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Optimal Design of Steel Structures Using Innovative Black Widow Algorithm Hybridized with Greedy Sensitivity-Based Particle Swarm Optimization Technique

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ABSTRACT

This paper presents a Greedy Sensitivity-based analysis implemented on the Particle Swarm Optimization search engine (GSPSO). The effectiveness of the method focuses mainly on providing an intelligent population to enter meta-heuristic algorithms. As a meta-heuristic method in the second stage, the recently introduced Black Widow Optimization (BWO) algorithm was selected and improved by the authors. It is based on three operators: cannibalism, crossover, and mutation, whose main stage is Cannibalism. The advantage of this stage is that those designs that do not match the solutions close to the global optimal are eliminated, and the more effective solutions remain. To examine the proposed approach, five optimization examples, including three two-dimensional benchmark frames and two three-dimensional structures, have been used. The results show that the greedy sensitivity-based PSO technique can improve computational efficiency in solving discrete variable structural optimization problems. The hybridized BWO (BGP) with this technique was able to obtain very good results in terms of convergence speed and performance accuracy. Overall, compared to the performance of BWO, between 50 and 75% improvement in the total number of analyzes was achieved. In addition, a slight improvement in the weight of the evaluated structures was also reported. Compared to other hybrid algorithms, very competitive and promising results were obtained.

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1. Introduction

1.1. Motivation

Optimization, as an approach to adopt the best solution, is one of the enhanced most active areas in various engineering design problems [1]. Computing technologies are the basis for the rapid growth of meta-heuristic algorithms [2–4]. These algorithms perform strategic searches without the need to calculate the implicit gradients of optimization formulations [5]. They are generally classified into three categories, including methods based on 1. physical and chemical processes, 2. swarm-based, and 3. evolution-based and biological [6]. Swarm-based algorithms refer to how members of a group interact with each other or with their environment. Particle Swarm Optimization (PSO) [7] is one of the most popular algorithms in this category. Among the most recent ones in this category are the Mountain Gazelle Optimizer (MGO) [8], Wild Horse Optimizer (WHO) [9], Pelican Optimization Algorithm (POA) [10], Seagull Optimization Algorithm (SOA) [11], Coyote Optimization Algorithm (COA) [12], Squirrel Search Algorithm (SSA) [13], Alpine Skiing Optimization (ASO) [14] and African Vultures Optimization Algorithm (AVOA) [15], etc. The answer obtained by these algorithms usually converges reasonably close to the optimal solution. Hence, the optimal solutions obtained by such algorithms are also called quasi-optimal [16]. This has encouraged researchers to come up with more efficient algorithms for finding optimal global solutions.

1.2. Research gap

A detailed review of the algorithms used in solving civil engineering problems shows that mostly combined and improved versions of the algorithms are used in order to offer more generalised and acceptable global results. For example, Kaveh and Talatahari used an improved Ant Colony Optimizer (IACO) for frame optimization [17]. An adaptive hybrid evolutionary firefly algorithm has been developed for shape and size optimization of truss structures [18]. An enhanced colliding bodies optimization method [19] proposes a mechanism to avoid falling into local optimum. Similarly, An enhanced imperialist competitive algorithm is also proposed to solve the problem of local optimum [20]. Or in another study, Differential evolution is combined with the eagle strategy [21]. Differential evolution has also been used in combination with the symbiotic organisms search process As such, one may refer to studies conducted using PSO-WOA [22], Hybrid Ant Lion Optimizer (ALO) [23], and Hybrid Tabu search algorithm [24]. One of the main reasons researchers have developed many different optimization algorithms recently, could be the diversity on problems seeking global optimum solutions. For instance, an optimization algorithm may work well for functions minimization but struggles for highly constrained industrial or multi-objective problems. To solve such issues, improved, enhanced, and hybrid versions of algorithms are used and sometimes lead to the construction of new algorithms with a completely different approach, such as multi-start algorithms. However, it is impossible to name one unique algorithm to elaborate for all optimization problems. However, a challenging passion has always been existed among researchers to outperform one more generalised promissing technique to tackle yet more diversed vaeiety of problems.

1.3. Current research contribution

Swarm-based methods use the three principles of evaluation, comparison, and imitation that exist in collaborative behaviors in nature [25]. In this study, by making one of the most active crowd intelligence techniques known as PSO, attempts will be made to achieve a technique that can reduce the computational efforts needed to handle problems in hand by introducing a hybridised meta-heuristic algorithm. The standard PSO approach alone often ends up in local optima, due to a premature convergence and therefore a failure to achieve an accurate design solution. But if somehow the search space is split wisely into suboptimal spaces, the problem of getting stuck in the local optimum may be solved automatically. This idea will be the basis of the proposed design of the authors, and from there mostly combined approaches are used to solve engineering design problems. It can be used as an optimization aid for other methods at the beginning of the solution. The theory of the method is explained in detail below.

1.4. Paper organization

First, a literature review for engineering problems will be given. The next section introduces the mathematical models for the benchmark problems that will be solved later in this study. The black widow algorithm will then be described; This algorithm will be used to combine with the proposed technique. A description of the proposed PSO-based technique will then be given. The following section adds the proposed technique to the black widow algorithm to complete the model. In the following section the performance of the hybrid approach will be evaluated by solving some benchmark problems in the field of structural design and compoarisons with data available in the literature will be assessed. The conclusions and recommendations will follow in the final sections and challenges of the proposed technique will be highlighted.

2. Algorithms and engineering problems

Optimization has been widely used in various fields of civil engineering, such as reliability [26,27], dampers [28–32], different types of concrete strength estimation [33,34], earthquake engineering [35,36], etc. This part examines a practical application of optimization in steel structures. For the discrete optimization of steel frames in 1991, Balling used a SA algorithm [37]. The total weight minimization of a six-story, asymmetrical building was the objective function in that study. In a related effort, Balling's frame was optimized discretely by May and Balling using a filtered SA (FiSA) strategy [38]. Discrete optimization was carried using the linearized branch and bound (LBandB) strategy. The impact of various neighborhood sizes on the effectiveness of the LB was subjected to a sensitivity analysis. Moreover, a number of case studies were used to examine the impact of various FiSA hyperparameter settings. The wide-range (W) shape sections from AISC were used to create 11 groups of structural elements for columns and girders in both studies.

Pezeshk [39] proposed an automated method based on the non-linear optimum design of steel frame structures in 2000. The design process adhered to the specifications set forth by AISC-LRFD and the available W-section elements. Fuzzy discrete multicriteria optimization (FDMCO) of steel frames was studied by Sarma and Adeli in 2000 [40]. In order to achieve this, the objective function was established as total cost minimization given three concurrent design criteria as follows: minimizing cost, minimizing weight and minimizing the number of different section types. To achieve the best performance, four different combinations of the FDMCO's effective parameters were looked at.

A decade later, Kaveh et al. [41] suggested using a discrete design variable-based performance-based seismic design of steel frames with an ACO algorithm as a solver. Based on the lateral drift, four performance levels were taken into account in the structure's nonlinear analysis (i.e. operational, ready for occupancy right away, life-safety-related, and collapse-prevention). Four earthquakes with probabilities of 50%, 20%, 10%, and 2% over a 50-year period were used to calculate the seismic loadings.

Alberdi and Khandelwal [42,43] conducted a comparison study on the effectiveness of nine algorithms in 2015 for reducing the weight of steel frames. Regardless of the variable space and the initial trials, the effectiveness of the employed algorithms was evaluated in terms of convergence consistency. The best solvers in this case study were DDHS and TS, according to the results of the simulations. A modified dolphin echolocation optimization (MDEO) algorithm was used by Gholizadeh and Poorhoseini [44] to optimize steel frames. The step locations were chosen for this modified algorithm using one-dimensional Gauss chaotic maps. A comparison of the proposed algorithm's performance with the original dolphin echolocation (DEO) algorithm and some other algorithms that had previously been applied to the same examples was made. For the MDEO algorithm to perform at its peak, a sensitivity analysis of a critical parameter called power was carried out.

In 2019, an investigation was carried by Bybordiani and Kazemzadeh Azad [45] into the ideal configuration of a steel-braced frame with dynamic soil-structure interaction. A rigid base and a half-space were thought to be the foundations of typical steel frames. The unbounded soil domain was modeled using a typical massless foundation. Based on two sets of ground motions, the seismic time-history analysis was applied to the model. The optimization was handled by the BB-BC algorithm. Using five optimization algorithms PSO, CSS, TLBO, GWO, and improved GWO (IGWO)—Zakian [46] tackled steel moment-resisting frames while taking into account natural frequency constraints. Eigenvalue analysis was used to determine the structure's natural frequency to achieve this. According to the results, the top solvers were TLBO, IGWO, and PSO. Steel concentrically braced frame (SCBF) collapse-performance-aided optimization was taken into account by Hassanzadeh and Gholizadeh [47] using the CMO algorithm. Three main steps were suggested to achieve this goal: (1) size and topology optimization based on seismic performance-based analysis; (2) producing fragility curves for the optimal solutions using incremental dynamic analysis; and (3) comparing fixed and optimized braces configurations in terms of minimum weight and collapse capacity. Based on the three levels of risk, the performance-based analysis was carried out: 1. instant occupancy, and 2. life safety; and 3. collapse prevention. (Please send me his work. The cross-section and location of the braces in the frame were designated as the design variables. According to the findings, topology optimization produced a more significant response with a noticeably higher level of collapse safety.

Kaveh [48] used a variety of optimization algorithms in 2020 to solve steel frame optimization problems, including the ABC, BB-BC, cyclical parthenogenesis algorithm (CPA), CS, thermal exchange optimization (TEO), water evaporation optimization algorithm (WEOA), and TLBO algorithms. WEO, CS, and TEO were the best optimizers for more accurate solution ns, while TEO, TLBO, and WEO had faster convergence rates.

