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Performance of the Modified Dolphin Monitoring Operator for Weight Optimization of Skeletal Structures

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Abstract

In this study, the Modified Dolphin Monitoring (MDM) operator is used to enhance the performance of some metaheuristic algorithms. The MDM is a recently presented operator that controls the population dispersion in each iteration. Algorithms are selected from some well established algorithms. Here, this operator is applied on Differential Evolution (DE), Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Vibrating Particles System (VPS), Enhanced Vibrating Particles System (EVPS), Colliding Bodied Optimization (CBO) and Harmony Search (HS) and the performance of these algorithms are evaluated with and without this operator on three well-known structural optimization problems. The results show the performance of this operator on these algorithms for the best, the worst, average and average weight of the first quarter of answers.

Keywords

Modified Dolphin Monitoring (MDM) operator, weight optimization, frame structures, truss structures, frequency constraints, metaheuristic algorithms

1 Introduction

Optimization methods are categorized into two general groups consisting of mathematical programming methods and metaheuristic approaches. Nowadays metaheuristic algorithms have been widely used for solving optimization problems because these have not some of the defect corresponding to the first group of methods and are easy to use and require affordable computational time [1]. Many metaheuristic algorithms are introduced in the last two decades, some of these are as follows:

Genetic Algorithm (GA) [2], Differential Evolution (DE) [3], Particle Swarm Optimization (PSO) [4], Bat algorithm [5], Dolphin Echolocation Optimization (DEO) [6], Simplified Dolphin Echolocation (SDE) algorithm [7, 8], Grey wolf optimizer [9], Vibrating Particles system and its enhanced version (VPS and EVPS) [10, 11], MODRO algorithm [12], Colliding bodies Optimization (CBO) [13], Harmony Search (HS) [14], Krill Herd (KH) algorithm [15], Electro search algorithm [16], Moving Morphable Components (MMCs) [17], Jaya algorithm [18], Slap Swarm Algorithm (SSA) [19], Improved fruit fly optimization algorithm [20], Differential Big Bang-Big Crunch algorithm [21].

Metaheuristic algorithms have found many applications in different areas of applied mathematics, engineering, medicine, economics, and other sciences [22]. In optimization problems, there are always some requirements that should be minimized such as material, time, cost of the project and etc, and ultemately the final aim is gaining an economical result. As mentioned, many metaheuristic methods are introduced in last two decades, maybe it can be expressed that all of them have some opportunities in comparison with other methods for each problem. But there is a basic question and that is where each metaheuristic algorithm is suitable, especially, when a problem is evaluated for the first time and there is no previous optimal answer available. In this situation, it is possible that the selected algorithm to be entrapped in local optima. Also, it is possible that the obtained answer have a great

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difference with the optimum one. In the practical application of the metaheuristic methods, all of the answers near to the optimum answer are valuable but the answers with a great difference with the optimum answer are not valuable and it is not clear for the problems that are being solved for the first time. In other words, some algorithms are not suitable for several optimization problems and also, some algorithms should be tunned for a specific set of problems. The MDM operator has some feature for controlling the population dispersion in each variable and iteration. Addition of this operator to any algorithm prevents the algorithm to be trapped in local optima in comparison to the algorithm without this operator. Generally, this operator enhances the performance of the algorithms and the optimum designs of all algorithms with this operator are closer to each other corresponding to a suitable value.

It should be noted this operator does not cause any change in the main steps of the metaheuristic algorithms. Optimum design of structures is performed to gain a suitable design with more economical structural cost. In this study, Modified Dolphin Monitoring (MDM) operator is used to enhance the performance of seven metaheuristic algorithms when applied to three well-known structural optimization problems. These problems consist of the optimum weight design of a truss and a frame designed in according to AISC constraints [23] and one truss structure with frequency constraints. The results are presented for seven algorithms with and without the MDM operator. Benefits of using this operator are presented in the last part of section 2.

This paper is organized as follow: In the first section introduction is presented. A brief explanation of seven algorithms and the MDM operator is provided in section 2 and the formulation of the objective function is introduced in section 3. Section 4 consists of three well-known structural optimization problems with a brief explanation of their constraints and finally the concluding remarks are presented in section 5.

2 A brief review of seven metaheuristic algorithms and the MDM operator

2.1 Differential Evolutionary

As Differential Evolutionary (DE) method was presented by Storn and Price [3]. This method is based on calculating the difference between two randomly selected vectors. Initial vectors are created randomly in a permissible range. For the next steps, according to the difference of the vectors and crossover operator, all vector are updated.

2.2 Particle Swarm Optimization

Particle Swarm Optimization (PSO) algorithm was proposed by Kennedy and Eberhart [4]. This algorithm adopted from the behaviour of the animal flacking. In the first step, the algorithm creates a random population in permissible range. The velocity determines the next location of each population according to global best and the population best positions.

2.3 Genetic Algorithm

Genetic algorithm (GA) was introduced by Holland [2] that was inspired by biological evolution. The initial population is generated randomly in the permissible search space. This algorithm selects the better populations for next steps, and using a crossover and mutation operators tries to improve the populations.

2.4 Vibrating Particles Systems

Vibrating Particles Systems (VPS) algorithm was developed by Kaveh and Ilchi Ghazaan [24]. This method is adapted from the free vibration of single degree of freedom systems with viscous damping so that each answer is modelled as a particle that moves to its equilibrium position. New positions are updated according to a historically best position.

2.5 Enhanced Vibrating Particles System

Enhanced Vibrating Particles System (EVPS) is a modified version of the VPS algorithm that was presented by the authors [11]. This algorithm employs some new approach to gaining the optimum answer.

2.6 Colliding Bodies Optimization

Colliding Bodies Optimization (CBO) algorithm was introduced by Kaveh and Mahdavi [13]. This algorithm is based on a one-dimensional collision between two bodies with each agent being modeled as an object. Initial agents are generated randomly in a permissible range. Next steps is performed according to velocities and the masses of each agent.

