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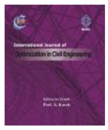

JAYA ALGORITHM WITH PASSIVE CONGREGATION FOR DESIGN OF STRUCTURES WITH DIAGONAL MEMBERS

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ABSTRACT

Partricular features of overpassing local optima and providing near-optimal soultion in practical time has led researchers to apply metaheuristics in several engineering problems. Optimal design of diagrids as one of the most efficient structural systems in tall buildings has been concerned here. Jaya algorithm as a recent paramter-less optimization method is employed to solve the problem using a set of available sections. Furthermore, passive congregation is embedded in Jaya without adding any extra control parameters. Applyig the method in a number of real-size structural examples including diagrids, exhibits performance improvement by the new hybrid algorithm with respect to Jaya.

Keywords: Tall Building, Lateral Resisting System, Jaya, Passive Congregation, Sizing Optimization

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1. INTRODUCTION

Different complexity of real-world problems has led investigators to imply a vast range of optimization methods to solve them. Meta-heuristics are a popular class of algorithms that can provide near-optimal solutions in practical time with proper operators to overpass local optima [1,2]. In this regard, some of the widely applied methods can be addressed as Evolutionary Algorithms [3–5], Differentioal Evoultion [6], Harmony Search [7], Ant Colony Optimization[8], Particel Swarm Optimization [9], Artificial Bee Colony[10], Charged System Search [11], Firefly algorithm [12], Colliding Bodies Optimization [13], Teahcing-Learning-Based Optimization[14], Water Evaopration Optimization [15] and Falcon Optimization Algorithm [16] among several others.

The widest subset of the aformentioned algorithms falls in the category of directional

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search [17,18]; as they construct their new solutions by summing on a number of directed vectors. Particel swarm optimization and differentioal evoultion [6] are well-known algorithms in this class while some of the others are not; including popular genetic algorithm [19] and ant colony optimization [20].

Jaya Algorithm, JA [21] is the simplest method in this class that improvises just two guided directions for walking throught the search space; the direction toward the best solution and the one backward from the worst. Its parameter-less design, cancells the need to tune any control parameters rather than common population size and number of iterations.

Although JA is easy to implement and of practiacal interest [22], its effectiveness is not very good compared to some other more tunable methods. The present study attempts improvement of Jaya by modifying its formula as well as adding an extra search direction. The method takes merit of some exploitative operator called passive congregation that has already revealed successive results in the previous studies [23]. The proposed hybrid method is then applied to the problem of optimal sizing in real-size structures; particularly to the design of diagrids that are efficient load-resisting systems in tall buildings. Numerical examples are provided to evaluate the proposed enhancement in the performance of Jaya for continuous and discrete sizing problems.

2. JAYA ALGORITHM AND ITS NEW VARIANT

Rao developed a simple population-based algorithm called *Jaya Algorithm* and a number of its variants for function optimization [21,24]. Some investigators has considered JA a metaheuristic algorithm eventhough it is not inspired by any specific natural phenomenon [22]. This algorithm is considered here due to its parameter-less structure that does not require tuning any specific parameter rather than common population size or number of iterations [25]. In its original form, Jaya forces a typical i^{th} search agent (X_i^k) to move toward the best agent of the population (X_{Best}^k) at current iteration k and move backward from its worst (X_{Worst}^k) by:

$$X_i^{k+1} = X_i^k + rand \otimes (X_{Best}^k - \left|X_i^k\right|) - rand \otimes (X_{Worst}^k - \left|X_i^k\right|) \tag{1}$$

The sign $\otimes$ stands for element-wise multiplication while the function $rand$ randomly genaretes a vector between 0 and 1.

Such a walking step is followed by a *greedy replacement*: if the newcomer vector X_i^{k+1} is better than X_i^k, it is accepted to take place of X_i^k; otherwise the current vector is kept unchanged. Consequently, the objective function should be evaluated for every X_i^{k+1} vector at each iteration. The aforementioned walking step is modified here in three-folds;

First: the absolute sign is cancelled as for structural sizing problems

Second: passive congregation is embedded into such an algorithm. This operator shares the information among the current memory by randomly picking up one of its search agents for each design variable[23]. The selected vector at the iteration k forms X_{PC}^k .

Third: The resulting velocity vector is implemented via two stages; each one followed by greedy selection/replacement. The first is given by:

$$V_{i,1}^{k+1} = rand \otimes (X_{Gbest}^{k} - X_{i}^{k}) - rand \otimes (X_{Worst}^{k} - X_{i}^{k}) \quad (2)$$

and the second part is governed by passive congregation as:

$$V_{i,2}^{k+1} = rand \otimes (X_{PC}^{k} - X_{i}^{k}) \quad (3)$$

Hence, the first candidate newcomer solution is obtained via $X_i^{k+1} = X_i^k + V_{i,1}^{k+1}$; followed by a greedy replacement. Addition of $V_{i,2}^{k+1}$ to the resulted design vector, gives the second candidate newcomer which is subjected to another greedy replacement. The process is repeated for the other search agents in the population and the entire loop is iterated until convergence.

The above modifications form a new variant of JA; called *Jaya Algorithm with Passive Congregation*, JAPC. It has no parameters more than population size; *N* and the maximum number of iterations; *K*. Pseudocode of the proposed JAPC is given in Figure 1.

```
Set control parameters : N, K
Randomly initialize a population Pop of N solution vectors
For k = 1 to K do
  Evaluate Fitness of Pop
  Update global best vector
    For i = 1 to N do
      generate a candidate soultion by Eq.2
      perform greedy replacement
      generate another candidate soultion by Eq.3
      perform greedy replacement
  EndFor
EndFor
Announce updated Gbest as the optimal solution
```

Figure 1. Pseudo-code of the proposed JAPC.

