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PRACTICAL OPTIMIZATION OF PEDESTRIAN BRIDGES USING GRID SEARCH SENSITIVITY BASED PSO

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ABSTRACT

Pedestrian bridge is a structure constructed to maintain the safety of citizens in crowded and high-traffic areas. With the expansion of cities and the increase in population, the construction of bridges is necessary for easier and faster transportation, as well as the safety of pedestrians and vehicles. In this article, it is decided to consider the most economical cross-sections for these bridges according to the design regulations and codes of Practice in order to achieve the minimum weight, which will ultimately reduce the cost of construction and production and the usage of less resources. For this purpose, new GSS-PSO algorithm has been used and its results have been compared with GA and PSO algorithms, by the means of which an enhancement of PSO algorithm is seen. This enhancement on the conventional PSO technique reduces the search space more desirably and swiftly to a space close to the global optimum point. This algorithm has been implemented with MATLAB mathematical software and has been integrated with SAP2000v22 structural design software for analysis and optimum design under resistance and displacement constraints. The final results of the analyses are compared with an already designed and implemented infrastructure. In addition to a bridge optimization, a bench-mark frame optimization was also used in order for a better comparison between this algorithm and the other ones.

Keywords: pedestrian bridges, GSS-PSO algorithm, metaheuristics, applications of algorithms

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1. INTRODUCTION

Optimization algorithms provide useful tools for steel structure designers by which the topology, size and shape of steel structures profiles can be optimized [1, 2]. The costs associated with structural elements are not necessarily proportionate with their weight, and

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minimizing the total cost should be the ultimate goal of structural optimization, but structural weight still constitutes a significant part of the cost [3, 4]. Hence, optimizing structural weight in today's world with declining work resources is quite important for structural designers [5, 6].

The designer of steel structures has to select sections from a catalog list that contains specific profiles available in the market. Therefore, design problems for steel structures could justifiably be considered a discrete problem [7, 8].

In recent years, several Swarming intelligent (SI) algorithms, mimicking the social behavior of birds, insects, and other animals have developed [9]. For example, one may refer to particle swarm optimization (PSO), which is a popular SI algorithm based on the intelligence and movement of flocks of birds and similar to their behavior [10, 11]. The main difference between PSO and other evolutionary computational techniques such as Genetic Algorithms (GA) [12] is that PSO has no evolutionary operators such as crossovers and mutations. In addition, PSO requires fewer parameters than GA and is implemented with only a few lines of code in each programming language [9, 13]. Also, in line with various issues, the performance of this algorithm has greatly improved over the past decade and has been published under various articles. One of these improvements is called GSU-PSO [14], which is based on a hybrid Grid Search Univariate method and PSO. In this method, using the grid search method, the entire search space is divided into a series of grids. The objective function is calculated with a randomly generated population. Finally, using the method obtained from the univariate method, the variables of the best particle are allowed to correct their values step by step and finally it will reach the global optimum solution [15, 16]. In this study, the GSS-PSO method will be introduced and implemented to optimize the weight of pedestrian bridges. The bridge weight minimization under all the applied design constraints, according to AISC allowable stress Code of Practice, will be utilized. For this purpose, three algorithms GA, PSO, GSS-PSO are used, the results of which will be presented in the following sections.

To carry the analysis of the bridge in the optimization process, SAP2000 software has been used to design according to the AISC allowable stress regulations [17] and in order to connect MATLAB software to the latest version of SAP2000, a toolbox developed for MATLAB by Javanmardi and Ahmadi Nedushan Used under the name SM Toolbox.

2. WEIGHT OPTIMIZATION OF STEEL STRUCTURES ACCORDING TO AISC

The purpose of optimizing a typical pedestrian bridge in the present study is to find the lowest possible weight according to AISC / ASD 360-16 design constraints. This may be achieved by reducing the cross section of the elements as variables to the lowest possible. Thus, Eq. 1 states that:

$$f(x) = \sum_{i=1}^{N} \gamma_i . x_i . l_i \tag{1}$$

where γ_i is the element density i, x_i is the variable i, l_i is the length of the i^{th} variable and N is the number of members in the structure. According to AISC / ASD 360-16, the design of structural members has various constraints, including resistance and displacement constraints, as follows:

Resistance constraints:

As we know, real structures are subject to different loads and net axial and even bending forces rarely occur in members and most of the interaction of forces affects the member, so the design must be according to Equation C-H1-1 of AISC/ASD 360-16 regulation.

$$\frac{f_a}{F_a} + \frac{C_m f_b}{\left(1 - \frac{f_a}{F_e'}\right) F_b} \leq 1.0 \tag{2}$$

in which F_a and F_b are, respectively, the axial and flexural allowable stresses permitted by this specification, and f_a and f_b are the corresponding stresses due to the axial force and the bending moment, respectively. The allowable axial stress, f_a, was usually determined for an effective length that is larger than the actual member length for moment frames. The term $\frac{1}{1-\frac{f_a}{F_e'}}$ is the amplification of the inter-span moment due to member deflection multiplied by the axial force (the *P*-δ effect). C_m accounts for the effect of the moment gradient.