2.7 Harmony Search

Harmony Search (HS) algorithm was proposed by Geem et al. [14]. This method is based on the promotion process of a musician. Initial vectors are generated using random numbers in a feasible space. This algorithm consists of some operators. Next vectors is updated using these operators.

2.8 Modified Dolphin Monitoring operator

Dolphin monitoring (DM) was introduced by Kaveh and Farhoudi [25] for the first time. This algorithm was enhanced DM operator and presented Modified Dolphin monitoring (MDM) by Kaveh et al. [26]. It should be noted that this operator was used for layout optimization of planar braced frames [27]. These operators control the population dispersion for each variable and iteration. DM expresses that the mode value for all population for each variable should be repeated as a specified magnitude for each iteration. If the number of mode repetition is bigger or smaller than this specified this value some approaches are used to until these two values are equal [25]. MDM operator determines a range and expresses that all values for all population and each variable should be in this range in certain numbers [26]. The range is equal to average ± (15%) standard deviation for each variable and the certain number is calculated according to Eq. (1).

$$MP_i = 10 + 60\left[\frac{i-1}{Maximum\ number\ of\ iterations - 1}\right], \quad (1)$$

where MP_i is the number of values should be in the range in percent for the *i*th iteration.

MDM operator applies to metaheuristic algorithms and enhances the performance of them to find the optimum design. In fact, this operator gives the ability to the algorithms to escape from the local optima. If the selected algorithm is not suitable for a specified problem or the parameters of the algorithm is not turned properly, this operator will help the algorithm to find an appropriate answer. The pseudocode of the MDM operator is as follow:

```
for j=1:number of variables
   while available papulation dispersion index(j) ~=
mandatory papulation dispersion(j)
      if available papulation dispersion index(j) > mandatory
papulation dispersion(j)
         if rand<0.5
            a random value from population which are in the
range = a random value
            from available population which are out of the
range;
         else
            a random value from population which are in the
range = values that are randomly
            generated within
            the feasible range for the jth variable;
         end
      elseif available papulation dispersion index(j) <
mandatory papulation dispersion(j)
         if rand<0.5
            a random value from population which are out of
the range = the best available
            optimal variable for the stage;
         else
            a random value from population which are out
of the range = values that are in the desired range;
         end
      end
   end
end
```

In above pseudocode, available population dispersion index is the percent of the population in the mentioned range for each variable and mandatory population dispersion is the number of values which should be in the range in percent for the ith iteration according to Eq. (1). It should be noted that, if the population within the defined range is not equal to the value specified in Eq. (1), the MDM operator replaces the new values in the answers with some mechanisms that are presented in the pseudocode of the MDM operator. These approaches improve the search ability power of the metaheuristic algorithms. Based on the explanations, this operator:

- Controls the population dispersion for each variable and iteration,
- Controls the speed of the convergence,
- Enhances the algorithm's ability to escape from local optima,
- Balancing between exploration and exploitation of the algorithms,
- Enhances the searchability of algorithms,

and obtains a suitable answer as an optimal answer.

3 Formulation of the optimization problems

In this section, the goal is to minimize the weight of skeletal structures satisfying certain design requirements. Design requirements for the first two problems are the strength and displacements constraints according to LRFD-AISC specification [23], and the third one considers frequency constraints. The mathematical formulation of optimal design of the problems can be presented as follow:

$$\text{Find } \{x\} = [x_1, x_2, ..., x_{ng}] \quad x_i \in S_i$$
$$\text{To minimize } W(\{x\}) = \sum_{i=1}^{nm} \rho_i A_i L_i, \quad (2)$$

where $\{x\}$ is a set of design variables containing the cross-sectional area of W-sections; *ng* is the number of design variables; $W(\{x\})$ is the weight of the skeletal structure; *nm* is the number of elements of the skeletal structure; ρ_i presents the material density of the ith member; A_i and L_i present the cross-sectional area and the length of the ith member, respectively. It above equation, x_i is the number of a W-section and A_i is the cross-sectional area of the ith group.

In this study, two problems are considered as discrete optimization and one is for continues optimization problem. To control the requirements of each problem, penalty approach is used according to the following equation:

$$fitness(x) = (1+\varepsilon_1.\upsilon)^{\varepsilon_2} \times w\{(x)\}, \upsilon = \sum_{j=1}^{nc} \max(0,\upsilon_i) \ . \qquad (3)$$

fitness(x) and υ are the fitness function and the sum of the violations for each problem. In this study, ε_1 and ε_2 are set to 0.3 and 1, respectively, and *nc* is the total number of requirements for each individual design. It should be noted that specified constraints for each problem are presented in subsequent section.

4 Numerical problems

In this section, three well-known skeletal structures are considered to investigate the performance of the MDM operator on seven algorithms. All results are presented with and without the incorporating this operator. As mentioned in section 3, minimizing the weight of three skeletal structures is conducted in this study, these problems are as follow:

- A 3-bay 24-story steel frame with AISC-LRFD [23] constraints.
- A 582-bar tower truss structure with AISC-LRFD [23] constraints.
- A 72-bar spatial truss structure with frequency constraints.

It should be noted that all problems have been solved 30 times independently, also, the number of population and number of iterations are taken as 60 and 1000, respectively.

