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Optimum design of steel frame structures by a modified dolphin echolocation algorithm

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Abstract. Dolphin echolocation (DE) optimization algorithm is a recently developed meta-heuristic in which echolocation behavior of Dolphins is utilized for seeking a design space. The computational performance of meta-heuristic algorithms is highly dependent to its internal parameters. But the computational time of adjusting these parameters is usually extensive. The DE is an efficient optimization algorithm as it includes few internal parameters compared with other meta-heuristics. In the present paper a modified Dolphin echolocation (MDE) algorithm is proposed for optimization of steel frame structures. In the MDE the step locations are determined using one-dimensional chaotic maps and this improves the convergence behavior of the algorithm. The effectiveness of the proposed MDE algorithm is illustrated in three benchmark steel frame optimization test examples. Results demonstrate the efficiency of the proposed MDE algorithm in finding better solutions compared to standard DE and other existing algorithms.

Keywords: steel structure; optimization; Dolphin echolocation; meta-heuristic

1. Introduction

In the field of structural engineering one of the serious problems is designing the cheapest possible structures with the minimum amount of used material. In the face of increase in price of materials, the civil engineers and the manufacturers are forced to reduce the costs of construction and shorten the implementation period to maintain their competitiveness. The use of modern optimization methods thus becomes a great opportunity in the area of civil and structural engineering. Optimum design of structures is a computationally difficult problem. The difficulty lays in complex relationships between design variables and constraints of the optimization problem and the large dimensions of the design space. This necessitates that an efficient algorithm to be utilized for dealing with such problems (Gholizadeh and Fattahi 2014).

In the recent decades meta-heuristic optimization algorithms have been developed based on some natural phenomena. Every meta-heuristic method consists of a group of search agents that explore the feasible region based on randomization and some specified rules (Kaveh and Farhoudi 2011) inspired the laws of natural phenomena. Meta-heuristics are more and more popular in different research areas as they are simple to design and implement, and are very flexible (Yang *et*

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al. 2013, Gandomi *et al*. 2013). Based on a huge number of publications in the field of meta-heuristic applications, genetic algorithm (GA) (Holland 1975, Goldberg 1989), particle swarm optimization (PSO) (Eberhart and Kennedy 1995), firefly algorithm (FA) (Yang 2008) and bat algorithm (BA) (Yang 2010) are the most popular meta-heuristics and many successful applications of theme have been reported. During the recent years, many new meta-heuristics have been proposed by researchers. Charged system search (CSS) is one of the recent meta-heuristics proposed by Kaveh and Talatahari (2010a) that uses the electric laws of physics and the Newtonian laws of mechanics to guide the charged particles (CPs) to search the design space. Gandomi and Alavi (2012) proposed krill herd algorithm (KHA) based on the simulation of the herding behavior of krill individuals for solving benchmark optimization problems. Talatahari *et al*. (2014) proposed a hybrid algorithm based on the concepts of CSS to optimum seismic design of steel frames considering four performance levels. Talatahari *et al*. (2015) introduced a new hybrid eagle strategy with differential evolution (ES-DE) to optimum design of frame structures. Kaveh and Farhoudi (2013) proposed a new meta-heuristic entitled Dolphin echolocation (DE) based on the strategies used by dolphins in their hunting process. Dolphins produce a kind of voice to locate the target, doing this dolphin change sonar to modify the target and its location. This fact is mimicked as the main feature of the DE (Kaveh and Farhoudi 2013).

One of the powerful and popular computational tools in nonlinear dynamics is chaos theory (Pecora and Carroll 1990). Combination of chaos with meta-heuristic optimization algorithms to tune the algorithmic parameters is an efficient computational strategy in the field of optimization (Gandomi and Yang 2014). The chaotic sequences based GA (Gharooni-fard *et al.* 2010), PSO (Gandomi *et al.* 2013a), HS (Alatas 2010a), FA (Gandomi *et al.* 2013b), ant colony optimization (ACO) (Gong and Wang 2009), artificial bee colony (ABC) (Alatas 2010b), imperialist competitive algorithm (ICA) (Talatahari *et al*. 2012), simulated annealing (SA) (Mingjun and Huanwen 2004), krill herd algorithm (KHA) (Wang *et al*. 2014) and Cuckoo search (CS) (Wang *et al*. 2014) demonstrate their computational merits in comparison with their standard versions.

In the present study, a modified Dolphin echolocation (MDE) meta-heuristic is proposed by incorporating chaotic maps into the DE algorithm. The proposed MDE is employed to tackle size optimization problem of steel frame structures.

2. Formulation of optimization problem

For optimal design of a steel frame including *ne* members collected in *ng* design groups, the design variables of each design group are usually selected from a given standard profile list. In this case, the optimization problem may be formulated as follows

$$\text{Minimize:} \quad w(X)=\sum_{i=1}^{ng}\rho_i A_i \sum_{j=1}^{nm} L_j \tag{1}$$

$$\text{Subject to:} \quad g_k(X)\le 0\,,\; k=1,2,\cdots,nc \tag{2}$$

$$X=\{x_1 \quad x_2 \quad \ldots \quad x_i \quad \ldots \quad x_{ng}\}^{\mathrm{T}} \tag{3}$$

where x_i is an integer value expressing the sequence numbers of steel sections assigned to *i*th group; *w* represents the weight of the frame, ρ_i and A_i are weight of unit volume and cross-sectional area of the *i*th group section, respectively; *nm* is the number of elements collected in the *i*th group; L_j is the length of the *j*th element in the *i*th group; $g_k(X)$ is the *k*th behavioral constraint.

The lateral displacement and inter-story drift constraints are usually taken as

$$g_{\delta} = \frac{(\delta / H)}{R} - 1 \leq 0 \tag{4}$$

$$g_{d_k} = \frac{(d_k / h_k)}{R_I} - 1 \leq 0 \quad , \quad k = 1,...,ns \tag{5}$$

where δ is the maximum lateral displacement; H is the height of the frame structure; R is the maximum drift index; d_k is the inter-story drift; h_k is the story height of the *k*th floor; ns is the total number of stories; and R_I is the inter-story drift index permitted by the code of practice.

