INTERNATIONAL JOURNAL OF OPTIMIZATION IN CIVIL ENGINEERING
Int. J. Optim. Civil Eng., 2023; 13(3):309-325

OPTIMUM DESIGN OF THE FRAME STRUCTURES USING THE FORCE METHOD AND THREE RECENTLY IMPROVED METAHEURISTIC ALGORITHMS

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ABSTRACT

In this paper, three recently improved metaheuristic algorithms are utilized for the optimum design of the frame structures using the force method. These algorithms include enhanced colliding bodies optimization (ECBO), improved shuffled Jaya algorithm (IS-Jaya), and Vibrating particles system - statistical regeneration mechanism algorithm (VPS-SRM). The structures considered in this study have a lower degree of statical indeterminacy (DSI) than their degree of kinematical indeterminacy (DKI). Therefore, the force method is the most suitable analysis method for these structures. The robustness and performance of these methods are evaluated by the three design examples named 1-bay 10-story steel frame, 3-bay 15-story steel frame, and 3-bay 24-story steel frame.

Keywords: Enhanced colliding bodies optimization, improved shuffled Jaya algorithm, vibrating particles system - statistical regeneration mechanism algorithm, force method, structural optimization, metaheuristic algorithms.

Received: 15 February 2023; Accepted: 6 April 2023

[DOI: 10.22068/ijoce.2023.13.3.556]

1. INTRODUCTION

Optimization has grown in popularity as a research topic over the last four decades. Optimization is the process of determining the function's minimal or maximum value while satisfying the considered constraints [1, 2]. Metaheuristic algorithms are simple and do not need the gradient informant, so they are very popular than other optimization methods [3, 4]. Therefore, structural optimizers utilize metaheuristic algorithms as optimization methods for their problems.

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According to the no-free lunch theorems, a single optimization method cannot solve all types of optimization problems [5]. As a result, researchers develop new meta-heuristic algorithms that draw inspiration from various sources. Meta-heuristic algorithms can be classified into four classes based on their source of inspiration. The first class is the evolutionary-based algorithms which are inspired by biological evolution behaviors. Genetic Algorithm (GA) [6], Shuffled Complex Evolution (SCE) [7], Biogeography-Based Optimizer (BBO) [8], and Monkey King Evolutionary (MKE) [9] are examples of this group. The second category of algorithms is human-based algorithms. These algorithms mimic human behavior, such as Harmony Search Algorithm (HS) [10], Imperialist Competitive Algorithm (ICA) [11], Social emotional optimization algorithm (SEOA) [12] , Tiki-Taka Algorithm (TTA) [13], League championship algorithm (LCA) [14], Soccer Game Optimization (SGO) [15], Shuffled Shepherd Optimization algorithm (SSOA) [16], Past Present Future Algorithm (PPF) [17], and Volleyball Premier League Algorithm (VPL) [18].

The third type of algorithm is swarm-based, which mimics the social behavior of various animals. Particle Swarm Optimization (PSO) [19], Emperor Penguin Optimizer [20], Killer Whale Algorithm (KWA) [21], , Dragonfly algorithm (DA) [22], Animal Migration Optimization Algorithm [23], Bird Swarm Algorithm (BSA) [24], Butterfly Optimization Algorithm (BOA) [25], and Fruit Fly Optimization (FFO) [26] are the example of this group. The final class of algorithms is physics-based algorithms, which employ physical laws to generate a new solution in each iteration, such as, Sonar Inspired Optimization (SIO) [27], Radial Movement Optimization (RMO) [28], Ray Optimization [29], Lightning Search Algorithm (LSA) [30], Tug of War Optimization (TWO) [31], Electro-magnetism Optimization (EMO) [32], and Ions Motion Optimization (IMO) [33].

Developing new metaheuristic algorithms is helpful in handling new optimization problems. However, improving the existing algorithms is more suitable to handle the different optimization problems. For example, Kaveh and Talatahari [34] presented a new version of the charged system search for the optimum truss structure design. Nabati and Gholizadeh [35] introduced the modified version of the Newton algorithm for the performance-based optimization of the steel frame. Alkayem et al. [36] presented a novel oppositional unified particle swarm gradient-based optimizer for structural damage detection problems. Kaveh and Zaerreza [37] applied the metaheuristic algorithms for reliability-based design optimization of the steel frame. Ilchi Ghazaan et al. [38] developed the hybrid version of the colliding bodies optimization for the optimal design of the truss and frame structures. Dehghani et al. [39] presented a modified version of the adolescent identity search algorithm for the optimum design of the frame structures.

The displacement and force methods are the two well-known structural analyzing methods [40]. The computing time required by these methods is proportional to the number of equations that must be solved to obtain the stress or displacement of the nodes. The number of equations depends on the degree of kinematical indeterminacy (DKI) and the degree of statical indeterminacy (DSI). The DKI and DSI values represented the number of equations to be solved using the displacement and force methods, respectively. Although the time difference is not significant during a single analysis, the time gap grows over the optimization process owing to many structural analyses. Therefore, the researchers applied the force method instead of the displacement method with the optimization problem has less

[DOI: 10.22068/ijoce.2023.13.3.556]

DSI than DKI. For example, Kaveh and Malakoutirad [41] applied the force method for the optimum design of the structures using the hybrid genetic algorithm and particle swarm optimization. Kaveh and Rahami [42] applied the force method for the optimum design of the truss structures.