4.1 A 3-bay 24- story steel frame with AISC-LRFD constraints

A 3-bay 24 story frame consisting of the schematic, applied loads and the numbering of the member groups is illustrated in Fig. 1. 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 elastic

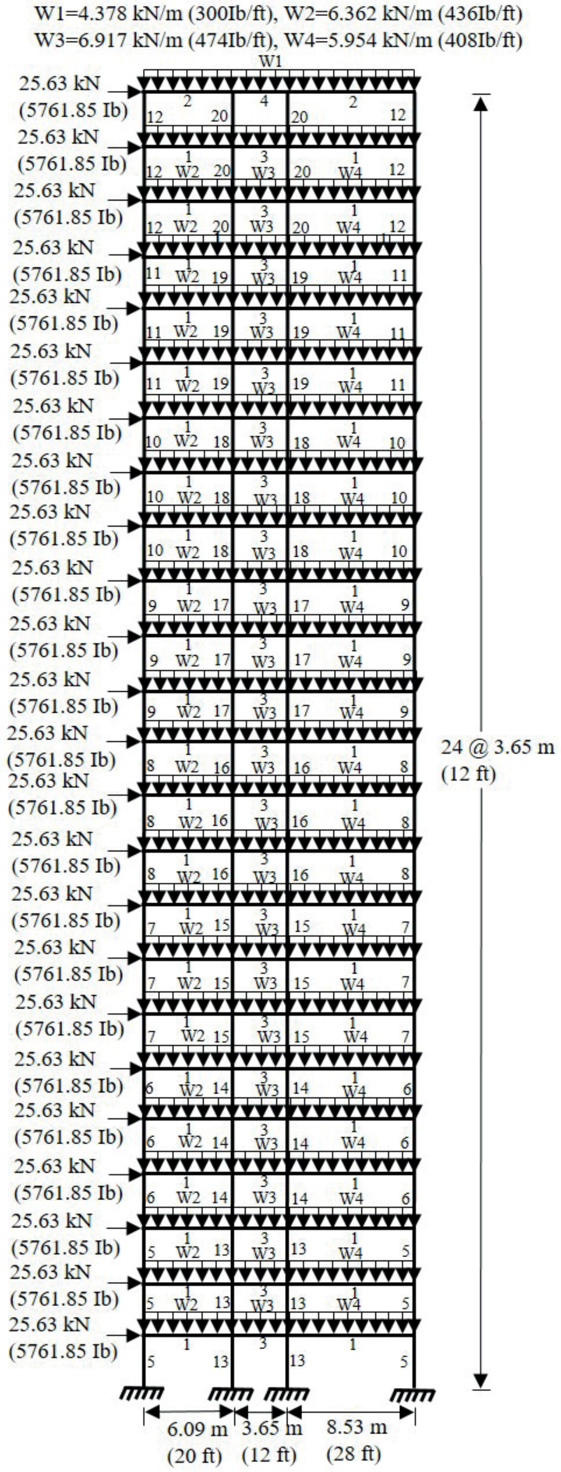

Fig. 1 Schematic of a 3-bay 24-story frame

ity 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. According to AISC-LRFD [23] constraints are as follow:

(a) Maximum lateral displacement

$$\frac{|\Delta_T|}{H} - R_k \le 0 \; . \tag{4}$$

(b) The inter-story drift constraints

$$\frac{|d_i|}{h_i} - R_l \le 0 ; i = 1, 2, ..., ns \; . \tag{5}$$

(c) Strength constraints

$$\begin{aligned} &\frac{P_u}{2\phi_c P_n} + \left[\frac{M_{ux}}{\phi_b M_{nx}} + \frac{M_{uy}}{\phi_b M_{ny}} \right] - 1 \le 0; \; for \frac{P_u}{\phi_c P_n} < 0.2 \\ &\frac{P_u}{\phi_c P_n} + \frac{8}{9}\left[\frac{M_{ux}}{\phi_b M_{nx}} + \frac{M_{uy}}{\phi_b M_{ny}} \right] - 1 \le 0; \; for \frac{P_u}{\phi_c P_n} \ge 0.2 \end{aligned} \tag{6}$$

where Δ_T is the maximum lateral displacement of the roof; H is the height of the frame structure; R_k is the maximum drift index (in this study it is equal to); 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_1 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 [23](tension or compression); $\O_c$ is the resistance factor ($\O_c$ = 0.9 for tension and $\O_c$ = 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 [23] (for two-dimensional frames M_{uy} = 0 and M_{ny} = 0); and $\O_b$ presents the flexural resistance reduction factor ($\O_b$ = 0.90).

Table 1 contains the results of seven algorithms consisting of DE, PSO, GA, VPS, EVPS, CBO and HS with the effect of the MDM operator and without this effect. In this table, the best, worst and mean weights for all and mean weight of the first quarter of answers for each method is presented.

It can be seen that the lightest design is found by EVPS-MDM which is 893.95 kN. Although all optimum designs with the effect of MDM operator have reached suitable

Table 1 Results of seven algorithms with and without the effect of the MDM operator for the 3-bay 24- story frame