The stress constraints of members subjected to axial and flexural stresses are as follows:

If the code of practice is selected ASD-AISC (1989)

$$\text{for } \frac{f_a}{F_a} > 0.15; \begin{cases} g_{\sigma_l} = [\dfrac{f_a}{F_a} + \dfrac{C_{mx}\, f_{bx}}{(1 - \dfrac{f_a}{F'_{ex}})\, F_{bx}} + \dfrac{C_{my}\, f_{by}}{(1 - \dfrac{f_a}{F'_{ey}})\, F_{by}}] - 1 \leq 0 \\ g_{\sigma_l} = [\dfrac{f_a}{0.6 F_y} + \dfrac{f_{bx}}{F_{bx}} + \dfrac{f_{by}}{F_{by}}] - 1 \leq 0 \end{cases} \quad , \quad l = 1,...,ne \tag{6}$$

$$\text{for } \frac{f_a}{F_a} \leq 0.15; \quad g_{\sigma_l} = [\frac{f_a}{F_a} + \frac{f_{bx}}{F_{bx}} + \frac{f_{by}}{F_{by}}] - 1 \leq 0 \quad , \quad l = 1,...,ne \tag{7}$$

If the flexural member is under tension, then the second part of Eq. (6) is used.

In which f_a represents the computed axial stress; f_{bx} and f_{by} are the computed flexural stresses due to bending of the member about its major (x) and minor (y) principal axes, respectively. F'_{ex} and F'_{ey} are the Euler stresses about principal axes of the member; F_a represent the allowable axial stress under axial compression force alone, and is calculated depending on elastic or inelastic buckling failure mode of the member using ASD-AISC (1989). The allowable bending compressive stresses about major and minor axes are designated by F_{bx} and F_{by}; C_{mx} and C_{my} are the reduction factors, introduced to counterbalance overestimation of the effect of secondary moments. Also, F_y is the material yield stress.

If the code of practice is selected LRFD-AISC (2001)

$$\text{for } \frac{P_u}{\phi_c P_n} < 0.2; \quad g_{\sigma_l} = [\frac{P_u}{2\phi_c P_n} + (\frac{M_{ux}}{\phi_b M_{nx}} + \frac{M_{uy}}{\phi_b M_{ny}})] - 1 \leq 0 \quad , \quad l = 1,...,ne \tag{8}$$

$$\text{for } \frac{P_u}{\phi_c P_n} \geq 0.2; \quad g_{\sigma_l} = [\frac{P_u}{\phi_c P_n} + \frac{8}{9}(\frac{M_{ux}}{\phi_b M_{nx}} + \frac{M_{uy}}{\phi_b M_{ny}})] - 1 \leq 0 \quad , \quad l = 1,...,ne \tag{9}$$

where P_u is the required strength (tension or compression); P_n is the nominal axial strength (tension or compression); ϕ_c is the resistance factor; M_{ux} and M_{uy} are the required flexural strengths in the x and y directions; respectively; M_{nx} and M_{ny} are the nominal flexural strengths in the x and y directions; and ϕ_b is the flexural resistance reduction factor (ϕ_b=0.9).

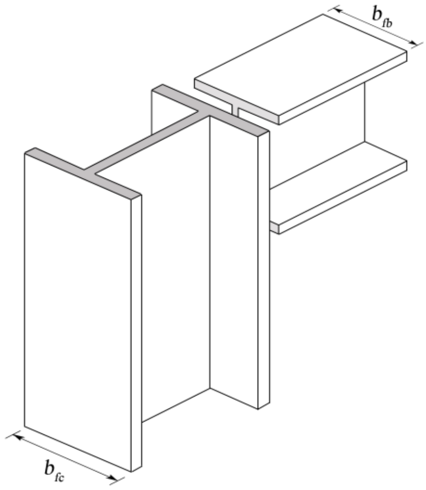

Fig. 1 Practical demands of beam-column joint

The effective length factor, K, for beam and bracing members is taken equal to unity. This parameter for columns is calculated from the following approximate Eqs. (10) and (11) respectively for braced and unbraced frames, developed by Dumonteil (1992), which are accurate to within about −1.0% and +2.0% of the exact results (Hellesland 1994)

$$K=\frac{3G_AG_B+1.4(G_A+G_B)+0.64}{3G_AG_B+2.0(G_A+G_B)+1.28} \tag{10}$$

$$K=\sqrt{\frac{1.6G_AG_B+4(G_A+G_B)+7.5}{G_A+G_B+7.5}} \tag{11}$$

where G_A and G_B refer to stiffness ratio or relative stiffness of a column at its two ends.

In order to satisfy practical demands geometric constraints should be considered in beam-column framing joints (Hasancebi *et al*. 2011). Considering Fig. 1 the following geometric constraints may be considered for 2D frames

$$g_{B_m}=\frac{b_{fb}}{b_{fc}}-1\le 0 \quad , \quad m=1,...,nj \tag{12}$$

where b_{fb} and b_{fc} are the flange width of beam and column, respectively; nj is the number of joints.

In the present work, the exterior penalty function method (EPFM) is employed to handle the design constraints. The EPFM transforms the basic constrained optimization problem into the unconstrained formulation. In this case, the pseudo unconstrained objective function can be represented as follows

$$\Psi(X,r_p)=w(X)\left(1+r\left(\max\{0,\ g_\delta\}\right)^2+r\sum_{k=1}^{ns}(\max\{0,\ g_{d_k}\})^2+r\sum_{l=1}^{ne}(\max\{0,\ g_{\sigma_l}\})^2+r\sum_{m=1}^{nj}(\max\{0,\ g_{B_m}\})^2\right) \tag{13}$$

where Ψ and r are the pseudo objective function and a positive penalty parameter, respectively.

3. Dolphin echolocation algorithm

The echolocation behavior of Dolphins in the natural world has been described in (Au 1993) and here the basic concepts which are necessary for formulation of DE are briefly explained.

A dolphin is able to generate sounds in the form of clicks. Frequency of these clicks is higher than that of the sounds used for communication and differs between species. When the sound strikes an object, some of the energy of the sound-wave is reflected back towards the dolphin. As soon as an echo is received, the dolphin generates another click. The time lapse between click and echo enables the dolphin to evaluate the distance from the object; the varying strength of the signal as it is received on the two sides of the dolphin's head enabling him to evaluate the direction. By continuously emitting clicks and receiving echoes in this way, the dolphin can track objects and home in on them. The clicks are directional and are for echolocation, often occurring in a short series called a click train. The click rate increases when approaching an object of interest (Au 1993).

Regarding an optimization problem, it can be understood that echolocation is similar to optimization in some aspects; the process of foraging preys using echolocation in dolphins is similar to finding the optimum answer of a problem. As mentioned in the previous part, dolphins initially search all around the search space to find the prey. As soon as a dolphin approaches the target, the animal restricts its search, and incrementally increases its clicks in order to concentrate on the location. The method simulates dolphin echolocation by limiting its exploration proportional to the distance from the target. For making the relationship much clear, consider an optimization problem. Two phases can be identified: in the first phase the algorithm explores all around the search space to perform a global search, therefore it should look for unexplored regions. This task is carried out by exploring some random locations in the search space, and in the second phase it concentrates on investigation around better results achieved from the previous stage. These are obvious inherent characteristics of all meta-heuristic algorithms (Kaveh and Farhoudi 2013).