3. STRUCTURAL SIZING DESIGN

Design of structural members to reduce cost of material consumption has received interest for decades as a rewarding optimization problem. Here, performance of the proposed method is evaluated in two sets of examples; first: continuous design of real-size pin-jointed structures and second: discrete design of planar diagrids against simultaneous gravitational and wind loading. Results of each example is obtained via 10 independent trial runs applying an external penalty function as:

$$Fitness(X) = -w(X).(1 + k_p \sum_q \max(0, g_q(X))) \tag{4}$$

with w being the structural weight, $g_q(X)$ denoting the corresponding constraint. The penalty factor k_p is taken 50 for truss examples.

3.1 Continuous sizing design of pin-jointed structures

In this section, area of every m^{th} truss element; A_m is treated as a continuous variable during minimization of the structural weight, w . Supposing the truss has N_g member groups, the problem is defined as:

$$\begin{aligned}
&Minimize \;\; w(X) = \rho \sum_{j=1}^{Ng} \sum_m A_m l_m \\
&Subject\ to \\
&g_\sigma(X) = \frac{|\sigma|}{\sigma^{allowable}} - 1 \le 0 \\
&g_d(X) = \frac{|\Delta|}{\Delta^{allowable}} - 1 \le 0 \\
&x_j^L \le x_j \le x_j^U, \quad j = 1, \ldots, N_g
\end{aligned} \tag{5}$$

where x_j^L and x_j^U denote lower and upper bounds on j^{th} design variable (area of member group), respectively. Δ stands for the joint displacement while member stress is denoted by σ. The allowable stress is calcuated taking into account the bukling reduction factors due to code of practice [26,27] as:

$$\sigma_{tension}^{allowable} = 0.6F_y \tag{6}$$

$$\sigma_{compression}^{allowable} = \begin{cases} \dfrac{12\pi^2 E}{23\lambda^2} & \text{for } \dfrac{\lambda}{C_c} \ge 1 \\ (1 - \dfrac{\lambda^2}{2C_c^2})F_y \Big/ (\dfrac{5}{3} + \dfrac{3}{8}\dfrac{\lambda}{C_c} - \dfrac{\lambda^3}{8C_c^3}) & \text{for } \dfrac{\lambda}{C_c} < 1 \end{cases} \tag{7}$$

where $C_c = \sqrt{2\pi^2 E / F_y}$ and $\lambda = k\, l/r$ stands for the member slenderness ratio. The effective length factor is denoted by k, where l and r denote the member length and section gyration radius, respectively. The elasticity modulus is E while F_y stands for the yield stress. Gyration radius is obtained by an interpolated relation of the form $r = \alpha A^{0.6777}$.

3.1.1 Design of 120-bar dome

This example is treated as a well-studied problem in literature [15,28–30]. Fig.2 demonstrates such a dome structure with symmetric geometry. Material properties include density: $\rho = 0.288\, lb/in^3$, elasticity modulus: $E = 30450\, ksi$ and yield stress: $F_y = 58\, ksi$. Member areas are decoded from 7 symmetric groups. These design variables are confined within 0.775 to 20.000 in^2. In such a system of units $\alpha = 0.4993$ for calculating the gyration radii. Structural loading consists of $13.489\, kips\, (60kN)$ at node 1, $6.744\, kips\, (30kN)$ at nodes 2 to 13 and $2.248\, kips\, (10kN)$ at the other free nodes. The allowable displacement is taken $0.1969\, in\, (0.5\, cm)$ in each orthogonal direction.

Sizing optimization of 120-bar dome is performed here by JA and JAPC with a population size of 30 and 12000 function calls. Table 1 gives the results of present work among ones that have revealed feasible designs. As can be noticed, the proposed methods have achieved competitive results with the others regarding the best, mean and required computational effort to obtain feasible designs. In addition, JAPC has shown superior-quality results with respect to JA with the same number of analyses provided that both have started with identical population in each run.

Table 1: Comparison of the results for 120-bar dome design.

Sections (in^2)	IRO[29]	VPS [31]	WEO[32]	MSPSO[33]	CBO [30]	JA	JAPC
A1	3.0252	3.0244	3.0243	3.0244	3.0273	.0242	3.0254
A2	14.8354	14.7536	14.7943	14.7804	15.1724	14.6024	14.5754
A3	5.1139	5.0789	5.0618	5.0567	5.2342	5.0465	5.1228
A4	3.1305	3.1371	3.1358	3.1359	3.1139	3.1426	3.1385
A5	8.4037	8.4829	8.4870	8.4830	8.1038	8.5729	8.5166
A6	3.3315	3.3012	3.2886	3.3104	3.4166	3.3277	3.3415
A7	2.4968	2.4963	2.4967	2.4977	2.4918	2.4972	2.4962
Best (lb)	33256.5	33249.9	33250.2	33251.2	33286.3	33256.93	33256.29
Feasible best (lb)	33256.5	-	-	-	-	33256.93	33256.29
Mean (lb)	33280.9	33253.6	33280.9	33257.3	33398.5	33264.06	33263.36
NFE	18300	8280	19510	15000	14960	12000	12000