Element group	Optimal W-Shaped sections						
	DE	PSO	GA	VPS	EVPS	CBO	HS
1	W30x90	W30x108	W30x90	W30x90	W30x90	W30x108	W30x90
2	W8x18	W10x112	W6x15	W14x68	W6x15	W8x18	W8x18
3	W24x62	W18x143	W27x84	W27x84	W24x55	W24x55	W24x62
4	W6x8.5	W5x16	W6x8.5	W10x39	W6x9	W6x8.5	W6x9
5	W14x145	W14x233	W14x132	W14x159	W14x159	W14x132	W14x159
6	W14x109	W14x120	W14x109	W14x82	W14x132	W14x120	W14x176
7	W14x120	W14x132	W14x82	W14x90	W14x109	W14x90	W14x99
8	W14x90	W14x90	W14x90	W14x53	W14x74	W14x90	W14x82
9	W14x61	W14x109	W14x90	W14x61	W14x61	W14x61	W14x61
10	W14x38	W14x120	W14x53	W14x90	W14x38	W14x48	W14x48
11	W14x38	W14x90	W14x34	W14x34	W14x30	W14x38	W14x30
12	W14x26	W14x53	W14x22	W14x61	W14x22	W14x22	W14x22
13	W14x90	W14x82	W14x90	W14x90	W14x90	W14x90	W14x90
14	W14x109	W14x74	W14x99	W14x145	W14x99	W14x90	W14x82
15	W14x90	W14x145	W14x109	W14x132	W14x90	W14x90	W14x90
16	W14x82	W14x233	W14x82	W14x193	W14x90	W14x74	W14x82
17	W14x74	W14x132	W14x61	W14x90	W14x74	W14x74	W14x68
18	W14x61	W14x145	W14x53	W14x99	W14x61	W14x53	W14x53
19	W14x30	W14x22	W14x34	W14x48	W14x38	W14x30	W14x34
20	W14x22	W14x193	W14x22	W14x22	W14x22	W14x22	W14x22
Best weight (kN)	**901.64**	**1362.655**	**920.525**	**1025.656**	**894.03**	**962.55**	**905.48**
Worst weight (kN)	**994.0635**	**2891.41**	**1020.923**	**1149.656**	**953.6786**	**1026.734**	**987.8225**
Mean weight (kN)	**915.8925**	**1879.07**	**945.6831**	**1081.354**	**904.0907**	**978.5107**	**925.4**
Mean weight of the first quarter of the best answers (kN)	**900.3324**	**1468.32**	**918.7998**	**1037.241**	**896.0129**	**952.9905**	**899.0706**

Element group	Optimal W-shaped section using MDM operator						
	DE	PSO	GA	VPS	EVPS	CBO	HS
1	W30x90	W30x90	W30x90	W30x90	W30x90	W30x90	W30x90
2	W10x22	W6x15	W5x19	W6x15	W6x15	W6x15	W6x15
3	W24x55	W24x55	W24x55	W21x44	W24x55	W24x55	W24x55
4	W6x16	W6x8.5	W6x8.5	W6x8.5	W6x8.5	W6x8.5	W8x10
5	W14x159	W14x159	W14x159	W14x145	W14x159	W14x132	W14x159
6	W14x132	W14x132	W14x109	W14x159	W14x132	W14x109	W14x132
7	W14x109	W14x109	W14x120	W14x99	W14x109	W14x90	W14x99
8	W14x74	W14x74	W14x90	W14x74	W14x74	W14x90	W14x90
9	W14x68	W14x53	W14x61	W14x68	W14x61	W14x61	W14x68
10	W14x38	W14x43	W14x38	W14x61	W14x38	W14x74	W14x43
11	W14x34	W14x34	W14x38	W14x30	W14x34	W14x30	W14x30
12	W14x22	W14x22	W14x22	W14x22	W14x22	W14x22	W14x22
13	W14x90	W14x90	W14x90	W14x109	W14x90	W14x99	W14x90
14	W14x99	W14x99	W14x109	W14x99	W14x99	W14x109	W14x99
15	W14x90	W14x90	W14x90	W14x109	W14x90	W14x109	W14x99
16	W14x90	W14x90	W14x82	W14x99	W14x90	W14x90	W14x82
17	W14x68	W14x82	W14x74	W14x74	W14x74	W14x82	W14x68
18	W14x61	W14x61	W14x61	W14x48	W14x61	W14x43	W14x61
19	W14x34	W14x34	W14x30	W14x38	W14x34	W14x38	W14x34
20	W14x22	W14x22	W14x22	W14x22	W14x22	W14x22	W14x22
Best weight (kN)	**896.1678**	**895.3705**	**896.55**	**901.58**	**893.9539**	**897.29**	**896.7**
Worst weight (kN)	**904.5019**	**959.6632**	**989.14**	**1002.944**	**896.5583**	**980.59**	**950.42**
Mean weight (kN)	**898.19**	**918.9328**	**922.18**	**937.41**	**894.9684**	**928.4**	**918.7902**
Mean weight of the first quarter of the best answers (kN)	**895.63**	**896.0737**	**915.4977**	**922.44**	**893.9616**	**899.2201**	**898.47**

values. Fig. 2 illustrates the convergence curves of the seven algorithms with and without the effect of the MDM operator for the best optimal design and average answer of all runs for this problem.

4.2 A 582-bar tower truss structure with AISC-LRFD constraints

The schematic of the 582-bar tower truss with the height of 80 m is presented in Fig. 3. The symmetry of the tower around x-axis and y-axis is considered to group the 582 members into 32 independent size variables. A single load case is considered consisting of the lateral loads of 5.0 kN applied in both x and y directions and a vertical load of –30 kN applied in the z-direction in all nodes of the tower. A discrete set of 137 economical standard steel sections selected from W-shape profile list based on area and radii of gyration properties is used to size the variables. The lower and upper bounds on size variables are taken as 39.74 cm^2 and 1387.09 cm^2, respectively. The stress limitations of the members are imposed according to the provisions of AISC-LRFD [23]. The other constraint is the limitation of nodal displacements (these should not be more than 8.0 cm or 3.15 in. in any direction). Also, the maximum slenderness ratio is limited to 300 for tension members, and it is recommended to be 200 for compression members according to AISC-LRFD design code provisions [23].

Optimal, the mean and the mean weight of the first quarter of the best answers are provided in Table 2.

Table 2 shows that the best designs are achieved with EVPS, EVPS-MDM and DE-MDM which are 21.032 m^3. Fig. 4 illustrates the convergence histories using the mentioned algorithms with the effect of the MDM operator and without this effect for best optimal design and mean answer.

