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Simplified dolphin echolocation algorithm for optimum design of frame

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Abstract. Simplified Dolphin Echolocation (SDE) algorithm is a recently developed meta-heuristic algorithm. This algorithm is an improved and simplified version of the Dolphin Echolocation Optimization (DEO) method, based on the baiting behavior of the dolphins. The main advantage of the SDE algorithm is that it needs no empirical parameter. In this paper, the SDE algorithm is applied for optimization of three well-studied frame structures. The designs are then compared with those of other meta-heuristic methods from the literature. Numerical results show the efficiency of the SDE algorithm and its competitive ability with other well-established meta-heuristics methods.

Keywords: meta-heuristic algorithms; dolphin echolocation optimization; simplified dolphin echolocation optimization; frame structures

1. Introduction

Optimization is a popular topic in structural engineering extensively applied to optimal design of structures (Saka and Geem 2013, Aydoğdu *et al.* 2016, Aydogdu *et al.* 2017, Kaveh 2017, Kaveh and Bolandgerami 2017).

In recent decades, many new meta-heuristic algorithms have been presented some of which can be listed as: Genetic Algorithms (GA) (Holland John 1975), Particle Swarm Optimization (PSO) (Eberhart and Kennedy 1995), Ant Colony Optimization (ACO) (Dorigo *et al.* 1996), Differential Evolution (DE) (Storn and Price 1997), Harmony Search (HS) (Geem *et al.* 2001), Big-Bang Big-Crunch (BBBC) (Erol and Eksin 2006), Artificial Bee Colony (ABC) (Karaboga and Basturk 2007), Ray Optimization (RO) (Kaveh and Khayatazad 2012), Grey Wolf Optimization (GWO) (Mirjalili, Mirjalili *et al*. 2014), Cuckoo Search (CS) (Yang and Deb 2010), Water Cycle Algorithm (WCA) (Eskandar *et al.* 2012), Dolphin Echolocation Optimization (DEO) (Kaveh and Farhoudi 2013), Colliding Bodies Optimization (CBO) (Kaveh and Mahdavi 2014), Enhanced Colliding Bodies Optimization algorithm (ECBO) (Kaveh and Ilchi Ghazaan 2014), Water Evaporation Optimization (WEO) and accelerated version (AWEO) (Kaveh and Bakhshpoori 2016), Pigeon Colony Algorithm (PCA) (Yi *et al.* 2016), social spider optimization (Aydogdu *et al*. 2017), Tug of War Optimization (TWO) (Kaveh and Zolghadr 2016), Simplified Dolphin Echolocation algorithm (SDE) (Kaveh and Hosseini 2014).

In this study, weight optimization of three frame structures is assessed. Sections are selected from a standard set of steel sections of the American Institute of Steel Construction (AISC) wide-flange W-shapes.

Dolphin Echolocation Optimization (DEO) is one of the recently developed meta-heuristics (Kaveh and Farhoudi 2013). This algorithm was simplified, modified and introduced as Simplified Dolphin Echolocation (SDE) method (Kaveh and Hosseini 2014). The DEO algorithm and its simplified version (SDE) are based on the hunting technique of dolphins. Dolphins send echo in different directions and listen to the reflections and then move towards their prey. During approaching the bait, dolphins continue sending echoes in order to increase the probability of successful hunting. The optimal solution acts as model's bait in the algorithm. In this study, SDE is used for size optimization of three well-studied frame structures.

This paper is organized as follows: After this introductory section, a brief explanation of the SDE algorithm for structural optimization problems is presented in section 2. Three well-known benchmark problems are studied in section 3, and finally, concluding remarks are provided in the final section.

2. The SDE algorithm for structural optimization problems

This section briefly provides the SDE algorithm for discrete optimization of frame structures. Firstly, a general explanation of this algorithm is presented as follow:

Dolphins first send a click in different directions for hunting. Then, they find their bait based on the reflection and move toward it. Sending and receiving the click continues until catching the bait and thus the probability of catching the bait increases at any moment. In the SDE algorithm, this increase of probability is indicated as

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$$P_{Li} = P_{L1} + (1 - P_{L1})\frac{Li - 1}{LN - 1} \quad (1)$$

where P_{Li}, Li and LN are the probability of the ith loop, the number of the ith loop and number of loops, respectively; P_{L1} is the probability of the first loop usually obtained approximately as 0.1 (10%). Also, this P_{L1} can be considered as equations presented in Ref. (Kaveh and Hosseini 2014).

Lower P_{Li} is first seen as exploration search mode and the algorithm enters into exploitation phase by increasing the amount of this value.

The parameter AC is considered for indicating the accuracy of every variable in the SDE algorithm. It displays the number of decimal places for each variable, it should be noted that this parameter is equal to 1 for discrete optimization the parameter R is supposed as one-fifth of the search space for all variables individually.

2.1 Step by step summary of the SDE algorithm for discrete optimization

İnitial parameters of the SDE algorithm consisting of: number of loops (LN), number of locations (this parameter is similar to the number of population in other algorithms), the probability of the first loop (P_{L1}), the accuracy of every parameter (AC=1; for discrete optimization) and R parameter are initialized.

Step 1: Generate the L matrix

Matrix L is generated by random numbers (in the permissible range for every variable) in the first loop; these random numbers consist of the sequence numbers of the W-sections. So, the initial sections for each group of the frame are determined. However, the matrix L is generated in the subsequent loops according to the steps of the algorithm.

Step 2: Compute P_{Li}

This parameter is calculated according to Eq. (1).

Step 3: Calculate fitness

Before calculating the fitness, L matrix should be ordered. This ordering has a high impact on quality of the optimum answers. The SDE algorithm considers a triangle distribution in the neighborhood of the answers for all variables and all locations. In those cases where the triangular distribution is located outside the permissible range, it is reflected into the range (like a mirror).