In this paper, for the first time, three improved algorithms named the enhanced colliding bodies optimization (ECBO), improved shuffled Jaya algorithm (IS-Jaya), and Vibrating particles system - statistical regeneration mechanism algorithm (VPS-SRM) are applied to the optimum design of the frame structures using the force method. The structures considered in this study have lower DSI than DKI. Hence the force method is faster than the displacement method. In addition, Kaveh and Zaerreza [43] demonstrate the effectiveness of the force method on the structures analyzed in this work. For this purpose, the force method is utilized as the structural analysis method.

2. FORCE METHOD

There are different types of force methods, including the topological force method [44], integrated force method, algebraic force method, and graph theoretical force method [45, 46]. The graph-theoretical force method is easier to implement than other force methods, and the resultant flexibility matrix is sparser than the other force methods [47]. This study employs the graph-theoretical force method as a result.

Considered the structure with γ time statically independent. In order to obtain the stress of the member using Eq. (1), the γ independents unknown are eliminated from the structure.

$$\boldsymbol{r} = \boldsymbol{B}_0\boldsymbol{p} + \boldsymbol{B}_1\boldsymbol{q} \tag{1}$$

where $\boldsymbol{r}$ represents the stress of the members, $\boldsymbol{p}$ represents the joint loads; $\boldsymbol{q}$ represents the forces of redundants; $\boldsymbol{B}_0$ and $\boldsymbol{B}_1$ are rectangular matrices with *m* rows and *n* and γ columns, respectively; *n* represents the number of joint load components, and m represents the number of independent member components.

In Eq.1, the force of redundants is unknown. Therefore, the load-displacement relationship and the virtual work concept are employed to eliminate q from Eq. (1). The Eq.(1) is restructured as illustrated below:

$$\boldsymbol{v}_0 = [\boldsymbol{B}_0^t\boldsymbol{F}_m\boldsymbol{B}_0 - \boldsymbol{B}_0\boldsymbol{F}_m\boldsymbol{B}_1(\boldsymbol{B}_1^t\boldsymbol{F}_m\boldsymbol{B}_1)^{-1}\boldsymbol{B}_1^t\boldsymbol{F}_m\boldsymbol{B}_0]\boldsymbol{p} \tag{2}$$

$$\boldsymbol{r} = [\boldsymbol{B}_0 - \boldsymbol{B}_1(\boldsymbol{B}_1^t\boldsymbol{F}_m\boldsymbol{B}_1)^{-1}\boldsymbol{B}_1^t\boldsymbol{F}_m\boldsymbol{B}_0]\boldsymbol{p} \tag{3}$$

where the $\boldsymbol{v}_0$ represents the displacement associated with the force components of $\boldsymbol{p}$, $\boldsymbol{F}_m$ is the unassembled flexibility matrix, $\boldsymbol{G} = \boldsymbol{B}_1^t\boldsymbol{F}_m\boldsymbol{B}_1$ is known as the flexibility matrix of the structure.

In various variations of the force method, the $\boldsymbol{B}_0$ and $\boldsymbol{B}_1$ matrices are produced in various ways. Using the graph-theoretical force method, the spanning forest is generated from

[DOI: 10.22068/ijoce.2023.13.3.556]

structural supports in order to construct the $\boldsymbol{B}_0$ matrix. Calculating each sub-matrix of the $\boldsymbol{B}_0$ by transferring each joint load to a support node. More details are accessible in Refs. [43, 47].

For the form of the $\boldsymbol{B}_1$, the set of the cycle basis is required. Various algorithms exist for discovering the cycle basis. Nevertheless, the Kaveh's methods produce a sparser matrix than other techniques. After generating the cycle basis using the Kaveh methods, one element of each cycle is cut at its initial node, and six bi-actions are applied. In the $\boldsymbol{B}_1$ sub-matrix, the columns represent the internal forces at the lower-numbered end of the *i*th member when six bi-actions are applied at the *j*th cut. More details are accessible in Refs. [46, 47].

3. IMPROVED METAHEURISTICS

3.1 Enhanced colliding bodies optimization

Enhanced colliding bodies optimization algorithm (ECBO) is developed by Kaveh and Ilchi Ghazaan [48]. ECBO is one of the famous improved metaheuristic algorithms which is used in different fields such as reliability assessment of trusses [49], and reliability-based optimization of the dome trusses [50]. ECBO algorithm starts with the solutions generated randomly in the search space, each of which is called as Colliding Body (CB). Then, CBs are evaluated, and the specified mass for them is calculated using Eq (4).

$$m_i = \frac{1/f(CB_i)}{\sum_{i=1}^{nCB} 1/f(CB_i)} \quad ; \quad i = 1,2,\dots,nCB \tag{4}$$

where $f(CB_i)$ represents the objective function value of the ith CB, and nCB is the number of colliding bodies. After that, the specified number of the best solution are stored in the memory named colliding memory (CM). This memory is updated in each iteration of the optimization. Using CM, the vector of solutions saved in CM is added to the current population, and the same number of the current worst CBs are deleted in each iteration. Next, the candidate solutions are sorted based on their mass and divided into two district groups. The first fifty percent of the sorted population is considered the first group and named stationary CBs, while the next half of them are assumed to be moving objects. The moving CBs are moving toward the stationary CBs. The velocities of the stationary and moving CBs are calculated as follows:

$$v_i = 0 \quad ; \quad i = 1,2,\dots,\frac{nCB}{2} \tag{5}$$

$$v_i = CB_{i-\frac{nCB}{2}} - CB_i \quad ; \quad i = \frac{nCB}{2}+1, \frac{nCB}{2}+2,\dots,nCB \tag{6}$$