In recent years, many metaheuristic algorithms have been created to address the shortcomings of earlier ones as much as possible. The applications of those algorithms to real-world and benchmark engineering problems have since been the subject of numerous investigations. The complexity of structural engineering-related problems has been found to make them the most difficult of all. The engineering optimization research community has therefore given them a lot of attention. However, a comparative analysis that outlines the salient aspects of the available studies in this field is lacking. This study proposes a hybrid optimization technique, using a developed approach for determining the best designs for steel structural problems.

3. Optimization of steel structures

One of the main purposes of optimizing steel frames is to minimize their weight (W) according to some engineering design constraints. W may be defined as:

$$W = \sum_{i=1}^{N} \gamma_i . x_i . l_i \quad (1)$$

Where γ_i : i^{th} element density

x_i : i^{th} member variable

l_i : i^{th} member length

N : Number of members

According to the American Institute of Steel Construction (AISC) code, any structural design must satisfy the following constraints:

3.1. Resistance limitations

3.1.1. Allowable stress design (ASD) method

Real structures are subjected to different loads that mostly affect the interaction of forces on the members, as a result of which the design must be according to Equations given in the AISC-ASD regulation. It states that:

$$C_1 = \frac{f_a}{F_a} + \frac{f_{bx}}{F_{bx}} + \frac{f_{by}}{F_{by}} \leq 1.0 \quad (2)$$

$$C_2 = \frac{f_a}{0.6F_y} + \frac{f_{bx}}{F_{bx}} + \frac{f_{by}}{F_{by}} \leq 1.0 \quad (3)$$

$$C_3 = \frac{f_a}{F_a} + \frac{C_{mx} f_{bx}}{\left(1 - \frac{f_a}{F'_{ex}}\right) F_{bx}} + \frac{C_{my} f_{by}}{\left(1 - \frac{f_a}{F'_{ey}}\right) F_{by}} \leq 1.0 \quad (4)$$

Where F_a : Axial allowable stresses

F_b : Flexural allowable stresses

f_a : Corresponding stresses due to the axial force

f_b : Corresponding stresses due to the bending moment

$\frac{1}{1-\frac{f_a}{F_e'}}$: Amplification of the inter-span moment (the P-δ effect).

C_m: impact of the gradient's moment

In compression and Euler stress computation, calculation of the effective length (K) is required. Thus,

$$F_e = \frac{\pi^2 E}{(KL/r)^2} \tag{5}$$

Where F_e : Euler stresses

K : Effective length factor that calculated by means of the following equations [49]:

for braced frames:

$$K = \frac{3G_A G_B + 1.4(G_A + G_B) + 0.64}{3G_A G_B + 2(G_A + G_B) + 1.28} \tag{6}$$

and for unbraced frames:

$$K = \sqrt{\frac{1.6G_A G_B + 4(G_A + G_B) + 7.5}{G_A + G_B + 7.5}} \tag{7}$$

Where:

$$G = \frac{\Sigma\left(\frac{EI}{L}\right)_{Column}}{\Sigma(EI/L)_{Beam}} \tag{8}$$

In the above equation, G_A and G_B refer to the coefficient of relative stiffness of the column at both ends.

3.1.2. Load and resistance factor design (LRFD) method

The strength constraints, C_4 *and* C_5, were determined as indicated in the AISC-LRFD against both axial and bending forces:

$$C_4 = \frac{P_u}{2\varphi_c P_n} + \left(\frac{M_{ux}}{\varphi_b M_{nx}} + \frac{M_{uy}}{\varphi_b M_{ny}}\right) \leq 1 \quad ; \quad \frac{P_u}{\varphi_c P_n} < 0.2 \tag{9}$$

$$C_5 = \frac{P_u}{\varphi_c P_n} + \frac{8}{9}\left(\frac{M_{ux}}{\varphi_b M_{nx}} + \frac{M_{uy}}{\varphi_b M_{ny}}\right) \leq 1 \quad ; \quad \frac{P_u}{\varphi_c P_n} \geq 0.2 \tag{10}$$

Where P_u: Required axial strength

P_n: Nominal axial strength

M_{ux}: Required flexural strength (major axis)

M_{nx}: Nominal flexural strength (major axis)

M_{uy}: Required flexural strength (minor axis)

M_{ny}: Nominal flexural strength (minor axis)

φ_c: Resistance factor for compression

φ_b: Resistance factor for bending

3.2. Displacement limitations

According to the AISC, the maximum lateral displacement is given by:

$$\nu^{\Delta} = R - \frac{\Delta_T}{H} \leq 0 \qquad (11)$$

and inter-story displacements:

$$\nu_j^d = R_t - \frac{d_j}{h_j} \leq 0 \quad j = 1,2,\dots,ns \qquad (12)$$

where R : Maximum drift index

Δ_T : Maximum lateral displacement

H: Structure's elevation

d_j : Drift of inter-story

h_j : elevation of the j^{th} story

ns : No. of stories

R_t : Permitted drift index (For stories)

4. Review of black widow optimization (BWO) algorithm

The BWO algorithm [50] is very similar to the Genetic Algorithm (GA) as an evolutionary computational method. The algorithm starts with the initial population of the black widow spider and goes through three other steps, including Procreate, Cannibalism, and Mutation. One of the main advantages of this algorithm is in the Cannibalism stage, where the significantly degraded black widow spiders are eliminated. This may avoid destructive scattered individuals in the process. Fig. 1 indicates the flowchart of the BWO algorithm. The following is a brief description of the steps of the BWO algorithm:

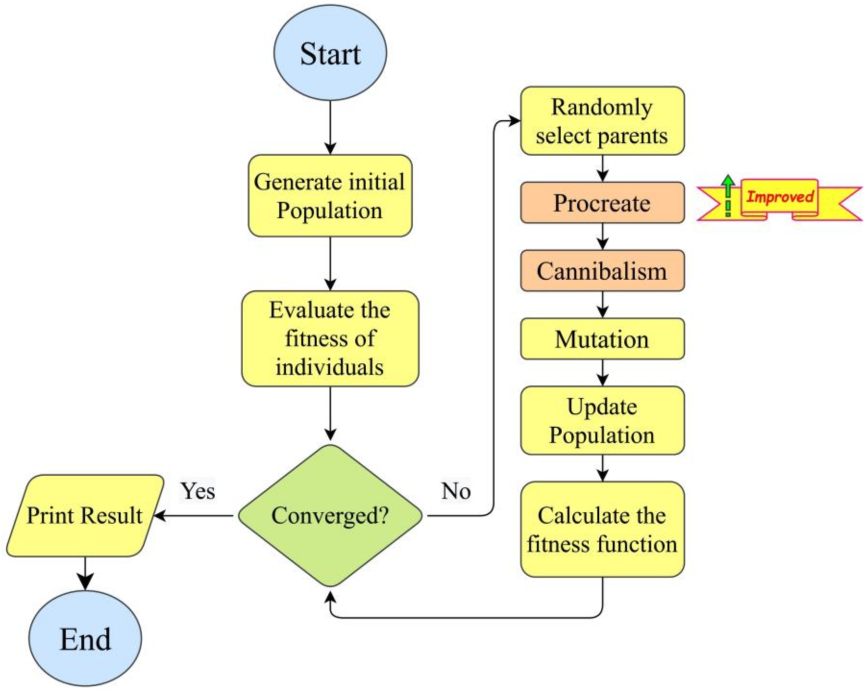

Fig. 1. Flowchart of the BWO Algorithm.

4.1. Initial population

In multivariate optimization problems, a black widow is a design vector containing a set of variables for the problem. Thus, for the design number ides, it is given as shown below:

$$design_{ides} = Widow_{ides} = \left[\mathrm{x}_1, \mathrm{x}_2, \cdots, \mathrm{x}_{\mathrm{N_{var}}}\right]_{ides} \tag{13}$$

And the objective function is defined as follows:

$$\text{Objective Function}_{ides} = \mathrm{f}(\mathrm{widow})_{ides} = \mathrm{f}\left(\mathrm{x}_1, \mathrm{x}_2, \cdots, \mathrm{x}_{\mathrm{N_{var}}}\right)_{ides} \tag{14}$$

The Fitness function for minimizing or maximizing a problem may be computed using different constraints handling approaches. In the present study, the following method, based on Adaptive Penalty Formulation was utilized [51]:

After calculating the objective function of all individuals of the population, also the amount of violation of design constraints and as a result, the amount of normalized fitness of each design of the population, the maximum and minimum of the fitness functions in the population are computed as the sequence followed from Eqn. 15 until it leads to Eqn. 21:

$$\tilde{f}(x) = \frac{f(x) - f_{min}}{f_{max} - f_{min}} \tag{15}$$

The rate of normalized violation for each individual of the population is equal to:

$$c(x) = \frac{1}{m} \sum_{j=1}^{m} \frac{v_j(x)}{v_{max,j}} \tag{16}$$

$v_j(x)$ is the maximum value of the j^{th} constraint and $v_{max,j}$ is the maximum value of the j^{th} constraint violation in the population .The modified fitness value is then formulated as follows:

$$n(x) = \begin{cases} c(x) & if\ r_f = 0 \\ \sqrt{\tilde{f}(x)^2 + c(x)^2} & otherwise \end{cases} \quad (17)$$

Where r_f is equal to the number of feasible solutions per total population.