4.3 A 72-bar spatial truss structure with frequency constraints

The third problem is a 72-bar spatial truss that as illustrated in Fig. 5. This truss structure has 20 nodes and 48 degrees of freedom, and four non-structural masses of 2270.0 kg are attached to the nodes 1–4. All elements of the structure

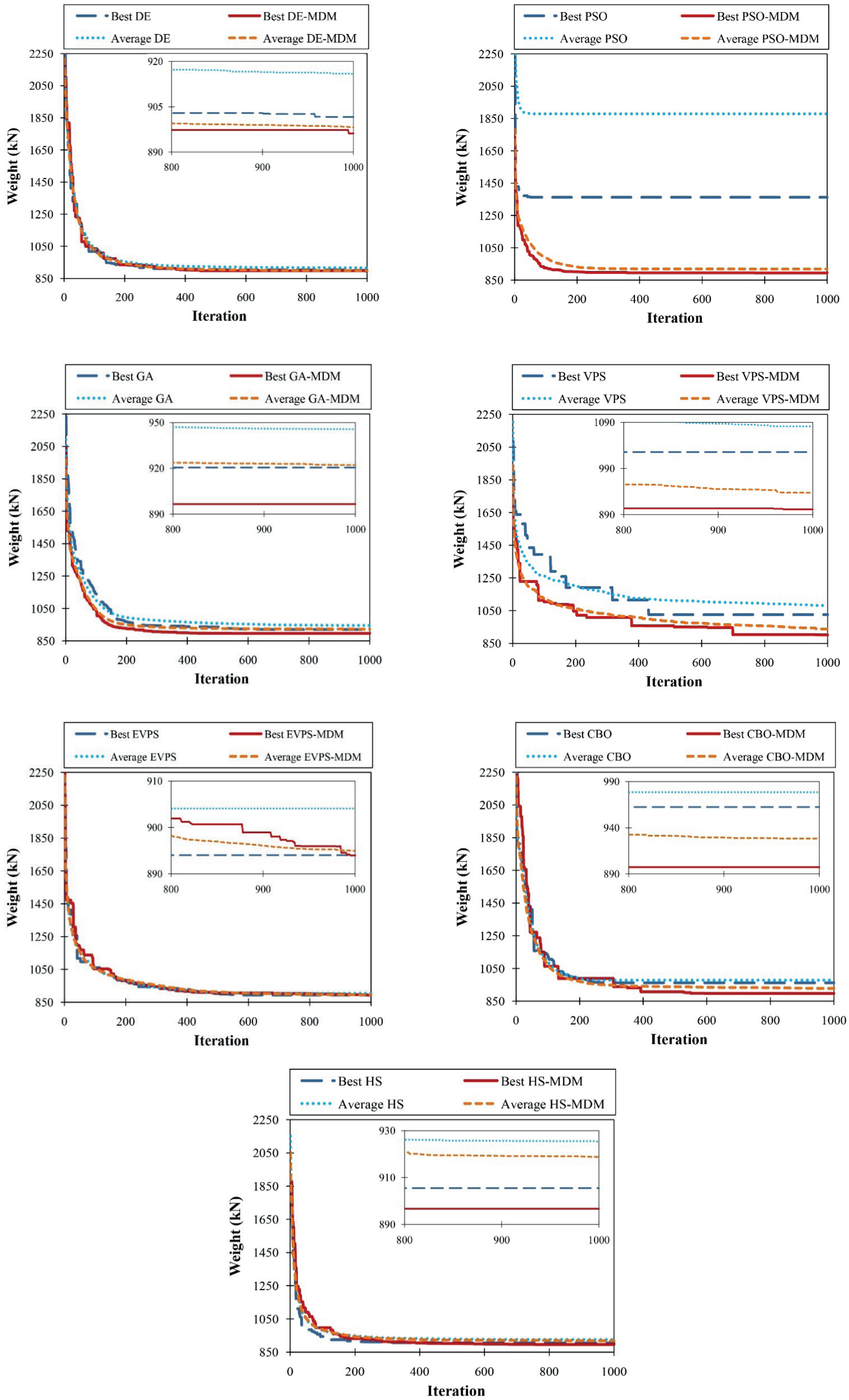

Fig. 2 Convergence curves of the seven algorithms with the effect of the MDM operator and without this effect for best optimal design and average answers for the 3-bay 24-story frame.

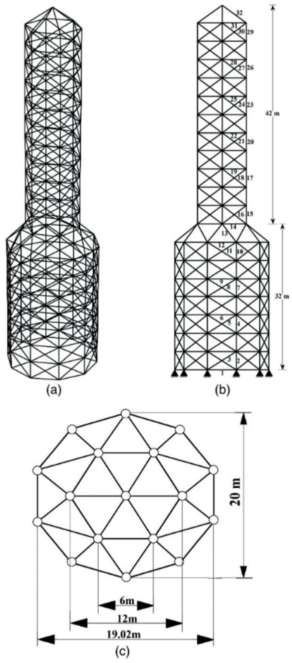

Fig. 3 Schematic of the 582-bar tower truss

have a modulus of elasticity E = 6.89×1010 N/m^2, density ρ = 2770 kg/m^3, and cross-sectional area A = 0.0025 m^2. In this problem, the layout of the truss is considered unchanged during the optimization and only the size optimization of this truss structure is investigated according to frequency constraints (ω_1 = 4 Hz and ω_3 6 Hz). Also, the minimum cross-sectional of all design variables is considered as 0.64510-4 m^2.

Table 3 reports a comparison of the optimal results gained by the utilized algorithms for the effect of this operator and without this effect. It can be seen that the optimal weight is obtained by EVPS algorithm with the effect of the proposed operator.

Fig. 6 shows the penalized weight convergence history curves obtained by the seven used algorithms with the effect of the MDM operator and without this effect for best optimal design and average answer of all runs of this problem.