As most of the meta-heuristics provide better performance in sorted design spaces, it would better if prior to starting the search process, the design space to be sorted out. For each design variable alternatives of the design space should be sorted in an ascending or descending order. In the case that the alternatives have more than one characteristic, ordering should be performed according to the most important one.

Moreover, a curve according to which the convergence factor should change during the optimization process should be assigned. Here, the change of convergence factor (CF) is considered to be according to the following curve (Kaveh and Farhoudi 2013)

$$PP(Loop_i) = PP_1 + (1 - PP_1)\frac{Loop_i^{power} - 1}{(LoopsNumber)^{power} - 1} \tag{14}$$

where PP is the predefined probability, PP_1 is the convergence factor of the first loop, $Loop_i$ is the number of the current loop, *power* is the degree of the curve and *Loops Number* is number of loops in which the algorithm should reach to the convergence point.

The main steps of DE algorithm for discrete optimization are as follows (Kaveh and Farhoudi 2013):

1. Initiate NL locations for a dolphin randomly. This step contains creating $L_{NL\times NV}$ matrix, in which NL is the number of locations and NV is the number of variables (or dimension of each location).

2. Calculate the *PP* of the loop using Eq. (14).

3. Calculate the fitness of each location. Fitness should be defined in a manner that the better answers get higher values. In other words the optimization goal should be to maximize the fitness.

4. Calculate the accumulative fitness according to dolphin rules as follows:

(a)

for i = 1 to the number of locations
  for j = 1 to the number of variables
    find the position of $L(i , j)$ in jth column of the Alternatives matrix as A.
  for k = *-Re to Re*

$$AF_{(A+k)\,j} = \frac{1}{R_e} \times (R_e - |k|) \times Fitness(i) + AF_{(A+k)\,j} \tag{15}$$

  end
 end
end

where $AF_{(A+k)j}$ is the accumulative fitness of the ($A+k$)th alternative (numbering of the alternatives is identical to the ordering of the Alternative matrix) to be chosen for the jth variable; R_e is the effective radius in which accumulative fitness of the alternative A's neighbors are affected from its fitness. This radius is recommended to be not more than 1/4 of the search space. *Fitness*(i) is the fitness of location i.

It should be added that for alternatives close to edges (where $A+k$ is not a valid; $A+k<0$ or $A+k>LA_j$), the AF is calculated using a reflective characteristic. Thus, if the distance of an alternative to the edge is less than R_e, it is assumed that the same alternative exists where picture of the mentioned alternative can be seen, if a mirror is placed on the edge.

(b) In order to distribute the possibility much evenly in the search space, a small value of ε is added to all the arrays as $AF=AF+\varepsilon$. Here, ε should be chosen according to the way the fitness is defined. It should be less than the minimum value achieved for the fitness.

(c) Find the best location of this loop and name it "The best location". Find the alternatives allocated to the variables of the best location, and let their *AF* be equal to zero.

5. For variable $j_{(j=1 \text{ to } NV)}$, calculate the probability of choosing alternative $i_{(i=1 \text{ to } ALj)}$, according to the following relationship

$$P_{ij} = \frac{AF_{ij}}{\sum_{i=1}^{LAj} AF_{ij}} \tag{16}$$

6. Assign a probability equal to *PP* to all alternatives chosen for all variables of the best location and devote rest of the probability to the other alternatives according to the following formula

for j = 1: Number of variables
  for i = 1: Number of alternatives
    if i = The best location(j)

$$P_{ij} = PP \tag{17}$$

    else

$$P_{ij} = (1 - PP)P_{ij} \tag{18}$$

    end
  end

end

Calculate the next step locations according to the probabilities assigned to each alternative.

Repeat Steps 2-6 as many times as the *Loops Number*.

The values of DE parameters have been given by Kaveh and Farhoudi (2013).

4. Modified dolphin echolocation algorithm

An efficient meta-heuristic optimization algorithm should possess balanced exploration and exploitation characteristics. For a meta-heuristic with dominant exploration characteristic the convergence rate would be slow while the dominant exploitation characteristic results in trapping in local optima. In the both cases, the meta-heuristic is not able to find the global or even near global optima. The diversification via randomization provides a good way to balance between exploration and exploitation and avoids the solutions being trapped at local optima. Employing a uniform distribution is not the only way to achieve randomization (Gholizadeh *et al.* 2014). With the development of theories and applications of nonlinear dynamics, chaos concept has attracted great attention in various fields of science and technology (Lin *et al.* 2012). The chaos has the property of the non-repetition, ergodicity, pseudo-randomness and irregularity (Pecora and Carroll 1990) and the track of chaotic variable can travel ergodically over the whole design space. In the last years, many successful combinations of the chaotic sequences with various meta-heuristic optimization algorithms have been reported in literature (Gandomi and Yang 2014). Such a combination of chaos with meta-heuristics has shown some promise once the right set of chaotic maps is used. It is still not clear why the use of chaos in an algorithm to replace certain parameters may change the performance, however, empirical studies indeed indicate that chaos can have high-level of mixing capability, and thus it can be expected that when a fixed parameter is replaced by a chaotic map, the solutions generated may have higher mobility and diversity. For this reason, it may be useful to carry out more studies by introducing chaos to other, especially newer, meta-heuristic algorithms (Gandomi and Yang 2014).

In meta-heuristic algorithms randomness is often achieved by using uniform or Gaussian probability distributions. As chaos can have very similar properties of randomness with better statistical and dynamical properties, past studies (Gandomi and Yang 2014) demonstrated the computational advantages of replacing such randomness by chaotic maps. In order to enable the algorithm to provide diverse solutions, such dynamical mixing is vital.