The effective length *K* to compute compression and Euler stresses factors is required.

$$F_e = \frac{\pi^2 E}{(KL/r)^2} \tag{3}$$

For column members, *K* values are calculated by SAP2000 from the following equations [18]:

for sidesway inhibited frames:

$$K = \frac{3G_A G_B + 1.4(G_A + G_B) + 0.64}{3G_A G_B + 2(G_A + G_B) + 1.28} \tag{4}$$

And for sidesway uninhibited frames:

$$K = \sqrt{\frac{1.6G_A G_B + 4(G_A + G_B) + 7.5}{G_A + G_B + 7.5}} \tag{5}$$

$$where\ \ G = \frac{\Sigma\left(\frac{EI}{L}\right)_{Column}}{\Sigma(EI/L)_{Beam}} \tag{6}$$

where, G_A and G_B are the stiffness ratios of columns and girders at the two end joints A and B of the column section, respectively.

Displacement constraints:

The real design constraints, based on AISC/ASD 360-16 regulation may be as follows:

Maximum lateral displacement:

$$v^{\Delta} = R - \frac{\Delta_T}{H} \leq 0 \tag{7}$$

Inter-story displacements:

$$v_j^d = R_t - \frac{d_j}{h_j} \leq 0 \quad j = 1,2,\dots,ns \tag{8}$$

R is the maximum drift index; Δ_T is the maximum lateral displacement; H is the height of the frame structure; d_j is the inter-story drift; h_j is the story height of the j-th floor; ns is the total number of stories and R_t is the inter-story drift index permitted by the code of practice.

3. REVIEW OF PSO ALGORITHM

Since the GSS-PSO algorithm uses the PSO search engine, it is primarily worthened to introduce PSO algorithm. It basically maintains a population of particles (x_1, x_2, ..., x_p) that are evenly distributed in the search space. In the PSO algorithm, each particle represents a potential answer to an optimization problem.

Thus, if one denotes the number of particles as P, Kennedy and Eberhart proposed the position of the i^{th} particle, x_i be updated in the following manner:

$$x_{k+1}^i = x_k^i + v_{k+1}^i \tag{9}$$

Each particle in PSO is associated with a constructed velocity v_{k+1}^i, which indicates the rate of change of position for the i^{th} particle.

$$v_{k+1}^i = \omega_k v_k^i + c_1 r_1 (P_k^i - x_k^i) + c_2 r_2 (P_k^g - x_k^i) \tag{10}$$

Equation (10) calculates the new particle velocity v_{k+1}^i, based on the current velocity v_k^i and the two other terms, the distance of its current position x_k^i from the best position of the ith particle in its own history, P_k^i and the best position of all particles P_k^g up to that increment of time and iteration.

k represents the iteration number. r_1 *and* r_2 represent uniform random numbers between 0 and 1, respectively.

c_1 *and* c_2 are the two positive numbers called cognitive and social learning coefficients, respectively, here set as fixed values.

The inertia weight ω_k is employed to control the impact of the previous history of velocities on the current velocity, thus to influence the trade-off between global (wide-ranging) and local (nearby) exploration abilities of the particles [10, 19, 20, 21].

4. GSS-PSO ALGORITHM

The GSS-PSO algorithm is a meta-heuristic algorithm based on improving the performance of the PSO algorithm through sensitivity analysis. This algorithm consists of two parts: first, a grid search followed by a sensitivity analysis. The next part is to carry PSO based optimization.

In the first part, primarily the search space is gridded where it was divided into a number of sub-divisions causing the scope of the search to be determined. Then the objective function is evaluated at all points. The performance of each particle (value of the objective function) is measured by connecting the MATLAB code to the SAP2000v22 software enabled via the SM toolbox and the point with the lowest standard deviation (DCV) is then selected.

Then, based on a step size where 10% of the value of the variables is selected, the values of the variables are changed and the objective function is recalculated. After calculating the new objective function and comparing it with the previous value, the sensitivity analysis was carried out on each variable using the Forward Finite Diffrence (FFD) method; the lower the sensitivity, the more the variable needs to be changed, and the higher the sensitivity, the less this need to be changed. So we sort the sensitivities from small to large and normalize the values, and then subtract from a big number, which we also consider 10% of the maximum sensitivity here to get new sensitivities, this sensitivity Will be the direction of the values towards the optimal answer and the variables of other points will also change according to these values.

