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DISCRETE AND CONTINUOUS DESIGN OPTIMIZATION OF TOWER STRUCTURES USING THE JAYA ALGORITHM

ABSTRACT

The Jaya algorithm (JA) which is very recently developed metaheuristic method is proposed for design optimization of tower structures. The distinctive characteristic of JA is that it does not use algorithm-specific parameters. The algorithm has a very simple formulation where the basic idea is to approach the best solution and escape from the worst solution. Continuous design optimization of 72-bar spatial tower and discrete design optimization of 244-bar spatial tower structure are used to demonstrate the validity of JA. The results show that the JA can obtain better designs than those of the other metaheuristic optimization methods in terms of optimized weight, standard deviation and number of structural analyses.

Keywords: Design Optimization, Discrete Design Variables, Continuous Design Variables, Tower Structures, Jaya Algorithm

1. INTRODUCTION

Metaheuristic optimization methods, for example, charged system search (CSS) [1], firefly algorithm (FFA) [2], teaching-learning-based optimization (TLBO) [3], flower pollination algorithm (FPA) [4], swallow swarm optimization algorithm (SSO) [5], and water evaporation optimization (WEO) [6] have been successfully used in different engineering problems. Tower structures are also used as benchmark design examples to evaluate the efficiency of metaheuristic algorithms. Hybrid big bang-big crunch algorithm (HBB-BC) [7], self-adaptive harmony search (SAHS) [8], teaching-learning-based optimization (TLBO) [9] and cultural algorithm [10] have been used for continuous design optimization of tower structures. Moreover; genetic algorithms (GAs) [11] and multi-metaheuristic based search method (MMSM) [12] have been employed for discrete design optimization of tower structures. Increasing of the computational speed has promoted the emerging of new metaheuristic methods for solving different optimization problems. The efficiency of new metaheuristic methods is verified by different benchmark design examples, for example, mathematical function problems, machine design, tower structures and so on. Although almost all new methods claim that the proposed method is very competitive with the most popular state-of-the-art optimizers, finding the global optimum at a reasonably computational time for all problems remains an unresolved problem in metaheuristic optimization. Rao [13] developed an interesting metaheuristic algorithm called JAYA algorithm (JA) for solving several benchmark functions. The

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distinctive feature of JA is that it has a very simple formulation and does not require internal parameters. The JA have been used for optimization of a micro-channel heat sink [14] and mechanical design problems [15]. The main objective of this study is to evaluate the competency of the JA for design optimization of tower structures. Test structures presented in this study are the 72-bar spatial tower including 16 continuous variables and the 244-bar spatial tower including 26 discrete design variables. The results obtained by the JA are compared with those of other state-of-the-art metaheuristic optimization methods. The capability of JA is investigated in terms of minimum weight, standard deviation on optimized weight and required number of structural analyses in the optimization process.

2. RESEARCH SIGNIFICANCE

The tower structures are commonly used in the field of structural engineering. Therefore, the economic design of this structures is of great importance. For that purpose, an algorithm is developed for the optimum design of tower structures in this study.

3. MATERIAL, METHOD AND PROCESS

3.1. Formulation of Design Optimization

Formulation of design optimization includes the weight minimization of tower structures subjected to displacement, stress and buckling constraints. The formulation is summarized as follows:

Find $A=[A_1, A_2,....., A_{ng}]$

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

subjected to the following design constraints

$$\sigma_i^c \le \sigma_i \le \sigma_i^t , \quad i=1,2,....,nm \quad (2)$$

$$\delta_{\min} \le \delta_j \le \delta_{\max} , \quad j=1,2,.....,ndof \quad (3)$$

$$A_{\min} \le A_k \le A_{\max} \text{ or } A_k \in S = \{A_1, A_2,...., A_{ncs}\} \quad k=1,2,....,ng \quad (4)$$

where the A vector contains the design variables, W(A) is the weight of tower structure, γ_i and L_i are the material density and the length for the i-th member, A_k is the cross-sectional area for the k-th member group (i.e. design variable), σ_i^c and σ_i^t are the allowable compression and tension stresses for the i-th member, $\delta_{\min}$ and $\delta_{\max}$ are the allowable displacements for the j-th degree of freedom, nm is the number of members in the tower structure, ndof is the number of degree of freedom, ng is the number of member groups (number of design variables), A_{min} and A_{max} are the lower and upper cross-sectional areas for continuous design optimization, S is the section list for discrete design optimization, ncs is the number of profiles in the section list.