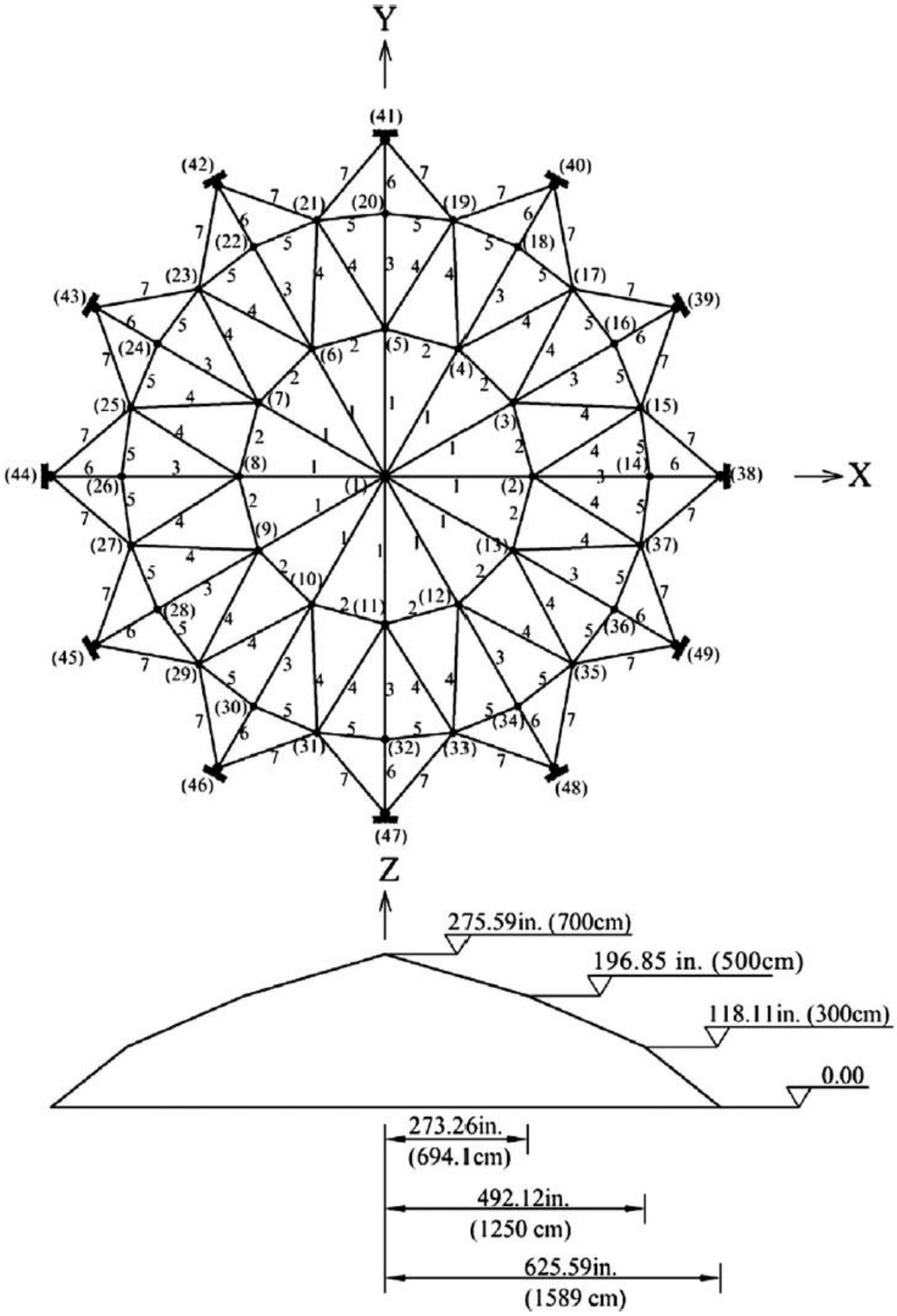


Figure 2. 120-bar dome [30].

3.1.2 Design of 2386-bar tower

As a large-scale continuous example, sizing design of a 2386-bar tower truss is studied. The model's geometry and member grouping have already been introduced in literature [34]; however, this example is treated here with continuous design variables. They are member areas that continuously vary between 40 cm^2 and 1600 cm^2. The employed material has a density of $\rho = 7850\ kg/m^3$, elasticity modulus of $E = 210\ GPa$ while the yield stress is $F_y = 253.1\ MPa$. The stress constraints are evaluated due to allowable stress design procedures with Eq.6 and Eq.7. Maximal nodal displacement is confined within 5 *cm* in each direction. 220 member groups are considered for this example.

Table 2: Statistcal results of weight*(kg)* for 2386-bar tower example.

	Best	Mean	Worst	Best Feasible
JA	4820755.4	5189121.6	5514447.3	4820755.4
JAPC	4089653.7	4389348.6	4716060.9	4089653.7

