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Layout, Topology, and Size Optimization of Steel Frame Design using Metaheuristic Algorithms: A Comparative Study

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Abstract: Determining the topology, layout, and size of structural elements is one of the most important aspects in designing steel seismic-resistant structures. Optimization of these parameters is beneficial to find the lightest weight of the structure, thus reducing construction cost. This study compares the performance of three metaheuristic algorithms, namely, Particle Swarm Optimization (PSO), Symbiotic Organisms Search (SOS), and Differential Evolution (DE). Three study cases are used in order to find the lightest structural weight without violating constraints based on SNI 1726:2019, SNI 1729:2020, and SNI 7860:2020. The results of this study show that SOS has better performance than other algorithms.

Keywords: Optimization; metaheuristic; steel seismic-resistant structure; SNI 1726:2019; SNI 1729:2020; SNI 7860:2020.

Introduction

During the building design process, earthquake load is one of the parameters that govern the final structural design, especially in countries where earthquakes frequently occur such as Indonesia, which is located at the juncture of three tectonic plates along the Pacific "Ring of Fire." Therefore, a building built in Indonesia must have enough stiffness and ductility to sustain its integrity when an earthquake strikes. This is achieved by using a material and lateral load-resisting system that accommodates those requirements.

Due to its high strength, uniformity, and ductility [1], steel is the most common structural building material. In steel structures, the commonly used lateral load-resisting system are concentrically braced frame and moment frame. The concentrically braced frame is mainly used as studies have shown this lateral load-resisting system to have increased stiffness and lower inter-story drift [2,3]. There are many types of concentrically braced frames that can be used such as X-bracing and single diagonal bracing. X-bracing is mainly used because it can sustain both tension and compression forces at the same time, with good stiffness when an earthquake occurs. Single diagonal bracing is used because of smaller roof level displacement produced by the system compared to X-bracing [4]. Consequently, using both X-bracing and single diagonal bracing is beneficial for the overall performance of the structure.

Another commonly used lateral load-resisting system in steel structures is the moment frame. This is widely used in steel structures, especially in locations with low to moderate seismic activity where strength usually governs the design process. Advantages of the moment frame are high ductility and architectural versatility with good collapse mechanism (side sway mechanism), which is achieved by developing a plastic hinge at the ends of beams [1].

The goal of structural design in buildings is to find the minimum structural weight required and, thus, the lowest construction cost. Generally, engineers use their previous experience with trial-and-error to find the best possible topology and size of structural elements. However, this method is not effective and usually takes a lot of time to find the best combination [5]. This initiates researchers to develop a model to produce the optimum layout, topology, and size of steel structural elements.

Many studies have used metaheuristic algorithms as an optimizer for structural optimization problems [6–8]. Hasançebi et al. [6] implemented the Bat Inspired (BI) algorithm on four practical truss structures. Toğan [7] used the Teaching–Learning Based Optimization (TLBO) algorithm to minimize the total weight of a moment frame. Emanuel et al. [8] compared several nature-inspired algorithms to reduce the cost of a steel deck floor system. These studies showed that metaheuristic algorithms are capable of solving structural optimization problems with good results at reasonable computational cost.

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Numerous studies have also been conducted on the optimization of concentrically braced frames and moment frames [9–11]. Kaveh and Farhoudi [9] utilized Dolphin Monitoring (DM) on metaheuristic algorithms to improve the result of concentrically braced frame optimization to find the minimum weight of the structure. Gholizadeh and Ebadijalal [10] implemented a performance-based design method using Center of Mass Optimization (CMO) to reduce the overall weight of a concentrically braced frame. Murren and Khandelwal [11] optimized a moment frame using the Design-driven Harmony Search (DDHS) algorithm to find the optimum sections with least weight. However, few studies have considered both concentrically braced and moment frames in the optimization process using metaheuristic algorithms to find the minimum weight of the structure.