To account for the violation of constraints in a design, however small they may be, a penalization term as given in Eqn. 18 is used:

$$p(x) = (1 - r_f) \times X(x) + r_f \times Y(x) \quad (18)$$

Where $X(x)$ and $Y(x)$ maybe defined as in Eqns. 19 and 20, respectively.

$$X(x) = \begin{cases} 0 & if\ r_f = 0 \\ c(x) & otherwise \end{cases} \quad (19)$$

$$Y(x) = \begin{cases} 0 & \text{for feasible solutions} \\ \tilde{f}(x) & \text{for infeasible solutions} \end{cases} \quad (20)$$

Finally, the value of the fitness function for each member of the population is obtained from the following equation:

$$F(x) = n(x) + p(x) \quad (21)$$

To start the optimization process then, a $N_{pop} \times N_{var}$ matrix is formed. The parents are then randomly selected to perform the reproductive stage of the mating operation, after which the female will eat the male black widow.

4.2. Procreate

The act of fertilization between male and female and childbearing is called reproduction. The phenomenon of reproduction in living organisms is done in several ways. In some animals or insects, a male mates with several females to produce offspring. In the original BWO algorithm, males and females were paired each time they reproduced. In this article, an improved version of this operator is applied. Some males and females are mated in the new operator at each stage. This practice simulates polygamy among black widow spiders. As it produces more children in each step, this action makes the search space more and better explored at this stage. Generally, the search area studied in this operator has increased in an improved way. The primary operator of this method is described following. In this algorithm for multiplication, an $1 \times N_{var}$ array is produced, known as alpha which contains random values between zero and one. They are used to generate children y1 and y2 from parents represented by x1 and x2 as shown in Eqn. 22:

$$\begin{cases} y_1 = \propto \times\, x_1 + (1 - \propto) \times x_2 \\ y_2 = \propto \times\, x_2 + (1 - \propto) \times x_1 \end{cases} \quad (22)$$

4.3. Cannibalism

Three types of cannibalism have been observed in the behavior of this type of spider; The first is sexual cannibalism, in which a female black widow eats a male she has mated after mating. Another type of cannibalism is sibling eating, in which strong spiders eat their weak siblings, and the third type of cannibalism is often seen when a mother spider eats her baby. In this algorithm, the rate of cannibalism (CR) is determined based on the number of survivors, an accomplishment related to the values of the Fitness functions as a result of which the weak spiders are spotted and eaten.

4.4. Mutation

At this point, after randomly selecting Mutepop (based on mutation rate) spiders from the total population, each of the chosen widows randomly exchanges three elements in their array. Table 1 shows the pseudo-code of the BWO.

Table 1
The pseudo-code of BWO Algorithm.

The BWO Algorithm

Initialize: Maximum number of iterations, Rate of procreating, Rate of Cannibalism, Rate of mutation;
while Stop condition not met do
  for i = 1 to nr do
    Randomly select two solutions as parents from pop1.
    Generate D children using Eq.19.
    Destroy father.
    Based on the cannibalism rate, destroy some of the children (newly achieved solutions).
    Save the remaining solutions into pop2.
  End for
  Based on the mutation rate, calculate the number of mutation children nm.
  for i = 1 to nr do
    Select a solution from pop1.
    Mutate randomly one chromosome of the solution and generate a new solution.
    Save the new one into pop3.
  End for
  Update pop=pop2+pop3.
  Returning the best solution.
  Return the best solution from pop.
End while

5. Greedy sensitivity-based PSO (GSPSO) technique

The GSPSO algorithm generally consists of two parts: In the first part, the potential region is identified using a method derived from the Greedy search approach. Then, using an approach inspired by the univariate technique [52], the variables of the best design change values stepwise with normalized perturbation values until the change of variables causes violation of constraints or somewhat greater than a step before. In the second part, the search is pursued using the PSO search engine in a more confined range for each variable according to the findings of the previous step. More details of these steps may be summarized below:

5.1. Greedy partitioning the search space

In a constrained minimization problem say, an effective way to evaluate a reasonable restrained search space containing the optimum design is to allocate a certain boundary to the problem initially. Then, using a greedy-wise search approach, the search area is divided into a number of sub-parts. To the number of sub-parts defined, designs will be generated whose design variables for each design contain the mean value in that sub-part, followed by the fitness function evaluation, accordingly. With regard to the fitness functions determined, the fittest design will be selected to carry sensitivity analysis upon its design variables, as a result of which a new confined boundary for each variable will be obtained. The search space for all problems attempted in this research is divided into three sub-parts.

5.2. Relaxing variables to desired values

According to the above description, to set the best values for the variables primarily at this stage, the first two directions of motion are created for each variable, one to reduce the arbitrary value and the other to increase it. In each direction, the objective function and the constraint violation are calculated, and according to Eq. 21, the fitness function and the direction in which the fitness value is improved will be determined. Preferably the value by which the constraint violation is zero will be selected.

5.3. Moving variables in the endorsed direction

After determining the optimal path for all variables, their values change to improve the performance of the target. Then the univariate method is activated. Thus, the first variable changes its value while the other variables are kept constant, and the fitness functions are calculated. Until the fitness function's value is improved, the changes are sustained; otherwise, the corresponding variable will relax to its last value. This procedure is repeated for all variables until an improved performance at this stage is found. Also, during this process, if the value of a variable reaches the neighborhood of either bound and shows a further tendency to change more, it is allowed to enter the neighboring region until no improvement occurs.

5.4. PSO algorithm takes action

At this stage, the PSO algorithm comes into play, where, according to Fig. 2, by centralizing the value found for each variable a predefined *n-design* randomly set of values are produced within a 20% margin to its either side. This is repeated for all variables in the first iteration. The margin P narrows itself through iterations based on $P = 20.5 - 0.5\ (current\_iteration)$.

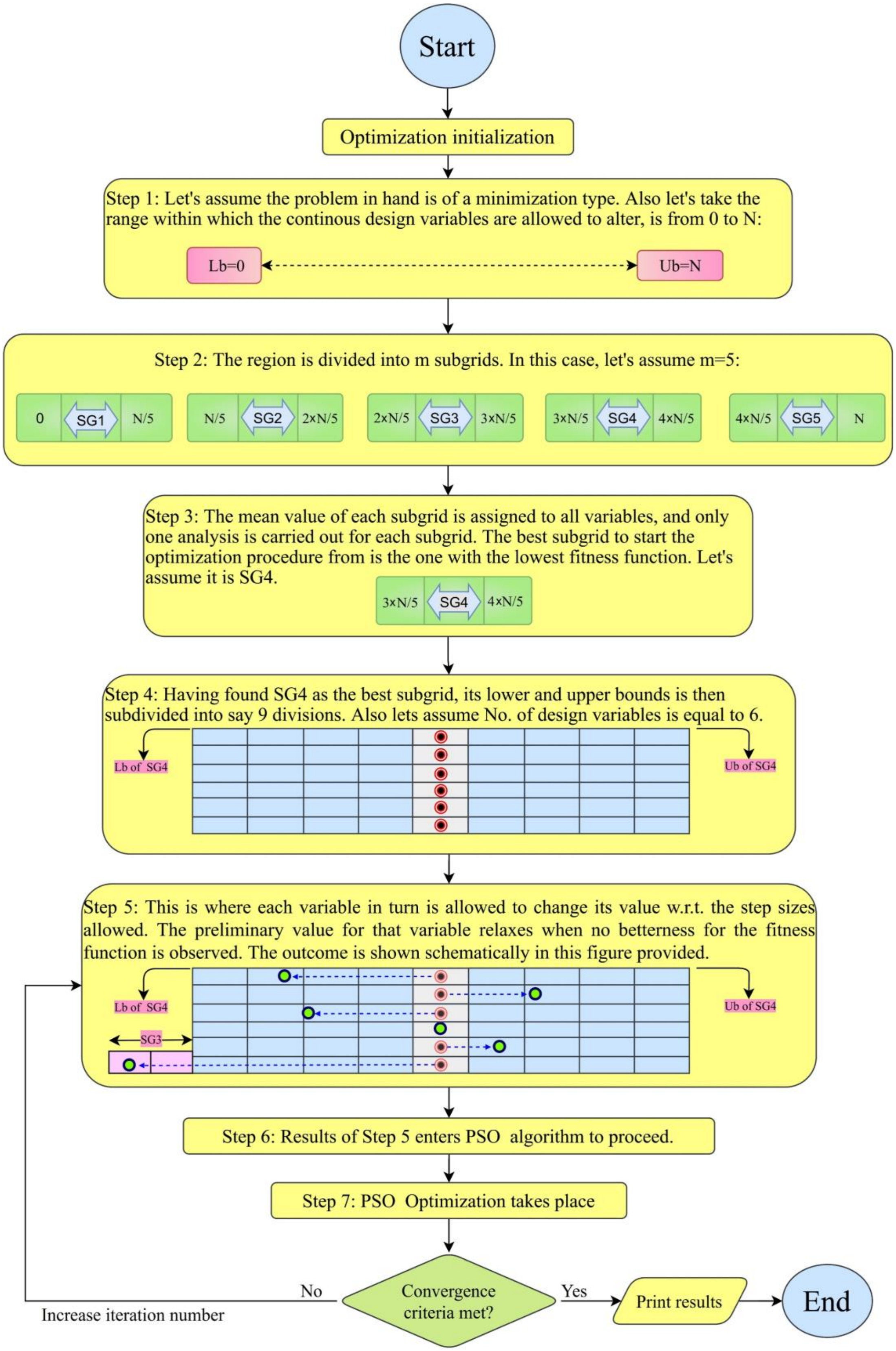

Fig. 2. Flowchart of the GSPSO Algorithm.