The aim of the optimum design of frame structures is to minimize the weight of frame structures satisfying certain design constraints. Design constraints include strength and displacements constraints according to the LRFD-AISC specification (AISC 2001). In fact, the aim of the SDE algorithm in this research is to find a suitable set of design variables to reach the best weight without violation. The mathematical formulation can be expressed as follow:

$$\text{Find } \{x\} = [x_1, x_2, ..., x_{ng}] \qquad x_i \in W_i$$

$$\text{To minimize } W(\{\mathrm{x}\}) = \sum_{i=1}^{nm} \rho_i A_i L_i \quad (2)$$

where $\{\mathrm{x}\}$ is a set of design variables containing the sequence numbers of the W-sections; ng is the numbers of member groups (number of design variables); $W(\{\mathrm{x}\})$ is the weight of the structure; nm is the number of elements of the structure; ρ_i shows the material density of member i; A_i and L_i denote the cross-sectional area and the length of member i, respectively. Here, x_i is the number of a W-section and A_i is its cross-sectional area for the ith group. As mentioned, in this study, discrete optimization is considered, and the ith variable can be selected from W-sections list for ith member group of frame sections.

$$W_i = (w_{i,1}, w_{i,2}, ..., w_{i,r(i)}) \quad (3)$$

Thus the problem can be solved as a discrete optimization problem, $r(i)$ is the last available W-section. The frame structure is analyzed and checked for design constraints for each location of L matrix according to the following equation (to control the constraints, the penalty approach is utilized)

$$fitness(x) = (1 + \varepsilon_1 . \upsilon)^{\varepsilon_2} \times w\{(x)\}, \upsilon = \sum_{j=1}^{nc} \max(0, \upsilon_i) \quad (4)$$

Fitness (x) and v are the fitness function and the sum of the violations of design. In this study, ε_1 and ε_2 are set to 0.3 and 1, respectively and nc is the total number of constraints for each individual design. In fact, in discrete optimization, algorithms find the numbers associated with the W-sections and then these values are interpreted as properties of the corresponding W-sections. Also, as mentioned, violations are managed with penalty approach. According to the AISC-LRFD (AISC 2001), constraints are as follow:

Maximum lateral displacement

$$\frac{|\Delta_T|}{H} - R_k \le 0 \quad (5)$$

The inter-story drift constraints

$$\frac{|d_i|}{h_i} - R_l \le 0; i = 1, 2, ..., ns \quad (6)$$

Strength constraints

$$\begin{aligned} &\frac{P_u}{2\phi_c P_n} + \left[\frac{M_{ux}}{\phi_b M_{nx}} + \frac{M_{uy}}{\phi_b M_{ny}}\right] - 1 \le 0; \ for \frac{P_u}{\phi_c P_n} < 0.2 \\ &\frac{P_u}{\phi_c P_n} + \frac{8}{9}\left[\frac{M_{ux}}{\phi_b M_{nx}} + \frac{M_{uy}}{\phi_b M_{ny}}\right] - 1 \le 0; \ for \frac{P_u}{\phi_c P_n} \ge 0.2 \end{aligned} \quad (7)$$

where Δ_T is the maximum lateral displacement of the roof; H is the height of the frame; R_k is the maximum drift index (in this study it is equal to $\frac{1}{300}$); d_i is the inter story drift; h_i is the story height of the ith floor; ns is the total number of stories; R_l shows the inter story drift index and its limitation is like R_k index; P_u is the required strength (tension or compression); P_n is the nominal axial strength (tension or compression); $\varnothing_c$ is the resistance factor ($\varnothing_c$ = 0.9 for tension and $\varnothing_c$ = 0.85 for compression); M_u (containing M_{ux} and M_{uy}) is the required flexural strengths; M_n (containing M_{nx} and M_{ny}) is the nominal flexural strengths (for two-dimensional frames M_{uy}=0 and M_{ny}=0); and $\varnothing_b$ presents the flexural resistance reduction factor ($\varnothing_b$ = 0.90). The nominal axial strength is evaluated according to the AISC-LRFD (AISC 2001).

Step 4: Calculate the accumulative fitness, *AF* matrix

The intended triangular distributions should somehow be integrated. Therefore, a matrix called Accumulative Fitness (*AF*) is used which adds all the triangular distributions in each alternative. In fact, *AF* matrix puts all the fitness together (considering triangular distributions) for all variables.

Then, the highest value is considered equal to P_{Li} and the remaining probability (1- P_{Li}) is assigned to other alternatives. A hypothetical curve for each variable is considered, where the horizontal axis is the alternative value and the vertical axis is the corresponding *AF* value. Fig. 1 illustrates this hypothetical curve. This figure shows the probability of each W-section for being the optimum answer for each variable.

Step 5: Generate $AFArea_{ij}$

The goal is the sub-curved area of the *AF* (according to Fig. 1) to be equal to 1. Thus, Eq. (8) is used. It should be noted that the entire search space is numbered and considered as an alternative.

$$AFArea_{ij} = \frac{Area_{ij}}{\sum_{i=1}^{N} Area_{ij}} \tag{8}$$

where $AFArea_{ij}$ and $Area_{ij}$ are the modified *AF* sub-curved area and the *AF* sub-curved area for the *i*th alternative and *j*th vtheariable, respectively.

Step 6: Create *L* matrix for the next loop

The required number of values is picked up from the obtained $AFArea_{ij}$ for the next loop. These values must be arranged for the formation of the *L* matrix.

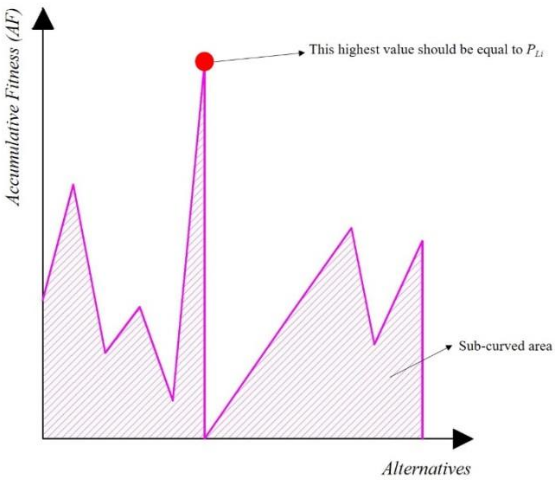

Fig. 1 The hypothetical curve

Ordering is performed in a way that a variable that is to be sorted is arranged against the values taken from the $AFArea_{ij}$, and a constant value is assigned to other variables. Then, the *fitness* value of each *location* is calculated and they are sorted in terms of their *fitness* value and this is done for all variables. Choosing this constant value is influential on some problems. Upon completion of the operation, the sorted *L* matrix is generated. To improve the search functionality of the algorithm, one can replace random values in the permissible range with *L* matrix values in 30% of the occasions. For further clarity, the flowchart of the SDE algorithm is presented in Fig. 2 and the pseudo code of the SDE algorithm for discrete optimization problems is presented in the following:

```
%%Pseudo code of the SDE algorithm%%
Set the initial parameter of the SDE algorithm
LN=number of loops;
NV=number of variables;
CL=1;
AC=1; % for discrete optimization this parameter is equal to 1.
Location=select to enough value
R=1/5 of the search space for all variables;
PL1=0.1 or can be calculated according to Kaveh and Hosseini research (2014);
L=random W-section for each variable;
while CL<=NL
    CL=CL+1;
    PL(CL)= considering as Eq. (1);
    L=reorder L matrix according to section 2.1;
    Fitness=calculating using Eq. (4)
    Fitness= considering triangle distribution according to section 2.1;
    Accumulative Fitness= considering the effect of all Fitness together in each alternative;
    assigning the probability of PL(i) to highest value and (1-PL(i) to others;
    for j=1:NV
        for i=1:Alternatives
        Area(i,j)=calculating according to sub curve of Accumulative Fitness;
        end
    end
    AFArea=considering as Eq. (8);
    L= select the necessary W-section from AFArea;
    for j=1:NV
        for i=1:locations
            if rand<0.3
                L(i,j)=Select a random W-section for jth variable;
            end
        end
    end
  end while
```