This research investigates the performance of three metaheuristic algorithms, namely, PSO, DE, and SOS, in optimizing the steel frame layout, topology, and size for both concentrically braced and moment frames. Three study cases are presented with five design requirements from SNI 1726:2019 [12], SNI 1729:2020 [13], and SNI 7860:2020 [14] to analyze the performance of the algorithms.

Metaheuristic Optimization Algorithms

The steel frame layout, topology, and size optimization process are very complex as they are highly constrained problems. Therefore, the following metaheuristic algorithms selected for this study have been developed for decades by researchers: Particle Swarm Optimization (PSO), Differential Evolution (DE), and Symbiotic Organisms Search (SOS). These three algorithms are selected because these algorithms already tested could find the solution of high constrained problem in many research, especially structural problem optimization [15].

Particle Swarm Optimization

Introduced by Kennedy and Eberhart in 1995 [16], PSO is inspired from observing how flocks of birds look for food. In the process, birds tend to fly to where they can get the most food for their group. This process is started by locating each particle randomly. At each iteration, each particle will move according to a speed vector determined from each particle's best location and overall particles' best location as shown in Equation (1). After moving, each particle will renew its location using Equation (2):

$$v_i(t+1) = wv_i(t) + r_1c_1\left(X_{pbest}(t) - X_i(t)\right) + r_2c_2\left(X_{gbest}(t) - X_i(t)\right), \quad (1)$$

$$X_i(t+1) = X_i(t) + v_i(t+1), \quad (2)$$

where $v_i(t+1)$ is the speed vector, w is the inertia weight parameter, $v_i(t)$ is the initial speed vector, c_1 is a cognitive parameter, c_2 is a social parameter, $X_{pbest}(t)$ is the location of particle personal best, $X_i(t)$ is the initial location of particle, $X_{gbest}(t)$ is the location of particle global best, and $X_i(t+1)$ is the new location of the particle.

Differential Evolution

In 1997, Storn and Prince developed a new algorithm, called DE [17]. It consists of three stages after producing a random population (initialization): mutation, crossover, and selection. At the mutation stage, three random populations are combined and mutated to a mutant vector by multiplying a factor F, which has value that varies from 0 to 2. The process is shown in Equation (3):

$$v_{i,G+1} = x_{r_1,G} + F \,.\left(x_{r_2,G} - x_{r_3,G}\right). \quad (3)$$

At the crossover stage, a trial vector is created. This process will ensure the vector's diversity as the initially generated vector is combined with the mutant vector with variable *CR* as a value between 0 and 1. The process is shown in Equations (4)–(6):

$$u_{i,G+1} = u_{1i,G+1},\ u_{2i,G+1}, \ldots,\ u_{Di,G+1}, \quad (4)$$

$$u_{ji,G+1} = v_{ji,G+1} \quad if(randb(j) \le CR)\ or\ j = rnbr(i), \quad (5)$$

$$u_{ji,G+1} = v_{ji,G+1} \quad if(randb(j) > CR)\ and\ j \ne rnbr(i). \quad (6)$$

At the selection stage, a fitness value is compared from the trial vector and initial population. The one with the better fitness value will be chosen for the next iteration process.

Symbiotic Organisms Search

SOS was introduced by Cheng and Prayogo in 2014 [18]. This algorithm is inspired by the natural phenomenon of symbiosis, which describes the relationship between organisms. The three types of symbiosis used in SOS are mutualism, commensalism, and parasitism. In the mutualism phase, organisms will interact to mutually benefit each other. Organisms are updated if their new fitness value is better than their old fitness value as shown in Equations (7)–(9):

$$X_{inew} = X_i + rand(0,1) * (X_{best} - Mutual\_Vector * BF_1), \quad (7)$$

$$X_{jnew} = X_i + rand(0,1) * (X_{best} - Mutual_{Vector} * BF_2), \quad (8)$$

$$Mutual\_Vector = \frac{X_i + X_j}{2}, \quad (9)$$

where X_{inew} is the new *i*-th organism candidate of the ecosystem, X_{jnew} is the new *j*-th organism of the ecosystem, BF is a random number between 1 and 2,

X_{best} is the best organism in the current iteration, and $Mutual\_Vector$ represents the organism's relationship. In the commensalism phase, organism X_i interacts with organism X_j without modifying organism X_j as shown in Equation (10):

$$X_{inew} = X_i + rand(-1,1) * \left(X_{best} - X_j\right). \tag{10}$$

If X_{inew} have better fitness value than X_i, X_{inew} will replace X_i from the ecosystem.