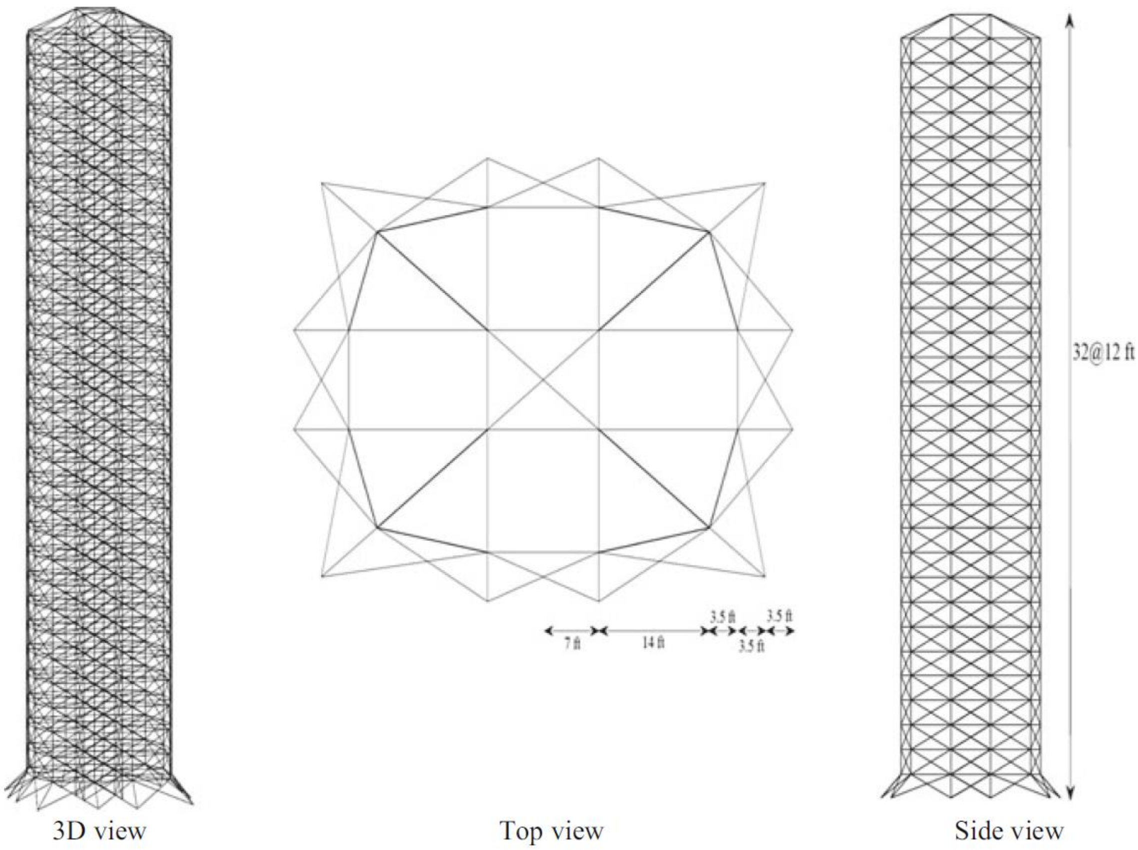


Figure 3. 2386-bar tower [35]

According to Table 2, JAPC has been superior to JA not only in the best result, but also in the worst and mean weights. Both methods have exhibited coefficient of variation as small as 4% via 10 independent runs. Fig. 4 shows that in some runs, JA is slower while in some others JAPC has elapsed a bit more time. Nevertheless, mentioned superiority of JAPC over JA is obtained with negligible difference in their computational time.

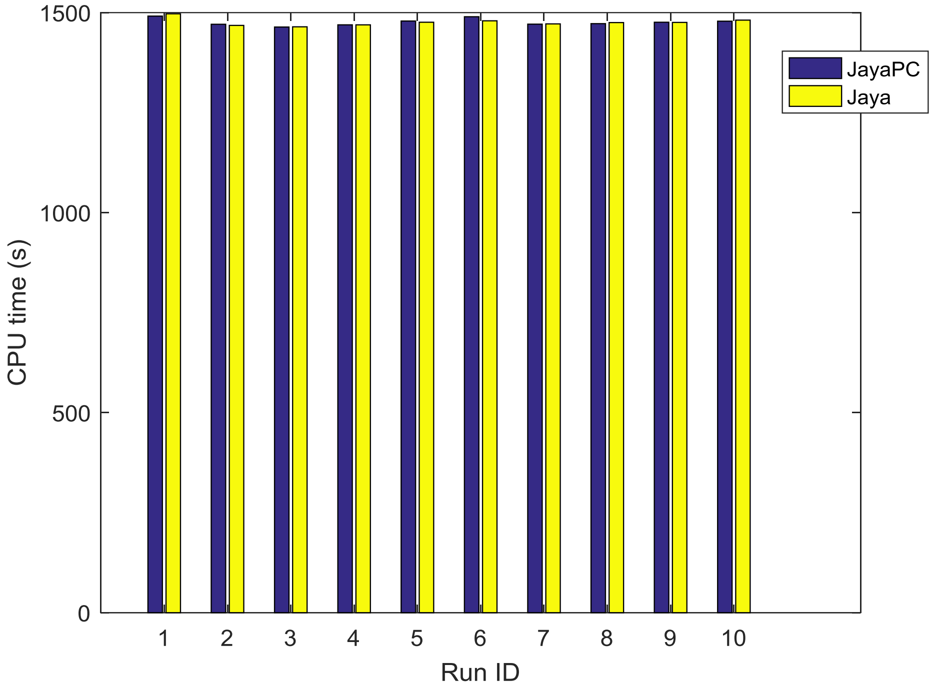
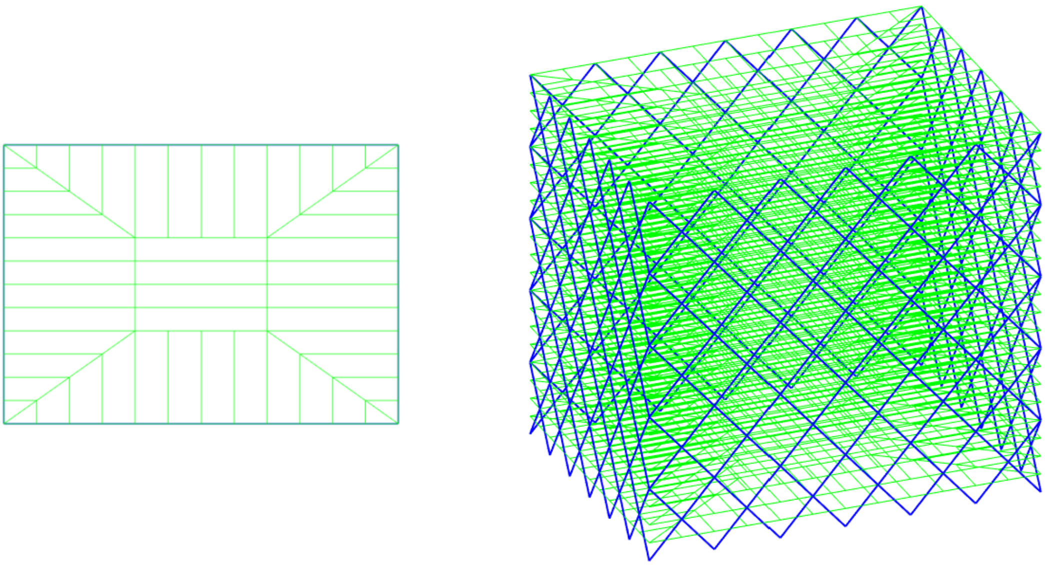


Figure 4. CPU time comparison of JA and JAPC in 2386-bar model.



(a) (b)

Figure 5. A 20-story diagrid system: (a) plan, (b) 3D view.