6. A hybrid black WIDOW and GSPSO algorithm (BGP)

The BGP algorithm is a hybrid optimization technique that combines the BWO evolutionary algorithm with the GSPSO swarm intelligence algorithm. The GSPSO operator has been used to boost the BWO. The output of this combination shows that the presence of congestion intelligence not only reduces the number of analyses but also, to some extent, improves the final response. For problems with continuous variables where many variables are involved or with large catalog lists to select values for variables from, the proposed algorithm may be effective because initially, using the greed search step, the search area is reduced and a proper range of changes for each variable is determined to some extent. Then, using BWO, by removing the Sub-optimal solutions, a set of most probable solutions enters GSPSO .There, a more accurate exploration of the search space for each variable yields a more accurate range of changes. The end of this operation is left to the powerful engine of the PSO algorithm to finally get the best solution that should perform the global optimum solution. The above explanations are summarized in the flowchart of the BGP algorithm, illustrated in Fig. 3.

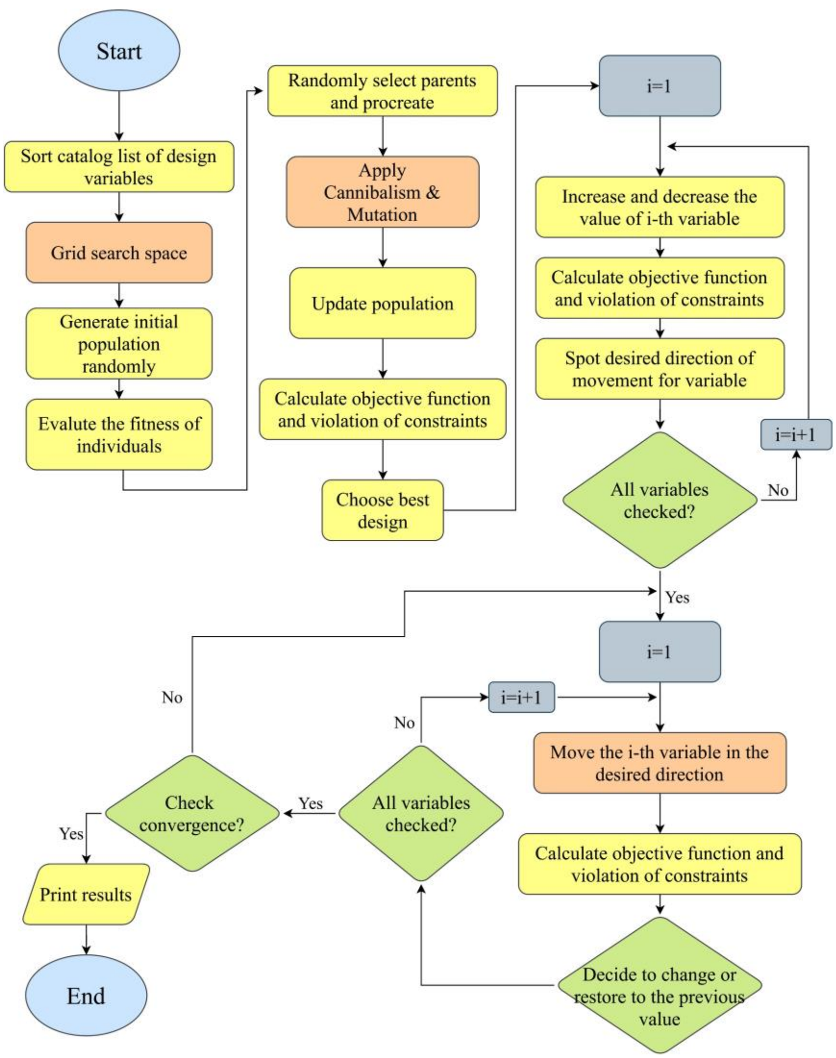

Fig. 3. Flowchart of the BWO-GSPSO (BGP).

7. Examples - results and discussions

7.1. Constrained mathematical function

7.1.1. Keane's bumpy function (KBF)

The mathematical function selected here to evaluate the proposed algorithm's applicability is one of the most challenging functions in the literature due to its highly bumpy manner. Keane's global optimization problem is a constrained multimodal minimization problem defined as:

$$Minimize\ f(x) = -\left|\{\sum_{i=1}^{m} cos^4(x_i) - 2\prod_{i}^{m} cos^2(x_i)\}/(\sum_{i=1}^{m} ix_i^2)^{0.5}\right| \quad (23)$$

subject to:

$$g_1(x) = 0.75 - \prod_{i=1}^{m} x_i < 0\ ,\ g_2(x) = \sum_{i=1}^{m} x_i - 7.5m < 0; x_i < 10 \quad (24)$$

The number of variables for this problem is set to 50. Each method was run 30 times, and the maximum number of iterations was set to 500 as a termination criterion for consistency in all cases. The results are documented in Table 2. The "Best" indicates the best fitness value found throughout the runs, and "Mean" and "Median" are computed according to the following:

"$\text{Mean} = \frac{\text{SUM of the terms}}{\text{number of terms}}$" and "$\text{Median} = \text{middle of the set of numbers}$"

They are related to 30 times running of the optimization procedure.

Table 2
Results of the Kean's Bumpy Function.

Algorithm	Best	Mean	Median
GA	-7.74E-01	-7.44E-01	-7.20E-01
PSO	-7.88E-01	-7.65E-01	-7.54E-01
BWO	-8.07E-01	-7.65E-01	-7.88E-01
GAGGS [53]	-3.65E-01	N/A	N/A
PBGA [54]	-8.20E-01	-8.09E-01	-8.11E-01
BGP	**-8.22E-0.1**	**-7.80E-0.1**	**−7.85E-01**

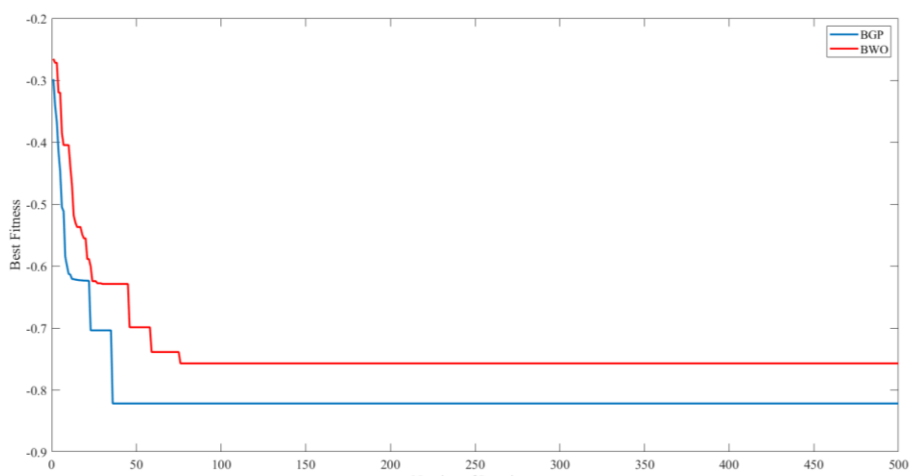

Fig. 4. Convergence history of the Bumpy function.

As illustrated in Fig. 4, the BGP algorithm performed the best optimal solution after 30 iterations, where a more accurate outcome was accomplished compared to the other three algorithms.

7.2. Design examples

Firstly, it is to be noted that in solving the engineering design problems through the BGP algorithm proposed here, discrete variables were used, the catalog list details of which are given distinctly for each problem attempted. The examples studied utilize two types of cross-sectional areas; W sections are used for frames and pipes for bridges. The sections are sorted from small to large to ease the optimization procedure. It should be noted that the maximum number of analyzes, for the first three attempted structural problems with 10, 15, 24 number of story frames, is set to 20,000.

7.2.1. One-Bay ten-story frame

Fig. 5 shows the shapes and loads on a one-span, ten-story frame structure. This frame is one of the standard design problems. The catalog list of the beam elements uses all the W sections specified in the AISC code without restriction, but the column catalog list is limited to groups W12 and W14 only. This frame is designed according to the AISC-LRFD code, and the permissible limit for drift floors is smaller than the floor height, divided by 300. The modulus of elasticity (E) is 200 GPa, and the yield stress (f_y) is 248.2 MPa.

Table 3
Results of one-bay ten-story structure.

Variable No.	Algorithm				
	PSO	BWO	CPA [48]	BB-BC [55]	BGP
1	W33X118	W40X149	W40X149	W33X118	W33X118
2	W33X118	W30X90	W30X108	W30X90	W30X90
3	W21X83	W24X84	W30X90	W30X99	W24X84
4	W16X57	W12X58	W21X55	W18X60	W21X68
5	W12X230	W12X230	W12X279	W14X283	W12X230
6	W12X170	W12X170	W12X252	W12X252	W12X170
7	W12X136	W14X132	W14X211	W14X211	W14X132
8	W12X96	W12X96	W14X176	W12X190	W12X96
9	W12X74	W14X61	W14X145	W14X145	W14X61
Weight (KN)	298.49	290.69	281.65	280.1	280.08
No. of analyses	19,000	18,100	11,150	14,800	3,800

According to Fig. 6 and Table 3, the proposed BGP algorithm resulted in more satisfactory results than the BWO algorithm by exhibiting a faster convergence and a more comprehensive optimum weight for the structure.The number of analyzes required by BGP is about 75% less than that of BWO, and the weight has been reduced by about 4%. In the following, some more benchmark structural problems are examined to more firmly evaluate the potential of the proposed algorithm.