Table 2 Results of seven algorithms with and without the effect of the MDM operator for the 582-bar tower truss

Element group	Optimal sections						
	DE	PSO	GA	VPS	EVPS	CBO	HS
1	39.74186	39.74186	39.74186	39.74186	39.74186	39.74186	41.87088
2	159.3545	159.3545	143.8707	169.0319	159.3545	136.1288	123.2256
3	45.67733	45.67733	53.2257	45.67733	45.67733	53.2257	58.90311
4	109.6772	109.6772	115.4836	128.3868	109.6772	114.1933	114.1933
5	45.67733	45.67733	45.67733	47.35474	45.67733	45.67733	47.35474
6	39.74186	41.87088	39.74186	45.67733	39.74186	39.74186	41.87088
7	90.96756	90.96756	94.19336	75.48372	85.80628	90.96756	100.645
8	45.67733	45.67733	45.67733	49.35474	45.67733	45.67733	45.67733
9	39.74186	41.87088	39.74186	47.35474	39.74186	39.74186	39.74186
10	81.29016	85.80628	90.96756	84.51596	85.80628	84.51596	66.45148
11	45.67733	45.67733	45.67733	47.35474	45.67733	45.67733	49.35474
12	126.4514	128.3868	118.0643	114.1933	126.4514	128.3868	109.6772
13	140.6449	128.3868	128.3868	123.2256	140.6449	143.8707	167.7416
14	92.90304	92.90304	92.90304	100.645	92.90304	92.90304	92.90304
15	136.1288	143.8707	149.6771	143.8707	140.6449	143.8707	123.2256
16	58.90311	58.90311	58.90311	66.45148	58.90311	58.90311	58.90311
17	114.1933	118.0643	123.2256	136.1288	114.1933	114.1933	128.3868
18	45.67733	45.67733	45.67733	47.35474	45.67733	45.67733	49.35474
19	39.74186	45.67733	39.74186	56.70956	39.74186	39.74186	47.35474
20	75.48372	81.29016	81.29016	75.48372	75.48372	75.48372	100.645
21	45.67733	45.67733	45.67733	53.2257	45.67733	45.67733	49.35474
22	39.74186	39.74186	39.74186	41.87088	39.74186	39.74186	47.35474
23	41.87088	45.67733	47.35474	53.2257	41.87088	39.74186	39.74186
24	45.67733	45.67733	45.67733	45.67733	45.67733	45.67733	45.67733
25	39.74186	39.74186	39.74186	56.70956	39.74186	39.74186	49.35474
26	39.74186	41.87088	39.74186	66.45148	39.74186	41.87088	41.87088
27	45.67733	47.35474	45.67733	47.35474	45.67733	45.67733	45.67733

Element group	Optimal cross sections using MDM operator						
	DE	PSO	GA	VPS	EVPS	CBO	HS
28	39.74186	39.74186	39.74186	53.2257	39.74186	39.74186	49.35474
29	39.74186	39.74186	39.74186	74.1934	39.74186	39.74186	57.09666
30	45.67733	45.67733	45.67733	49.35474	45.67733	45.67733	53.2257
31	39.74186	47.35474	39.74186	58.90311	39.74186	39.74186	41.87088
32	45.67733	47.35474	45.67733	62.64504	45.67733	45.67733	45.67733
Best weight (m^3)	**21.03382**	**21.20483**	**21.22301**	**22.57956**	**21.03264**	**21.20394**	**22.16075**
Worst weight (m^3)	**21.44113**	**22.08113**	**21.36968**	**24.12907**	**21.19636**	**21.69758**	**22.88688**
Mean weight (m^3)	**21.22183**	**21.55488**	**21.21097**	**23.2212**	**21.08794**	**21.48144**	**22.43518**
Mean weight of the first quarter of the best answers (m^3)	**21.07914**	**21.30911**	**21.1322**	**22.84546**	**21.03296**	**21.34984**	**22.21064**

Element group	Optimal cross sections using MDM operator						
	DE	PSO	GA	VPS	EVPS	CBO	HS
1	39.74186	39.74186	39.74186	39.74186	39.74186	39.74186	39.7419
2	159.3545	159.3545	136.1288	128.3868	159.3545	136.1288	159.3545
3	45.67733	45.67733	53.2257	58.90311	45.67733	53.2257	45.6773
4	109.6772	109.6772	115.4836	115.4836	109.6772	114.1933	118.0643
5	45.67733	45.67733	45.67733	45.67733	45.67733	45.67733	45.6773
6	39.74186	39.74186	39.74186	39.74186	39.74186	39.74186	39.7419
7	85.80628	85.80628	94.19336	90.96756	85.80628	90.96756	94.1934
8	45.67733	45.67733	45.67733	47.35474	45.67733	45.67733	45.6773
9	39.74186	39.74186	39.74186	39.74186	39.74186	39.74186	39.7419
10	85.80628	81.29016	90.96756	84.51596	85.80628	84.51596	90.9676
11	45.67733	45.67733	45.67733	45.67733	45.67733	45.67733	45.6773
12	126.4514	126.4514	118.0643	128.3868	126.4514	128.3868	128.3868
13	140.6449	140.6449	136.1288	140.6449	140.6449	140.6449	128.3868
14	92.90304	92.90304	92.90304	92.90304	92.90304	92.90304	75.4837
15	140.6449	140.6449	146.4513	143.8707	140.6449	143.8707	118.0643
16	58.90311	58.90311	58.90311	58.90311	58.90311	58.90311	100.645
17	114.1933	114.1933	118.0643	115.4836	114.1933	115.4836	123.2256
18	45.67733	45.67733	45.67733	45.67733	45.67733	45.67733	45.6773
19	39.74186	39.74186	39.74186	39.74186	39.74186	39.74186	39.7419
20	75.48372	75.48372	81.29016	81.29016	75.48372	75.48372	84.516
21	45.67733	45.67733	45.67733	45.67733	45.67733	45.67733	45.6773
22	39.74186	39.74186	39.74186	39.74186	39.74186	39.74186	39.7419
23	41.87088	45.67733	47.35474	45.67733	41.87088	45.67733	45.6773
24	45.67733	45.67733	45.67733	47.35474	45.67733	45.67733	45.6773
25	39.74186	39.74186	39.74186	39.74186	39.74186	39.74186	39.7419
26	39.74186	39.74186	39.74186	39.74186	39.74186	39.74186	39.7419
27	45.67733	45.67733	45.67733	45.67733	45.67733	45.67733	45.6773
28	39.74186	39.74186	39.74186	39.74186	39.74186	39.74186	39.7419
29	39.74186	39.74186	39.74186	39.74186	39.74186	39.74186	39.7419
30	45.67733	45.67733	45.67733	45.67733	45.67733	45.67733	45.6773
31	39.74186	39.74186	39.74186	39.74186	39.74186	39.74186	39.7419
32	45.67733	45.67733	45.67733	45.67733	45.67733	45.67733	45.6773
Best weight (m^3)	**21.03264**	**21.03289**	**21.204**	**21.4155**	**21.03264**	**21.19361**	**21.599**
Worst weight (m^3)	**26.87214**	**21.34015**	**21.97769**	**23.53377**	**21.19361**	**21.38257**	**23.58114**
Mean weight (m^3)	**21.38674**	**21.17073**	**21.25325**	**21.6641**	**21.05411**	**21.21835**	**21.7845**
Mean weight of the first quarter of the best answers (m^3)	**21.03452**	**21.06625**	**21.0653**	**21.5781**	**21.03264**	**21.19418**	**21.6417**