Stress and displacement constraints are handled by using a penalty function. The penalized objective function (F_p) is obtained as the product between the tower weight (W(A)) and the penalty function (ψ_p) as follows:

$$F_p = W(A) \times \psi_p \quad (5)$$

The penalty function is defined as:

$$\psi_p = (1+\phi)^{\varepsilon} \quad (6)$$

where ε is the penalty function exponent selected as 2 in this study, ϕ is the summation of the stress and displacement penalties, given as:

$$\phi = \sum_{i=1}^{nm} \phi_\sigma^i + \sum_{j=1}^{nn} \phi_\delta^j \tag{7}$$

The stress constraint penalty ϕ_σ^i for the i-th member and the displacement constraint penalty ϕ_δ^j for the j-th degree of freedom are, respectively, expressed as:

$$\begin{cases} \phi_\sigma^i = 0 & if \quad \sigma_i^c \le \sigma_i \le \sigma_i^t \\ \phi_\sigma^i = \dfrac{\left|\sigma_i - \sigma^{t,c}\right|}{\left|\sigma^{t,c}\right|} & if \quad \sigma_i < \sigma_i^c \ or \ \sigma_i > \sigma_i^t \end{cases} \tag{8}$$

$$\begin{cases} \phi_\delta^j = 0 & if \quad \delta_{\min} \le \delta_j \le \delta_{\max} \\ \phi_\delta^j = \dfrac{\left|\delta_j - \delta^{\max,\min}\right|}{\left|\delta^{\max,\min}\right|} & if \quad \delta_j < \delta_{\min} \ or \ \delta_j > \delta_{\max} \end{cases} \tag{9}$$

3.2. The JAYA Algorithm

The JA quite recently developed optimization method is firstly proposed by Rao [13]. The word “Jaya” originally means “victory” in Sanskrit. The algorithm is based on the concept that the solution obtained for a given optimization problem which 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) [13]. The most important feature of JA is that the JA has not any algorithm-specific parameters whereas the other metaheuristic optimization algorithms have algorithm-specific parameters. The JA only requires two standard control parameters which are the population size (i.e. number of solutions 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:

$$A_{k,l,it}^{new} = A_{k,l,it} + r_{1,k,it}\left(A_{k,best,it} - \left|A_{k,l,it}\right|\right) - r_{2,k,it}\left(A_{k,worst,it} - \left|A_{k,l,it}\right|\right) \tag{10}$$

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. (10) further enhances the exploration ability of the algorithm [13]. The JA consists of following steps:

- Set the population size (np) and the termination criterion, generate the initial population randomly,
- Identify the best and worst solutions in the population,

- Modify all design variables based on the best and worst solutions by using Eq. (10) and obtain new solution,
- If the new solution is better than previous one, replace the new solution with the previous one. Otherwise, keep the previous solution,
- If the termination criterion is satisfied, terminate the optimization process and report the optimum solution. Otherwise, go to II.

3.3. The JA for Design Optimization of Tower Structures

In design optimization of tower structures, the JA is initialized by randomly generated tower designs as the population size np, (i.e. number of tower designs in the population) and penalized objective function values for all tower designs are calculated by using equations (1)-(9). After that, the best design with the lowest penalized objective function value $f_p^{best}(A)$ and the worst tower design with the highest penalized objective function value $f_p^{worst}(A)$ are identified. All design variables is modified by using equations (10) and hence, a new tower design is obtained. Penalized objective function value for the new design ($f_p^{new}(A)$) is calculated. If the penalized objective function of new design ($f_p^{new}(A)$) has better than previous design ($f_p^{pre}(A)$), (i.e. $f_p^{new}(A) < f_p^{pre}(A)$), the new design is replaced with the previous one. Otherwise; the previous design is unchanged. The same process is repeated for all tower designs in the population and iteration is completed. When maximum iteration number is exceeded, the optimization process is terminated. The design satisfying all constraints with the lowest penalized objective function is assigned as the optimum design. The flowchart of JA for design optimization of tower structures is illustrated in Figure 1.