Due to the ergodicity and mixing properties of chaos, algorithms can potentially carry out iterative search steps at higher speeds than standard stochastic search with standard probability distributions (Coelho and Mariani 2008). In the present study, in order to achieve such potential the well-known Gauss (He *et al*. 2001), Logistic (Li *et al*. 2011) and Sinusoidal (Li *et al*. 2011) one-dimensional chaotic maps, respectively defined by Eqs. (19) to (21), are combined with the newly developed DE meta-heuristic algorithm.

$$x^{t+1} = \begin{cases} 0 & \text{if } x^t = 0 \\ \dfrac{1}{x^t} - \left[\dfrac{1}{x^t}\right] & \text{otherwise} \end{cases} \tag{19}$$

$$x^{t+1} = 4x^t(1 - x^t) \tag{20}$$

$$x^{t+1} = \sin(\pi x^t) \tag{21}$$

In order to calculate the next step locations based on the probability of each alternative the above chaotic maps are employed. For this purpose, the following steps are added to the original DE and the resulted algorithm is termed as modified dolphin echolocation (MDE) algorithm. It should be noted that steps 1 to 6 of the MDE are same as those of the DE. For the MDE, steps 7 to 9 are as follows:

7. Calculate the cumulative sum of each row of the *P* matrix (*CP*).
8. Generate a $NL \times NV$ matrix based on chaotic maps, termed as chaotic matrix (*CM*).
9. Calculate new locations as follows:

```
for i = 1: Number of variables
      for j = 1: Number of locations
            count the number, N, of values at the ith row of CP that are less than CM(i,j).
            new location (i,j) = N.
      end
end
Repeat Steps 2-9 as many times as the Loops Number.
```

All the required computer programs for performing optimization task are coded in MATLAB (2009) platform.

5. Numerical examples

Three benchmark steel frame optimization problems are solved by the proposed MDE algorithm and the results are compared with those of reported in literature. For all examples, PP_1=0.15, R_e=5, ε=1 (Kaveh and Farhoudi 2013), *NL*=50 and the best value of *power* is determined by sensitivity analysis. As the convergence rate of the algorithm is sensitive to the variations in *power* and in order to brevity and conciseness we have performed a sensitivity analysis only based on the different values of *power*. To achieve this, fifteen values 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0, 1.1, 1.2, 1.3 1.4 and 1.5 are considered for *power* and MDE is employed to perform 20 independent optimization runs in each case. In addition, our computational experiences in this study reveal that the best results of all examples are obtained in the case of Gauss one-dimensional chaotic map. Therefore, for brevity, only the results obtained by employing Gauss map are presented for each numerical example.

5.1 A 3-bay 15-story planar frame

The configuration, applied loads and grouping details of the structural members of a 3-bay 15-story frame structure are shown in Fig. 2.

There are 11 design variables in this example including 10 column sections and 1 beam sections related variables. The section of the beam and column element groups are chosen from all W-shaped sections. The material has a modulus of elasticity *E*=205 GPa and yield stress of F_y=248.2 MPa. In addition, the allowable tensile and compressive stresses are used according to the LRFD specification. Also, the maximum lateral displacement and maximum inter-story drift are limited to 23.5 cm and *h*/300, respectively, where *h* is the height of a story. In this example, the geometric constraints are not considered during the optimization process. The effective length factors of the members are calculated as $K_x \geq 0$ for a sway-permitted frame and the out-of-plane effective length factor is specified as K_y=1.0. Each column is considered as non-braced along its

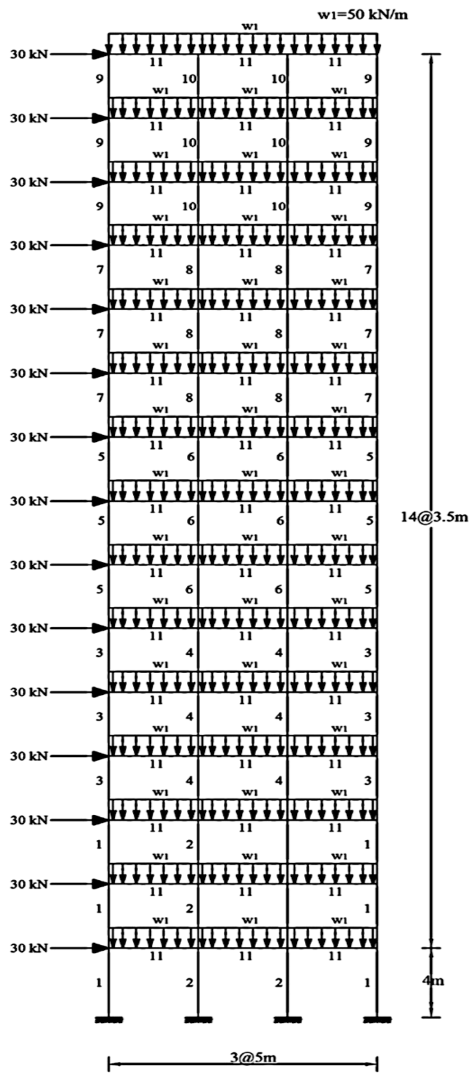

Fig. 2 Topology of the 3-bay 15-story frame

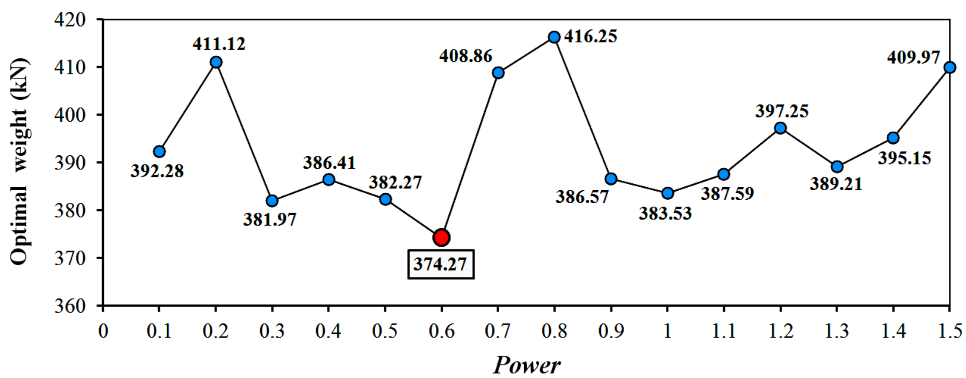

Fig. 3 The results of sensitivity analysis for the 3-bay 15-story frame

length, and the unbraced length for each beam member is specified as one-fifth of the span length.

In this example, for the MDE meta-heuristic algorithm the sensitivity analysis is performed considering *Loops Number*=100 and the results shown in Fig. 3 demonstrate that the best value for the *power* parameter is equal to 0.6.

The best results of the MDE and those of reported in literature are compared in Table 1. Moreover, The convergence histories of DE (Kaveh and Farhoudi 2013) and MDE are compared in Fig. 4.

It can be observed that the MDE finds an optimal solution which is 12.22%, 10.35%, 9.29% and 5.33% lighter than those of the HPSACO (Kaveh and Talatahari 2009), ICA (Kaveh and Talatahari 2010b), CSS (Kaveh and Talatahari 2012) and DE (Kaveh and Farhoudi 2013), respectively. Also, Fig. 3 implies that the convergence rate of MDE is better than that of DE.