Therefore, in subsequent repetitions, this sensitivity and its orientation become more precise, and the most maneuver is performed around the response area, thus preventing irrelevant outcomes. This section seeks to generate a sequence of improved approximations at the minimum point. In the second part, each particle moves within the previously limited search space, updating its speed and position based on the best positions ever discovered by itself and all other particles. Therefore, particles tend to move to a better position in the search area. The whole process is repeated until the values are converged to the global optimal solution. The concepts expressed is displayed in the flowchart of Figure 1.

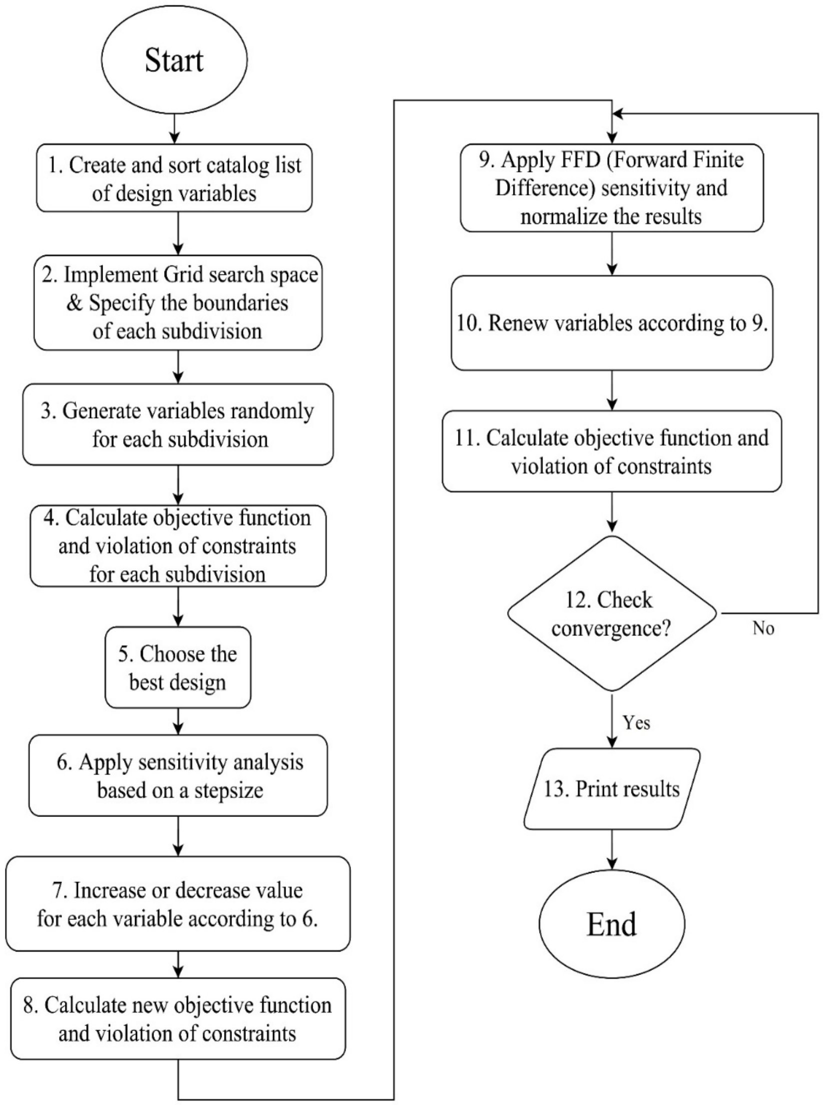


Fig. 1. Flowchart of GSS-PSO

5. DESIGN EXAMPLES

5.1 Design of 3-bay 15-story frame

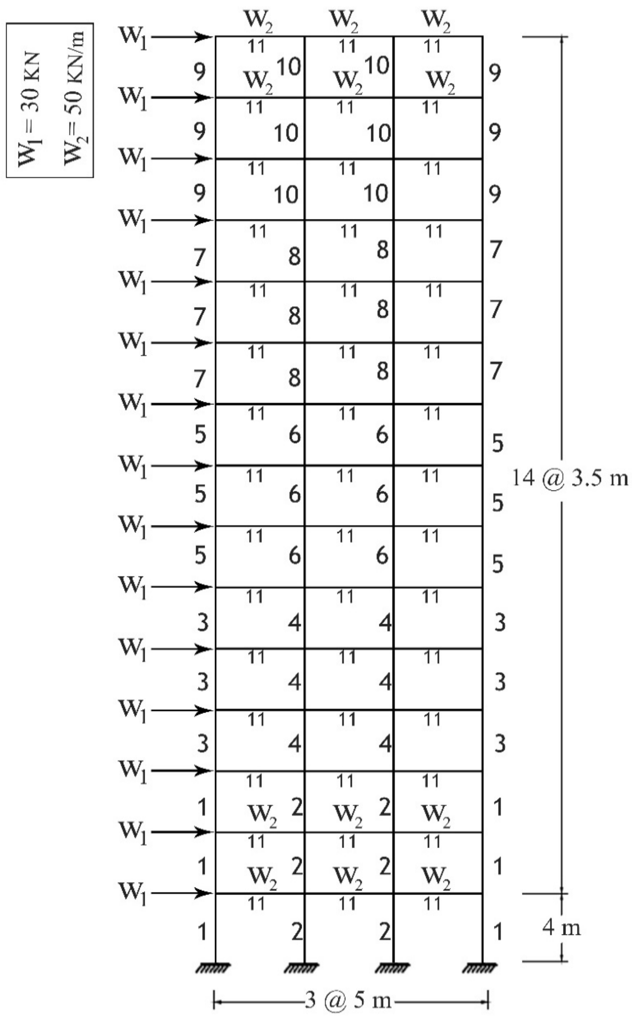


Fig. 2. The 3-bay 15-story steel frame structure

A fifteen-story frame structure with three openings containing 105 members is studied here with the loading as shown in Figure 2. The displacement and resistance constraints are considered according to AISC in the limit state (LRFD) for the problem. The modulus of elasticity and the yield stress are equal to 200 GPa and 248.2 MPa, respectively. Beams and columns groups of elements are selected from all 267 W cross section profiles of the AISC standard list.

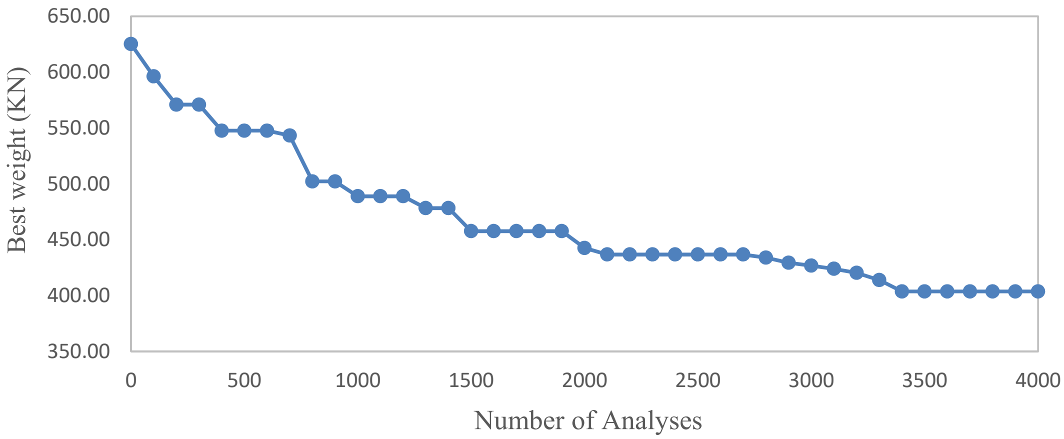


Fig. 3. Convergence history for the 3-bay 15-story frame obtained by GSS-

Table 1: Optimization results obtained for the 3-bay 15-story frame problem

Group No.#	**AISC W-shapes**#					
	PSO[1]#	HPSACO[2]#	HBB-BC[3]#	ICA[4]#	ES-DE[5]#	**GSS-PSO**#