3.4. Test Structures

Two tower structures optimized with various metaheuristic methods in the current literature are considered in this study to demonstrate the efficiency of the JA algorithm. The test structures are the 72-bar spatial tower structure with 16 continuous design variables and the 244-bar spatial tower structure with 26 discrete design variables. The JA was executed twenty times for each design example starting from twenty randomly generated initial populations. The best design obtained over the twenty runs and the corresponding numbers of structural analyses required in the optimization process are reported in tables. Average optimized weight, worst optimized weight and standard deviation on optimized weight recorded in the independent optimization runs also are reported. The JA was coded in the MATLAB environment and a standard linear elastic finite element solver was implemented by the authors to perform the structural analyses entailed by the optimization process.

3.5. Continuous Design Optimization of the 72-Bar Spatial Tower

The 72-bar spatial tower is illustrated in Figure 2. The structure has the material density of 2768kg/m^3 and the modulus of elasticity of 68947MPa. Optimization of the structure is realized by using HBB-BC [7], SAHS [8], TLBO [9] and CA [10]. The structure is grouped into 16 design variables. The two independent loading conditions are applied to the structure as follows: (i) 22.241kN in the positive x and y-directions and in the negative z-direction at node point 17; (ii) 22.241kN in the negative z-direction at node points 17, 18, 19 and 20.