3.2 Discrete sizing design of diagrids

As tall buildings are vulnerable to large displacements or drifts, they need effective lateral-resisting systems. Diagrids are one of the most recent systems that are installed by mega braces in the outer tube of a building. Since such diagonal members can resist both lateral and gravitatinal loads, the columns may be omitted in diagrid systems. Fig.5 demonstrates schematic of a sample diagrid structure.

Several investigators have paid attention to design and behavior of diagrids against wind or earthquake effects [36–40]. The present study concerns design of diagrid systems for minimal weight provided that all behavior constraints are satisfied due to Iranian code of practice [26]. The sizing optimization problem is thus formulated as:

$$\begin{aligned} &\textit{Minimize} \quad && w(X) = \rho \sum_{j=1}^{Ng} \sum_{m} A_m l_m \\ &\textit{Subject to} \quad && g_m(X) = h\left(\frac{M_{u,x}}{\phi M_{n,x}}, \frac{M_{u,y}}{\phi M_{n,y}}\right) - 1 \le 0 \\ & && x_j \in \{x_j^L, \dots, x_j^U\} \qquad j = 1, \dots, N_g \end{aligned} \tag{8}$$

Material density ρ is taken $7850\ kg/m^3$. $A_m$and l_m stand for the m^{th} member area and length, respectively. g_m denotes the combined stress constraint due to design code as using a function $h(.)$ of the ultimate and nominal moments (M_u and M_n) of every m^{th} member in each direction. φ stands for the corresponding capacity-reduction factor. The structural elements including beams, columns and diagonal bracings are subdivided to N_g member groups. Such a constrained formulation is transformed to the unconstrained form using a penalty approach.

In the present work, the design variables are taken integer section indices that are chosen from a discrete list of structrual profiles. Every design variable x_j is confined within its corresponding integer lower/upper bounds; known as x_j^L and x_j^U , repectively.

Two examples of steel diagrid frames are considered here with 12 and 20 stories. Typical bay length is $4\ m$ while the story heights are $3\ m$. Elastic modulous and density of the employed material are taken $196.2\ GPa$ and $235.4\ MPa$, respectively. Available sections to be chosen during optimization, are listed in Table 3.

Live and dead loads are uniformly exerted on beams as $14.7\ kN/m$ ($15.0\ kgf/$cm) and $23.5\ kN/m$ ($24.0\ kgf/$cm), respectively. Wind loading is calculated by the following relation due to Iranian code of practice [41]. At the construction site, the base wind speed is considered $130\ km/h$.

$$p = I_w \times q \times C_e \times C_g \times C_p \tag{9}$$

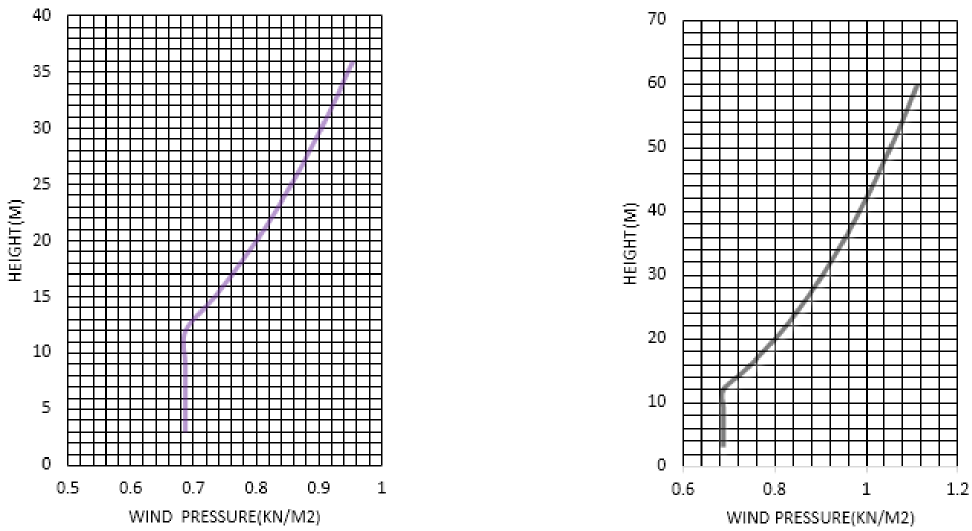
where I_w, q and C_p are the importance factor, basic wind pressure for the site and outsider pressure factor, respectively. The factor C_g addresses gust effect factor while C_e stands for exposure coefficient. Popular wind-resistant design codes recommend to test different cases of wind loading and apply the most critical one to the structure. Resulting wind pressure at the building side is depicted in Fig.6 for each model. The design procedure is due to Iranian code of steel design [26]. Effective loading combinations are thus applied as in Table 4.

Table 3: Discrete section list for diagrid examples

Section ID	Section Name	Area ($10^{-4}m^2$)	Section ID	Section Name	Area ($10^{-4}m^2$)
1	W10x19	36.26	15	W12x72	136.13
2	W10x33	62.65	16	W12x79	149.68
3	W10x39	74.19	17	W12x87	165.16
4	W10x49	92.90	18	W12x96	181.94
5	W10x54	101.94	19	W14x22	41.87
6	W10x60	113.55	20	W14x43	81.29
7	W10x77	145.8	21	W6x15	28.58
8	W12x19	35.94	22	W6x20	37.87
9	W12x26	49.35	23	W8x24	45.68
10	W12x30	56.71	24	W8x28	53.23
11	W12x45	85.16	25	W8x31	58.90
12	W12x53	100.64	26	W8x35	66.45
13	W12x58	109.68	27	W8x40	75.48
14	W12x65	123.23	28	W8x45	90.97

Table 4: Applied factors to combine loading conditions

Load condition: Combination ID	Dead Load	Live Load	Wind Load
1	1.4	0	0
2	1.2	1.6	0
3	1.2	0	0.7
4	1.2	1.0	1.4
5	0.9	0	1.4