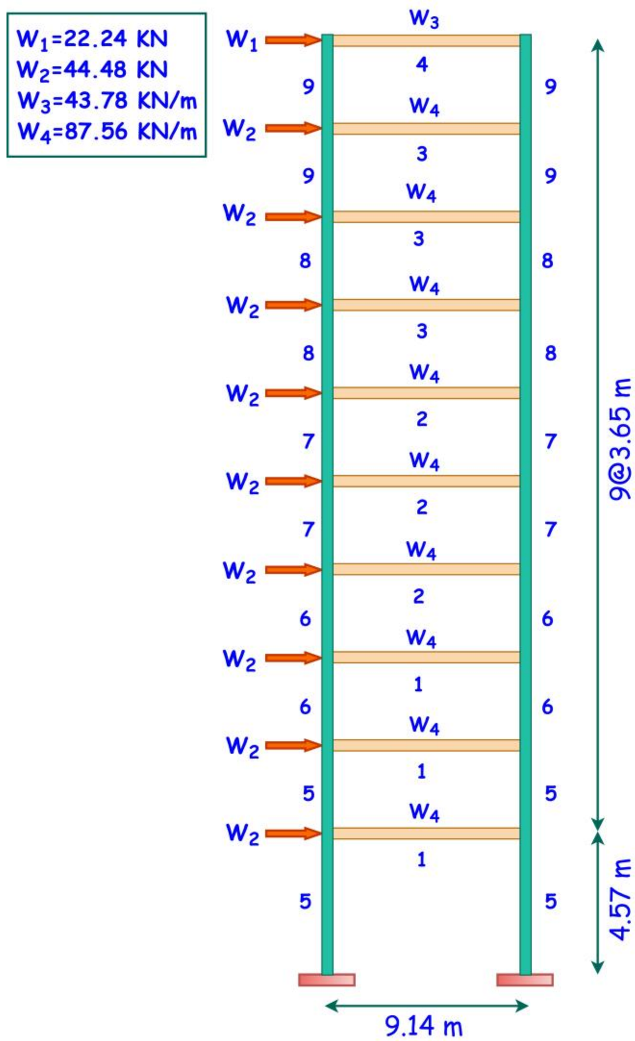

Fig. 5. Visual view of the one-bay ten-story structure.

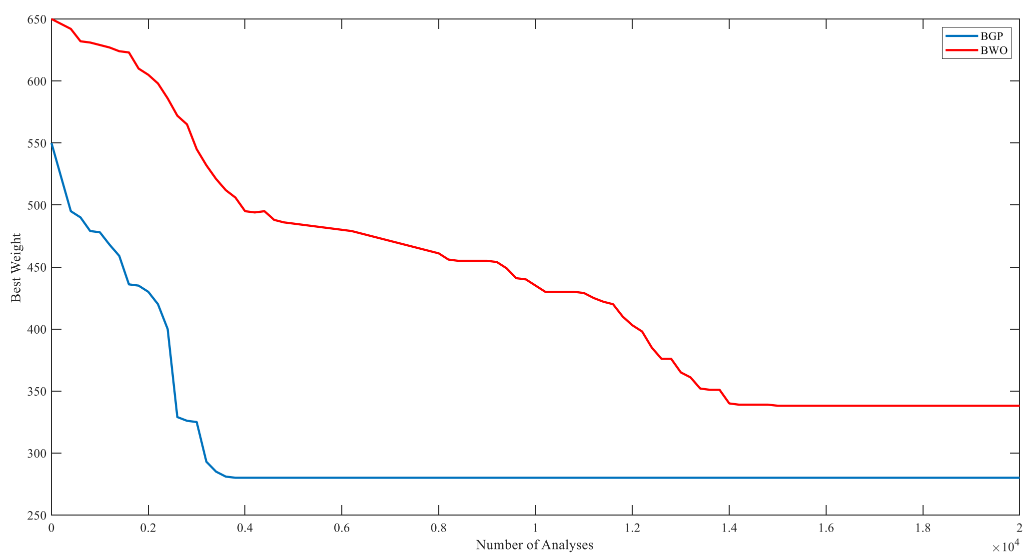

Fig. 6. Convergence history of the 1-bay 10-story frame.

7.2.2. Three-Bay fifteen-story frame

A 3-span, 15-story frame structure with 105 members, including the loading, is illustrated in Fig. 7. Yield stress and the modulus of elasticity equal 248.2 MPa and 200 GPa, respectively. There are 1 and 10 group elements as the total design variables for the beams and columns, respectively. The catalog list of group elements for both beams and columns is selected from all the profiles of the AISC W-section list. This frame is also designed according to the AISC-LRFD code.

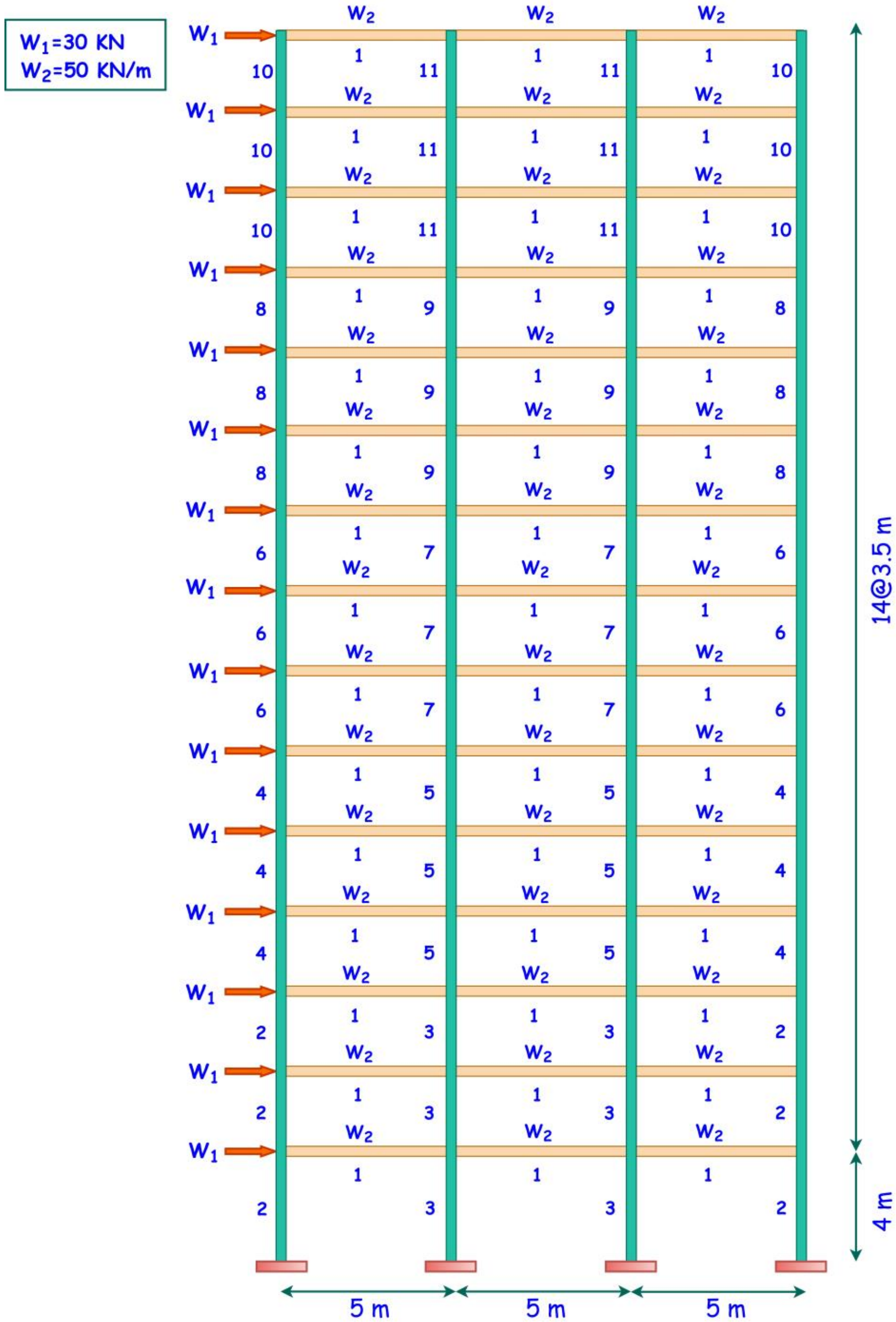

Fig. 7. Visual view of three-bay fifteen-story structure.

Table 4
Results of 3-bay 15-story structure.

Variable No.	PSO	BWO	HPSACO [56]	ICA [57]	ES-DE [21]	BGP
1	W21X48	W18X40	W21X44	W21X44	W21X48	W21X101
2	W36X170	W30X132	W21X111	W24X117	W18X106	W33X169
3	W24X229	W36X170	W18X158	W21X147	W36X150	W12X79
4	W10X100	W24X103	W10X88	W27X84	W12X79	W36X135
5	W21X111	W33X169	W30X116	W27X114	W27X114	W30X99
6	W18X86	W36X160	W21X83	W14X74	W30X90	W24X84
7	W18X143	W14X82	W24X103	W18X86	W10X88	W18X50
8	W16X57	W12X53	W21X55	W12X96	W18X71	W24X68
9	W27X84	W18X65	W27X114	W24X68	W18X65	W18X35
10	W14X34	W14X34	W10X33	W10X39	W8X28	W10X33
11	W18X97	W8X40	W18X46	W12X40	W12X40	W18X40
Weight (KN)	502.15	445.22	426.36	417.46	415.06	400.26
No. of analyses	28,000	18,500	6800*	6000*	4050*	4,400

*These results have not been performed with SAP2000 software and are not comparable in terms of the number of analyzes.

As shown in Fig. 8 and the results recorded in Table 4, the optimum design of the frame is obtained after 4,400 analyses and a minimum weight of 400.26 KN using BGP. The optimum design found using BWO is 445.22 KN with 18500 frame analyses. The BGP algorithm reduced the total number of analyzes by 76.22% and the weight by 10.1%.