In the parasitism phase, a parasite vector is created by cloning organism X_i with a random variable. Then, organism X_j serves as a host for the parasite vector. The parasite vector will replace X_j in the ecosystem if the parasite vector has a better fitness value than X_j.

Formulation of the Optimization Problem

Mathematical Optimization Model

In this study, minimizing the overall structural weight is performed using the topology and placement (layout) of bracings and size of members as optimization variables. The objective function of this study is as follows:

$$Minimize\, f(x) = \gamma \textstyle\sum_{i=1} A_i L_i, \tag{11}$$

where $f(x)$ is the objective function, γ is the density of steel, A_i is the cross section area of i-th member, and L_i is the length of i-th member.

The members must satisfy design requirements from SNI 1726:2019, SNI 1729:2020, and SNI 7860:2020 [11-13] to ensure the integrity of the structure. Design requirements used in this study are shown in Table 1.

Table 1. Design Requirements for Optimization Process

No	Design Requirement	Formula	References
1	Inter-story drift	$\Delta \le 0.02h_{sx}$	[11]
2	Stability	$\theta \le 0.1$	[11]
3	Shear, flexural, and axial capacity	$R_u \le \phi R_n$	[12]
4	Axial–flexural member interaction	for $\frac{Pr}{Pc} \ge 0.2$ $f = \frac{Pr}{Pc} + \frac{8}{9}\left(\frac{Mr}{Mc}\right) \le 1$ for $\frac{Pr}{Pc} < 0.2$ $f = \frac{Pr}{2Pc} + \left(\frac{Mr}{Mc}\right) \le 1$	[12]
5	Capacity design	Moment frame: $\frac{\sum Mpc}{\sum Mpb} > 1$ Concentrically braced frame: P_{max} (compression) = 0.3 min($R_y f_y A_g$, 1.14$F_{cre} A_g$) P_{max} (tension) = $R_y f_y A_g$	[13]

Table 2 summarizes the constraints used for the optimization process in this study. For every constraint violated in the optimization process, a penalty function will be applied to the structure. The value of the penalty depends on the severity of the violation. Table 3 reports the penalty function used for each constraint in this study. Coefficients of penalty functions are based on the trial and error method where it is observed that constraint g3(x) and g4(x) are the most common violated constraints followed by constraint g5(x), g1(x), and g2(x).

Table 2. Constraints for Optimization Process

Constraint	Design Requirement
$g_1(x)$	Inter-story drift
$g_2(x)$	Stability
$g_3(x)$	Member capacity
$g_4(x)$	Axial–flexural member interaction
$g_5(x)$	Capacity design

Table 3. Penalty Function for Each Constraint

Constraint	Penalty Function
$g_1(x)$	$25000^{2^{\log(3\frac{\Delta}{0.02h_{sx}})}}$
$g_2(x)$	$25000^{2^{\log(3\frac{\theta}{0.1})}}$
$g_3(x)$	$(\frac{Ru}{\phi Rn} - (\frac{Ru}{\phi Rn} \bmod 1))75000^{2^{\log(3(\frac{Ru}{\phi Rn} - (\frac{Ru}{\phi Rn} \bmod 1)))}}$
$g_4(x)$	$75000^{2^{\log(3f)}}$
$g_5(x)$	$65000^{2^{\log(3\frac{\sum Mpb}{\sum Mpc})}}$

Structural Model

The discrete approach is used for the optimization process. Thus, all structural elements used in this study are taken from a list of available standard profiles that is already sorted for highly ductile members as regulated from SNI 7860:2020 [13]. Tables 4 and 5 list available sections used for beam and column (wide flange) and bracing (HSS), respectively.