[DOI: 10.22068/ijoce.2023.13.3.556]

$$v_i' = \frac{\left(m_{i+\frac{nCB}{2}} + \varepsilon m_{i+\frac{nCB}{2}}\right) v_{i+\frac{nCB}{2}}}{m_i + m_{i-\frac{nCB}{2}}} \quad ; \quad i = 1,2, \dots, \frac{nCB}{2} \tag{7}$$

$$v_i' = \frac{\left(m_i - \varepsilon m_{i-\frac{nCB}{2}}\right) v_i}{m_i + m_{i-\frac{nCB}{2}}} \quad ; \quad i = \frac{nCB}{2} + 1, \frac{nCB}{2} + 2, \dots, nCB \tag{8}$$

$$\varepsilon = 1 - \frac{it}{MaxNITs} \tag{9}$$

where v_i is the velocities of the CBs before collision, v_i' is the velocities of the CBs after collision, ε is the coefficient of restitution (COR) decreasing linearly from unit to zero; it is the current iteration number of the algorithm; $MaxNITs$ is the maximum number of algorithm iterations. After calculating the velocities, the new position of the stationery and moving CBs are calculated using Eqs. (10) and (11).

$$CB_{new,i} = CB_{old,i} + rand_i \circ v_i' \quad ; \quad i = 1,2, \dots, \frac{nCB}{2} \tag{10}$$

$$CB_{new,i} = CB_{old,i-\frac{nCB}{2}} + rand_i \circ v_i' \quad ; \quad i = \frac{nCB}{2} + 1, \frac{nCB}{2} + 2, \dots, nCB \tag{11}$$

where $rand_i$ generates a uniformly distributed random vector in which each component is in the range of $[-1,1]$ and the sign ‘‘∘’’ is the element-by-element multiplication between two vectors.

In order to prevent the early convergence in the ECBO, the escape from the local optima mechanism is considered. If a randomly generated number in the range of $(0,1)$ is less than the specified value (i.e., pro), then escaping from the local optima mechanism is applied. In this mechanism, one of the design variables is selected randomly and regenerated randomly in the search space. The optimization process will be ended when the maximum number of iterations is reached.

3.2 Improved shuffled Jaya algorithm

The second algorithm considered in this study to investigate its performance in the optimum design of the frame structures using the force method is the improved shuffled Jaya algorithm (IS-Jaya). IS-Jaya is developed by Kaveh et al. [51] to improve the Jaya algorithm's performance. IS-Jaya performs well in both optimization problems with discrete and continuous design variables [52]. Like the other metaheuristic optimization method, this algorithm is started from the solution, which is randomly generated in the search space. Then the solutions are divided into subpopulations using the shuffled procedure. To this end,

[DOI: 10.22068/ijoce.2023.13.3.556]

first, all of the solutions are sorted based on their objective function. Then, equal to the number of subpopulations, the best solutions are selected and randomly added to each subpopulation. To place the second member of each subpopulation, the best solution of rest of solutions is selected and added randomly to each subpopulation. This process is repeated until all of the solutions are divided into subpopulations. More detail about the shuffled process is available in Ref [16]. Then, the step size for each solution is generated using Eq. (12).

$$Stepsize_i = rand \times (X_{best} - X_i) - rand \times (X_{worst} - X_i) \tag{12}$$

where the $rand$ is the random vector generated between 0 and 1. X_i is the considered solution. X_{best} and X_{worst} are the best and worst solutions for the subpopulation to which X_i belongs. After that, the new solution is calculated as follows.

$$X_i^{new} = X_i + Stepsize_i \tag{13}$$

Then, the escaping from local optima mechanism is applied. To do this, one solution in each subpopulation is selected, and one variable of them is regenerated using Eq. (14).

$$X_i^{new} = X_i^{new} + 0.1 \times randn \times (X_{max} - X_{min}) \tag{14}$$

in which $randn$ is the normally distributed random number. X_{max} is the upper bound of the search space. X_{min} is the lower bound of the search space. After that, the replacement strategy is applied. Using this strategy, the new solution is compared with their old solution in the aspect of the objective function, and the worst of them are omitted. Same as the ECBO, the IS-Jaya algorithm stopped when the maximum number of iterations is reached.