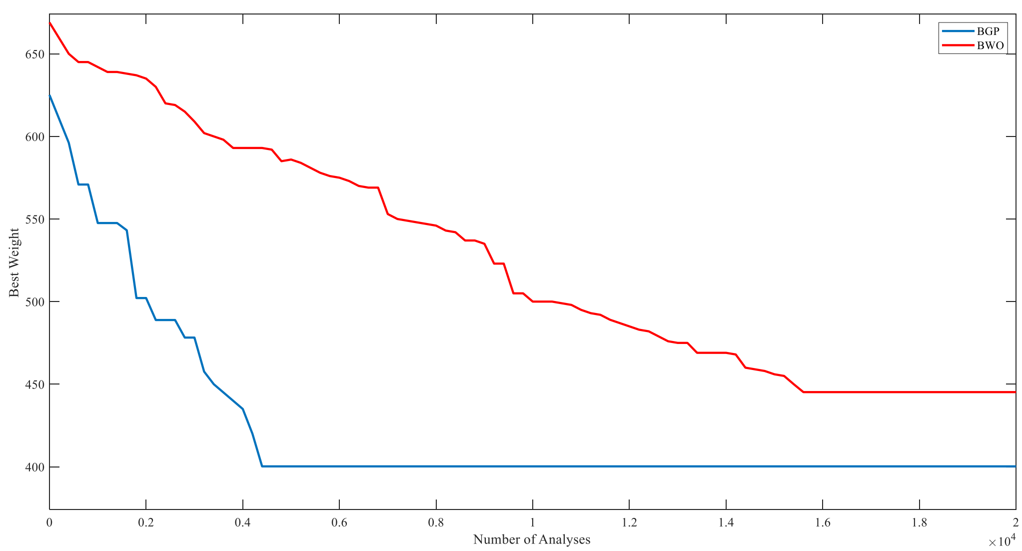

Fig. 8. Convergence history of the 3-bay 15-story frame.

7.2.3. Three-Bay twenty four-story frame

The third example is a 24-story 3-span frame problem with 168 elements, including 72 beams and 96 columns. This frame has been studied by many researchers [57]–[59]. The loading and the grouping of the elements are shown in Fig. 9. Thus, the total number of design variables is 20, four of which are for the beams and sixteen for the columns. f_y is equal to 230.3 MPa, and the modulus of elasticity is equal to 205 GPa. The frame is aimed for the optimum design according to the AISC-LRFD code. The maximum inter-story drift index is limited to 1⁄300, and the allowable displacement of the last floor is limited to 292.61 mm.

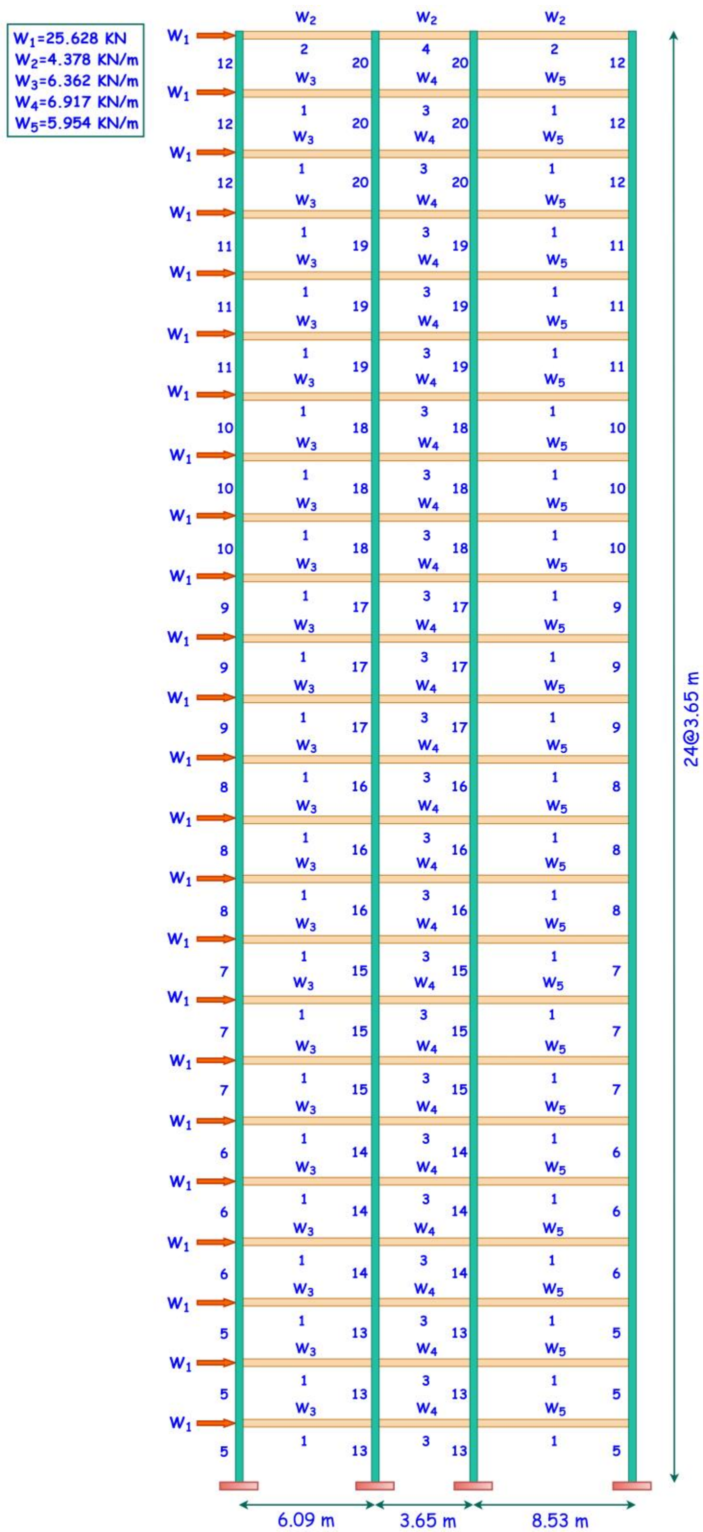

Fig. 9. Visual view of the three-bay twenty four-story structure.

Table 5
Results of 3-bay 24-story structure.

Variable No.	Algorithm						
	PSO	BWO	IACO [17]	HS [58]	HBBPSO [61]	CPA [48]	BGP
1	W21X62	W24X62	W30X99	W30X90	W30X90	W30X90	W30X90
2	W24X84	W24X94	W16X26	W10X22	W21X55	W8X18	W24X55
3	W18X106	W30X90	W18X35	W18X40	W21X48	W14X48	W12X35
4	W18X60	W44X230	W14X22	W12X16	W8X24	W6X8.5	W18X86
5	W14X120	W14X211	W14X145	W14X176	W14X176	W14X120	W14X145
6	W14X211	W14X233	W14X132	W14X176	W14X90	W14X159	W14X90
7	W14X145	W14X211	W14X120	W14X132	W14X99	W14X68	W14X120
8	W14X233	W14X257	W14X109	W14X109	W14X99	W14X82	W14X90
9	W14X99	W14X211	W14X48	W14X82	W14X74	W14X61	W14X82
10	W14X257	W14X159	W14X48	W14X74	W14X74	W14X68	W14X82
11	W14X74	W14X90	W14X34	W14X34	W14X38	W14X30	W14X74
12	W14X176	W14X132	W14X30	W14X22	W14X34	W14X22	W14X99
13	W14X176	W14X120	W14X159	W14X145	W14X145	W14X120	W14X43
14	W14X145	W14X109	W14X120	W14X132	W14X132	W14X109	W14X82
15	W14X68	W14X34	W14X109	W14X109	W14X109	W14X145	W14X61
16	W14X68	W14X99	W14X99	W14X82	W14X90	W14X109	W14X43
17	W14X30	W14X61	W14X82	W14X61	W14X74	W14X90	W14X22
18	W14X74	W14X22	W14X53	W14X48	W14X48	W14X53	W14X61
19	W14X74	W14X22	W14X38	W14X30	W14X38	W14X43	W14X30
20	W14X34	W14X22	W14X26	W14X22	W14X22	W14X22	W14X30
Weight (KN)	1103.98	1089.94	968.9	955.745	941.55	915.42	897.09
Number of analyses	40,000	15,500	N/A	14,651	8,000*	12,600	7,100

*These results have not been performed with SAP2000 software and are not comparable in terms of the number of analyzes.

According to Fig. 10 and Table 5, the weight of 897.09 KN is obtained for the mentioned frame after 7100 analyses using BGP. For BWO, weight of the structure has obtained 1089.94 KN after 15500 analyses. The BGP algorithm successfully reduced the number of analyses by 54.19% and the weight by 17.69%.

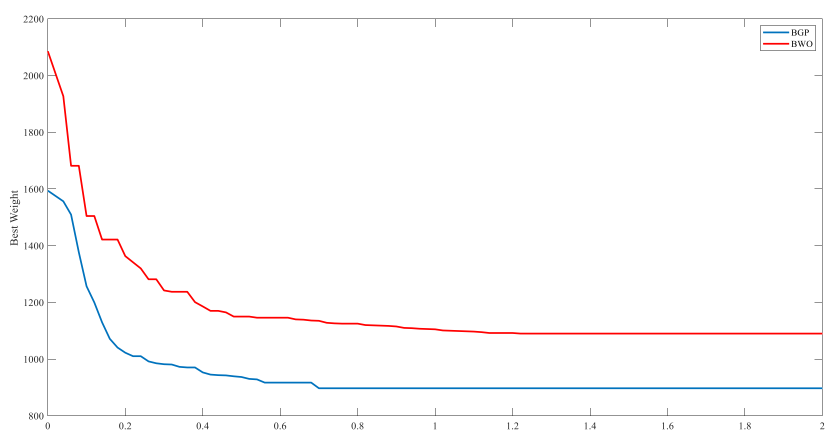

Fig. 10. Convergence history of the 3-bay 24-story frame.