1#	W33 X 118#	W21X 111#	W24 X 117#	W24 X 117#	W18 X 106#	**W21X44**#
2#	W33 X 263#	W18 X 158#	W21 X 132#	W21 X 147#	W36 X 150#	**W33X130**#
3#	W24 X 76#	W10 X 88#	W12 X 96#	W27 X 84#	W12 X 79#	**W18X143**#
4#	W36 X 256#	W30 X 116#	W18 X 119#	W27 X 114#	W27 X 114#	**W14X82**#
5#	W21 X 73#	W21 X 83#	W21 X 93#	W14 X 74#	W30 X 90#	**W21X101**#
6#	W18 X 86#	W24 X 103#	W18 X 97#	W18 X 86#	W10 X 88#	**W21X68**#
7#	W18 X 65#	W21 X 55#	W18 X 76#	W12 X 96#	W18 X 71#	**W14X82**#
8#	W21 X 68#	W27 X 114#	W18 X 65#	W24 X 68#	W18 X 65#	**W24X55**#
9#	W18 X 60#	W10 X 33#	W18 X 60#	W10 X 39#	W8 X 28#	**W30X90**#
10#	W18 X 65#	W18 X 46#	W10 X 39#	W12 X 40#	W12 X 40#	**W14X38**#
11 #	W21 X 44 #	W21 X 44 #	W21 X 48 #	W21 X 44 #	W21 X 48 #	**W18X40** #
Weight (KN)	496.68	426.36	434.54	417.466	415.06	**403.64**
Number of analyses#	# 50.000#	# 6800#	# 9900#	# 6000#	# 4050#	# **4000**#

1- particle swarm optimization [11]
2- heuristic particle swarm ant colony optimization [11]
3- hybrid Big Bang–Big Crunch optimization [22]
4- imperialist competitive algorithm [23]
5- eagle strategy algorithm with differential evolution [24]

The Convergence history for the 3-bay 15-story frame is shown in Figure 3. The global optimum design of the frame is obtained after 4000 analyzes with a minimum weight of 403.64 KN, an acceptable performance compared to the PSO [11], HPSACO [11], HBB-BC [22], ICA [23] and ES-DE [24] algorithms, each of which required 50,000, 6,800, 9900, 6000 and 4050 analyses, respectively, as displayed in Table 1. Also, an approximately 2.5% weight improvement has been recorded compared to the best algorithm on this list, namely ES-DE [24], endorsing a valid approach as proposed with satisfactorily results.