3.3 Vibrating particles system - statistical regeneration mechanism algorithm

The vibrating particles system - statistical regeneration mechanism algorithm (VPS-SRM) is the new improved version of the VPS, which is developed by Kaveh et al. [53]. VPS-SRM is started from the solution which is generated randomly in the search space. Then the new position of each candidate solution is generated. In the VPS-SRM, 80 percent of the solution is generated using the following equation.

$$Vp_i^{new} = w_1 \times (D \times A \times r_1 + HA) + w_2 \times (D \times A \times r_2 + GA) + w_3 \times (D \times A \times r_3 + BA) \tag{15}$$

where Vp_i^{new} is the new position of the *i*th agent in the search space. r_1, r_2, and r_3 are the random number which is generated between 0 and 1. w_1, w_2, and w_3 are the parameter of the algorithm, which sum of them is one. HA is the best solution obtained so far. The parameter like p is defined by the user within (0,1), and the random number within (0,1) is generated for each agent. If the $p < random\ number$, then w_3 is set to zero. D and A are defined as follows:

$$D = \left(\frac{Iter}{MaxIter}\right)^{-\alpha} \tag{16}$$

$$A = w_1 \times \left(HA - VP_i^{old}\right) + w_2 \times \left(GA - VP_i^{old}\right) + w_3 \times \left(BA - VP_i^{old}\right) \tag{17}$$

in which $Iter$ is the current number of the iteration. $MaxIter$ is the maximum number of the iteration. α is the user-defined parameter, and VP_i^{old} is the position of the ith particle in the previous iteration.

Remaining of the solutions are generated using the statistical regeneration mechanism (SRM). SRM is developed by Kaveh et al. [54] and applied to improve the different optimization methods, such as enhanced dandelion optimizer [55]. In order to apply the SRM, the mean and standard deviation of the solutions stored in the memory of the VPS are obtained. Then, the position of the considered agent is replaced with the best position of the best solution obtained so far. After that, in the first fifty percent of the optimization iteration, twenty percent of the positions are alternated using Eq. (18). Otherwise, only one of its positions is modified using Eq. (18):

$$Vp_i^{new} = U(Mean - Std - Sigma, Mean + Std + Sigma) \tag{18}$$

where U is the operator that returns a random number generated from the continuous uniform distribution with lower and upper endpoints specified by $Mean - Std - Sigma$ and $Mean + Std + Sigma$. $Mean$ and Std are the average and standard deviation of the solutions stored in the memory of the VPS. $Sigma$ is a parameter that helps the statistically regenerated mechanism to work efficiently when the entire population converges to the specified value and is defined as follows.

$$Sigma = \begin{cases} 5 & If\ Std < 0.01 \times (VP^{max} - VP^{min}) \\ 0 & otherwise \end{cases} \tag{19}$$

where VP^{max} and VP^{min} are the upper and lower bound of the search space.

In order to keep the solution in the search space, the harmony search-based boundary handling approach is employed. Harmony search-based boundary handling approach has the memory which is stored the best position obtained by the algorithm. The size of the memory is identical to the population size of the algorithm. The maximum number of iterations is considered as the termination condition of the algorithm. If the termination condition is satisfied, the optimization process is stopped, and the best solution stored in the memory is reported. Otherwise, the memory is updated, and the algorithm goes to the next cycle of optimization.

4. DESIGN EXAMPLES

In this study, three benchmark frames named 1-bay 10-story frame, 3-bay 15-story frame, and the 3-bay 24-story frame are considered to investigate the performance of the optimization algorithms. Here, for the first time, the performance of these algorithms is tested in these frames using the graph-theoretical force method. In these examples, AISC-LRFD requirements are fulfilled for the stress and displacement limitation. The population size and the maximum number of function evaluations are set to 20 and 20000, respectively. Other parameters of the algorithms are the same as their main paper.

4.1 The 1-bay 10-story steel frame

The 1-bay 10-story steel frame is the first problem considered in this study. The schematic view, loading condition, and member grouping of the problem is given in Figure 1. The section for beam elements is picked from the pool of the 267 W-section, and the section for the column members is picked from W 12 and W 14 sections. Members' yield stress and elasticity modulus are set to 36 ksi and 29000 ksi, respectively. The degree of statical indeterminacy (DSI) and degree of kinematical indeterminacy (DKI) of this structure are 30 and 60, respectively. Therefore, the force method is the optimal analysis method in this example.

