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Research Article

Jaya algorithm for design optimization of planar steel frames

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ABSTRACT

An efficient metaheuristic optimization method called Jaya Algorithm (JA) has gained wide acceptance among optimization researchers in various engineering problems recently. The main feature of JA is that it does not use algorithm-specific parameters and has a very simple formulation based on the concept of approaching the best solution and moving away from the worst solution. This study presents the JA formulation for design optimization of planar steel frames under strength and displacement constraints. The validity of JA is investigated by solving two benchmark design examples. The results demonstrated the superiority of JA over other state-of-the-art metaheuristic optimization methods in terms of optimized weight, number of structural analyses and several statistical parameters.

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Introduction

The metaheuristic optimization methods that mimic natural phenomena has been implemented for solving different design problems over the past three decades. A metaheuristic could be defined as the process of an iterative generation which sheds light on a heuristic by incorporating smartly different concepts for exploration and exploitation of the search space and achieving strategies in order to find near-optimum solutions [1]. Exploration and exploitation are the most significant concepts of finding the best solution in all metaheuristic optimization methods. Exploration provides generating diverse solutions in order to explore search space on a global scale whereas exploitation focuses on the search in a local region by exploiting the information. The balance between exploration and exploitation allows to identify regions containing high-quality solutions and move away from previously explored regions that are far from global optimum.

In the last two decades, the bio-inspired approaches (Genetic algorithm (GA) [2], Particle swarm (PSO) [3], Ant colony (ACO) [4], Honey bee mating (HBMO) [5], Enhanced honey bee mating (EHBMO) [6], Whale optimization algorithm (WOA) [7], Enhanced whale optimization algorithm (EWOA) [8] etc.) and physic-inspired approaches (Simulating annealing (SA) [9], Harmony search (HS) [10], Big-bang big-crunch [11], Colliding bodies (CBO) [12] etc.) have been proposed for the optimization problems and extended by enhancing their capabilities in optimization procedures such as the convergence, time consumption and achieving the near-global optima.

The structures should be designed by determining the optimum cross-sectional areas so as not to exceed the strength and displacement limits given in the relevant specifications. Meanwhile, resource and time management are some of the most challenging problems in structural engineering; however, structural designers can overcome these problems using metaheuristics to obtain the best design in terms of cost and safety. Since frame structures constitute the vast majority of the skeletal systems in structural engineering, the design optimization (i.e. optimum design) of planar steel frames is a common selected issue as a benchmark problem to investigate the efficiency of novel metaheuristics. Hence, various optimization methods have been proposed for the design optimization of steel frames under strength and displacement constraints specified in design specifications.

Just to overview the literature published in the past two decades, Camp et. al. [13] used the ant colony algorithm (ACO) that is to simulate the ant behavior to structural optimization of steel frames. Degertekin [14] utilized the harmony search (HS) based on the concept of searching for the best harmony in musical improvisation. The efficiency of HS was tested in the design optimization of planar steel frames in comparison with the genetic algorithm and ant colony optimization methods. In the study proposed by Saka [15], structural optimization algorithms including GA, SA and HS were reviewed and assessed comparing the optimization results of a steel frame design example for each method. Genetic algorithms, simulated annealing, evolution strategies, particle swarm optimizer, tabu search, ant colony optimization and harmony search are used for optimum design of real size steel frames by Hasancebi et al. [16]. Dogan and Saka [17] developed an optimum design algorithm based on particle swarm optimizer for planar steel frames. The superiority of the proposed algorithm was verified by optimizing three steel frames in comparison to SA and GA. An enhanced honey bee mating optimization method (EHBMA) for the optimum design of side sway steel frames was proposed by Maheri and Nerimani [6] in order to overcome trapping local optima and extend the search space of HBMO. The performance of the new method was evaluated with four design examples. Kaveh and Gaazan [8] proposed a new method called enhanced whale optimization algorithm (EWOA) to enhance the convergence speed and solution accuracy of the standard whale optimization algorithm (WOA). The efficiency of the EWOA was tested with four benchmark skeletal structures and the results were compared to standard WOA and other optimization methods. Carrero et. al. [18] implemented a search group algorithm (SGA) to three steel frame examples in order to investigate the efficiency of the method. The results demonstrated that the proposed method achieved competitive performance. Farshchin et. al. [19] applied a school-based optimization (SBO) algorithm that is an enhanced version of teaching-learning based optimization (TLBO) including multiple classrooms and multiple teachers for the optimum design of planar steel frames.