Table 4. List of Wide Flange Sections for Beam and Column

No.	**Section**	**No.**	**Section**
1.	WF 708x302x15x28	13.	WF 250x125x6x9
2.	WF 594x302x14x23	14.	WF 208x202x10x16
3.	WF 588x300x12x20	15.	WF 200x100x5.5x8
4.	WF 612x202x13x23	16.	WF 198x99x4.5x7
5.	WF 506x201x11x19	17.	WF 175x90x5x8
6.	WF 500x200x10x16	18.	WF 150x150x7x10
7.	WF 450x200x9x14	19.	WF 148x100x6x9
8.	WF 498x432x45x70	20.	WF 150x75x5x7
9.	WF 458x417x30x50	21.	WF 125x125x6.5x9
10.	WF 428x407x20x35	22.	WF 125x60x6x8
11.	WF 414x405x18x28	23.	WF 100x100x6x8
12.	WF 298x201x9x14	24.	WF 100x50x5x7

Table 5. List of HSS Sections for Bracing

No.	Section	No.	Section
1.	HSS 14x14x7/8	12.	HSS 5x5x3/8
2.	HSS 12x12x3/4	13.	HSS 5x5x5/16
3.	HSS 10x10x5/8	14.	HSS 4.5x4.5x3/8
4.	HSS 8x8x5/8	15.	HSS 4.5x4.5x5/16
5.	HSS 8x8x1/2	16.	HSS 4x4x1/2
6.	HSS 7x7x5/8	17.	HSS 4x4x3/8
7.	HSS 7x7x1/2	18.	HSS 4x4x5/16
8.	HSS 6x6x5/8	19.	HSS 4x4x1/4
9.	HSS 6x6x1/2	20.	HSS 3.5x3.5x3/8
10.	HSS 6x6x3/8	21.	HSS 3.5x3.5x5/16
11.	HSS 5x5x1/2	22.	HSS 3.5x3.5x1/4

Four topologies are available for this study as shown in Figure 1. Because there are 22 available sections for bracings, the topology will be defined by a range of numbers for each topology. For both bracings, a number 1–22 is used while the only first bracing and the only second bracing use a number 23–44 and 45–66, respectively. Without bracing topology uses number 0.

Optimization Results

In this research, three study cases are simulated using three algorithms: Differential Evolution, Particle Swarm Optimization, and Symbiotic Organisms Search. Each algorithm is run 30 times with 300 populations and 2,000 iterations for all three study cases to obtain the best solution and prevent random bias. The three study cases are three-story, six-story, and twelve-story frames, with five bays in each study case. Design parameters for all study cases are shown in Table 6.

Case Study 1: Three-story Frame

There are 18 columns, 15 beams, and 15 possible locations for bracing, which in total comprise 48 random variables. Thus, the variables have to be grouped in order to make the algorithm find the optimal solution more easily. Figure 2 shows the grouping variable of each element and the results are summarized in Table 7.

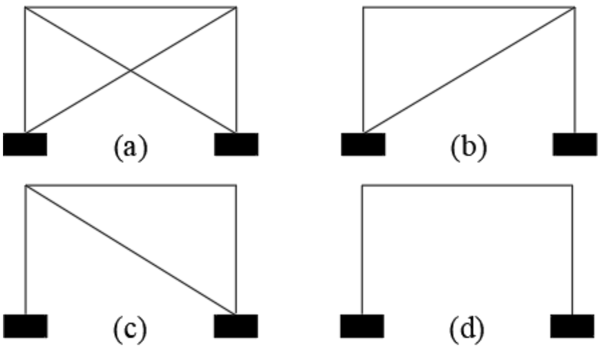

Figure 1. Topology Variables for Each Bay and Story: Both Bracing (a), Only First Bracing (b), Only Second Bracing (c), and Without Bracing (d)