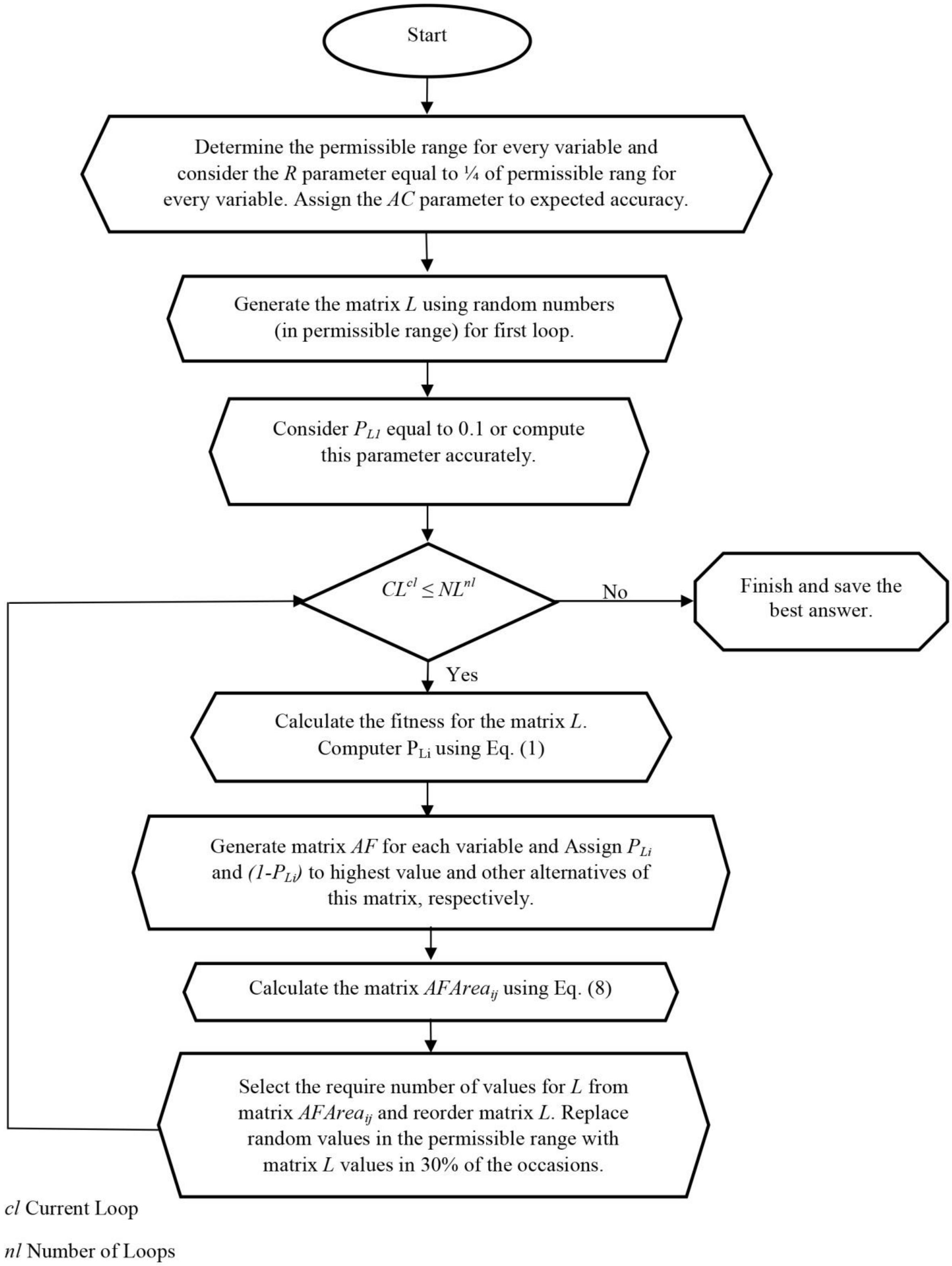

Fig. 2 Flowchart of the SDE algorithm.

3. Optimum design of steel frames using SDE algorithm

The SDE algorithm is applied to damage detection problems (Kaveh *et al.* 2016) and weight optimization of truss structures (Kaveh and Hosseini 2014) successfully. Thus the authors decided to investigate the ability of this algorithm for weight optimization of the frame structures.

In this section, three well-studied frame structures are considered to investigate the performance of the SDE algorithm to compare with some other meta-heuristic algorithms. Minimizing the weight of three frame structures is the aim of this study. These frames are:

A 1–bay 10-story frame
A 3-bay 15-story frame
A 3-bay 24-story frame

In this study, the value of *AC* algorithm parameter is assumed to be 1 and the number of loops is considered as 100; and the location sizes are assumed as 80, respectively. For more precise study, each problem has been solved 30 times independently and each run, objective function is evaluated 80000, 96000 and 168000 times for problems 1, 2 and 3, respectively. Also, for better comparison, five algorithms consisting of CBO (Kaveh and Mahdavi 2014), ECBO (Kaveh and Ilchi Ghazaan 2014), CBO-MDM (Kaveh *et al*. 2017), AWEO (Kaveh and Bakhshpoori 2016) and EVPS (Kaveh *et al*. 2017, Kaveh *et al.* 2018) are applied in this study. It should be noted that population size, number of independent runs and number of evaluating objective function are the same as the SDE algorithm for all problems. The results of the CBO, ECBO, CBO-MDM, AWEO, EVPS and SDE algorithms have no violation.

All problems and algorithms are coded in MATLAB and the frame structures are analyzed using the direct stiffness methods. It should be note that the purpose of optimal solution is the best answer among answers for each algorithm. For better evaluation, five metaheuristic algorithms are considered.