Most evolutionary and swarm-based intelligence algorithms require algorithm-specific parameters for tuning the optimization process. However, if the optimal parameter values cannot be obtained, the computational cost or convergence ability of the method will be adversely affected. In order to overcome this drawback, Rao [20] proposed a parameter-less evolutionary algorithm that has a powerful search engine and can be easily implemented for any optimization problem. The JA and its enhanced versions with various strategies have been utilized in large-scale real-life urban traffic light scheduling problems [21], parameter estimating of battery models [22], cost minimization of underground cable systems [23], structural damage detection [24]. Besides, the JA was used also for the optimum design of truss structures with both discrete and continuous variables [25,26]. The satisfactory performance of the JA in sizing optimization of truss structures encouraged the authors to use JA in the structural optimization of planar steel frames.

The main objective of this study is to minimize the weight of planar steel frames with the design constraints of American Institute of Steel Construction-Load and Resistance Factor Design (AISC-LRFD) [27] by using the JA. For this purpose, JA is applied to the design optimization of the two planar frames utilized as the classical benchmark problems in the literature.

The remaining parts of the study are organized as follows: Section 2 recalls the discrete sizing optimization of planar steel frames according to AISC-LRFD [27]. Section 3 outlines the main steps for the implementation of the JA. Section 4 describes the benchmark problems and discusses optimization results. Section 5 provides a brief conclusion of the study.

Design optimization of planar steel frames

Design optimization is the one with the minimum weight among the designs that satisfy the constraints. Cross-sectional areas are selected as design variables in the optimization problem. The objective of the optimization problem is to minimize the weight of steel frames under strength and displacement constraints by assigning the most proper steel profiles in a ready section list. The formulation of design optimization problem of planar frames can be stated as:

Find $A \in S = \{A_1, A_2, \ldots, A_i, \ldots, A_{ncs}\}$

to minimize

$$W(A) = \sum_{k=1}^{ng} A_k \sum_{i=1}^{nm} \gamma_i L_i$$

$k=1,2,\ldots,ng \quad i=1,2,\ldots,nm$ (1)

subject to $g_j(A) \le 0 \quad j=1,2\ldots nc$

where A is the vector including the design variables (i.e. member groups), S is the ready section list consists of steel profiles, $W(A)$ is the total weight of structure defined as an object function, γ_i and L_i are the material density and the length of i-th member, A_i is the cross-sectional area of the i-th member, $g_j(A)$ denotes the design constraints including strength and displacement constraints, nc is number of design constraints, ng is number of member group (i.e. design variables), nm is the number of members, ncs is the number of discrete cross-sectional areas in the steel profile list.

A penalty approach is utilized to distinguish the designs that satisfy or not satisfy design constraints. Accordingly, the penalized objective function is defined as follows:

$$W_p(A) = (1 + \varepsilon_1 \times \psi)^{\varepsilon_2} \times W(A) \quad (2)$$

$$\psi = \sum_{j=1}^{n} max\,[0, g_j(A)] \quad (3)$$

where $g_j(A)$ is the maximum violation values for each design constraint, n is the number of design constraints, ψ represents the sum of the violated constraints. ε_1 is the penalty constant set to 1, ε_2 is the exponent of the penalty function taken as 2. The penalty parameters allow the objective function to approach in a feasible direction.