Table 6. Design Parameters

No	Parameter	Value
1	Material properties	ρ = 78.5 kN/m^3 E = 2e8 kN/m^2 μ = 0.3 fy = 240 MPa Ry = 1.5
2	Geometry	Floor to floor height = 3 m Bay width = 5 m Three degrees of freedom (x,y,z) Rigid connection in each joint
3	Loads	Superimposed dead load: 6.3 kN/m^2 Live load: 1.96 kN/m^2 Earthquake loads: calculated according to SNI 1726:2019 [11], by considering, S_s = 0.6, S_1 = 0.3, I_e = 1, and seismic design category = D

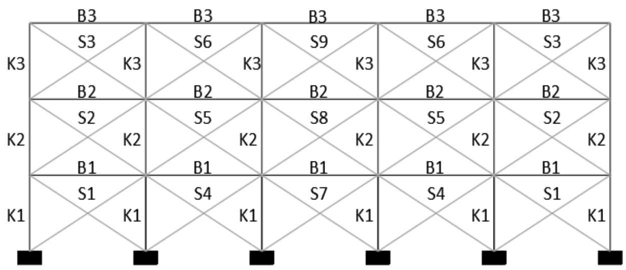

Figure 2. Column, Beam, and Bracing Grouping Variable for Three-story Frame

Table 7. Three-story Frame's Optimal Solution

Algorithm	Minimum (kN)	Maximum (kN)	Median (kN)	Mean (kN)	Standard Deviation	Success Rate
DE	104.13	108.69	104.13	105.21	1.35	30/30
PSO	113.75	216.67	173.54	165.07	29.11	30/30
SOS	104.13	104.13	104.13	104.13	0	30/30

Table 7 shows that DE and SOS are able to find an optimal solution with 104.13 kN in the moment frame structural system. Even though DE achieved the same optimal solution, SOS is better in terms of consistency by finding the optimal solution 30 times. Thus, with zero standard deviation, 104.13 kN is the best possible results from this study case. From 30 simulations of each algorithm, the median result is taken and drawn in a convergence graph to analyze the algorithm's behavior. The convergence graph is shown in Figure 3. Figure 4 visualizes the lightest structure with 114.88 kN if the structural system is forced to be a concentrically braced frame.

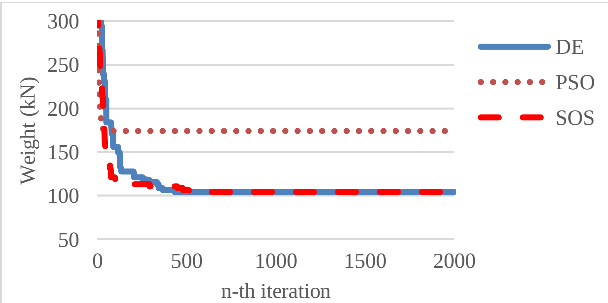

Figure 3. Convergence Graph Median Results for a Three-story Frame

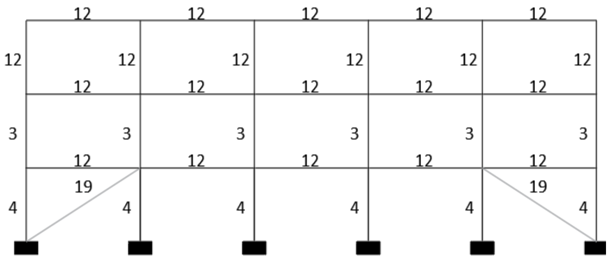

Figure 4. Lightest Structure for a Three-story Concentrically Braced Frame with Section Numbers Based on Tables 4 and 5

Case Study 2: Six-story Frame

For this case study, there are two phases of variable grouping. The first phase shown in Figure 5a is simulated until the 1,000th iteration and the second phase shown in Figure 5b is simulated from the 1,001st iteration until the 2,000th. Table 8 shows the optimal solution from each algorithm.