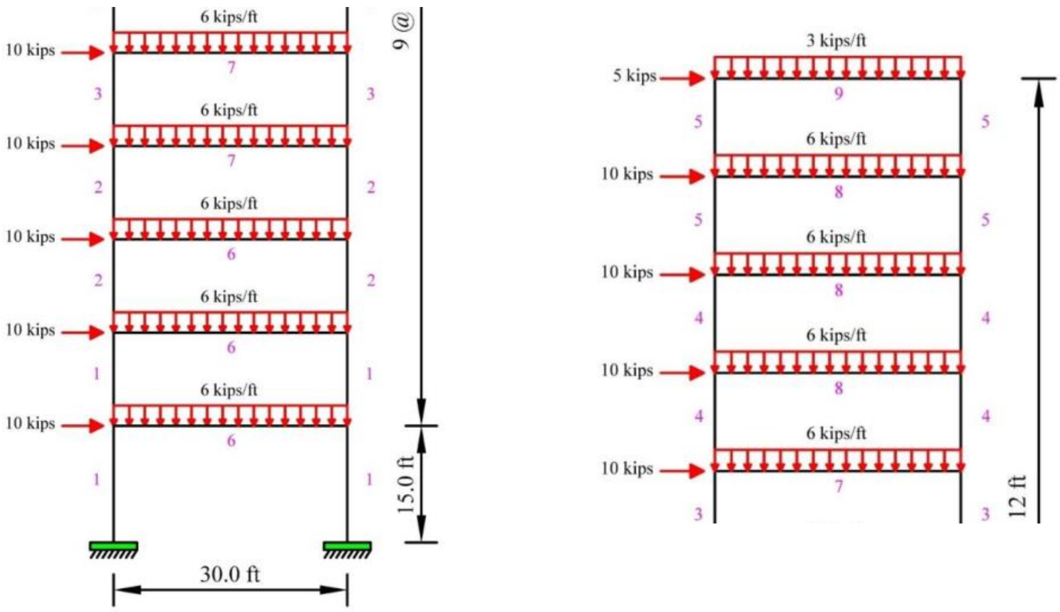

Figure 1. Schematic view of the 1- bay 10-story steel frame

The results obtained by the enhanced colliding bodies optimization (ECBO), improved shuffled-Jaya (IS-Jaya), Vibrating particles system - statistical regeneration mechanism algorithm (VPS-SRM), and particle swarm optimization- statistical regeneration mechanism algorithm (PSO-SRM) [43] are provided in Table 1. According to this table, IS-Jaya and

[DOI: 10.22068/ijoce.2023.13.3.556]

VPS-SRM can find the optimum result same as the PSO-SRM. In addition, the statistical result obtained by the IS-Jaya is better than VPS-SRM and ECBO. The convergence history of the algorithms is provided in Figure 2.

Table 1: Comparison results of the considered algorithms with another method in the 1-bay 10-story steel frame.

Element group	PSO-SRM [43]	ECBO	IS-Jaya	VPS-SRM
1	W14×233	W14×233	W14×233	W14×233
2	W14×176	W14×176	W14×176	W14×176
3	W14×159	W14×132	W14×159	W14×159
4	W14×99	W14×99	W14×99	W14×99
5	W14×61	W12×65	W14×61	W14×61
6	W33×118	W30×124	W33×118	W33×118
7	W30×90	W30×116	W30×90	W30×90
8	W27×84	W27×84	W27×84	W27×84
9	W18×46	W21×44	W18×46	W18×46
Best weight (lb)	64001.98	65717.98	64001.98	64001.98
Worst weight (lb)	66150.02	72911.97	66305.97	73385.99
Mean (lb)	64607.08	68238.81	64746.99	66701.71
SD (lb)	640.86	1723.33	667.67	2403.44

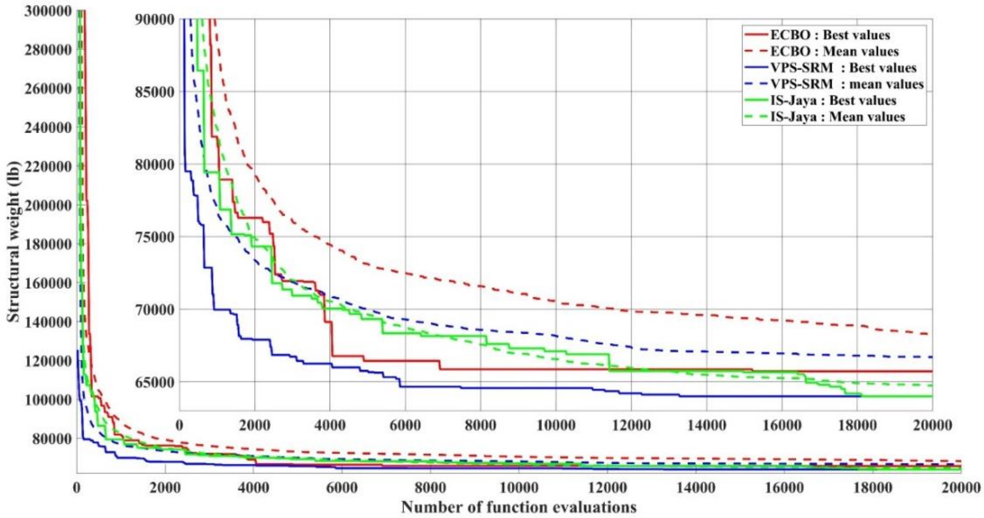

Figure 2. Convergence histories of the ECBO, VPS-SRM, and IS-Jaya for the 1-bay 10-story steel frame

4.2 he 3-bay 15-story steel frame

The second example employed for investigating the performance of these three algorithms is the 3 - bay 15 -story steel frame. The loading condition and element grouping are given in Figure 3. Cross sections of the members for both beam and column are selected from 267 W-section. Members' yield stress and elasticity modulus are set to 36 ksi and 29000 ksi, respectively. The maximum last story's sway is limited to 9.25 in. The DSI and DKI of this

[DOI: 10.22068/ijoce.2023.13.3.556]

example are 135 and 180, respectively, so the force method is the optimal analysis method.