5.2 Design of pedestrian bridge

A real pedestrian bridge has been optimized to evaluate the effectiveness of the GSS-PSO algorithm in minimizing its weight allowing for the member size changes. The bridge problem was chosen with all the necessary design information collected from a real bridge problem according to its actual geometry and sections as built.

Figure 4 shows the overview of the pedestrian bridge. It had been designed and built with conventional pipe sections. The initial weight of the bridge is 11.5 tons according to the data available.

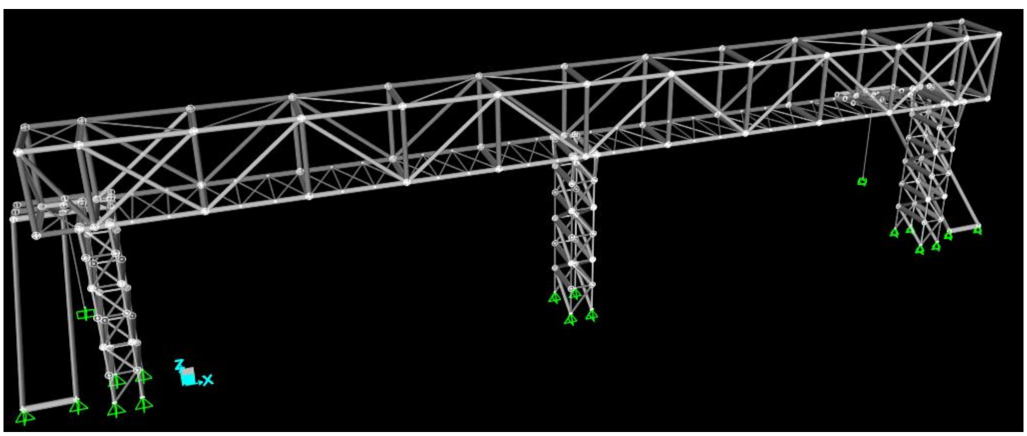


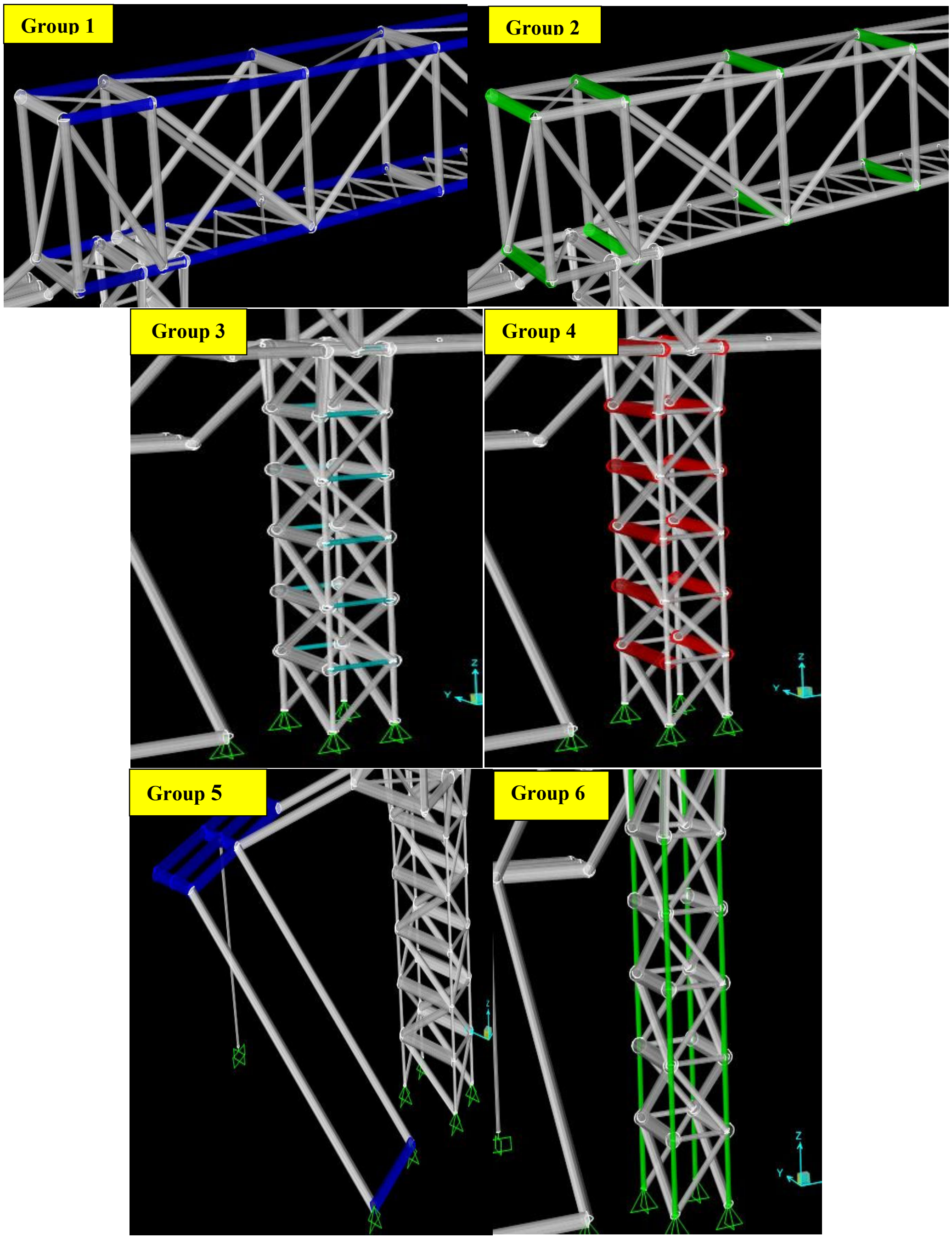
Fig. 4. Overview of the pedestrian bridge