(a) (b)

Figure 6. Windward pressure profiles for: a) 12-story model, b) 20-story model

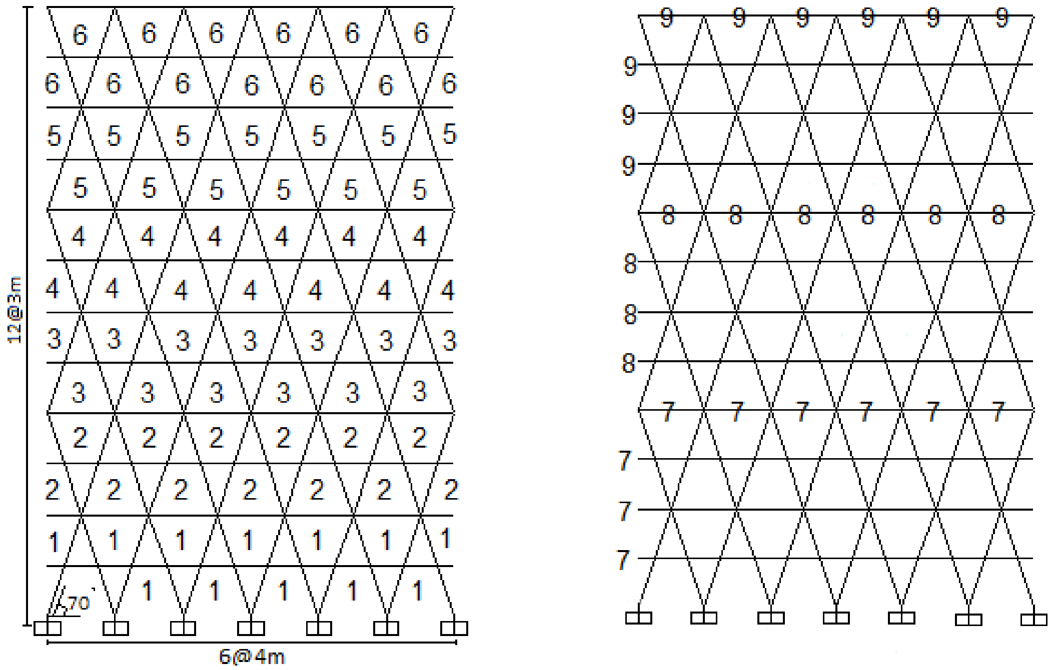
3.2.1 Design of 12-story diagrid

The perimeter frame of a 12-story diagrid is studied in this example. Geometry and grouping of such a planar structure is depicted in Fig.7; where each diagonal brace, covers two stories.

Applying wind effect is performed via lateral and vertical loading on the structure. A vertical suction force of 9.9 kN is applied at every roof node while lateral nodal wind forces are given in Table 5.

Table 5: Lateral wind loads at levels of 12-story diagrid

Story level	W(kN)	Story level	W(kN)
1	7.14	7	11.58
2	7.14	8	12.75
3	7.14	9	13.82
4	7.14	10	14.81
5	8.81	11	15.74
6	10.26	12	16.61



(a) (b)

Figure 7. Member grouping of 12-story example for: a) bracings, b) beams/columns.

As there are 9 member groups and 28 sections to be selected for each design variable, the search space cardinality is $28^9 \approx 10^{13}$. Such a discrete problem is solved here by $N = 20$

search agents via 1000 structural analyses. Here, the penalty factor is taken 10.

Fig.8 shows that in this example, the proposed JAPC have better convergence than JA. It is drawn for fitness instead of weight as the fitness takes into account both the raw cost function and the penalty of infeasibility. It is confirmed by the results of Table 6. The statistical results declares that not only in the best but also in the mean and worst cases, JAPC has overcame JA. Such superiority has been 15.5% in the best and 18.1% in the mean results. It is worth mentioning that despite JAPC, JA could not find a feasible design via the applied trial runs. The best feasible design of JAPC coinciding its minial weight, is given in Table 7 by optimal section indices.

Table 6: Statistcal results of weight*(kg)* for 12-story example.

	Best	Mean	Worst	Best Feasible
JA	56896.4	65924.6	78676.2	-
JAPC	49276.4	55780.0	67888.1	49276.4

Table 7: The feasible optimal design by JAPC for 12-story example.