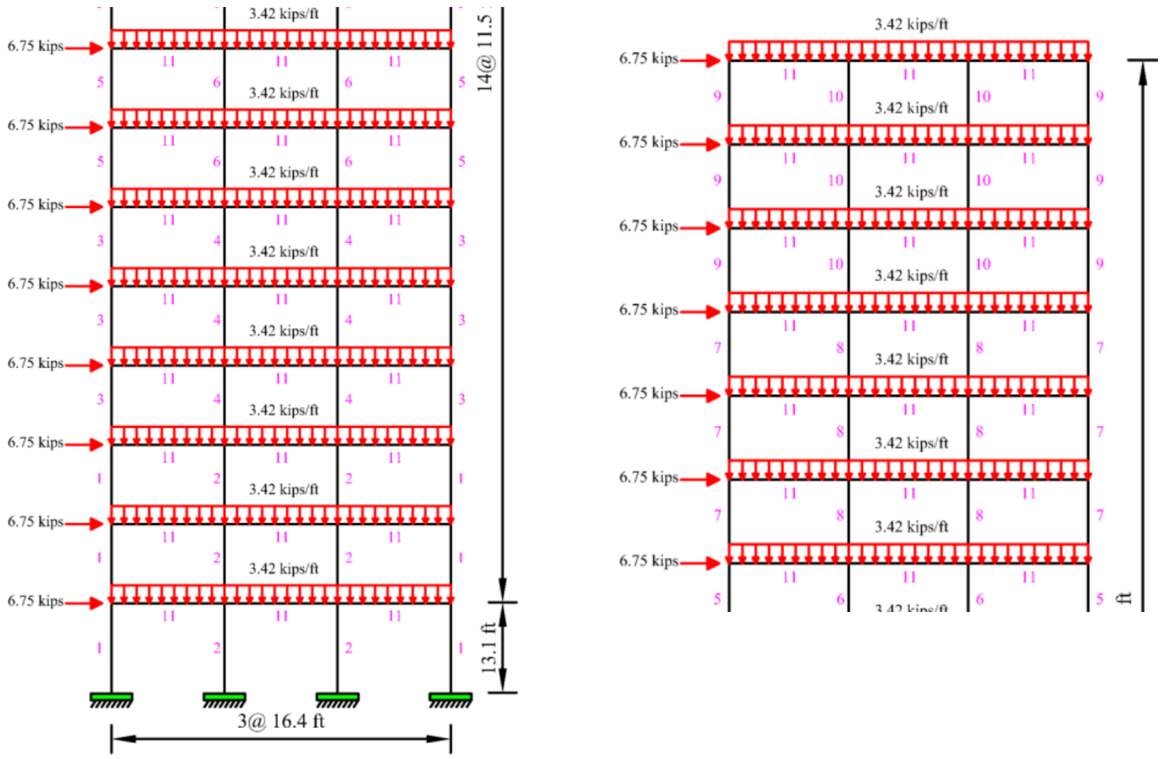

Figure 3. Schematic view of the 3-bay 15-story steel frame

Optimization results are summarized in Table 2. According to this Table, EVPS-SRM acquired the optimum weight (87123.97 lb) than other methods, including PSO-SRM (87183.39 lb) [43] ECBO (89768.38 lb), and IS-Jaya (87261.95 lb). Moreover, the average weight of the 30 independent runs of the EVPS-SRM is less than ECBO and IS-Jaya. The convergence history of the algorithms is provided in Figure 4. This figure shows that VPS-SRM converges to the optimum solution faster than other considered methods.

Table 2: Comparison results of the considered algorithms with another method in the 3-bay 15-story steel frame

Element group	PSO-SRM [43]	ECBO	IS-Jaya	EVPS-SRM
1	W12×96	W18×106	W14×99	W14×90
2	W27×161	W27×161	W27×161	W36×170
3	W27×84	W24×84	W27×84	W27×84
4	W21×111	W27×114	W24×104	W21×111
5	W14×61	W10×68	W21×68	W14×61
6	W30×90	W30×90	W18×86	W18×86
7	W8×48	W12×53	W8×48	W8×48
8	W12×65	W21×68	W12×65	W14×61
9	W6×25	W18×35	W8×28	W14×34
10	W8×40	W10×39	W10×39	W18×35

[DOI: 10.22068/ijoce.2023.13.3.556]

11	W21×44	W21×44	W21×44	W21×44
Best weight (lb)	87183.39	89768.38	87261.95	87123.97
Worst weight (lb)	88861.77	97950.19	95577.42	92135.22
Meant (lb)	87606.54	93624.38	88552.35	88513.65
SD (lb)	318.36	2039.44	1848.84	1673.72