For the optimum design found by MDE, the inter-story drifts profile is shown in Fig 5. The maximum value is 1.11 cm which is less than the allowable value of 1.16 cm. The maximum

Table 1 Optimum designs of the 3-bay 15-story planar frame

Design Variables	**HPSACO** (Kaveh and Talatahari 2009)	**ICA** (Kaveh and Talatahari 2010b)	**CSS** (Kaveh and Talatahari 2012)	**DE** (Kaveh and Farhoudi 2013)	**MDE**
1	W21×111	W24×117	W21×147	W12×87	W21×101
2	W18×158	W21×147	W18×143	W36×182	W27×146
3	W10×88	W27×84	W12×87	W21×93	W18×76
4	W30×116	W27×114	W30×108	W18×106	W24×104
5	W21×83	W14×74	W18×76	W18×65	W14×61
6	W24×103	W18×86	W24×103	W14×90	W27×84
7	W21×55	W12×96	W21×68	W10×45	W21×48
8	W27×114	W24×68	W14×61	W12×65	W21×62
9	W10×33	W10×39	W18×35	W6×25	W12×26
10	W18×46	W12×40	W10×33	W10×45	W14×38
11	W21×44	W21×44	W21×44	W21×44	W21×44
Weight (kN)	426.36	417.46	412.62	395.35	374.27
Analyses	6800	6000	5000	N/A	5000

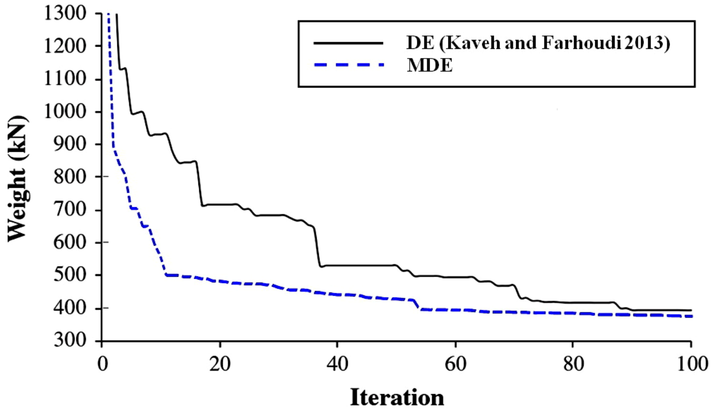

Fig. 4 Convergence histories of DE (Kaveh and Farhoudi 2013) and MDE for the 3-bay 15-story frame

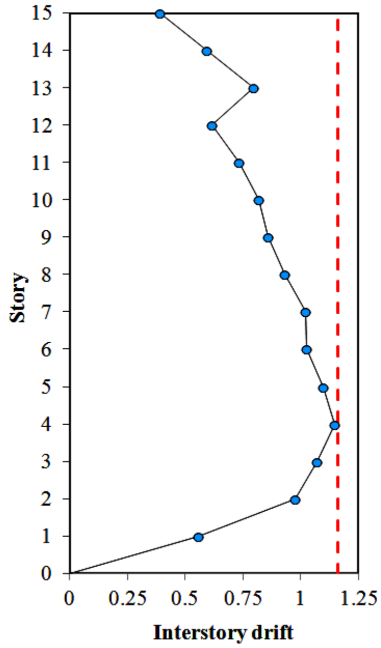

Fig. 5 Inter-story drifts profile for the optimal 3-bay 15-story frame found by MDE

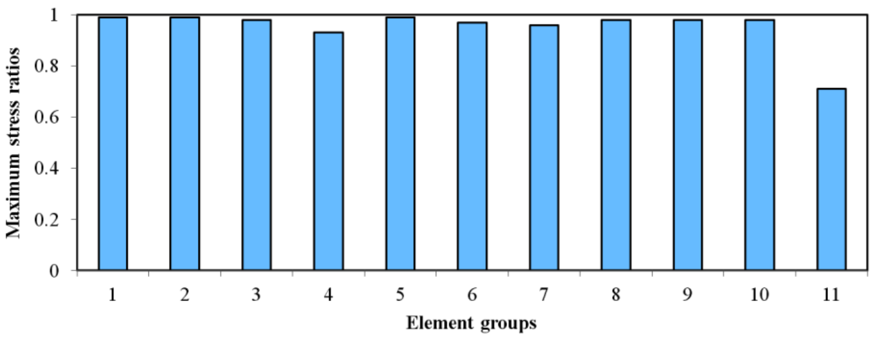

Fig. 6 Element group maximum stress ratios of the optimal 3-bay 15-story frame found by MDE

displacement is 12.19 cm which is less than its limit of 23.5 cm. Fig. 6 represents the maximum stress ratios in each element group of the frame. The maximum stress ratio is 0.9999. One can see that as well as the inter-story drift constraints, stress ratios are very close to the allowable value. In other words, both the inter-story drift and stress ratio constraints are active in this problem.

5.2 A 3-bay 24-story planar frame

Fig. 7 shows the 24-story frame and its loading and grouping conditions (Camp *et al*. 2005).

The design constraints are considered based on the LRFD specification. Also, the maximum lateral displacement and maximum inter-story drift are limited to H/300 and h/300, respectively, where H is the total height of the frame and h is the height of a story.

In this example, the geometric constraints are not checked and same as the first example $K_x \geq 0$