Constraints used in design optimization of frames

The design optimization of steel frames is subjected to displacement and strength constraints specified in the AISC-LRFD [27]. Strength constraints are described as following interaction equations expressed in AISC-LRFD against both bending and axial forces:

$$if\ \frac{P_u}{\phi_c P_n} \geq 0.2$$

$$g_{s,i}(A) = \frac{P_u}{\phi_c P_n} + \frac{8}{9}\left(\frac{M_{ux}}{\phi_b M_{nx}} + \frac{M_{uy}}{\phi_b M_{ny}}\right) - 1 \leq 0 \quad (4)$$

$$\text{if}\ \frac{P_u}{\phi_c P_n} < 0.2 \quad (5)$$

$$g_{s,i}(A) = \frac{P_u}{2\phi_c P_n} + \left(\frac{M_{ux}}{\phi_b M_{nx}} + \frac{M_{uy}}{\phi_b M_{ny}}\right) - 1 \leq 0$$

where $g_{s,j}(A)$ denotes the strength constraint for i-th member, P_u and P_n represent the required axial strength and the nominal axial strength for both compression and tension; M_{ux} and M_{nx} denote required flexural strength and nominal flexural strength about the x-direction (major axis); M_{uy} and M_{ny} are the required flexural strength and nominal flexural strength about the y-direction (minor axis). It should be noted that M_{ny}=0 for planar frames. ϕ_c is the axial resistance factor and taken as 0.90 for tension and 0.85 for compression; ϕ_b is the flexural resistance reduction factor and taken as 0.90.

Lateral displacement and interstory drift constraints used in this study could be defined as follows:

$$g_d(A) = \frac{\Delta_T}{H} - R \leq 0 \quad (6)$$

$$g_{is,n}(A) = \frac{d_n}{h_n} - R_I \leq 0 \qquad n = 1,2 \dots ns \quad (7)$$

where $g_d(A)$ and $g_{is,n}(A)$ are the lateral displacement and interstory drift constraints, Δ_T is the lateral displacement of the top story, H is the total height of the steel frame, R is the maximum displacement limit taken as 1/300, d_n is the inter-story drift of the n-th story, h_n is the height of the n-th story. ns is the number of stories. R_I denotes the interstory limit value specified as 1/300.

Jaya Algorithm (JA)

The JA recently developed optimization method is firstly proposed by Rao [20]. The word “Jaya” originally means “victory” in Sanskrit. The algorithm is based on the concept that the solution obtained for a given optimization problem should move toward the best solution and must avoid the worst solution. The algorithm always tries to get closer to success (i.e. reaching the best design) and then tries to avoid failure (i.e. moving away from the worst design) [20]. The most important feature of JA is not to have any algorithm-specific parameters unlike other metaheuristic. The JA only requires two standard control parameters which are the population size (i.e. number of steel design in the population) and maximum iteration number.

The implementation of JA is very simple and has only one equation for modifying the designs. $A_{k,l,it}$ denotes the value of the k-th design variable for the l-th design during the it-th iteration, the JA modifies the $A_{k,l,it}$ as follows:

$$A_{k,l,it}^{new} = A_{k,l,it} + r_{1,k,it}\left(A_{k,best,it} - \left|A_{k,l,it}\right|\right) - r_{2,k,it}\left(A_{k,worst,it} - \left|A_{k,l,it}\right|\right) \quad (8)$$

where $A_{k,l,it}^{new}$ is the new design variable for the $A_{k,l,it}$, $r_{1,k,it}$ and $r_{2,k,it}$ are the randomly generated real numbers in the range [0,1] for the k-th design variable at the it-th iteration. $A_{k,best,it}$ is the k-th design variable of the best design at the it-th iteration and $A_{k,worst,it}$ is the k-th design variable of the worst design at the it-th iteration. The term $r_{1,k,it}\left(A_{k,best,it} - \left|A_{k,l,it}\right|\right)$ indicates the tendency of the solution to move closer to the best solution, and the term $-r_{2,k,it}\left(A_{k,worst,it} - \left|A_{k,l,it}\right|\right)$ indicates the tendency of the solution to avoid the worst solution. It is worth pointing out that the random numbers r_1 and r_2 ensure good exploration of the search space and the absolute value of the candidate solution ($|A_{k,l,it}|$) considered in Eq. (8) further enhances the exploration ability of the algorithm [20].

As mentioned earlier, JA has no algorithm-specific parameter and only needs common control parameters as population size (np) and maximum iteration number (it_{max}). The optimization is terminated when the maximum iteration number is exceeded. However, each optimization run could find the best solution for a different value of it_{max}. Sensitivity analyses are required in order to find the most appropriate it_{max} value in each design example. Instead, the following formulation is implemented to terminate the search process when it is satisfied:

$$\frac{STD\left[W_p(A^1), W_p(A^2), \dots W_p(A^{np})\right]}{\sum_{i=1}^{ns}\left(\frac{1}{W_p(A^i)}\right)} \leq \varepsilon_{con} \quad (9)$$

where STD stands for the standard deviation, $W_p(A^i)$ is the penalized objective function of i-th design in the population, np is the population size, ε_{con} is the coefficient of convergence tolerance taken as 10^{-4}.