3.1 A 1–bay 10-story frame

Fig. 3 illustrates the schematic, applied loads and the numbering of the member groups for this frame structure. This frame consists of 11 joints and 30 elements. The element grouping results in 4 beam sections and 5 column sections for a total of 9 design variables. Each of the 4 beam element groups is selected from all 267 W-sections while the 5 column groups are chosen from only W14 and W12 sections.

The material has a modulus of elasticity equal to E =200GPa (29 000 ksi) and the yield stress of F_y=248.2MPa (36 ksi). The effective length factors of the members are calculated as $k_x \geq 1.0$ for a sway-permitted frame, and the out-of-plane effective length factor is specified as $k_y = 1.0$.

All columns are considered as non-braced along their length, and the non-braced length for all beam members are specified as $\frac{1}{5}$ of the span length. The frame is designed following the AISC-LRFD specifications (AISC 2001).

Table 1 provides the results of the present method and some other meta-heuristic algorithms. In this table the best, worst and mean weights for each algorithm are provided.

It can be seen that the lightest design is found by the EVPS and CBO-MDM which is 286.3 kN and the lightest design of GA (Pezeshk *et al.* 2000), DEO, CBO, ECBO, AWEO and SDE respectively are 1.8%, 8%, 8.6%, 7.72%, 6.22% and 0.8% heavier than the lightest weight of Table 1. Also from this table, it is obvious that the SDE algorithm has reached the lightest mean weight for all runs. Fig. 4 illustrates the convergence histories of the SDE for one of the best designs of the 1-bay 10-story frame. Figs. 5 and 6 show the existing stress ratios and inter-story drift for the optimal design of the SDE algorithm.

3.2. A 3-bay 15-story frame

Fig. 7 illustrates the schematic, applied loads and the numbering of the member groups for this problem, consisting of 64 joints and 105 elements. This problem is a well-known benchmark in structural optimization literature.

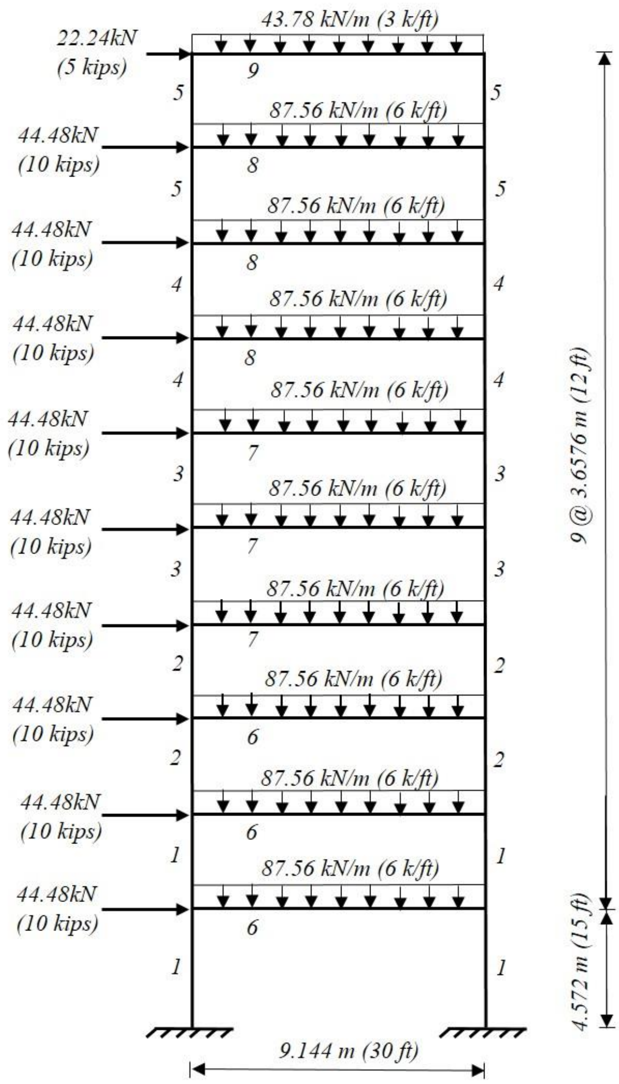

Fig. 3 Schematic of a 1-bay 10-story frame

Table 1 Optimal designs of the SDE and some other meta-heuristic algorithms for the 1-bay 10-story frame

Element group	Optimal W-Shaped sections							
	GA (Pezeshk *et al*. 2000)	**DEO**	**CBO**	**ECBO**	**CBO-MDM**	**AWEO**	**EVPS**	**SDE**
1	W14x233	W14x233	W14x233	W14x233	W14x233	W14x233	W14x233	W14x233
2	W14x176	W14x193	W14x176	W14x176	W14x176	W14x211	W14x176	W14x176
3	W14x159	W14x145	W14x132	W12x152	W14x159	W12x170	W14x159	W14x145
4	W14x99	W12x106	W14x99	W12x120	W14x99	W14x99	W14x99	W14x99
5	W12x79	W14x61	W14x61	W12x65	W14x61	W14x68	W14x61	W12x65
6	W33x118	W33x118	W30x148	W33x118	W33x118	W33x118	W33x118	W33x118
7	W30x90	W30x116	W30x116	W33x130	W30x90	W30x99	W30x90	W30x99
8	W27x84	W30x90	W27x102	W24x84	W27x84	W30x90	W27x84	W27x84
9	W24x55	W24x104	W16x50	W14x61	W18x46	W18x50	W18x46	W21x44
Best weight (kN)	289.12	306.76	308.44	305.94	284.01	301.69	284.01	286.3
Worst weight (kN)	-	328.24	324.07	330.95	296.07	328.55	297.24	286.3
Mean weight (kN)	-	325.37	310.93	315.52	287.63	316.28	286.43	286.3