Table 3 Results of seven algorithms with and without the effect of the MDM operator a for the 72-bar spatial truss

Element group	Optimal design cross sections (cm^2)						
	DE	PSO	GA	VPS	EVPS	CBO	HS
1	3.48171	3.66118	4.74713	3.30382	3.50739	3.52946	4.05312
2	7.98971	7.96971	7.52118	7.61671	8.02602	7.96004	7.96456
3	0.645	0.645142	0.645	0.765293	0.645	0.645	0.645
4	0.645	0.647933	0.645	0.735822	0.645	0.645	0.645
5	7.80517	8.01323	9.64392	7.41648	8.02012	8.23747	8.52025
6	7.88914	8.05452	8.32191	8.1082	7.91804	7.96806	7.98543
7	0.645	0.645012	0.645	0.657749	0.645	0.645	0.645
8	0.645	0.645	0.645	0.688567	0.645	0.645	0.645
9	12.95618	13.28061	10.64944	13.07056	12.93505	12.90876	11.4775
10	8.066	8.06162	7.97908	8.30767	8.08651	7.98602	8.42243
11	0.645	0.645804	0.645	0.689852	0.645	0.645	0.645
12	0.645	0.647075	0.645	0.669355	0.645	0.645	0.645
13	17.24166	16.56303	17.42695	17.76954	17.01553	16.809	17.66908
14	8.09083	7.94918	8.2568	8.03206	8.00434	8.12052	7.69537
15	0.645	0.645	0.645	0.697603	0.645	0.645	0.645
16	0.645	0.645884	0.645	0.709157	0.645	0.645	0.645
Best weight (kg)	326.8461	326.918	328.8411	328.5089	326.836	326.8382	327.4943
Worst weight (kg)	327.2173	327.7539	343.1666	332.8895	327.1547	327.2083	331.1311
Mean weight (kg)	326.9467	327.1117	332.8074	330.1385	326.9469	326.9932	328.9874
Mean weight of the first quarter of the best answers (kg)	326.8668	326.8995	329.629	328.8586	326.8399	326.8838	328.1162
Element group	Optimal design cross sections (cm2) using MDM operator						
	DE	PSO	GA	VPS	EVPS	CBO	HS
1	3.36539	3.46408	3.52378	3.96725	3.51423	3.47224	3.39257
2	7.9879	7.98384	7.5751	8.02878	8.0201	7.91655	7.56433
3	0.645	0.645	0.645	0.645	0.645	0.645	0.64517
4	0.645	0.645	0.645	0.645729	0.645	0.645	0.645007
5	8.03408	7.96783	8.26757	7.44775	8.23507	7.85295	7.92135
6	7.97055	8.00214	7.9479	8.08984	7.92286	7.96018	8.40782
7	0.645	0.645004	0.645	0.645	0.645	0.645	0.645
8	0.645	0.645	0.645	0.645	0.645	0.645	0.645011
9	12.70564	12.94365	11.99745	14.92544	12.68772	12.84103	12.69244
10	8.03294	8.1152	8.38802	7.91379	8.02236	8.10305	8.15031
11	0.645	0.645001	0.645	0.645326	0.645	0.645002	0.645051
12	0.645	0.645	0.645	0.645	0.645	0.645	0.645038
13	17.3718	17.10232	17.75176	15.6739	17.04146	17.31419	17.47851
14	8.04145	7.93454	8.16132	8.00375	8.06917	8.05503	7.95521
15	0.645	0.645	0.645	0.645754	0.645	0.645	0.645068
16	0.645	0.645	0.645	0.645	0.645	0.645	0.645
Best weight (kg)	326.8426	326.8351	327.2173	327.7539	326.831	326.8322	327.1657
Worst weight (kg)	327.1956	327.4619	339.7943	331.8207	327.012	327.1118	330.124
Mean weight (kg)	326.909	327.094	331.9036	329.4437	326.865	326.9341	328.889
Mean weight of the first quarter of the best answers (kg)	326.8505	326.8551	329.103	328.3882	326.8367	326.8617	327.959