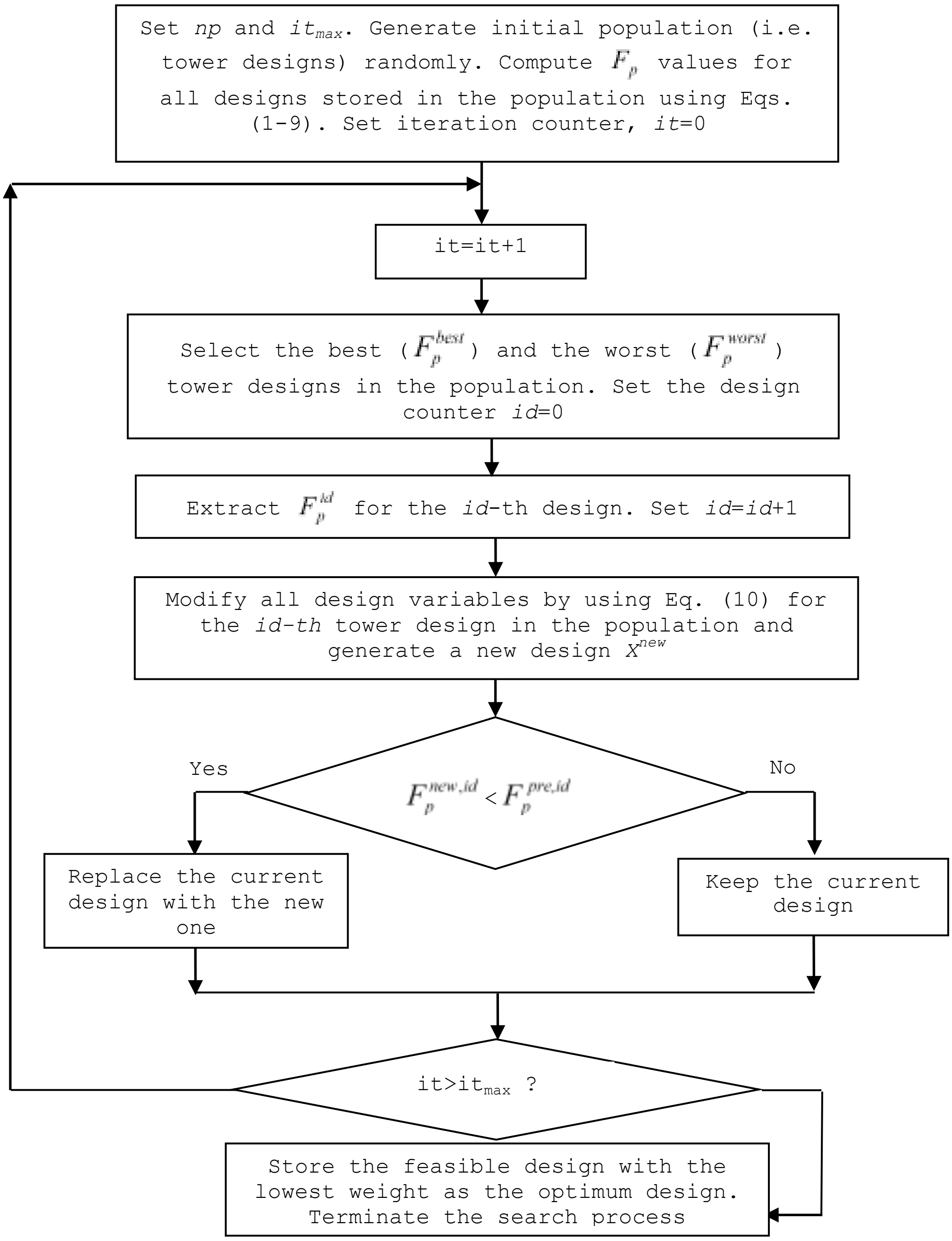

Figure 1. The flowchart of JA for design optimization of tower structures

The stress limit for all members is ±172.369 MPa in tension and compression. The displacement of nodes of the structure in all directions is restricted as ±0.635cm the lower limit value of cross-sectional areas is taken as $0.64516cm^2$.

The optimization results obtained by the JA and the aforementioned methods are reported in Table 1. The JA produced the lightest design with a weight of 172.192kg and the smallest standard deviation value (0.00093kg vs. between 0.18597kg and 0.83946kg) among all the methods presented in Table 1. SD, CV and NSA, respectively, stand for standard deviation, constraint violation percentage and number of structural analyses in Table 1.

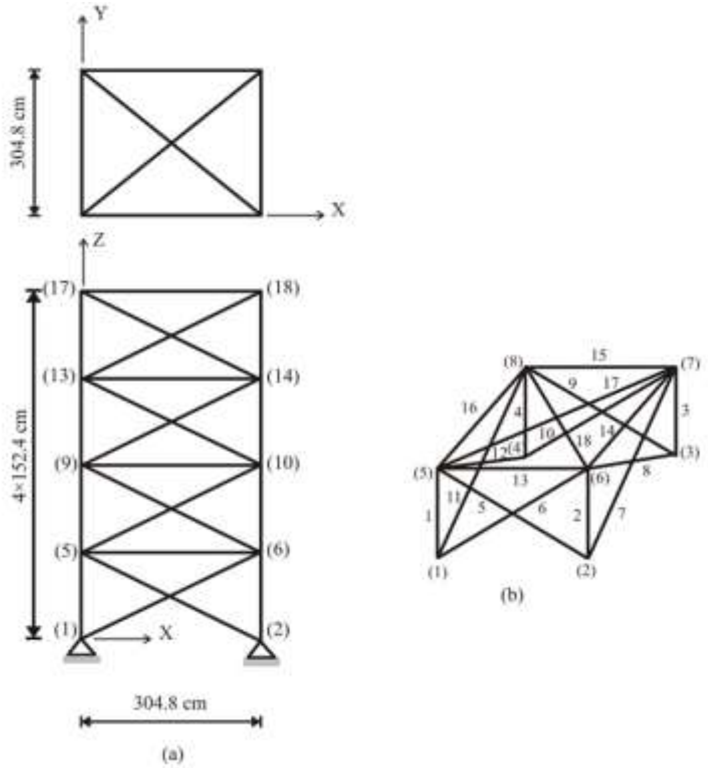

Figure 2. The 72-bar spatial tower (a) plan view (b) node and member numbering for the first storey