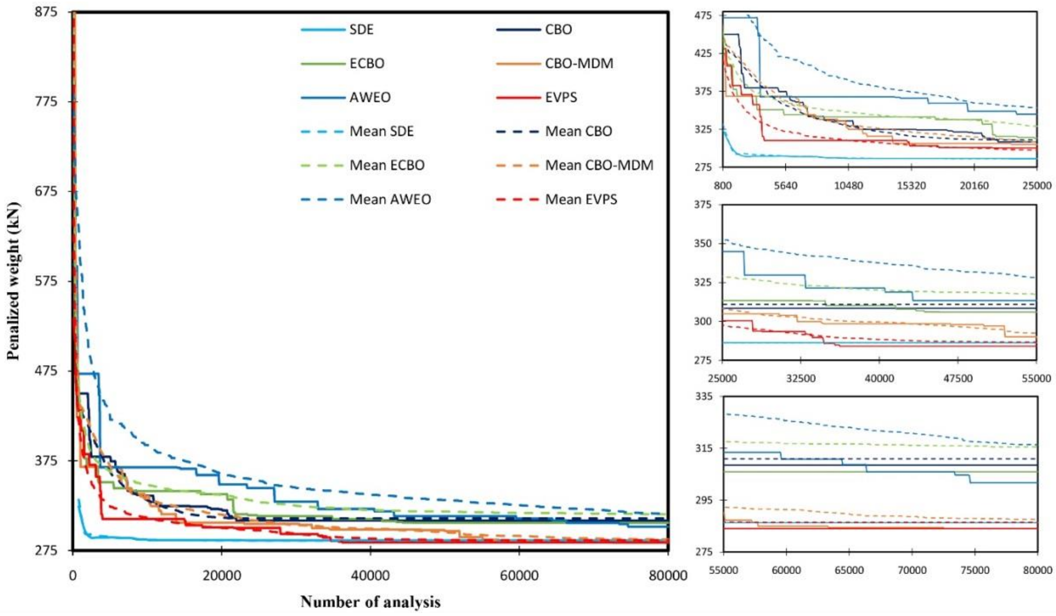

Fig. 4 Convergence curves of the optimal and mean design of the SDE algorithm for the 1-bay 10-story frame in comparison with other utilized metaheuristic algorithms

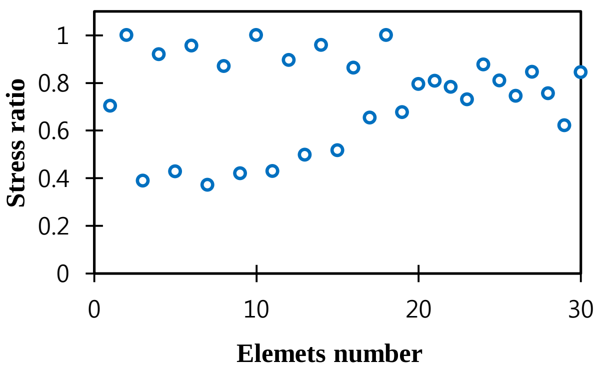

Fig. 5 Stress ratio for the lightest design of the SDE algorithm for the 1-bay 10-story frame

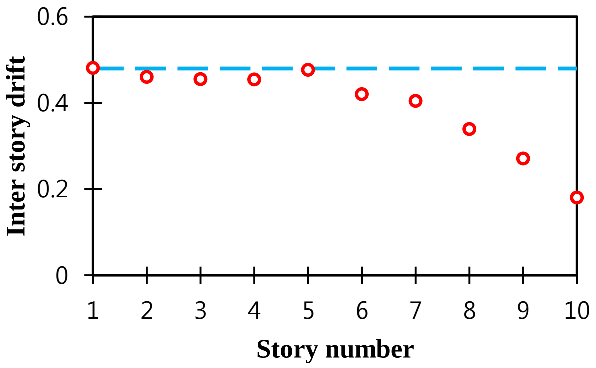

Fig. 6 Inter-story drifts for the lightest design of the SDE algorithm for the 1-bay 10-story frame

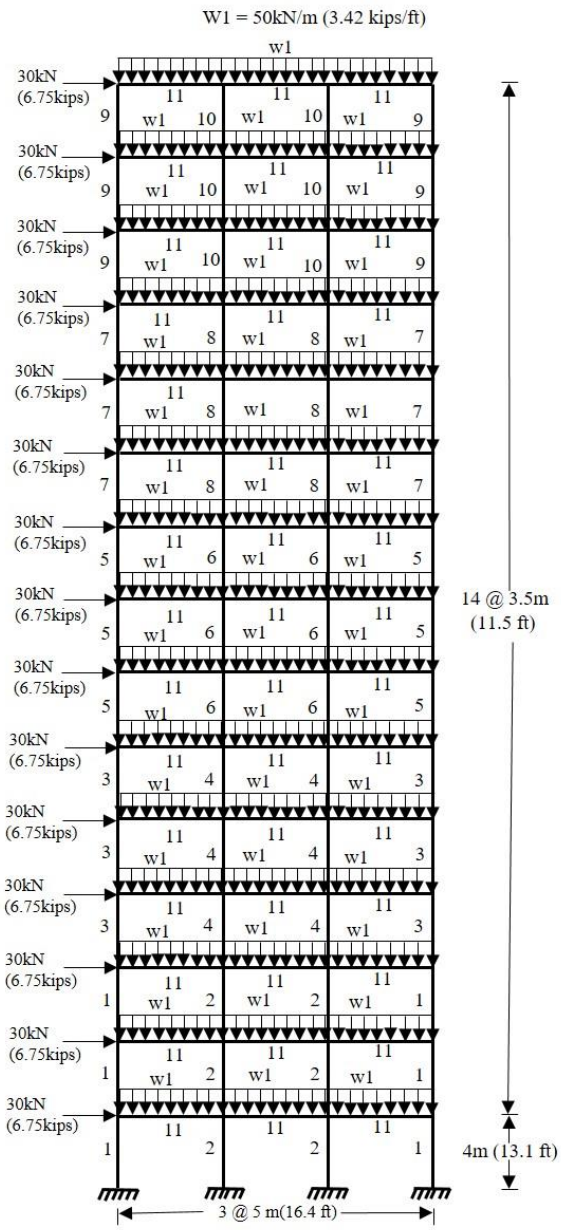

Fig. 7 Schematic of a 3-bay 15-story frame

Table 2 Optimal designs of the SDE and some meta-heuristic algorithms for the 3-bay 15-story frame

Element group	Optimal W-Shaped sections									
	EWOA (Kaveh and Ilchi Ghazaan 2016)	**DE** (Talatahari, Gandomi *et al.* 2015)	**ES-DE** (Talatahari, Gandomi *et al.* 2015)	**DEO** (Kaveh and Farhoudi 2013)	**CBO**	**ECBO**	**CBO-MDM**	**AWEO**	**EVPS**	**SDE**
1	W14x99	W21X122	W18X106	W12x87	W12x96	W12x106	W14x99	W18x143	W14x99	W14x90
2	W27x161	W33X141	W36X150	W36x182	W36x170	W27x161	W27x161	W24x162	W27x161	W36x170
3	W27x84	W14X82	W12X79	W21x93	W27x84	W27x84	W27x84	W24x84	W27x84	W27x84
4	W24x104	W30X108	W27X114	W18x106	W27x114	W24x104	W24x104	W33x118	W24x104	W24x104
5	W21x68	W30X108	W30X90	W18x65	W24x68	W16x67	W21x68	W12x65	W14x61	W14x61
6	W18x86	W12X79	W10X88	W14x90	W16x89	W16x89	W18x86	W18x97	W30x90	W30x90
7	W21x48	W14X61	W18X71	W10x45	W21x48	W21x48	W8x48	W12x50	W14x48	W14x48
8	W14x68	W18X71	W18X65	W12x65	W10x68	W24x68	W12x65	W21x68	W12x65	W12x65
9	W8x31	W6X25	W8X28	W6x25	W6x25	W12x30	W8x28	W8x28	W6x25	W6x25
10	W10x45	W24X62	W12X40	W10x45	W16x50	W10x39	W16x40	W16x40	W12x40	W12x40
11	W21x44	W21X48	W21X48	W21x44	W21x44	W21x44	W21x44	W21x44	W21x44	W21x44
Best weight (kN)	391.84	423.83	415.06	395.35	398.94	394.61	389.86	412.22	387.89	387.64
Worst weight (kN)	422.27	-	-	-	432.57	431.64	397.21	449.97	394	394
Mean weight (kN)	403.82	-	-	-	419.2	413.36	392.39	429.46	389.77	387.89