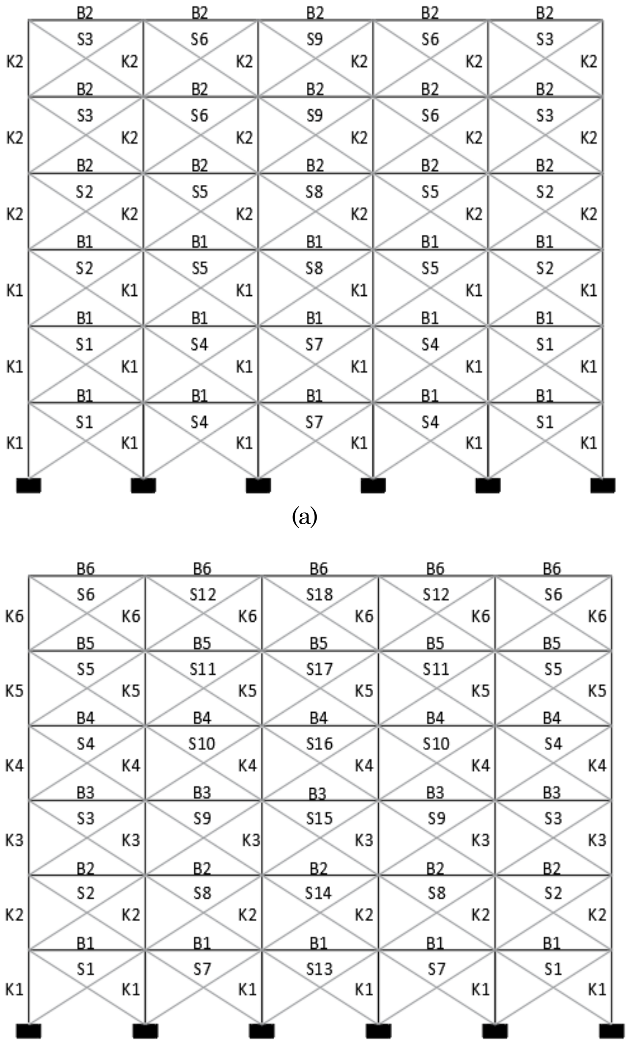

Figure 5. Column, Beam, and Bracing Grouping Variable for the First Phase (a) and Second Phase (b) of a Six-story Frame

Table 8. Six-story Frame's Optimal Solution

Algorithm	Minimum (kN)	Maximum (kN)	Median (kN)	Mean (kN)	Standard Deviation	Success Rate
DE	267.46	317.12	272.76	281.92	15.36	30/30
PSO	290.04	565.65	468.90	445.93	77.34	30/30
SOS	253.72	368.85	319.22	311.21	36.99	30/30

It is observed that SOS can find the best solution among the three algorithms with 253.72 kN in the moment frame structural system. Even though SOS has the best solution, DE still has the smallest standard deviation with 15.36 kN and PSO has the worst. Figure 6 shows the convergence behavior of each algorithm in process to get the solution and Figure 7 visualizes the lightest structure for a six-story concentrically braced frame.