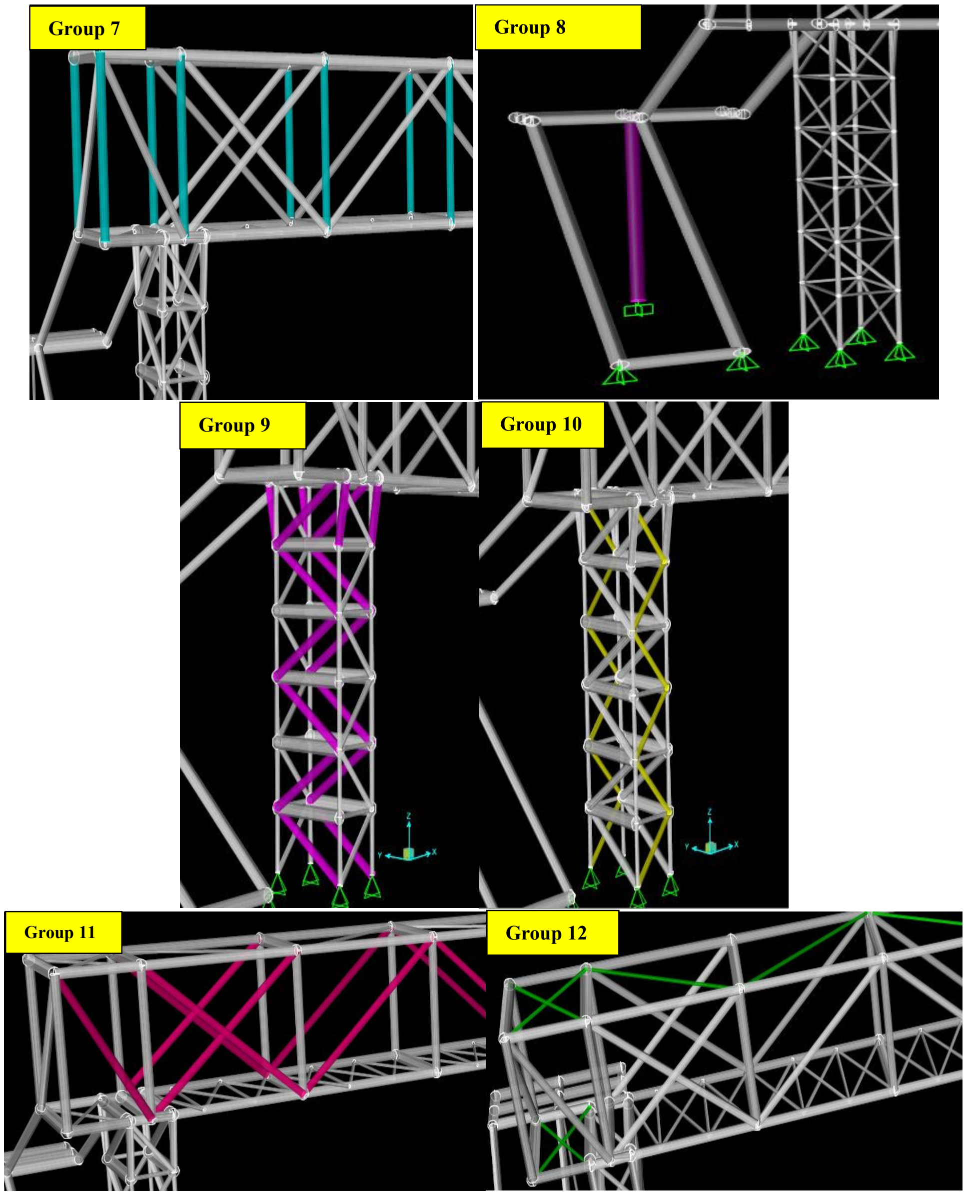
Table 2 shows the grouping of the bridge elements:

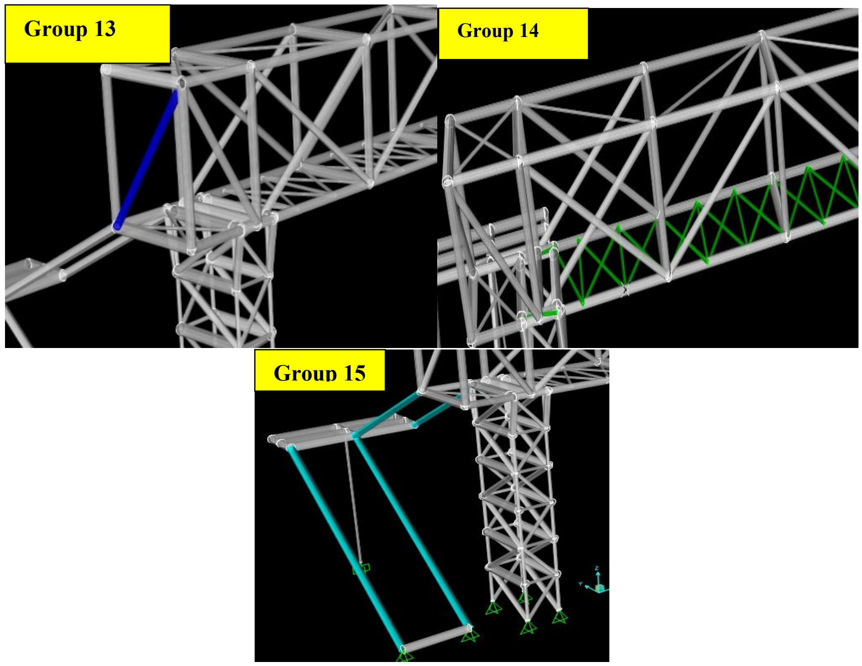
Table 2: Grouping of the bridge elements

Type	Beams					Columns			Braces						
Group No.	B1	B2	B3	B4	B5	C6	C7	C8	R9	R10	R11	R12	R13	R14	R15
Elements in each Group	60	26	36	48	26	72	26	2	48	36	26	18	2	82	8

For better visualization, parts for each group are shown in Figs. 5-19:


Group 1
Group 2
Group 3
Group 4
Group 5
Group 6


Group 7
Group 8
Group 9
Group 10
Group 11
Group 12



Figs. 5-19. An indication for each design variable (group) of the pedestrian bridge problem

The Pipe sections used to optimize the bridge are listed in Table 3:

Table 3: 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#**

Loading:

After applying the coefficients related to the earthquake load, dead and live loads are applied as the equivalent loads on the nodes in the direction of Gravity and the wind load is applied as the equivalent load of the node in the Y direction. Table 4 shows the values of the loads.

Table 4: Loads applied to the bridge

Types of Load	Location of the applied loads	Magnitudes (kgf/m^2)#
Dead#	Floor of the bridge	**120#**
Live#	Floor of the bridge	**1500#**
Wind#	Laterally (Bridge Base)	**35#**
Wind#	Laterally (Bridge Deck)	**158#**
Earthquake#	Laterally	**C=0.09, K=1.205#**

The bridge is designed in accordance with AISC / ASD 360-16 and the drift ratio constraint is used for the base that has a more critical position in the displacements, that is; inter story drift < story height / 300. The modulus of elasticity of the pipe sections is set to 200 GPa and the Yield limit stress f_y to 2400.