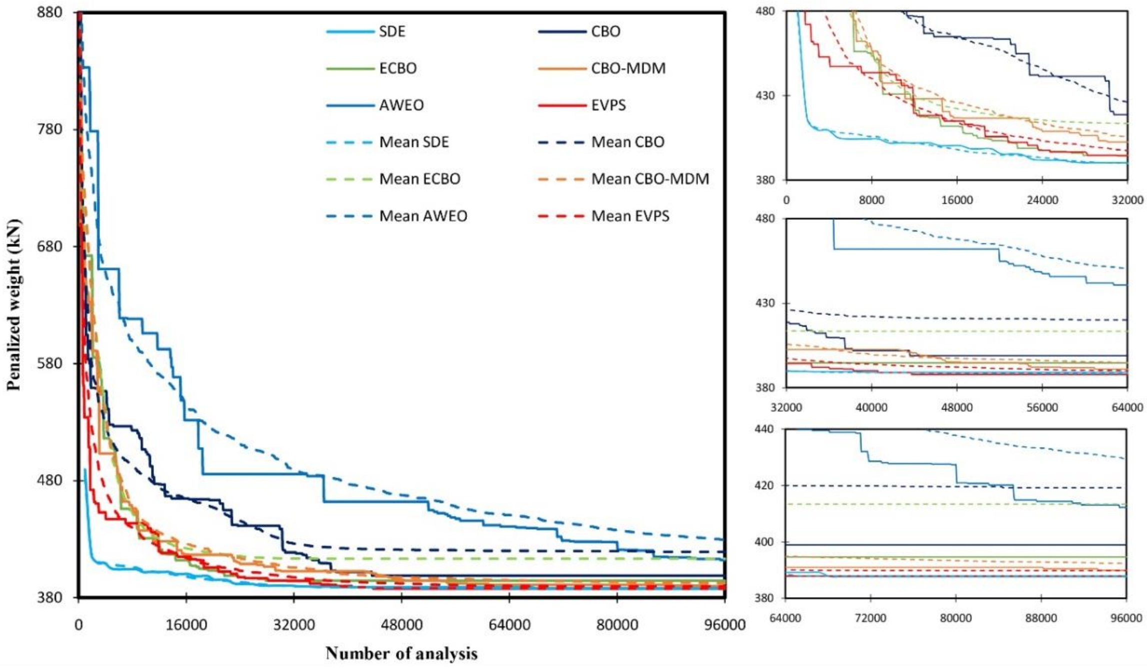

Fig. 8 Convergence curve for the optimal and mean design of the SDE algorithm of the 3-bay 15-story frame in comparison with other metaheuristic algorithms

The element grouping results are classified as 11 groups consisting of 10 column groups and 1 beam group. The material has a modulus of elasticity equal to E =200GPa (29 000 ksi) and the yield stress is 248.2MPa (36 ksi). 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 indicated as $k_y = 1.0$. Each column is considered as non-braced along its length, and the non-braced length for each beam member is determined as $\frac{1}{5}$ of the span length. The structure is designed following the AISC-LRFD specifications and using an inter-story drift displacement constrains (AISC 2001).

Table 2 provides the results of the present method and some other meta-heuristic algorithms. In this table the best, worst and mean weights for each algorithm are provided.

It can be seen that the lightest design is found by SDE which is 387.64 kN and the lightest design of EWOA (Kaveh and Ilchi Ghazaan 2016), DE (Talatahari *et al.* 2015), ES-DE (Talatahari *et al.* 2015), DEO

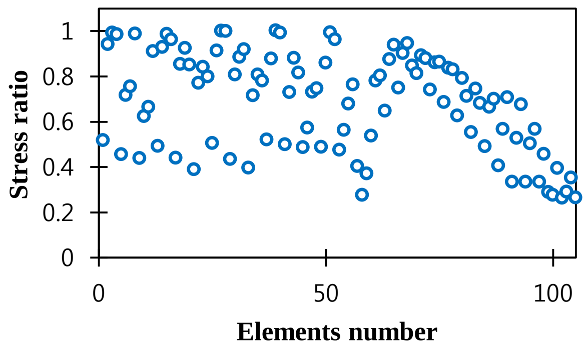

Fig. 9 Stress ratio for the optimal design of the SDE algorithm for the 3-bay 15-story frame

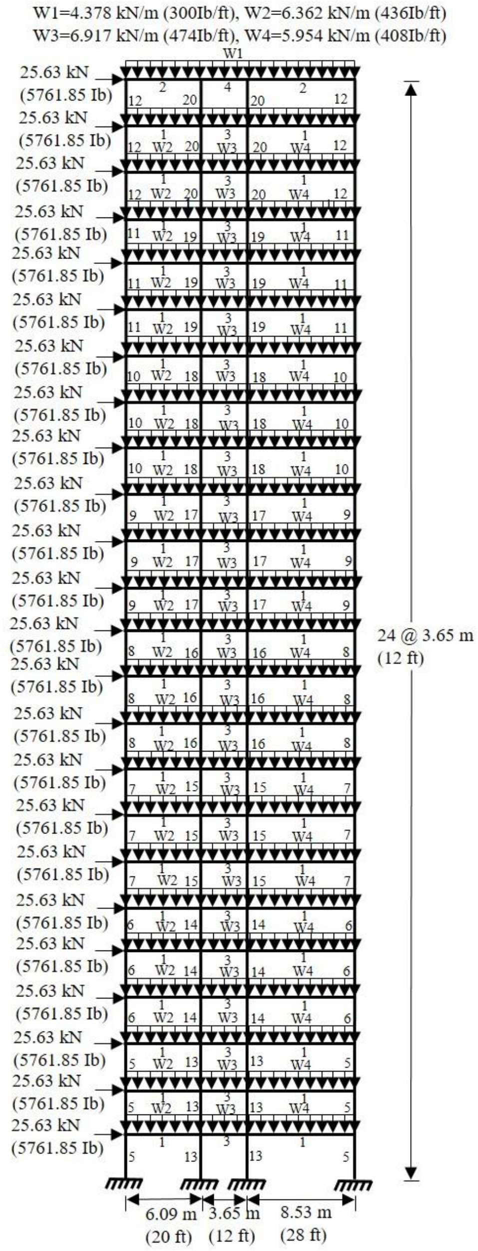

Fig. 10 Schematic of a 3-bay 24-story frame

Table 3 Optimal designs of the SDE and some meta-heuristic algorithms for the 3-bay 24-story frame