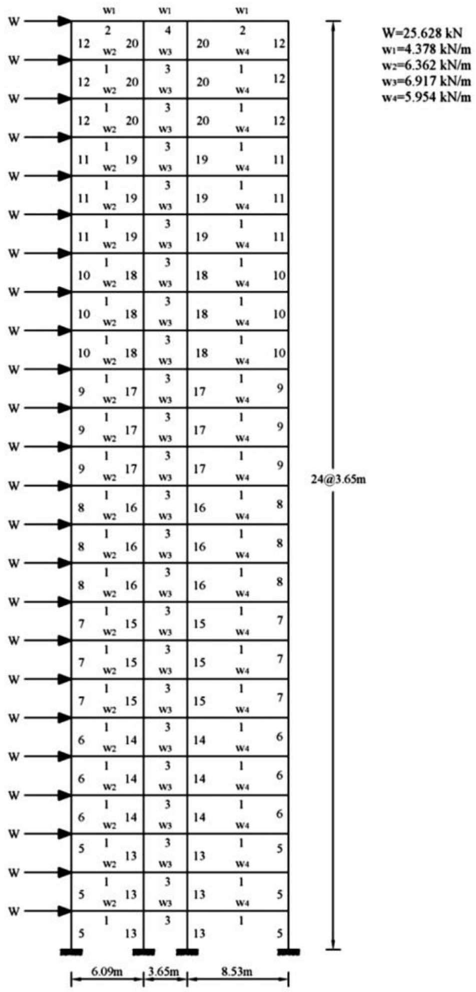

Fig. 7 Topology of the 3-bay 24-story frame

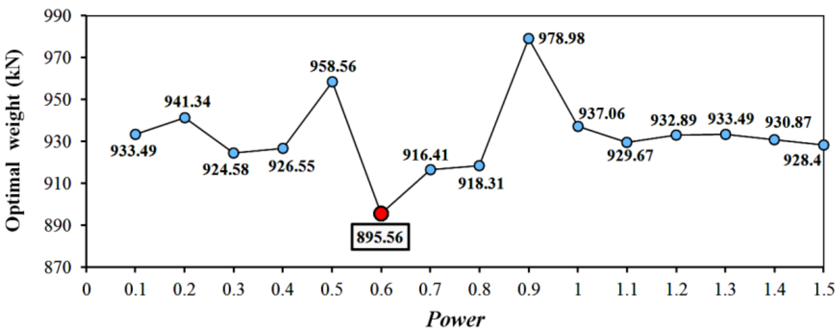

Fig. 8 The results of sensitivity analysis for the 3-bay 24-story frame

and K_y=1.0. The beams' sections are chosen from all W-shaped sections, while the section of columns is limited to W14 sections. In this example, E=205 GPa and F_y=230.3 MPa.

A sensitivity analysis is performed considering *Loops Number*=200. The results are depicted in Fig. 8 indicating that the best results are obtained for *Power*=0.6.

Table 2 compares the results of the MDE with those of reported in literature.

The results indicate that the optimum design of MDE is 8.63%, 6.3%, 0.82% and 1.8% lighter than those of the ACO (Camp *et al*. 2005), HS (Degertekin 2008), TLBO (Togan 2012) and DE

Table 2 Optimum designs of the 3-bay 24-story frame

Design Variables	**ACO** (Camp *et al*. 2005)	**HS** (Degertekin 2008)	**TLBO** (Togan 2012)	**DE** (Kaveh and Farhoudi 2013)	**MDE**
1	W30×90	W30×90	W30×90	W30×90	W30×90
2	W8×18	W10×22	W8×18	W6×20	W14×22
3	W24×55	W18×40	W24×62	W21×44	W24×55
4	W8×21	W12×16	W6×9	W6×9	W10×12
5	W14×145	W14×176	W14×132	W14×159	W14×132
6	W14×132	W14×176	W14×120	W14×145	W14×109
7	W14×132	W14×132	W14×99	W14×132	W14×120
8	W14×132	W14×109	W14×82	W14×99	W14×82
9	W14×68	W14×82	W14×74	W14×68	W14×61
10	W14×53	W14×74	W14×53	W14×61	W14×53
11	W14×43	W14×34	W14×34	W14×43	W14×26
12	W14×43	W14×22	W14×22	W14×22	W14×22
13	W14×145	W14×145	W14×109	W14×109	W14×99
14	W14×145	W14×132	W14×99	W14×109	W14×109
15	W14×120	W14×109	W14×99	W14×90	W14×99
16	W14×90	W14×82	W14×90	W14×82	W14×90
17	W14×90	W14×61	W14×68	W14×74	W14×82
18	W14×61	W14×48	W14×53	W14×43	W14×53
19	W14×30	W14×30	W14×34	W14×30	W14×43
20	W14×26	W14×22	W14×22	W14×26	W14×22
Weight (kN)	980.63	956.13	903.02	912.26	895.56
Analyses	15500	13924	12000	N/A	10000

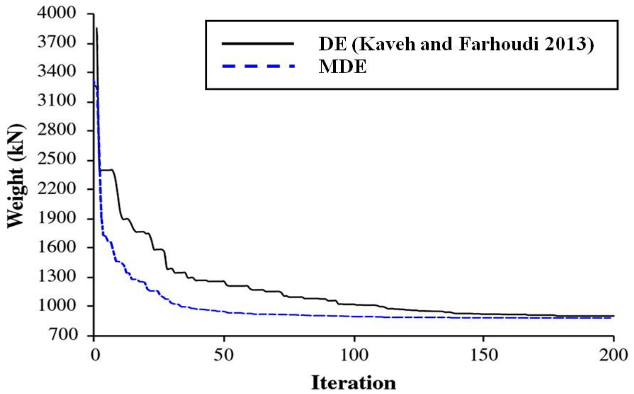

Fig. 9 Convergence histories of DE (Kaveh and Farhoudi 2013) and MDE for the 3-bay 24-story frame

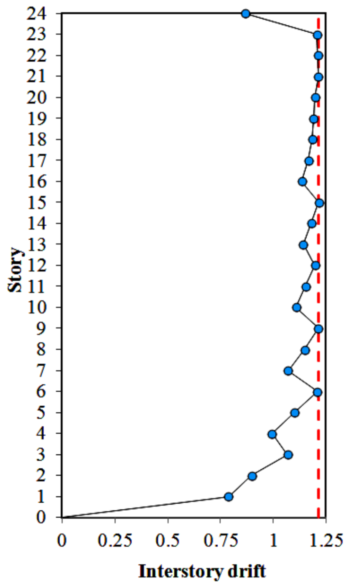

Fig. 10 Inter-story drifts profile for the optimal 3-bay 24-story frame found by MDE

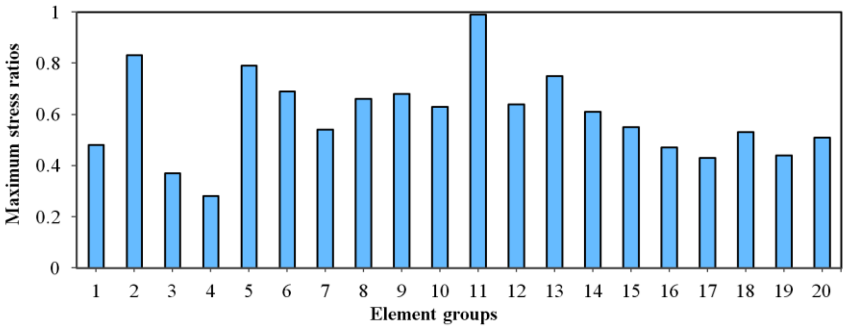

Fig. 11 Element group maximum stress ratios of the optimal 3-bay 24-story frame found by MDE

(Kaveh and Farhoudi 2013), respectively. Furthermore, the proposed MDE converges to its best solution at less computational effort in comparison with the other meta-heuristic algorithm. Fig. 9 compares the convergence histories of DE (Kaveh and Farhoudi 2013) and MDE indicating that the MDE possesses better convergence rate.