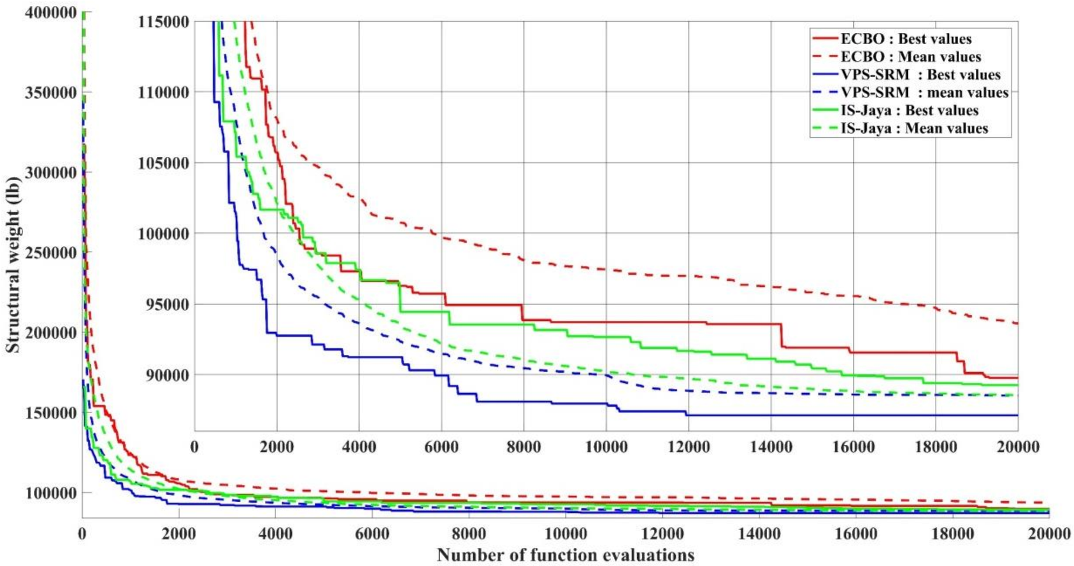

Figure 4. Convergence histories of the ECBO, VPS-SRM, and IS-Jaya for the 3-bay 15-story steel frame

4.3 The 3-bay 24-story steel frame

The last example *investigated* in this paper is the 3-bay 24-story steel frame. This frame is made up of 168 members, which are divided into 20 groups, as shown in Figure 5. The section of the column members is picked from W 14 sections, and beam members are selected from 267 W sections. The modulus elasticity of the members is quale to 29732 ksi, and the members' yield stress is set to 33.4 ksi. The DSI and DKI are 216 and 288. Hence, the force method is faster than the displacement method in this example.

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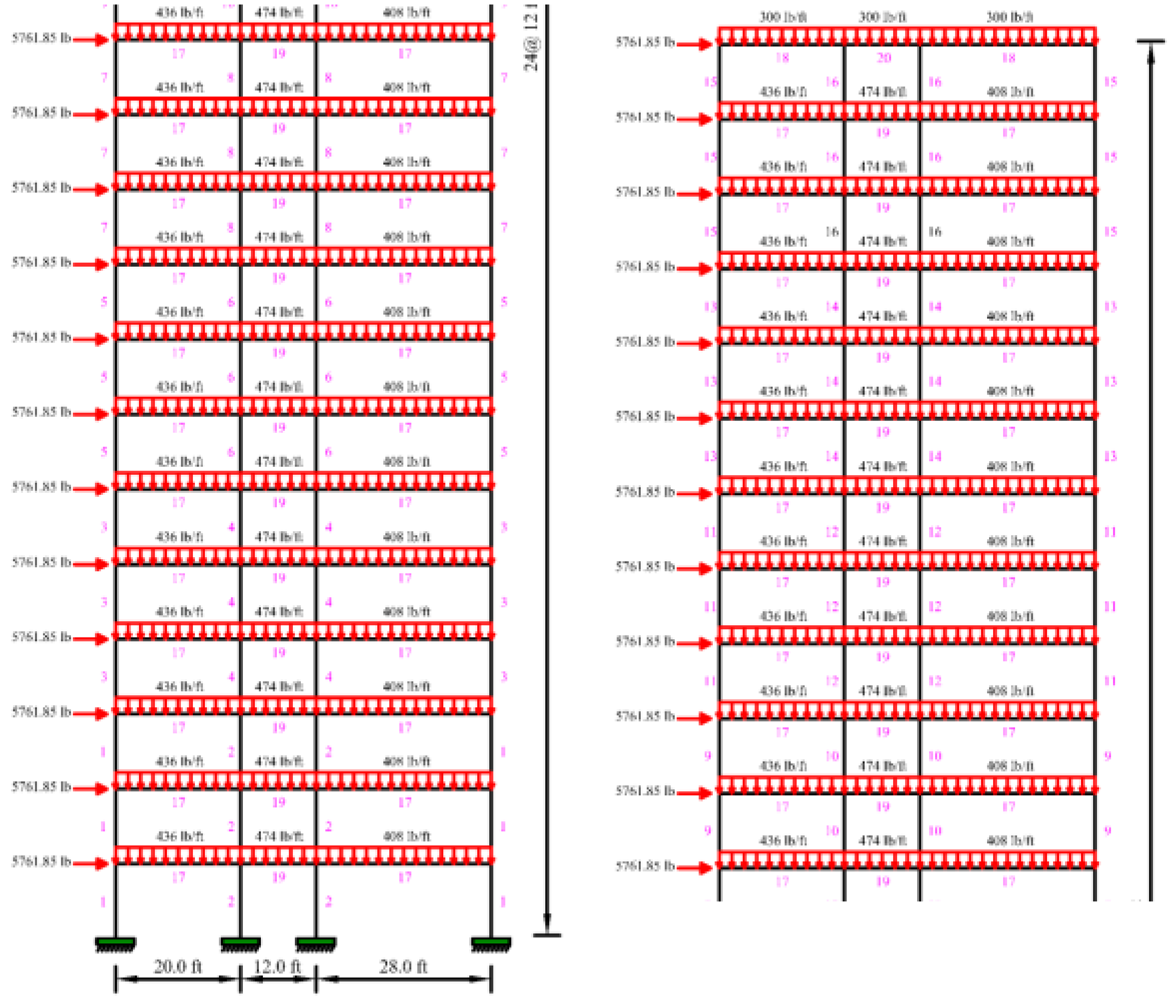

Figure 5. Schematic view of the 3-bay 24-story steel frame

According to Table 2, IS-Jaya acquired the optimum weight (201042.03 lb) than other methods, including PSO-SRM (201402.05 lb) [43] ECBO (203046.69 lb), and VPS-SRM (202392.03 lb). Also, the average weight and Standard deviation obtained by the IS-Jaya are better than ECBO and VPS-SRM. The convergence history of the algorithms is provided in Figure 6.