Implementation of JA for design optimization of steel frames

In design optimization of steel frames, the JA is initialized by randomly generated frame designs as the population size np (i.e. number of frame designs) and the penalty functions for each design are calculated by the results of structural analysis. The penalized functions are calculated at the rate of constraint violation. After that, the frame design with the lowest penalized function value $W_p(A_i^{best})$ and the highest penalized function value $W_p(A_i^{worst})$ is assigned to the best design and the worst design, respectively. Design variables are modified using Eq. (8). The new frame design is generated with modified design variables. The new penalized objective function $W_{p,new}(A)$ is calculated. If the new penalized objective function value is less than the previous one, ($W_{p,new}(A) < W_{p,pre}(A)$), the new design is replaced with the previous one. Otherwise, the previous design remains unchanged. This process is repeated for each frame design in the population, and then an iteration is completed. The optimization is terminated when the Eq. (9) is satisfied. The best design without constraint violation is reported as the optimum design.

The implementation of JA for design optimization of steel frames is summarized below.

Step 1: Generate the initial population (i.e. steel frame designs) Calculate the penalized objective function values $W_p(A)$ for all frame designs in the population using Eqs. (1-7). Set the iteration counter as *it*=0.

Step 2: Increase the iteration counter, *it*=*it*+1

Step 3: Determine the best and worst design of the population.

Step 4: Modify design variables of a steel frame by using Eq. (8) in the population. Obtain the new design by modifying design variables (A^{new}) and calculate the penalized function value $W_p(A^{new})$.

Step 5: If $W_p(A_i^{new}) < W_p(A_i^{pre})$, replace the *i*-th new design with the previous one, otherwise; unchanged the previous design. Repeat steps 4 and 5 for each frame design stored in the population.

Step 6: Terminate the optimization process if Eq. (9) is satisfied. Select the feasible design with the lowest objective function as the final optimum design. Otherwise, go to Step 2

Design Examples

To demonstrate the performance of JA, two benchmark frame examples as follows: three-bay fifteen-story steel frame and a three-bay twenty four-story steel frame are optimized according to provisions of AISC-LRFD [27] and the results are compared with other metaheuristic methods in the literature.

The JA was executed ten different times by using ten different initial populations. The population size was set to 20 for all examples. The statistical performance and robustness of algorithms are assessed and reported in related tables. The best, mean and worst weights for ten different runs are reported in the tables. The standard deviation of ten runs and number of structural analyses for the best design are also presented in tables. The optimum design of each example reported in other referenced studies was analysed using the given optimum steel profiles in order to check their constraint violations. If detected, the maximum violation percent of design constraints are reported in the tables.

The main program included JA was coded in the MATLAB R2017a [28], however; the structural analyses of steel frames are performed by OPENSEES [29]. Therefore, optimum design is carried out by constantly interacting with MATLAB and OPENSEES.

Three-Bay Fifteen-Story Frame

Three-bay fifteen-story planar frame was optimized firstly by Saka [15] using SA and GA according to AISC-LRFD [27]. The geometry and load conditions of the frame are shown in Figure 1. The frame consists of 105 members divided into 12 design groups. Member grouping is considered as consecutive three-story inner and outer columns form a distinct group, roof and intermediate story beams constitute a distinct group. The frame is subjected to gravity loading as well as wind loading considering 45 m/s wind speed and 6 m frame spacing [15]. The modulus of elasticity is 200 kN/mm^2. In this example, both interstory drift and lateral displacement of the top story are considered as displacement constraints and restricted to be smaller than 1.17 cm and 17.67 cm, respectively.