Table 1. Comparison of continuous design optimization of the 72-bar spatial tower

Design Variables A_i (cm^2)	HBB-BC [7]	SAHS [8]	TLBO [9]	CA [10]	JA This Study
A_1-A_4	12.28514	11.99998	12.13352	12.00598	12.15320
A_5-A_{12}	3.33032	3.36128	3.31741	3.28580	3.31492
A_{13}-A_{16}	0.64516	0.64516	0.64516	0.64516	0.64517
A_{17}-A_{18}	0.64516	0.64516	0.64516	0.64516	0.64516
A_{19}-A_{22}	8.11740	8.34192	8.20063	8.14779	8.14946
A_{23}-A_{30}	3.24838	3.29677	3.32322	3.25141	3.29788
A_{31}-A_{34}	0.64516	0.64516	0.64516	0.64516	0.64516
A_{35}-A_{36}	0.64516	0.64516	0.64516	0.64516	0.64517
A_{37}-A_{40}	3.34064	3.21935	3.43032	3.37522	3.38355
A_{41}-A_{48}	3.36386	3.23225	3.31225	3.38851	3.33021
A_{49}-A_{52}	0.64516	0.64516	0.64516	0.64522	0.64516
A_{53}-A_{54}	0.64968	0.64516	0.64516	0.66155	0.64573
A_{55}-A_{58}	1.01032	1.08387	1.00968	1.00620	1.00916
A_{59}-A_{66}	3.49741	3.76773	3.50257	3.57090	3.52104
A_{67}-A_{70}	2.66580	2.79354	2.63290	2.71135	2.66191
A_{71}-A_{72}	3.71354	3.35483	3.69870	3.62257	3.68149
Weight (kg)	172.210	172.645	172.197	172.224	172.192
Worstweight (kg)	N/A*	174.129	172.741	N/A	172.194
Mean weight (kg)	173.203	173.462	172.455	172.754	172.192
SD (kg)	0.54476	0.62595	0.18597	0.83946	0.00093
CV (%)	None	None	None	None	None
NSA	13200	13742	21542	18460	14341

Figure 3 illustrates the variation of structural weight with the number of structural analyses for the JA, SAHS [8], TLBO [9] and CA [10]. The first 15000 structural analyses are plotted in Figure 3 because the JA required about 15000 structural analyses to find optimum design. It can be observed from Figure 3 that the JA showed as efficient convergence capability as other methods.