Table 3: Comparison results of the considered algorithms with another method in the 3-bay 24-story steel frame

Element group	PSO-SRM [43]	ECBO	IS-Jaya	VPS-SRM
1	W14×159	W14×132	W14×159	W14×145
2	W14×132	W14×109	W14×132	W14×159
3	W14×109	W14×90	W14×109	W14×109
4	W14×74	W14×90	W14×74	W14×74
5	W14×82	W14×61	W14×68	W14×68

[DOI: 10.22068/ijoce.2023.13.3.556]

6	W14×48	W14×74	W14×38	W14×38
7	W14×30	W14×48	W14×34	W14×34
8	W14×22	W14×22	W14×22	W14×22
9	W14×90	W14×99	W14×90	W14×99
10	W14×99	W14×109	W14×99	W14×90
11	W14×90	W14×109	W14×90	W14×90
12	W14×90	W14×90	W14×90	W14×90
13	W14×61	W14×82	W14×68	W14×68
14	W14×53	W14×43	W14×61	W14×61
15	W14×34	W14×30	W14×34	W14×34
16	W14×22	W14×22	W14×22	W14×22
17	W30×90	W30×90	W30×90	W30×90
18	W6×15	W8×18	W6×15	W6×15
19	W24×55	W24×55	W24×55	W24×55
20	W6×8.5	W6×8.5	W6×8.5	W14×43
Best weight (lb)	201402.05	203046.69	201042.03	202392.03
Worst weight (lb)	207372.11	251333.56	216006.12	238176.41
Mean (lb)	203400.11	214820.81	205142.09	214012.51
SD (lb)	1539.31	11021.81	3964.48	9354.60

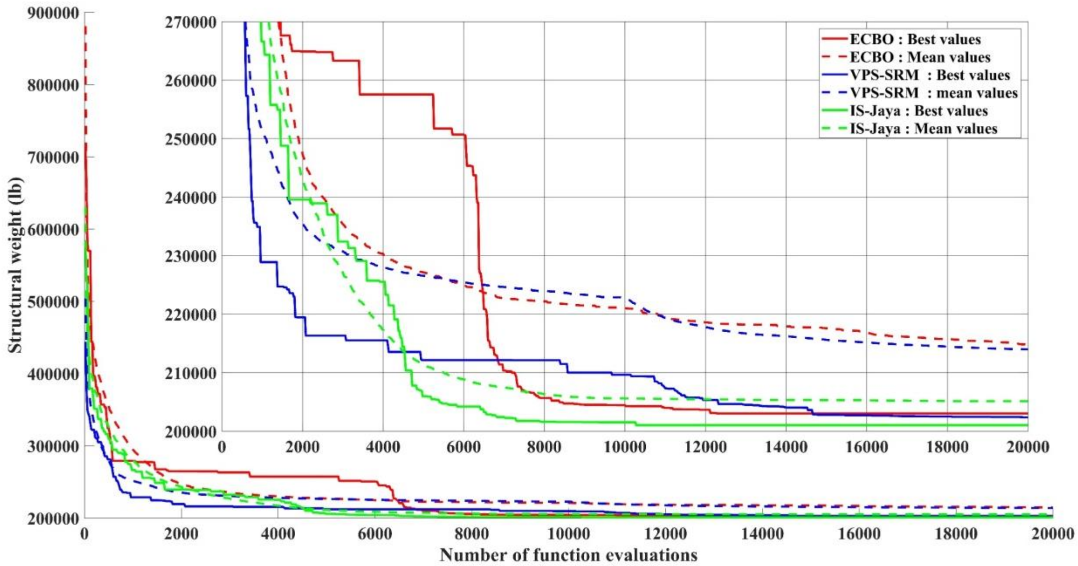

Figure 6. Convergence histories of the ECBO, VPS-SRM, and IS-Jaya for the 3-bay 24-story steel frame

5. CONCLUSOINS

In this study, the optimum design of the frame structures using the force method and three recently improved algorithms named enhanced colliding bodies optimization (ECBO), improved shuffled Jaya algorithm (IS-Jaya), and Vibrating particles system - statistical

[DOI: 10.22068/ijoce.2023.13.3.556]

regeneration mechanism algorithm (VPS-SRM) are investigated. The considered frames include the 1-bay 10-story steel frame, 3-bay 15-story steel frame, and 3-bay 24-story steel frame. Obtained results show that in the first example IS-Jaya and VPS-SRM acquired the optimum solution. In the second example, VPS-SRM can obtain the best solution. Also, the statistical results of the VPS-SRM are better than IS-Jaya and ECBO. In the last example, IS-Jaya acquired better results than other methods. This shows that the IS-Jaya and VPS-SRM have better performance than other considered methods and can be utilized in other optimization problem of the frame structures.

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