The lateral displacement of the optimum design found by MDE is 26.85 cm, which is less than the maximum displacement of 29.2 cm. The inter-story drift profile and element stress ratios of this optimum structure are shown in Figs. 10 and 11, respectively. The maximum inter-story drift and stress ratio are respectively equal to 1.21 cm and 0.9993 which are very close to their allowable values of 1.216 cm and 1.0. These results demonstrate that the solution is feasible. In this example, both the inter-story drift and stress ratio constraints dominate the optimum design.

5.3 A 3-bay 24-story braced planar frame

Fig. 12 depicts elevation and plan views of the 24-story braced frame (Hasancebi *et al.* 2010).

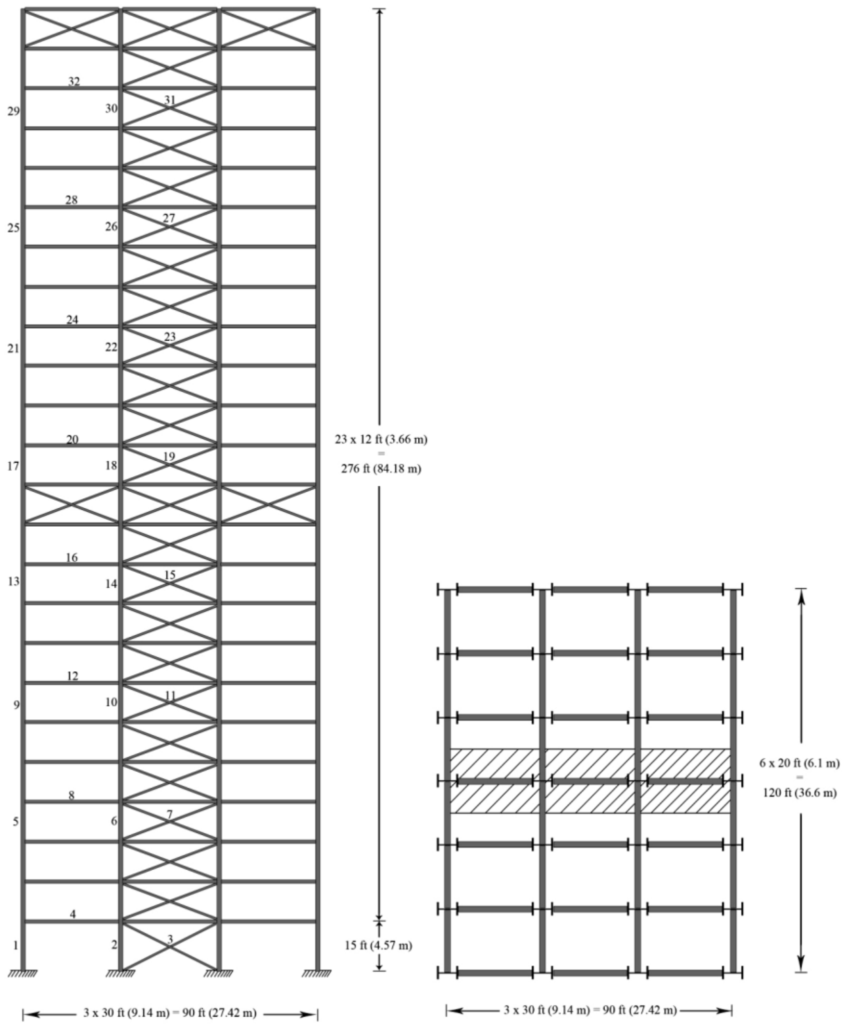

Fig. 12 224-Member 24-story braced planar steel frame

For checking the stress constraints, the provisions of ASD-AISC specification are employed. Geometric constraints are considered for practicality of the solution obtained as well as the work of Hasancebi *et al.* (2010). The maximum lateral displacements and inter-story drift are restricted to $H/400$ and $h/400$, respectively where H is the total height of the frame and h is the height of a story. In this example, E=203.8936 GPa and F_y=253.1 MPa.

The 224 members of the frame are collected in 32 member groups to satisfy practical fabrication requirements. As shown in Fig. 12 the exterior columns are grouped together as having the same section over three adjacent stories, as are interior columns, beams and braces. The wide-flange (W) profile list consisting of 297 ready sections is used to size column members, while beams and diagonals are selected from discrete sets of 171 and 147 economical sections selected from wide-flange profile list based on area and inertia properties in the former, and on area and radii of gyration properties in the latter. The frame is subjected to a single loading condition of combined gravity (dead, live and snow loads) and lateral (wind) loads that are computed as to ASCE 7-05 (2005) based on the following design values (Hasancebi *et al.* 2010): a uniformly distributed gravity load of 14.62 kN/m on top story beams and of 21.22 kN/m on other story beams. Wind loads acting at each floor level on windward and leeward faces of the frame are given in Table 3.

In order to find the best value of the *power* parameter a set of sensitivity analysis, considering *Loops Number*=600, is conducted and the results are shown in Fig. 13. It can be observed that the best results associated with *Power*=0.3.

Table 3 Wind loading on 24-story braced planar steel frame

Floor no.	Windward (kN)	Leeward (kN)
1	24.62	35.80
2	28.16	35.80
3	31.62	35.80
4	34.32	35.80
5	36.59	35.80
6	38.54	35.80
7	40.28	35.80
8	41.84	35.80
9	43.28	35.80
10	44.60	35.80
11	45.83	35.80
12	46.99	35.80
13	48.07	35.80
14	49.10	35.80
15	50.08	35.80
16	51.01	35.80
17	51.90	35.80
18	52.76	35.80
19	53.58	35.80
20	54.37	35.80
21	55.13	35.80
22	55.87	35.80
23	56.59	35.80
24	28.63	17.90

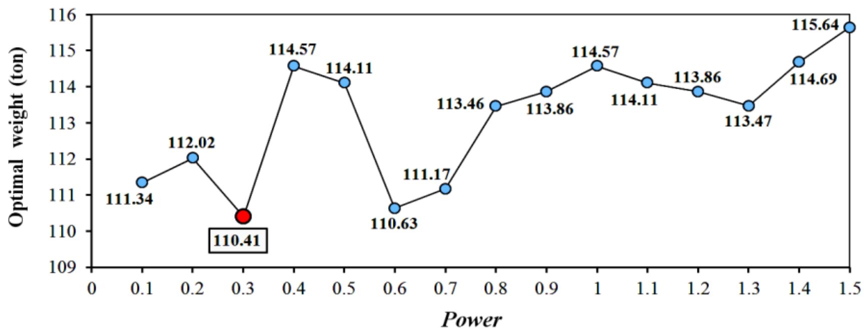

Fig. 13 The results of sensitivity analysis for the 24-story braced planar steel frame