Member Group	1	2	3	4	5	6	7	8	9
Section ID	5	4	13	12	4	4	27	4	25

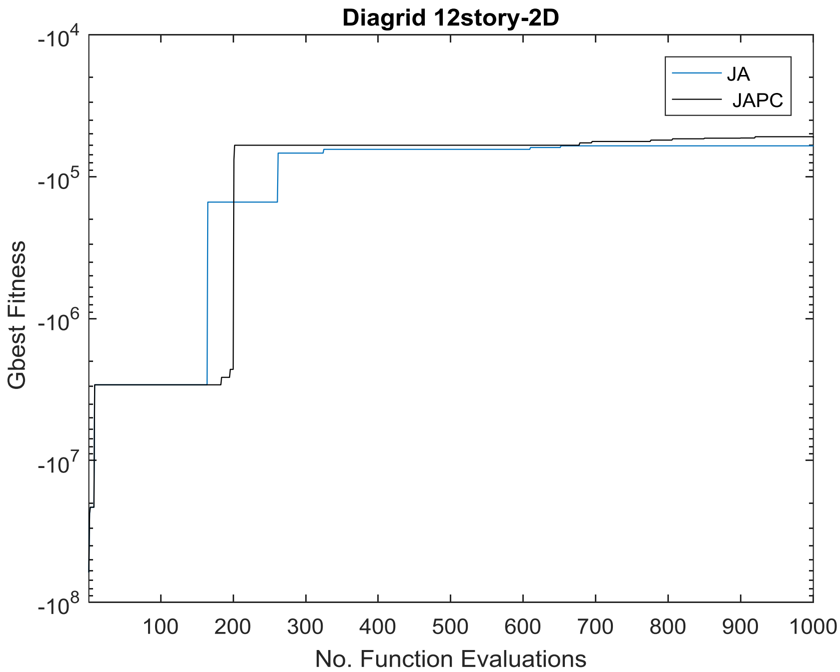
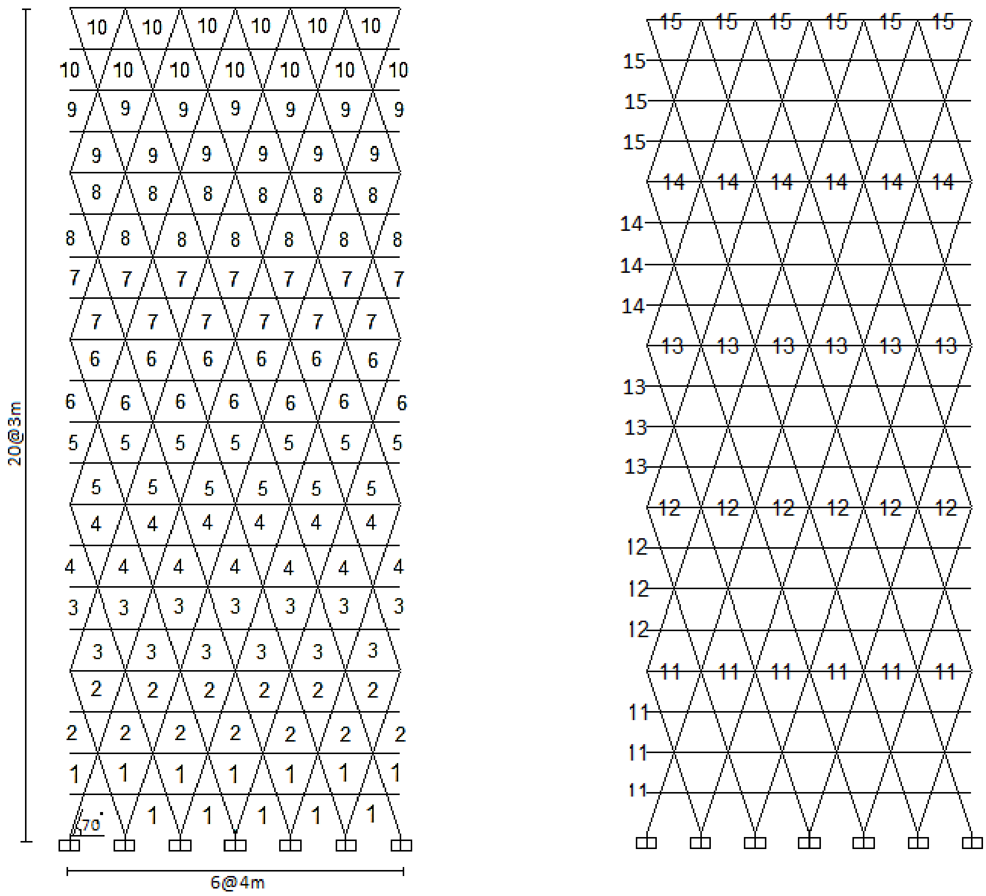


Figure 8. Convergence of JA and JAPC in 12-story planar model.

3.2.2 Design of 20-story diagrid

As depicted in Fig.9, this taller example of a building system includes 15 member groups. The amount of vertical suction force has increased to 13.64 kN while the other wind forces are directed horizontally as given in Table 8. The problem is solved for minimal weight subject to simultaneous gravitational and lateral forces.



(a) (b)

Figure 9. Member grouping of 20-story example for: a) bracings, b) beams/columns.

Table 8: Lateral wind loads at levels of 20-story diagrid.

Story level	W(kN)	Story level	W(kN)
1	4.36	11	12.96
2	4.36	12	13.83
3	4.36	13	14.65
4	4.36	14	15.40
5	6.00	15	16.14
6	7.45	16	16.81
7	8.79	17	17.52
8	9.97	18	18.18
9	11.04	19	18.79
10	12.03	20	19.39

The search space cardinality is $28^{15} \approx 5 * 10^{21}$ which is more than 100 milllion times the previous example. Therefore, the number of structural analyses has been increased to 5000. The problem is solved by JA and JAPC provided that the initial random population of size 20 is taken identical between them in every trial run.

Fig. 10 reveals considerable differnece in convergence quality of the best JAPC design over JA in the same run. It declares that JAPC has better search refinement in such a discrete example with relatively larger search space.

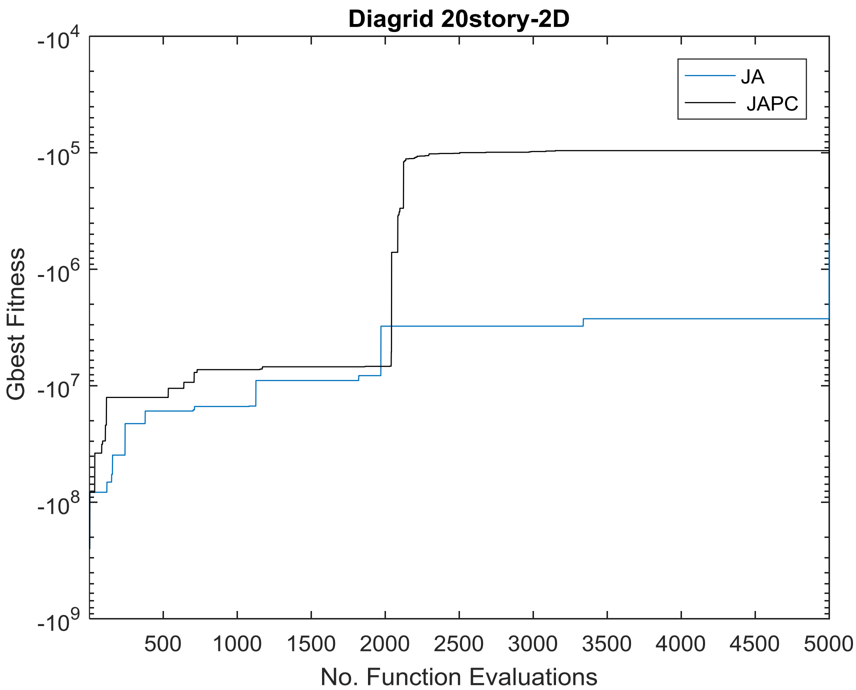


Figure 10. Convergence of JA and JAPC in 20-story planar – 1st experiment.