Element group	Optimal W-Shaped sections									
	EWOA (Kaveh and Ilchi Ghazaan 2016)	**DE** (Talatahari, Gandomi *et al.* 2015)	**ES-DE** (Talatahari, Gandomi *et al.* 2015)	**DEO** (Kaveh and Farhoudi 2013)	**CBO**	**ECBO**	**CBO-MDM**	**AWEO**	**EVPS**	**SDE**
1	W30x90	W30x90	W30x90	W30x90	W30x99	W30x90	W30x90	W30x90	W30x90	W30x90
2	W10x30	W21x48	W21x55	W6x20	W6x15	W10x33	W8x18	W8x18	W6x15	W6x15
3	W24x55	W21x44	W21x48	W21x44	W24x55	W21x48	W24x55	W24x55	W24x55	W24x55
4	W6x8.5	W27x129	W10x45	W6x9	W8x13	W12x16	W6x8.5	W6x8.5	W6x8.5	W6x8.5
5	W14x15	W14x176	W14x145	W14x159	W14x145	W14x176	W14x145	W14x193	W14x159	W14x159
6	W17x99	W14x120	W14x109	W14x145	W14x132	W14x120	W14x145	W14x120	W14x145	W14x132
7	W14x120	W14x132	W14x99	W14x132	W14x99	W14x120	W14x99	W14x132	W14x90	W14x109
8	W14x74	W14x132	W14x145	W14x99	W14x82	W14x82	W14x68	W14x82	W14x74	W14x74
9	W14x74	W14x109	W14x109	W14x68	W14x68	W14x82	W14x74	W14x61	W14x74	W14x61
10	W14x43	W14x53	W14x48	W14x61	W14x48	W14x38	W14x61	W14x38	W14x38	W14x38
11	W14x30	W14x61	W14x38	W14x43	W14x30	W14x34	W14x34	W14x34	W14x30	W14x34
12	W14x22	W14x30	W14x30	W14x22	W14x22	W14x53	W14x22	W14x22	W14x22	W14x22
13	W14x90	W14x99	W14x99	W14x109	W14x90	W14x90	W14x109	W14x82	W14x99	W14x90
14	W14x120	W14x132	W14x132	W14x109	W14x90	W14x145	W14x90	W14x109	W14x90	W14x99
15	W14x90	W14x109	W14x109	W14x90	W14x90	W14x90	W14x99	W14x82	W14x99	W14x90
16	W14x99	W14x74	W14x68	W14x82	W14x82	W14x90	W14x99	W14x82	W14x90	W14x90
17	W14x68	W14x82	W14x68	W14x74	W14x68	W14x61	W14x68	W14x68	W14x68	W14x74
18	W14x61	W14x82	W14x68	W14x43	W14x53	W14x61	W14x48	W14x68	W14x61	W14x61
19	W14x43	W14x48	W14x61	W14x30	W14x34	W14x38	W14x34	W14x43	W14x43	W14x34
20	W14x22	W14x82	W14x22	W14x26	W14x22	W14x26	W14x22	W14x34	W14x22	W14x22
Best weight (kN)	905.16	997.56	945.15	912.26	928.35	926.4821	903.58	913.51	898.91	894.13
Worst weight (kN)	1005.38	-	-	-	1023.46	1054.114	988.34	966.89	923.18	897.53
Mean weight (kN)	928.11	-	-	-	983.16	967.56	950.58	927.59	905.67	894.72

(Kaveh and Farhoudi 2013), CBO, ECBO, CBO-MDM,AWEO and EVPS, respectively, are 1.08%, 9.33%, 7.07%, 1.98%, 2.91%, 1.79%, 0.57%, 6.34% and 0.06% more heavy than the lightest weight obtained by the SDE algorithm. Also from Table 2 it is obvious that the SDE has reached the lightest mean weight for the worst and mean weights. Fig. 8 illustrates the convergence curve of the SDE for the 3-bay 15-story frame. Fig. 9 displays the existing stress ratios for the optimal design obtained by the SDE algorithm.

3.3 A 3-bay 24-story frame

A 3-bay 24 story frame consisting of the schematic, applied loads and the numbering of the member groups is illustrated in Fig. 10. This structure consists of 100 joints and 168 elements that are collected in 20 groups (16 column groups and 4 beam groups). The beam and column element groups are selected from all 267 W-shape and W-14 sections, respectively. The material has a modulus of elasticity equal to E = 205GPa (29,732 ksi) and a yield stress of f_y = 230.28 MPa (33.4 ksi). The effective length factors of the members are computed as $k_x \geq 1.0$ for a sway permitted frame and the out-of-plane effective length factor is determined as k_y = 1.0. All columns and beams are considered as non-braced along their lengths. The frame is designed according to the AISC-LRFD specifications using an inter-story drift displacement constraint (AISC 2001).

Table 3 illustrates the results of the present method and some other meta-heuristic algorithms. In this table the best, worst and mean weights for each algorithm are presented. It can be seen that the lightest design is found by applying SDE which is 894.13 kN and the lightest design of EWOA (Kaveh and Ilchi Ghazaan 2016), DE (Talatahari *et al*. 2015), ES-DE (Talatahari, Gandomi et al. 2015), DEO (Kaveh and Farhoudi 2013), CBO, ECBO, CBO-MDM, AWEO and EVPS, respectively, are 1.23%, 11.56%, 5.7%, 2.02%, 3.82%, 3.61%, 1.05%, 2.16% and 0.53% heavier than the lightest weight of the SDE algorithm.

As it can be observed from Table 3, it becomes apparent that the SDE algorithm has reached the lightest mean weight for the worst and mean weights. SDE also obtained a very good result for the best optimized answer compared to other algorithms.