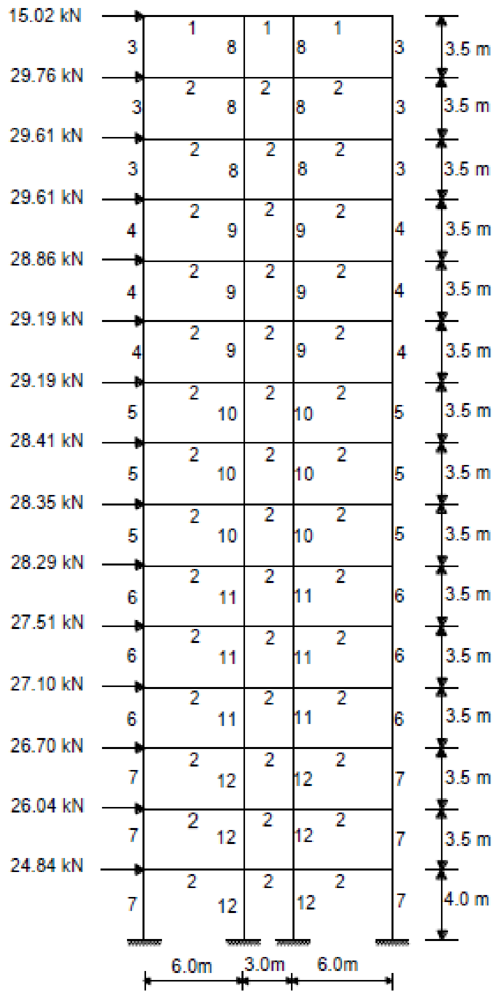

Figure 1. Three-bay fifteen-story frame

The optimum design results of JA and other methods in the literature are reported in Table 1. JA obtained the best design weighing of 34103 kg which is %8.71 lighter than the best design obtained using PSO [17], %13.1 lighter than the SA and %16.7 lighter than GA [15]. In addition, JA has found better a design with less structural analysis with lower standard deviation than the others. The maximum lateral displacement and interstory drift are 13.18 cm and 1.16 cm, respectively.

Besides, interaction ratio is 0.99 which means strength constraints govern the optimization process. It should be noted that the JA strictly satisfies the design constraints, however; PSO [17] violated displacement constraint as shown in Table 1.

Table 1. Comparison of optimum designs for three-bay fifteen-storey frame

Design variables	GA [15]	SA [15]	PSO [17]	**JA This study**
1	W21×50	W21×50	W6×9	**W8×21**
2	W24×55	W21×57	W21×44	**W21×44**
3	W10×39	W10×33	W10×33	**W14×30**
4	W14×53	W10×39	W10×33	**W16×40**
5	W14×53	W12×53	W14×53	**W18×50**
6	W14×68	W16×67	W21×111	**W24×68**
7	W24×117	W24×104	W21×111	**W24×104**
8	W14×43	W10×39	W14×61	**W8×28**
9	W14×48	W14×48	W14×61	**W14×43**
10	W14×68	W14×61	W24×76	**W21×62**
11	W14×109	W14×99	W27×94	**W30×90**
12	W16×100	W14×99	W27×102	**W30×108**
Best weight (kg)	40949	39262	37360	**34103**
NSA	25000	15500	7000	**7870**
Mean weight (kg)	N/A	N/A	N/A	**35381**
Worst weight (kg)	N/A	N/A	N/A	**37395**
SD	N/A	N/A	N/A	**1366**
Max CV (%)	None	None	116	**None**

The design history graph of optimization using PSO [17] and JA is plotted in Fig. 8. The convergence of JA is rather satisfying in comparison with PSO [17].