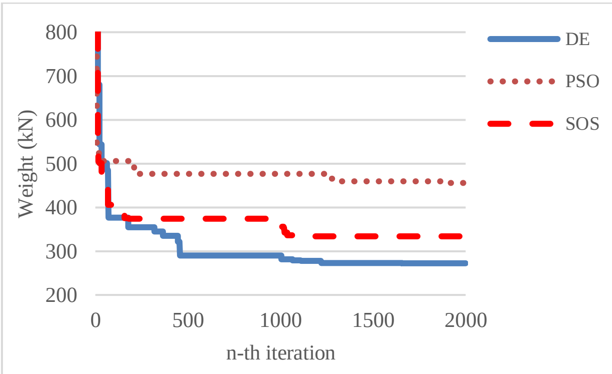

Figure 6. Convergence Graph Median Result for a Six-story Frame

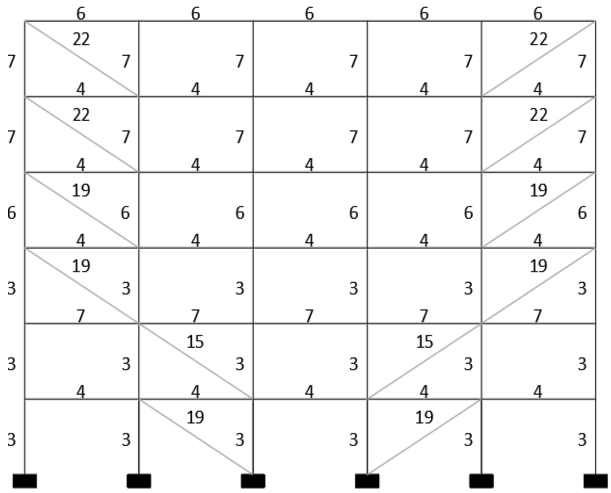

Figure 7. Lightest Structure for Six-story Concentrically Braced Frame with Section Numbers Based on Tables 4 and 5

Case Study 3: Twelve-story Frame

Variable grouping of the third case study is similar to the second case study. Grouping details can be seen in Figure 8 and Table 9 reports the optimization results.

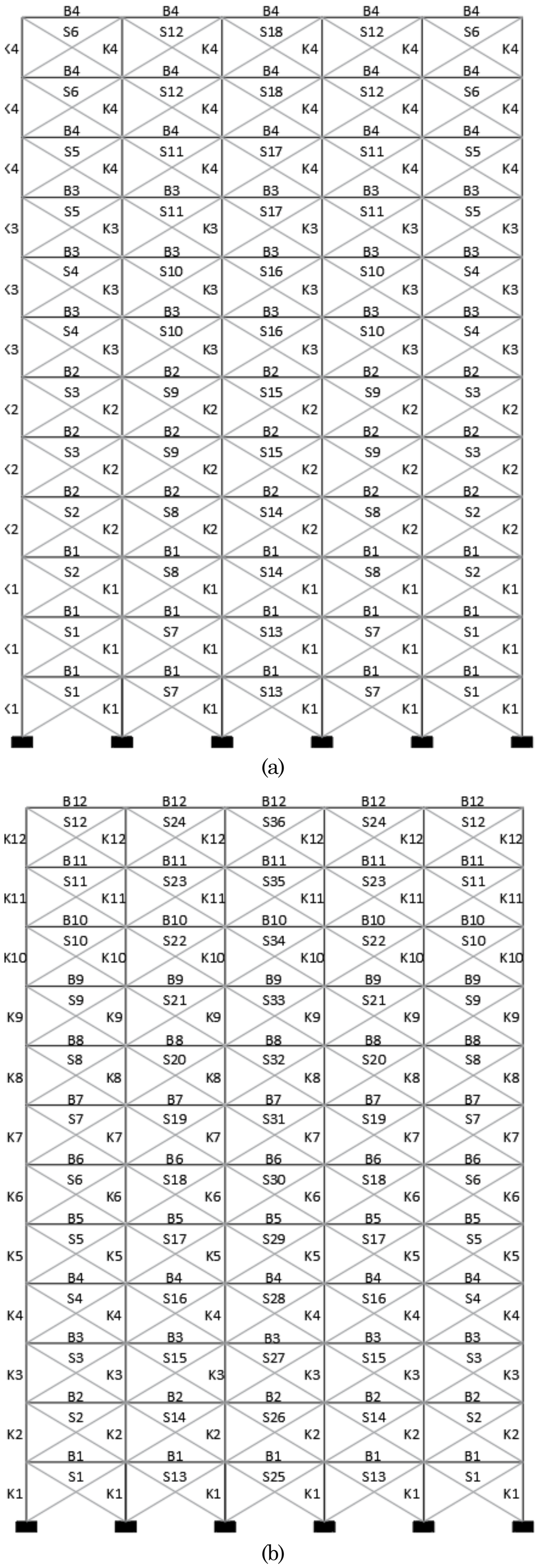

Figure 8. Column, Beam, and Bracing Grouping Variable for the First Phase (a) and Second Phase (b) of a Twelve-story Frame