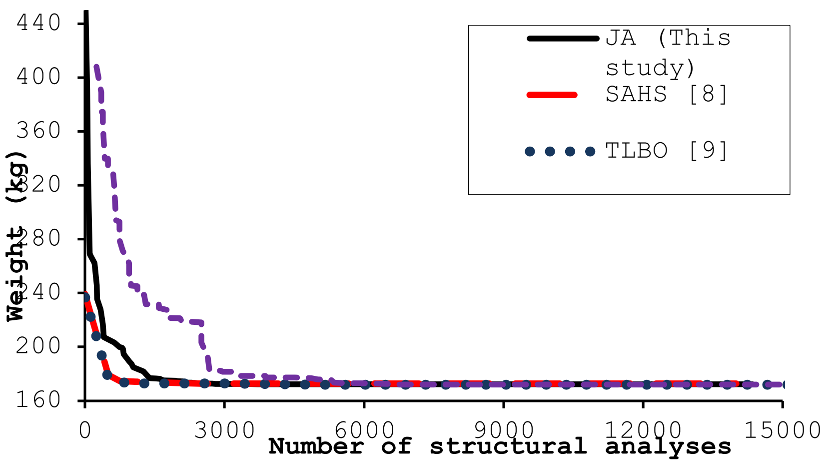

Figure 3. Comparison of convergence curves for the 72-bar spatial tower

3.6. Discrete Design Optimization of the 244-BAR Spatial Tower

The second test example is 244-bar spatial tower shown in Figure 4. The Young's modulus is 210000MPa and yield strength is 233.3MPa. The tower is grouped into 26 discrete design variables. Design variables are selected from discrete set listed in Table 2. The load conditions and nodal displacement limits for the structure are given in Table 3. The allowable tensile and compressive stresses are considered according to ASD-AISC (Allowable Stress Design-American Institute of Steel Construction) [16]. The allowable compressive stress is calculated as follows:

When $\lambda < C_c$ (inelastic buckling)

$$\sigma_c = \left(F_y \left[1 - \frac{\lambda^2}{2C_c^2} \right] \right) / \left(\frac{5}{3} + \frac{3\lambda}{8C_c} - \frac{\lambda^3}{8C_c^3} \right) \tag{11}$$

and when $\lambda > C_c$ (elastic buckling)

$$\sigma_c = \frac{12\pi^2 E}{23\lambda^2} \tag{12}$$

where E is the Young's modulus of elasticity, F_y is the yield strength, $C_c = \sqrt{2\pi^2 E / F_y}$ is the critical slenderness ratio, λ is the maximum slenderness ratio which is given as:

$$\lambda = \frac{KL}{r_i} \qquad i=x,y \tag{13}$$

where K is the effective length factor, L is the member length and r_i is the radius of gyration of the section. The allowable tension stress is calculated as:

$$\sigma_t = 0.60 F_y \tag{14}$$

Table 4 compares optimization results obtained by JA, GAs [11] and MMSM [12] method. The JA found the best design after 13326 analyses since MMSM [12] actually obtained an optimum design with a volume of 828018.98cm^3 (not 757637.35cm^3) after 20000 analyses. Besides, MMSM [12] has 10.52 % stress constraint violation whereas the JA satisfies design constraints. Figure 5 shows convergence curves for JA and MMSM [12]. It is clear that the JA has more powerful convergence capability than MMSM [12].