7.2.4. Two-Bay two-story irregular steel space frame

The Two-Bay Two-Story Irregular Steel Space Frame (Fig. 11) has twenty-one members, two groups of beams, and three groups of columns arranged as variables for it. The drift ratio limits are defined as 4 cm for top-story and 1 cm for inter-story, where H=4 m is the elevation of each story. The maximum beams deflection is restricted to 13.9 mm. This Space Frame is designed according to the AISC-LRFD code. The number of analyzes for this three-dimensional structure is set at 10,000. The results of Table 6 and Fig. 12 show that BGP has also shown acceptable performance in solving this problem.

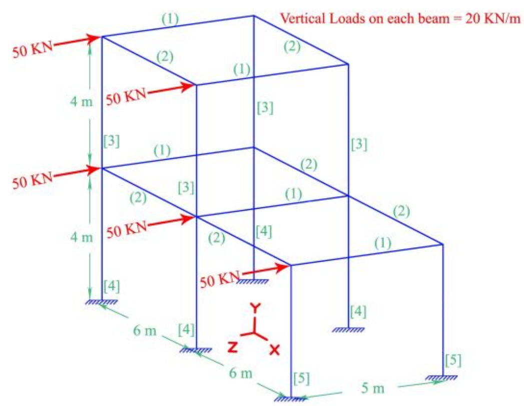

Fig. 11. 2-story 21-member irregular space frame.

Table 6
Statistical results of 2-story and 21-member irregular space frame.

Variable No.	Algorithm			
	ACO [62]	HS [62]	BWO	BGP
1	W18X40	W18X40	W12X22	W12X22
2	W14X22	W12X19	W18X35	W16X26
3	W18X35	W16X40	W16X26	W16X26
4	W18X46	W18X40	W14X38	W12X40
5	W12X30	W16X26	W16X26	W16X26
Weight (KN)	48.68	46.63	42.42	39.57
Number of analyses	10,000	10,000	10,000	10,000

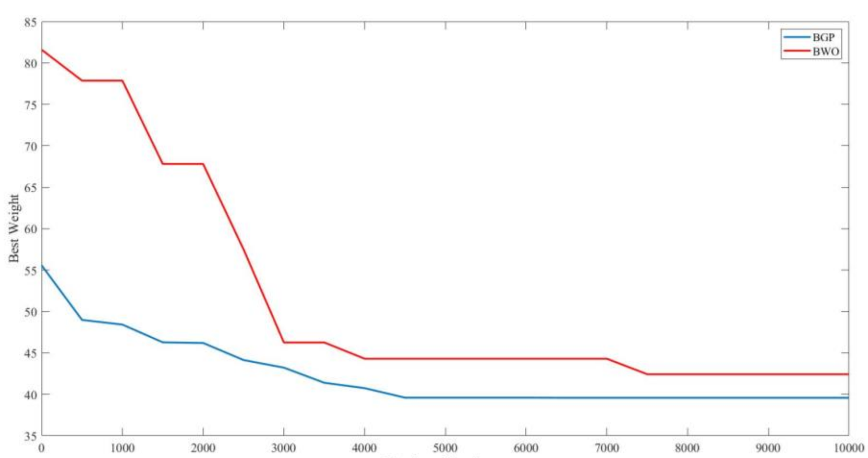

Fig. 12. Convergence history of the 2-story 21-member irregular space frame.

7.2.5. Real footbridge

In this example, a real footbridge is subjected to weight optimization to evaluate the proposed approach. SAP2000v22 software has been used for design based on AISC/ASD 360-16 code in the optimization process. To connect MATLAB to the SAP2000v22, a toolbox developed for MATLAB under the name SM Toolbox [63] was used.

Fig. 13 shows the dimensions of the footbridge. The constructed footbridge weight is 112.78 KN pursuant to the available drawings.

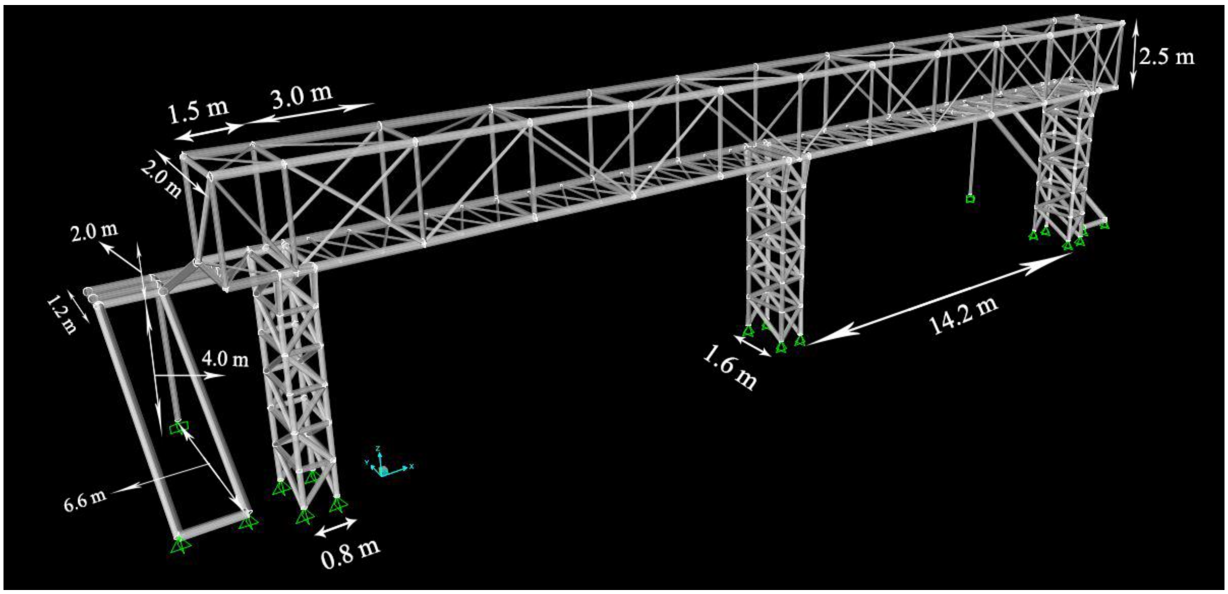

Fig. 13. Visual view of the Footbridge.

Table 7 indicates the grouping of the footbridge members and their color:

Table 7
Grouping of the footbridge members.

	Grouping														
Type	Beams					Columns			Braces						
Group No.	G1	G2	G3	G4	G5	G6	G7	G8	G9	G10	G11	G12	G13	G14	G15
Elements in each Group	60	26	36	48	26	72	26	2	48	36	26	18	2	82	8
Color															

Fig. 14 illustrates parts for each group of the footbridge.

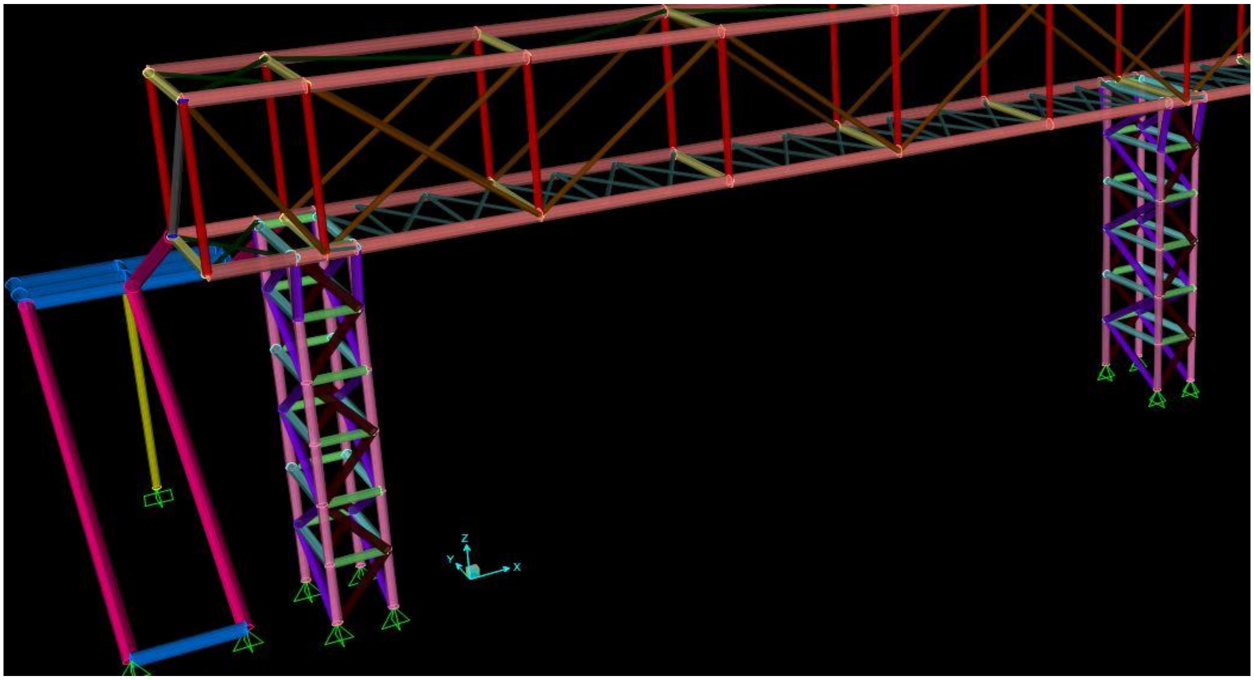

Fig. 14. Show groups according to the colors listed.

Table 8 lists the pipe sections used for optimization. The f_y and elasticity's modulus (E) is set to 2400 MPa and 200 GPa, respectively.

Table 8
Existing sections for optimization.