Table 4 Optimum designs of the 24-story braced planar steel frame

Design Variables	Hasancebi *et al.* (2010)				**MDE**
	ACO	**TS**	**ESs**	**SA**	
1	W14×120	W12×120	W14×109	W14×109	W12×120
2	W40×268	W36×280	W40×277	W40×277	W36×282
3	W10×45	W8×40	W10×39	W8×40	W14×38
4	W16×40	W16×45	W16×40	W16×40	W18×40
5	W33×118	W18×106	W30×108	W14×99	W24×104
6	W40×221	W30×191	W12×210	W12×190	W36×256
7	W8×35	W8×35	W8×35	W10×39	W6×20
8	W14×43	W16×45	W14×43	W16×45	W24×55
9	W14×90	W18×97	W27×94	W14×90	W30×99
10	W33×152	W40×167	W14×145	W14×145	W30×173
11	W14×43	W10×33	W8×35	W8×31	W6×20
12	W18×50	W16×45	W14×43	W16×45	W21×48
13	W30×90	W27×94	W30×90	W30×90	W30×108
14	W27×129	W10×112	W30×116	W27×114	W36×135
15	W8×35	W10×39	W8×40	W8×40	W8×24
16	W18×60	W16×50	W18×50	W18×50	W21×48
17	W21×83	W24×76	W21×73	W10×68	W21×73
18	W24×104	W18×97	W24×104	W24×104	W21×111
19	W8×31	W8×31	W8×31	W8×31	W6×20
20	W16×40	W16×50	W14×43	W16×45	W21×44
21	W21×62	W14×53	W24×76	W14×53	W21×55
22	W21×73	W14×68	W8×31	W12×72	W12×72
23	W8×31	W8×31	W8×31	W8×31	W10×22
24	W16×40	W16×40	W16×40	W16×40	W16×45
25	W16×67	W14×43	W16×40	W16×40	W12×45
26	W12×53	W12×45	W10×49	W10×54	W21×55
27	W10×33	W8×31	W8×31	W8×31	W6×15
28	W16×40	W16×40	W16×40	W16×40	W18×46
29	W14×53	W8×35	W8×31	W8×31	W16×36
30	W12×45	W10×33	W8×35	W8×35	W21×62
31	W10×33	W10×33	W8×31	W8×31	W6×15
32	W18×55	W18×55	W14×43	W14×43	W21×44
Weight (ton)	119.96	115.89	112.59	112.06	110.41
Analyses	50000	50000	50000	50000	30000

Comparison of the results of MDE with other algorithms is achieved in Table 4. The results indicate that the optimum design of MDE is 7.96%, 4.73%, 1.94% and 1.47% lighter than those of the ACO (Hasancebi *et al.* 2010), TS (Hasancebi *et al.* 2010), ESs (Hasancebi *et al.* 2010) and SA (Hasancebi *et al.* 2010), respectively. Furthermore, it can be observed that MDE finds the optimal solution performing 30000 structural analyses while the other algorithms require 50000 analyses to converge to their best solutions.

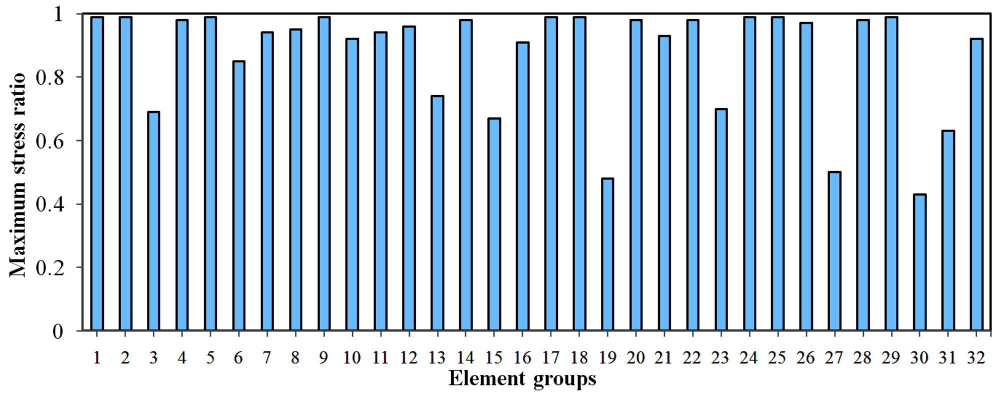

Fig. 14 Element group maximum stress ratios of the optimal 24-story braced planar steel frame found by MDE

For the optimum design found by MDE, the maximum value of displacement and inter-story drift are equal to 9.75 cm and 0.533 cm, respectively which are less than their allowable values of 22.19 cm and 0.915 cm. Fig. 14 presents the element stress ratios and the maximum value is equal to 0.9994. These results demonstrate that the stress ratio constraints dominate this feasible solution.

6. Conclusions

In the present study, MDE meta-heuristic algorithm is proposed for design optimization of steel frame structures. In the framework of MDE, the one-dimensional Gauss chaotic map is employed to calculate the next step locations based on the probability of each alternative. The ergodicity and mixing properties of chaos enables the MDE algorithm to search the design space at better performance in comparison with its standard version. Three planar steel frame examples are presented to illustrate the computational advantages of the proposed MDE meta-heuristic algorithm. In each design examples, the results of the proposed MDE are compared with those of four other algorithms proposed in other studies. In the first example, the weight of the optimal structure found by MDE is 12.22%, 10.35%, 9.29% and 5.33% lighter compared with those of the HPSACO, ICA, CSS and DE algorithms, respectively. The number of structural analyses required by the MDE is almost equal to those of the mentioned algorithms. In the second example, the weight reduction factors of MDE with respect to ACO, HS, MPSO and DE algorithms are respectively equal to 8.63%, 6.3%, 0.82% and 1.8% while the computational effort of MDE is less than those of the other algorithm. In the last and largest example, the optimum design of MDE is 7.96%, 4.73%, 1.94% and 1.47% lighter than those of the ACO, TS, ESs and SA meta-heuristics, respectively while the number of structural analyses achieved by MDE is 60% those of required by the other algorithms. The numerical results demonstrate that the MDE possesses better computational performance compared with the other meta-heuristic algorithms in terms of optimal weight and spent computational cost. In the sequel, the MDE can be efficiently used to implement optimization of steel frame structures.

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