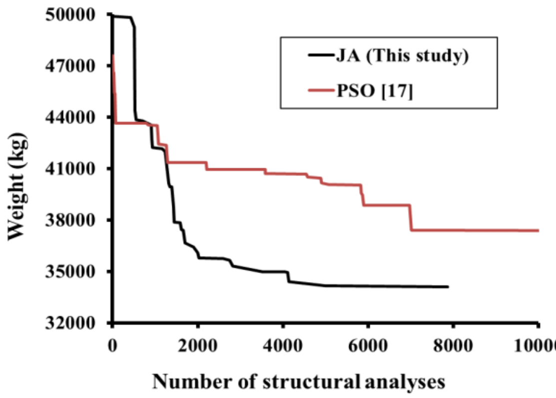

Figure 2. Comparison of convergence curves for the three-bay fifteen-story frame

Three-Bay Twenty-Four Story Frame

The second benchmark example is the three-bay twenty-four story frame consisting of 168 members that are collected in 20 groups shown in Fig. 3. The frame was originally designed by Davison and Adams [31], later optimized by PSO [13], HS [14], SGA [18], HBMO and EHBMO [6], WOA and EWOA [8] and SBO [19]. The material modulus of elasticity is 29782 ksi (205340 MPa) and the yield stress is taken as 33.4 ksi (230.3 MPa). All members are considered unbraced along their lengths. For each column, the effective length factor is calculated according to equations proposed by Dumonteil [30] for sway-permitted frames. The effective length factor of the out-of-plane columns (K_y) is considered as 1.0. The beam member groups could be selected from W-shaped sections in AISC standard profile list while the column members are limited to W14 cross-sections. The member grouping scheme is demonstrated in Fig. 3. Since all results in the literature are reported in imperial units, same units are used in here to prevent rounding errors. Table 2 lists results of optimum designs including JA and other referenced optimization methods.

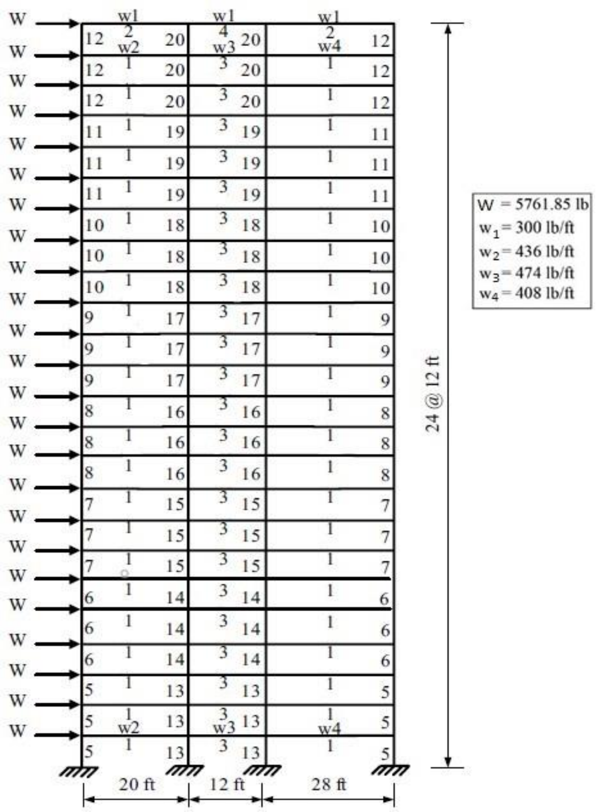

Figure 3. Three-bay twenty-four story frame (1 ft = 30.48 cm)