Table 9. Twelve-story Frame's Optimal Solution

Algo-rithm	Mini-mum (kN)	Maxi-mum (kN)	Median (kN)	Mean (kN)	Standard Deviation	Success Rate
DE	852.25	1108.80	1059.50	1047.90	55.08	30/30
PSO	1070.10	1348.50	1141.20	1145.10	59.59	16/30
SOS	640.30	1352.90	1070.30	990.76	227.47	30/30

From Table 9, it is inferred that all three algorithms can find an optimal solution with SOS as the optimum with 640.3 kN in the moment frame structural system. PSO cannot find an optimum solution for every simulation in twelve-story frame., This caused the algorithm to become stuck in local optima. While SOS has the best solution, DE has the most stable solution and lowest standard deviation. Figure 9 shows the convergence behavior of each algorithm in process to obtain the solution and Figure 10 visualizes the lightest structure for a twelve-story concentrically braced frame.

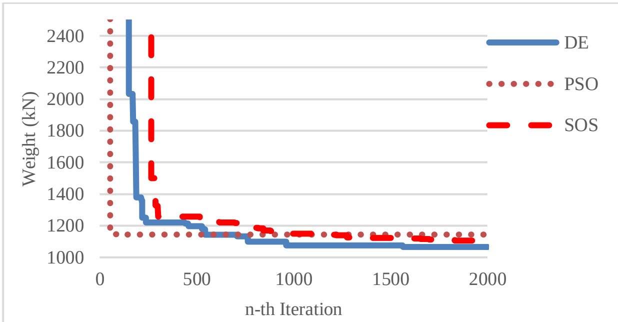

Figure 9. Convergence Graph Median Result for a Twelve-story Frame

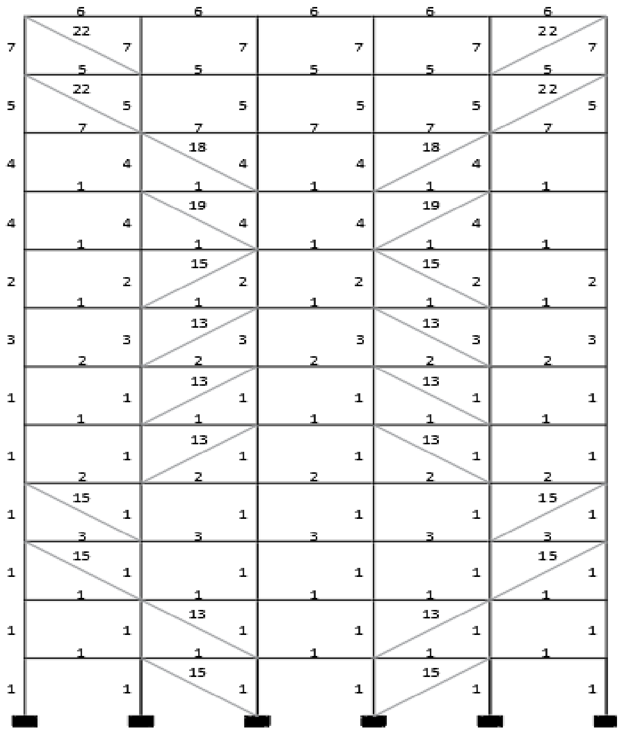

Figure 10. Lightest Structure for a Twelve-story Concentrically Braced Frame with Section Numbers Based on Tables 4 and 5

Conclusions

In this study, three metaheuristic algorithms, namely, PSO, SOS, and DE, are compared to solve the steel frame design problem. Three study cases with five objective functions are used to measure the performance of the algorithms. It is found that SOS is the best algorithm in term of the most optimum solution while DE is the most stable. It can also be concluded that using the moment frame is more effective than the concentrically braced frame in determining the lightest weight of a structure. Also, single diagonal bracing is more effective than X bracing.

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