms to further enhance the algorithm's performance for different problem types.
3. Hybridizing SA-EVPS with other metaheuristic algorithms or local search techniques to combine their respective strengths.
4. Applying SA-EVPS to other challenging structural optimization problems, including those with dynamic loads, nonlinear behavior, or discrete design variables.
5. Investigating the algorithm's performance on larger-scale problems with thousands of design variables, which are increasingly common in practical engineering applications.

The proposed SA-EVPS algorithm represents a significant step forward in the development of efficient and effective metaheuristic algorithms for structural optimization. Its self-adaptive nature makes it a promising tool for solving complex engineering design problems without the need for extensive parameter tuning or expert knowledge.

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