Table 5 shows the initial sections of the bridge and the sections obtained after optimization for each group:

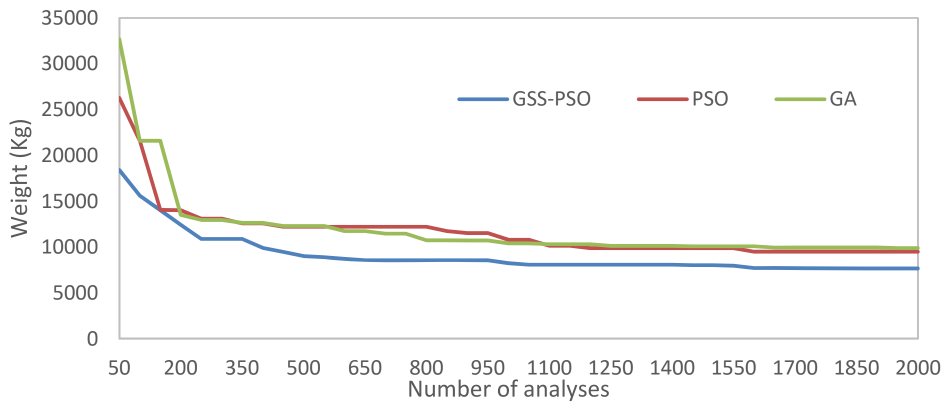


Fig. 20. Convergence histories for the pedestrian bridge using GA, PSO and GSS-PSO algorithms

Table 5: Optimum weights and sections of the bridge using GA, PSO and GSS-PSO algorithms

Groups name	Initial Sections	GA Optimum Sections	PSO Optimum Sections	**GSS-PSO Optimum Sections**
Group 1	PIPE-D168.3×4	PIPE-D219.1×3	PIPE-D219.1×3	**PIPE-D219.1×3**
Group 2	PIPE-D88.9×3.5	PIPE-D60.3×3	PIPE-D60.3×4	**PIPE-D60.3×3**
Group 3	PIPE-D168.3×3.5	PIPE-D60.3×3	PIPE-D140.3×4	**PIPE-D60.3×3**
Group 4	PIPE-D168.3×3.5	PIPE-D88.9×6	PIPE-D88.9×3	**PIPE-D60.3×3**
Group 5	PIPE-D168.3×3.5	PIPE-D219.1×6	PIPE-D219.1×4	**PIPE-D219.1×3**
Group 6	PIPE-D168.3×4	PIPE-D219.1×3	PIPE-D219.1×3	**PIPE-D76×3**
Group 7	PIPE-D168.3×3.5	PIPE-D114.3×3.5	PIPE-D114.3×3	**PIPE-D60.3×3**
Group 8	PIPE-D406.4×6.3	PIPE-D140.3×4.5	PIPE-D140.3×5	**PIPE-D140.3×3**
Group 9	PIPE-D88.9×3.5	PIPE-D114.3×5	PIPE-D76×3.5	**PIPE-D60.3×3**
Group 10	PIPE-D88.9×3.5	PIPE-D114.3×3	PIPE-D114.3×3	**PIPE-D60.3×3**
Group 11	PIPE-D168.3×4	PIPE-D88.9×6	PIPE-D140.3×4	**PIPE-D88.9×4**
Group 12	PIPE-D168.3×3.5	PIPE-D60.3×3	PIPE-D60.3×3	**PIPE-D60.3×3**
Group 13	PIPE-D88.9×3.5	PIPE-D60.3×3	PIPE-D60.3×3	**PIPE-D114.3×3**
Group 14	PIPE-D88.9×3.5	PIPE-D60.3×3	PIPE-D60.3×3	**PIPE-D60.3×3**
Group 15	PIPE-D168.3×4	PIPE-D168.3×4	PIPE-D168.3×4	**PIPE-D219.1×6**
Weight	11.5 ton	9.8 ton	9.5 ton	**7.6 ton**
Number of Analyses	-	2000	2000	**2000**

The convergence histories of the optimum results based on the three metaheuristic algorithms are illustrated in Figure 20. The GSS-PSO algorithm has a faster convergence rate than the other two algorithms and in the first 2000 analyzes the optimal solution is almost achieved. The PSO algorithm has shown the second promising performance with rather a slower act and more gradual convergence in the optimization process. In general, the GSS-PSO algorithm outperforms better in both convergence speed and the globality of the optimal solution.

6. CONCLUSION

The optimum design of pedestrian bridges under all the design constraints according to AISC Code of Practice is the objective of the present study. For that purpose, an innovative technique was employed inside which a modified PSO technique also plays a major role. It is a novel method inspired by the social behavior of animals such as birds or fish.

In the proposed technique here, randomly generated particles that were previously evenly distributed throughout the space, is consciously disturbed by dividing the search space into subspaces using a grid search method. This will cause the distribution of particles more attentive around the optimal solution.

Then, the sensitivity analysis was carried out where it consists of two parts: first, determining the orientation based on a step size and then followed by the Forward Finite Difference (FFD) method on the variables of the best particle under the presented spaces. They are allowed to adjust their values step by step, before tolerated to enter the modified PSO.

The proposed GSS-PSO method, was tested on a two-dimensional steel frame and a real three-dimensional pedestrian bridge. It displayed a high convergence speed, where a comparatively low number of analyzes was utilized with a more cost-effective optimal weight. This method is in particular recommended for problems where there are no borders predefined for the side constraints in the search space.

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