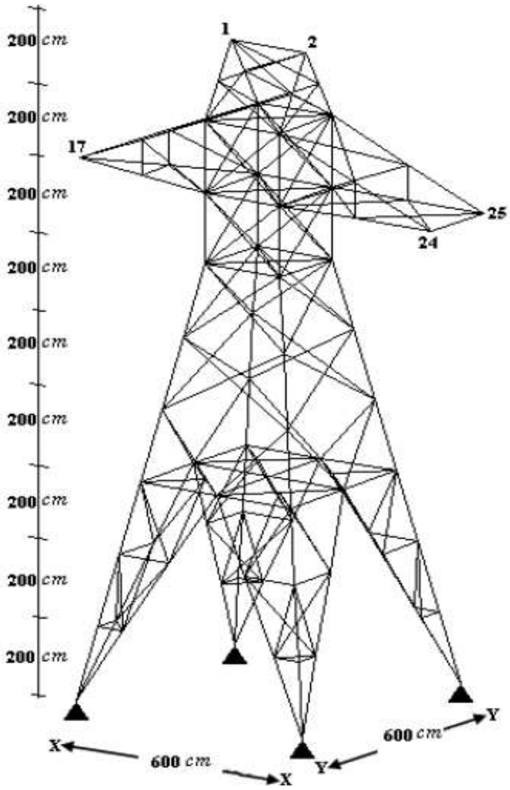

Figure 4. The 244-bar spatial tower

Table 2. Available cross-sections for the 244-bar spatial tower

No.	Section	A (mm^2)	r_i (mm)	No.	Section	A (mm^2)	r_i (mm)
1	L1.25X1.25X3/16	280.00	6.198	24	L4X4X1/4	1548.38	20.091
2	L2X2X1/4	312.26	10.109	25	L4X4X3/4	1845.16	20.015
3	L2X2X1/8	461.29	10.008	26	L4X4X3/8	2135.48	19.939
4	L2X2X3/16	605.16	9.931	27	L4X4X5/16	2419.35	19.863
5	L2X2X3/8	741.93	9.906	28	L4X4X5/8	2974.19	19.787
6	L2X2X5/16	877.42	9.881	29	L4X4X7/16	3509.67	19.761
7	L2.5X2.5X1/2	581.93	12.573	30	L5X5X1/2	1954.83	23.978
8	L2.5X2.5X1/4	767.74	12.471	31	L5X5X3/4	2329.03	25.146
9	L2.5X2.5X3/16	941.93	12.421	32	L5X5X3/8	2696.77	25.044
10	L2.5X2.5X3/8	1116.13	12.370	33	L5X5X5/16	3064.51	24.714
11	L2.5X2.5X5/16	1451.61	12.370	34	L5X5X5/8	3780.64	24.841
12	L3.5X3.5X1/2	703.22	15.138	35	L5X5X7/16	4477.41	24.765
13	L3.5X3.5X1/4	929.03	15.037	36	L5X5X7/8	5148.38	24.714
14	L3.5X3.5X3/8	1148.38	14.961	37	L6X6X1	2354.83	30.480
15	L3.5X3.5X5/16	1361.29	14.910	38	L6X6X1/2	2812.90	30.226
16	L3.5X3.5X7/16	1567.74	14.859	39	L6X6X3/4	3264.51	30.226
17	L3X3X1/2	1774.19	14.834	40	L6X6X3/8	3709.67	29.972
18	L3X3X1/4	1090.32	17.628	41	L6X6X5/16	4148.38	29.972
19	L3X3X3/16	1348.38	17.526	42	L6X6X5/8	4587.09	29.972
20	L3X3X3/8	1600.00	17.450	43	L6X6X7/16	5445.15	29.718
21	L3X3X5/16	1851.61	17.374	44	L6X6X7/8	6277.41	29.718
22	L3X3X7/16	2096.77	17.348	45	L6X6X9/16	7096.76	29.718
23	L4X4X1/2	1251.61	20.193				

Table 3. The load conditions and nodal displacement limits for the 244-bar spatial tower

Load Conditions	Joint Number	Loads (kN)		Displacement Limitations (mm)	
		X	Z	X	Z
1	1	-30	-	45	15
	2	-30	-	45	15
	17	-90	-	30	15
	24	-45	-	30	15
	25	-45	-	30	15
2	1	-	-360	45	15
	2	-	-360	45	15
	17	-	-180	30	15
	24	-	-90	30	15
	25	-	-90	30	15