No.	Outer Diameter(mm)	Thickness(mm)
1-7	60.3	**3, 3.5, 4, 4.5, 5, 5.5, 6**
8-14	76	**3, 3.5, 4, 4.5, 5, 5.5, 6**
15-21	88.9	**3, 3.5, 4, 4.5, 5, 5.5, 6**
22-28	114.3	**3, 3.5, 4, 4.5, 5, 5.5, 6**
29-35	140.3	**3, 3.5, 4, 4.5, 5, 5.5, 6**
36-42	168.3	**3, 3.5, 4, 4.5, 5, 5.5, 6**
43-49	219.1	**3, 3.5, 4, 4.5, 5, 5.5, 6**

7.2.5.1. Loads applied to the footbridge

Dead & live loads and wind loads as equivalent nodal loads and the direction of their application and coefficients related to earthquake loads are shown in Table 9.

Table 9
Amount and direction of loads applied to the footbridge.

Kind of Loads	somewhere load is applied	Direction	Magnitude (KN)
Dead	Floor	Gravity (Z)	**1.18**
Live	Floor	Gravity (Z)	**14.71**
Wind	Laterally (Base)	Y	**0.34**
Wind	Laterally (Deck)	Y	**1.55**
Earthquake	Laterally	X, Y	**C=0.09, K=1.205**

Table 10 and Fig. 15 show the optimal solutions found using GA, PSO, BWO and the combined BGP algorithms.

Table 10
Results of pedestrian bridge.

Groups name	GA [64]	PSO [64]	BWO	BGP
1	P219.1X3	P219.1X3	P168.3X4	**P168.3X4**
2	P60.3X3	P60.3X4	P60.3X6	**P76X3.5**
3	P60.3X3	P140.3X4	P76X5	**P60.3X3**
4	P88.9X6	P88.9X3	P88.9X4.5	**P76X3**
5	P219.1X6	P219.1X4	P168.3X3	**P219.1X3**
6	P219.1X3	P219.1X3	P114.3X3	**P88.9X3**
7	P114.3X3.5	P114.3X3	P88.9X4	**P168.3X3**
8	P140.3X4.5	P140.3X5	P168.3X6	**P168.3X3**
9	P114.3X5	P76X3.5	P60.3X4	**P60.3X3**
10	P114.3X3	P114.3X3	P60.3X3.5	**P60.3X4**
11	P88.9X6	P140.3X4	P114.3X3	**P114.3X3**
12	P60.3X3	P60.3X3	P60.3X3	**P88.9X3**
13	P60.3X3	P60.3X3	P60.3X3	**P114.3X3.5**
14	P60.3X3	P60.3X3	P60.3X4	**P60.3X3**
15	P168.3X4	P168.3X4	P168.3X4	**P168.3X4**
Weight (KN)	96.98	93.17	82.91	**78.19**
No. of analyses	2000	2000	2000	**2000**

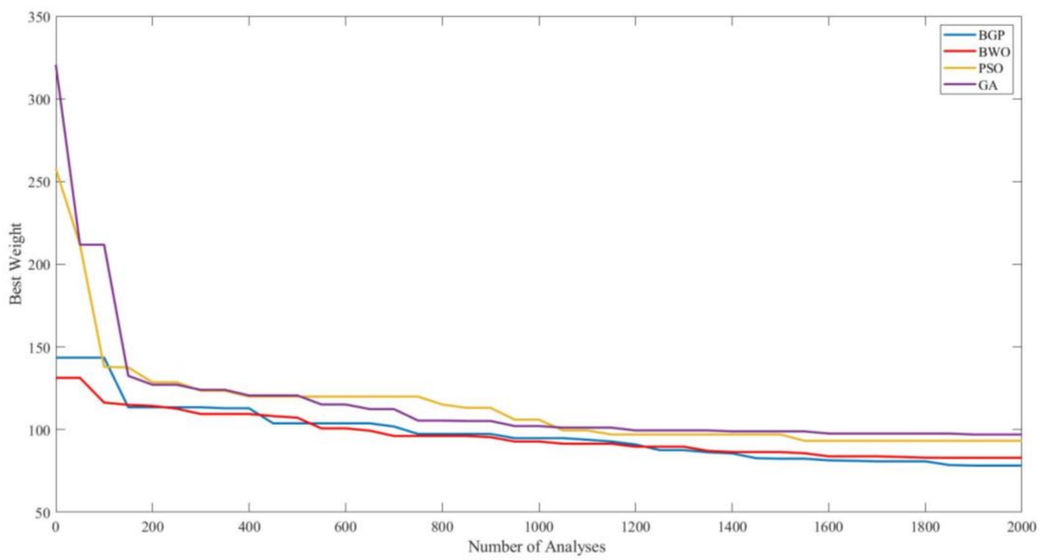

Fig. 15. Convergence history of the footbridge.

As one could also assess in the latest problems, the proposed BGP algorithm has a high performance in finding the global optimum solution with a lower number of analyses compared to other algorithms available in Table 10.

7.3. Discussions of optimization results

The convergence histories obtained by the BGP method for the first three design examples, including building frames (Figs. 6, 8, and 10), show that the proposed technique started its work from lower values at the beginning of the process. One of the goals of the GSPSO was to provide a desirable and processed initial population for the rapid advancement of optimization operations, and the results indicate the achievement of this initial goal. Providing a good initial population to achieve the global optimum is also very promising. For example, the convergence history of the 15-story frame exhibits a significant difference in convergence speed without causing premature convergence. Therefore, the number of analyzes has been greatly reduced. These results are not only compared to the original algorithm (BWO) but are generally less than what is reported in the references. The evaluation results of the method, both on design examples and mathematical examples, indicate the reliability of the proposed BGP method. BWO algorithm was chosen as an algorithm that was not used before to evaluate design examples in the literature. Any other meta-heuristic algorithm can be combined with the GSPSO technique. Therefore, according to the obtained results, it is strongly recommended as a proposed option for researchers who intend to increase the efficiency of a meta-heuristic. Especially in problems where the global optimum cannot be guaranteed, the present technique can provide the minimum optimal weight for the design of structures with standard sections with a very good difference.

8. Conclusions

This study introduces an intelligent search engine called Greedy Sensitivity-based PSO (GSPSO). This method partitions the search space in an organized way. The way this technique works is that by specifying the sensitivity of each variable in the created subsection, it starts changing the variables and searching the space of the solution space. This operation continues until an optimal subpart is determined for each variable, then this information is given to an optimization algorithm. In this literature, the well-known PSO method is used. The role of PSO in the second stage is to find a population of optimal designs according to the input information from the previous step. Next, when GSPSO introduces an optimal population, these data are given to the Black Widow Optimization (BWO) algorithm to perform the final optimization operation. The newly introduced BWO algorithm has a high ability to find the optimal solution by detecting the suboptimal areas of the search space and removing them. Due to the use of PSO and BWO algorithms, the name of the proposed method is BWO hybridized with Greedy Sensitivity-based PSO (BGP) technique.

To evaluate the performance of the BGP algorithm, weight minimization was performed on three two-dimensional steel frames and two three-dimensional structures. The results indicate that the proposed method has significantly reduced the number of analyzes in finding the optimal solution. Also, referring to the optimal solution obtained from BGP compared to other combined methods, it can be acknowledged that the proposed method has high accuracy in finding the optimal global solution. This way, the weight obtained in engineering design problems has improved significantly compared to other methods.

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Conflicts of interest

The authors declare no conflict of interest.

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Appendix

Table A 1 deals with the abbreviations mentioned in this article.

Table A 1
List of Abbreviations.

Row	Abbreviations	Meaning
1	ABC	Artificial Bee Colony
2	ACO	Ant Colony Optimizer
3	AISC	American Institute of Steel Construction
4	ALO	Ant Lion Optimizer
5	ASD	Allowable Stress Design
6	ASO	Alpine Skiing Optimization
7	AVOA	African Vultures Optimization Algorithm
8	BB-BC	Big Bang-Big Crunch
9	BGP	BWO hybridized with Greedy Sensitivity-based PSO
10	BWO	Black Widow Optimization
11	CMO	Cat and Mouse Optimization
12	COA	Coyote Optimization Algorithm
13	CPA	Cyclical Parthenogenesis Algorithm
14	CS	Chirp Scaling
15	CSS	Charged System Search
16	DDHS	Design-Driven HS
17	DE	Dolphin Echolocation
18	DEO	Dolphin Echolocation Optimization
19	FDMCO	Fuzzy Discrete Multicriteria Optimization
20	FiSA	Filtered SA
21	GA	Genetic Algorithm
22	GSPSO	Greedy Sensitivity-based Particle Swarm Optimization
23	GWO	Grey Wolf Optimizer
24	HBPSO	Hybrid Binary Particle Swarm Optimization
25	HS	Harmony Search
26	IACO	Improved Ant Colony Optimizer
27	IGWO	Improved Grey Wolf Optimizer
28	KBF	Keane's Bumpy Function
29	LBandB	Linearized Branch and Bound
30	LRFD	Load and Resistance Factor Design
31	MDE	Modified Dolphin Echolocation
32	MDEO	Modified Dolphin Echolocation Optimization
33	MGO	Mountain Gazelle Optimizer
34	POA	Pelican Optimization Algorithm
35	PSO	Particle Swarm Optimization
36	SA	Simulated Annealing
37	SCBF	Swiss Capacity Building Facility
38	SOA	Seagull Optimization Algorithm
39	SSA	Squirrel Search Algorithm
40	TEO	Thermal exchange optimization
41	TLBO	Teaching-Learning-Based Optimization
42	TS	Tabu Search
43	WEOA	Water Evaporation Optimization Algorithm
44	WHO	Wild Horse Optimizer
45	WOA	Whale Optimization Algorithm