Comparison of statistical report of Table 9, confirms such superiority in the best, worst and mean results. It can also be realized that this example is more complex than previous one in constraint handeling. Note that JA has not found feasible solution even in its best weight. In addition, the best feasible design of JAPC is heavier than its least-weight design of 89146.3 *kg* via the employed number of fucntion evaluations. The corresponding feasible design is reported in Table 10 with the structural weight of 95621.7 *kg*.

Table 9: Statistcal results of weight*(kg)* for 20-story example.

	Best	Mean	Worst	Best Feasible
JA	92150.3	111929.2	122388.3	-
JAPC	89146.3	96292.8	111223.1	95621.7

Table 10: The feasible optimal design by JAPC for 20-story example.

Member Group	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Section ID	17	16	15	14	13	4	12	12	4	12	2	12	10	9	3

In another experiment, the population size as the main control parameter of JA and JAPC, was increased to 50 without changing the number of structural analyses in each run. The penalty factor was also increased to 100, in order to test capability of the treated algorithms in constraint handling.

According to Table 11 even with 10 times higher penalty factor, JA has not yet obtained a feasible solution in 10 trials. However, JAPC has captured a feasible design with the weight of 111973.1 *kg* within 5000 *NFE*. It provides reasioning for high fitness difference in the convergence traces of JAPC over JA, as evident in Fig. 11. With fixed *NFE*, the number of iterations is higher for smaller populations. Hence, it is also realized that JAPC can find better feasible solutions with greater number of iterations provided that the computational efforts be taken the same.

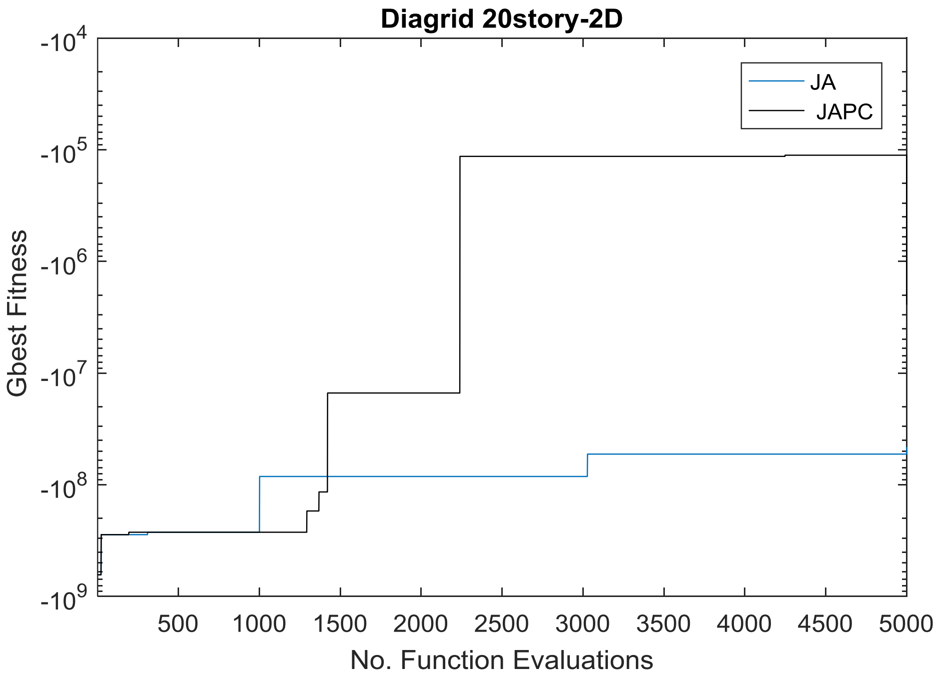


Figure 11. Convergence of JA and JAPC in 20-story planar – 2nd experiment

Table 11: Comparsion of the least infeasibility in the 1st and the 2nd sets of experiments for optimal design of 20-story example

	1st set		2nd set	
	Infeasibility	W (kg)	Infeasibility	W (kg)
JA	0.106	111576.7	0.290	127519.4
JAPC	0.000	95621.7	0.000	111973.1

5. CONCLUSION

A recent parameter-less algorithm was improved by embedding a passive congregation operator together with some other modifications. The proposed JAPC deserves the same number of control parameters that does not exert any extra tuning effort.

Treating a number of large-scale trusses, JAPC was found superior to JA and some other linerature methods in capturing feasible optimal design. It was found that embedd exploitation can help search refinement of JA in continuous problems.

The methods were then applied to practical problem of diagrid sizing for minimal material consumption provided that LRFD stress constraints are satisfied for axial and flexural elements. Since design variables are taken integer section indices, the problem is of discrete type. Numerical examples of diagrid optimization, exhibited superior effectiveness of JAPC over JA in all the treated cases; not only in the best but also in the mean and worst results. The fitness difference was greater for taller example of 20-story diagrid with respect to 12-story model.

It is obsevered that for more complex examples, JA has difficulties in capturing feasible designs. The proposed improvements, however, has enhanced the method so that it becomes capable of finding the best feasible design in all the treated examples. JAPC was found sensitive to the iteration number, so that it revealed better results with higher iterations when the total function calls is kept constant. In conclusion, the proposed JAPC keeps parameter-less structure of JA and is capable of exhibiting more efficient performance with better constraint handling.

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