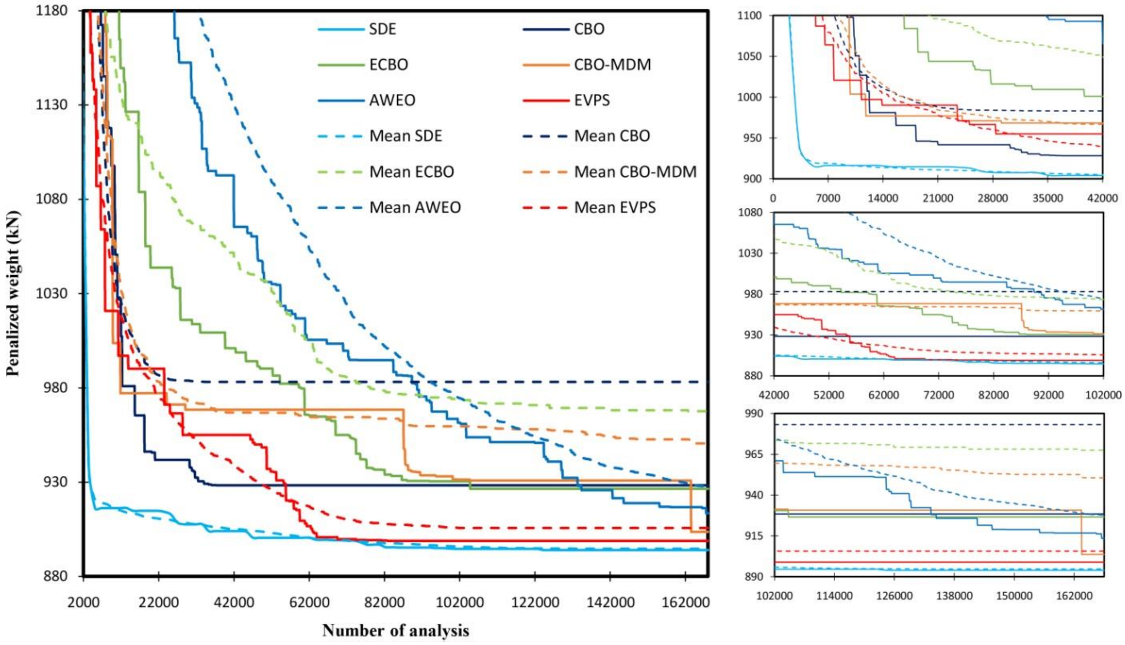

Fig. 11 Convergence curves of the optimal and mean design for the 3-bay 24-story frame using the SDE algorithm in comparison with other utilized metaheuristic algorithms

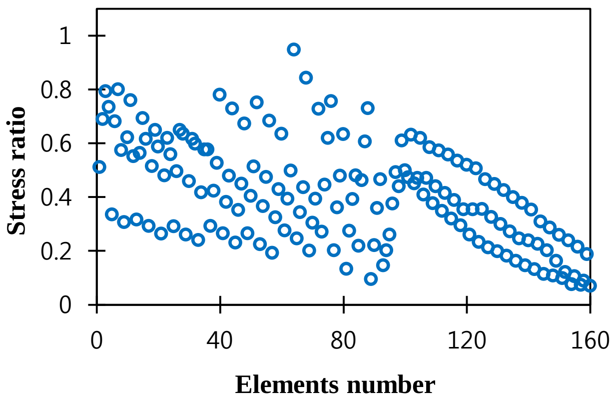

Fig. 12 Stress ratio for the optimal design of the 3-bay 24-story frame using the SDE algorithm

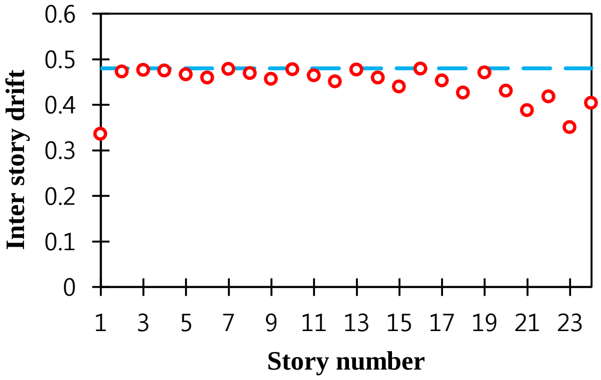

Fig. 13 Inter-story drifts for the lightest design of the SDE algorithm for the 3-bay 24-story frame

Fig. 11 illustrates the convergence curve of the SDE for the 3-bay 24-story frame. Figs. 12 and 13 show the existing stress ratios for the optimal design of the SDE algorithm.

4. Conclusions

According to the explanation of the SDE algorithm, in each iteration (without mentioning the details), all the effort of this algorithm is applied to rearranging the matrix *L*. This action results in generating a vector that has best numbers among all location sizes for all variables. It is expected that, this special vector be the best answer for each iteration (for some objective functions this may not be true). In fact, this vector is the result of all the effort of the SDE algorithm for each iteration. For next step, according to this vector and other locations, other sequences of algorithm are performed.

While the other algorithms, try to improve all the population in each iteration, smoothly. In other words, other algorithms do not try as much as the SDE algorithm to generate a special vector.

In this study, the simplified dolphin echolocation optimization (SDE) is utilized for size optimization of three well studied frame structures. These frames have been optimized by many researchers and some of their recent results are presented in this paper.

To evaluate the performance of the SDE algorithm, this method is compared to other meta-heuristic methods. The lightest design obtained by SDE is better than other methods in two of the three problems and other remaining problems and it has reached a very competitive answer in comparison to other meta-heuristic algorithms. In addition, the SDE algorithm has found the best mean in comparison to other methods.

At first glance to the provided convergence figures, the convergence speed of the SDE algorithm seems to be very high. However, it should be noted that this does not refer to the very high speed of the algorithm. In this algorithm, the analysis is not performed as the number of location sizes in each loop; rather, the objective function analysis is performed for each loop is equal to [Location sizes* (number of variables+1)]. Hence, the algorithm's speed is very low in each loop compared to other algorithms, but according to the results, very few loops are needed to reach the final answer compared to other algorithms. In other words, the SDE algorithm converges very fast in comparison with other algorithms and dispersion of results in this algorithm is very low compared to the other methods (according to mean weight in convergences diagram). Additionally, the quality of the obtained results is very good in each run. Due to these reasons, the low speed of the algorithm in each loop is compensated.

Finally, considering the quality of the answers obtained by the present algorithm in comparison to other algorithms, it is recommended to investigate other characteristics of the present algorithm when applied to other optimization problems.

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