Table 2. Comparison of optimum designs for three bay twenty four story frame

Design variables	ACO [13]	HS [14]	SGA [18]	HBMO [6]	EHBMO [6]	WOA [8]	EWOA [8]	SBO [19]	**JA This study**
1	W30×90	W30×90	W24×68	W10×22	W10×15	W30×90	W30×90	W30×90	**W30×90**
2	W8×18	W10×22	W21×55	W27×539	W36×256	W10×17	W10×30	W8×18	**W6×15**
3	W24×55	W18×40	W24×62	W8×21	W6×16	W21×62	W24×55	W21×48	**W24×55**
4	W8×21	W12×16	W12×87	W33×221	W27×146	W14×26	W6×8.5	W6×8.5	**W16×26**
5	W14×145	W14×176	W14×159	W14×145	W14×145	W14×109	W14×159	W14×152	**W14×159**
6	W14×132	W14×176	W14×145	W14×145	W14×120	W14×145	W14×99	W14×120	**W14×120**
7	W14×132	W14×132	W14×120	W14×68	W14×26	W14×109	W14×120	W14×109	**W14×109**
8	W14×132	W14×109	W14×99	W14×22	W14×26	W14×99	W14×74	W14×74	**W14×74**
9	W14×68	W14×82	W14×68	W14×48	W14×53	W14×53	W14×74	W14×82	**W14×82**
10	W14×53	W14×74	W14×48	W14×68	W14×99	W14×43	W14×43	W14×43	**W14×38**
11	W14×43	W14×34	W14×48	W14×132	W14×159	W14×34	W14×30	W14×34	**W14×53**
12	W14×43	W14×22	W14×34	W14×342	W14×30	W14×22	W14×22	W12×19	**W14×22**
13	W14×145	W14×145	W14×109	W14×159	W14×145	W14×120	W14×90	W14×109	**W14×90**
14	W14×145	W14×132	W14×82	W14×109	W14×26	W14×99	W14×120	W14×109	**W14×109**
15	W14×120	W14×109	W14×99	W14×99	W14×74	W14×109	W14×90	W14×99	**W14×90**
16	W14×90	W14×82	W14×109	W14×48	W14×26	W14×82	W14×99	W14×99	**W14×90**
17	W14×90	W14×61	W14×90	W14×43	W14×26	W14×90	W14×68	W14×68	**W14×61**
18	W14×61	W14×48	W14×74	W14×53	W14×26	W14×61	W14×61	W14×61	**W14×61**
19	W14×30	W14×30	W14×43	W14×176	W14×370	W14×38	W14×43	W14×34	**W14×22**
20	W14×26	W14×22	W14×43	W14×211	W14×109	W14×22	W14×22	W14×22	**W14×22**
Best weight (lb)*	220465	214860	194508	214848	188640	206520	203490	202422	**202125**
NSA	15500	13924	8010	2074	1826	19640	18820	14572	**18732**
Mean weight (lb)	229555	222620	213545	N/A	N/A	216475	208648	209560	**207949.2**
Worst weight (lb)	N/A	N/A	N/A	N/A	N/A	243143	226019	N/A	**216308.9**
SD	4561	N/A	7027	N/A	N/A	N/A	N/A	7052	**4204**
Max CV (%)	None	None	34	893	1766	None	None	None	**None**

*1 lb=0.4536 kg

The JA has the best design weighing of 202125 lb (91682 kg) in comparison to all methods reported in the table. It should be noted that the JA is overall the most efficient optimizer with the lightest feasible design and the lowest standard deviation value. The maximum interaction ratio and interstory drift of the optimum design obtained by JA are 0.95 and 0.479 in (1.33 cm). Although SGA [18] and EHBMO [6] found lighter designs weighing of 194508 lb (88227 kg) and 188640 lb (85565 kg) respectively, these designs violate constraints at high rates as %34 and %1766.

Fig. 4 illustrates the convergence history of JA and other algorithms to the optimum design. Despite the fact that number of structural analyses required by JA is 18732, it has the best performance in terms of convergence rate and reaching the optimum design as seen in Fig 4.

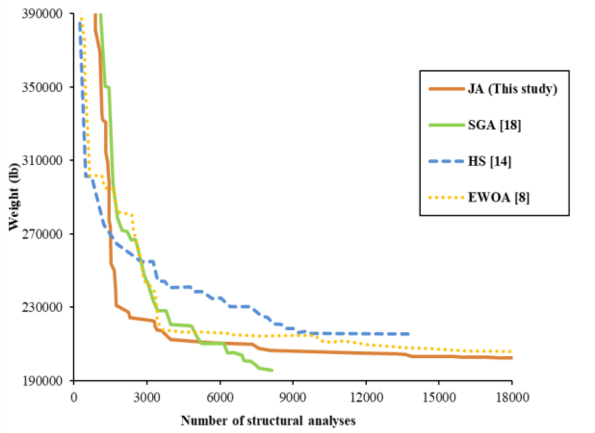

Figure 4. Comparison of convergence curves for the three-bay twenty-four story frame (1 lb= 0.4536 kg)

Conclusions

In this study, the standard JA was modified in order to improve its performance. Two planar steel frames previously optimized by various metaheuristic optimization methods are designed to demonstrate the validity of JA. The results obtained by JA were compared with those of other state-of-art metaheuristic optimization methods. Remarkably, JA found the best design compared to all methods in both examples and strictly satisfied the design constraints. The statistical parameters obtained by different runs of JA indicate that JA has better performance than the other algorithms in terms of robustness, convergence speed and feasibility.

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