Table 4. Comparison of discrete design optimization of the 244-bar spatial tower

Design Variables (A_i)	GAs [11]	MMSM [12]		This Study JA	
		Section	(mm^2)	Section	(mm^2)
A_1	-	L11/4x11/4x3/16	(280.00)	L11/4x11/4x3/16	(280.00)
A_2	-	L4x4x3/8	(1845.16)	L4x4x3/8	(1845.16)
A_3	-	L21/2x21/2x3/16	(581.93)	L2x2x3/16	(461.29)
A_4	-	L4x4x5/16	(1548.38)	L5x5x5/16	(1954.84)
A_5	-	L3x3x3/16	(703.22)	L3x3x3/16	(703.22)
A_6	-	L5x5x7/16	(2696.77)	L5x5x7/16	(2696.77)
A_7	-	L11/4x11/4x3/16	(280.00)	L11/4x11/4x3/16	(280.00)
A_8	-	L6x6x3/8	(2812.90)	L5x5x7/16	(2696.77)
A_9	-	L21/2x21/2x3/16	(581.93)	L11/4x11/4x3/16	(280.00)
A_{10}	-	L3x3x3/16	(703.22)	L11/4x11/4x3/16	(280.00)
A_{11}	-	L4x4x7/16	(2135.48)	L5x5x1/2	(3064.51)
A_{12}	-	L5x5x3/8	(2329.03)	L5x5x3/8	(2329.03)
A_{13}	-	L21/2x21/2x3/16	(581.93)	L21/2x21/2x3/16	(581.93)
A_{14}	-	L2x2x1/8	(312.26)	L11/4x11/4x3/16	(280.00)
A_{15}	-	L6x6x3/4	(5445.15)	L6x6x7/8	(6277.41)
A_{16}	-	L4x4x5/16	(1548.38)	L4x4x3/8	(1845.16)
A_{17}	-	L2x2x1/8	(312.26)	L11/4x11/4x3/16	(280.00)
A_{18}	-	L2x2x1/8	(312.26)	L11/4x11/4x3/16	(280.00)
A_{19}	-	L21/2x21/2x3/16	(581.93)	L11/4x11/4x3/16	(280.00)
A_{20}	-	L5x5x7/8	(5148.38)	L5x5x7/8	(5148.38)
A_{21}	-	L31/2x31/2x1/4	(1090.32)	L4x4x1/4	(1251.61)
A_{22}	-	L21/2x21/2x3/16	(581.93)	L11/4x11/4x3/16	(280.00)
A_{23}	-	L21/2x21/2x3/16	(581.93)	L11/4x11/4x3/16	(280.00)
A_{24}	-	L2x2x1/8	(312.26)	L11/4x11/4x3/16	(280.00)
A_{25}	-	L11/4x11/4x3/16	(280.00)	L11/4x11/4x3/16	(280.00)
A_{26}	-	L11/4x11/4x3/16	(280.00)	L11/4x11/4x3/16	(280.00)
Volume (cm^3)	920050	757637.35*		861705	
Worst Volume (cm^3)	N/A	N/A		869709.8	
Mean Volume (cm^3)	N/A	N/A		863374.8	
SD (cm^3)	N/A	N/A		2990.7	
CV (%)	N/A	10.52		None	
NSA	N/A	20000		13326	

*MMSM actually obtained an optimum design with a volume of 828018.98cm^3 (not 757637.35cm^3)

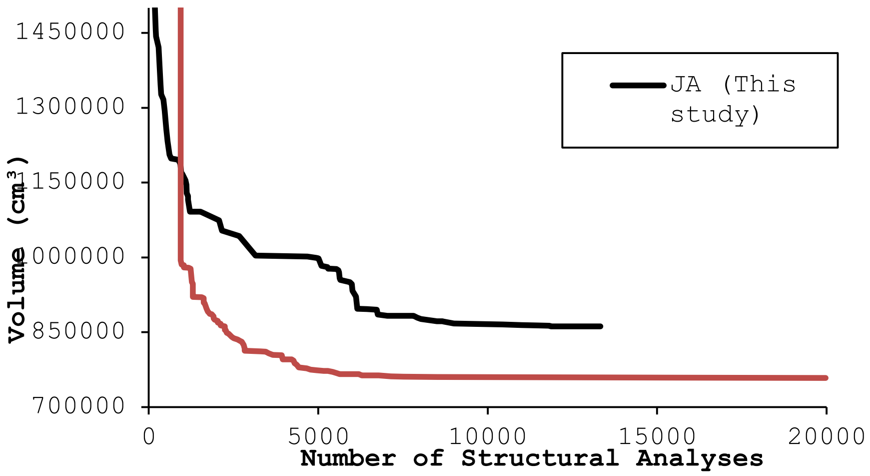

Figure 5. Comparison of convergence curves for the 244-bar spatial tower

4. CONCLUSIONS AND DISCUSSION

A very recently developed metaheuristic optimization method called Jaya algorithm is employed for discrete and continuous design optimization of tower structures for the first time. The validity of the JA is demonstrated by using the two tower structures. The design results showed that the JA could produce lighter designs than other metaheuristic optimization methods. Moreover; the JA has as efficient convergence capability as the other methods. Small standard deviation values for the JA proved the robustness of method. As a consequence of these results, the JA could be accepted as an efficient optimizer for discrete and continuous design optimization of tower structures.

NOTICE

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