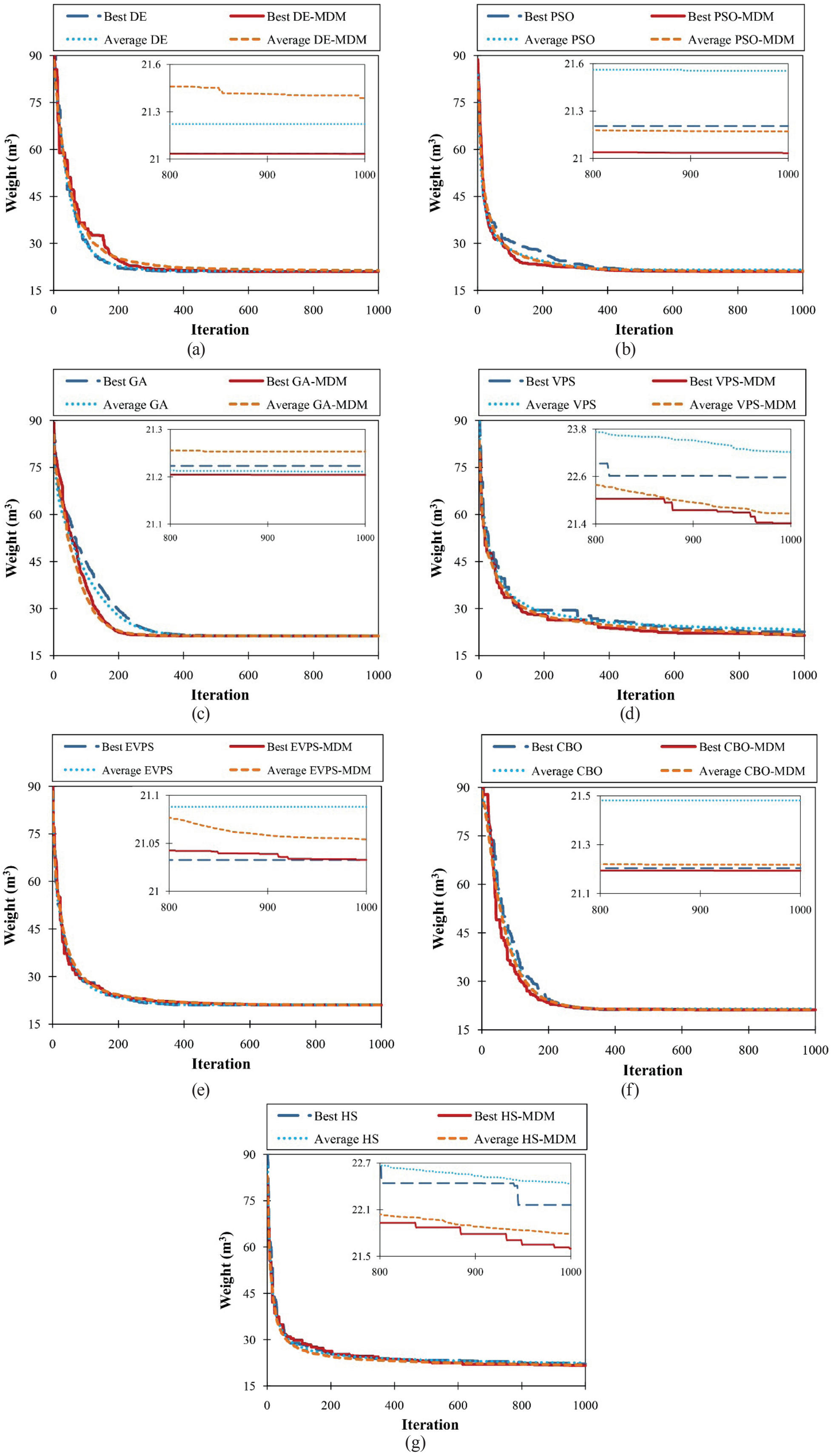

Fig. 4 Convergence curves of the seven algorithms with and without the effect of the MDM operator for the best optimal design and average answer for the 582-bar tower truss

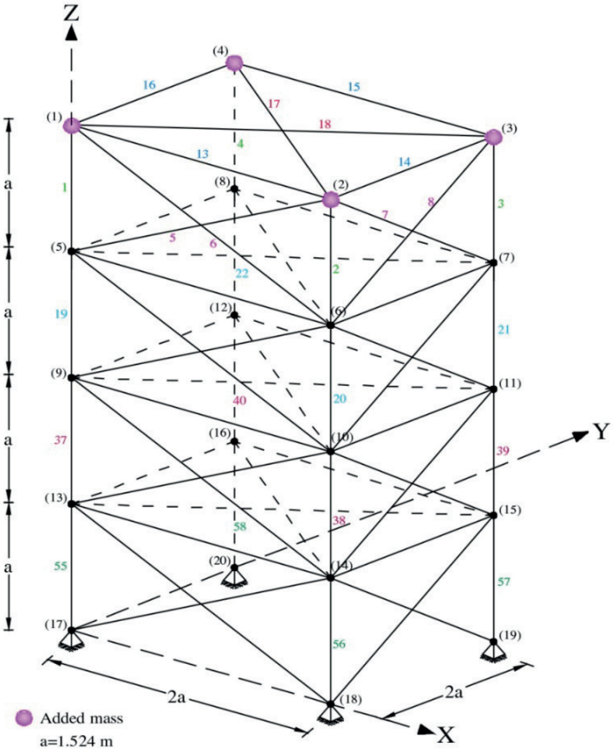

Fig. 5 Schematic of the 72-bar spatial truss.

5 Discussion

As mentioned in section 4, the number of independent runs, population size and the number of iterations are assumed to be large enough, so that we can expect suitable values for all algorithms and problems. However according to the tables and figures the following results can be obtained:

The optimum designs for all the problems are improved using the effect of the MDM operator. Also, mean weight and mean weight of the first quarter of the best answers are enhanced.

The quantity of the effect of the MDM operator is different for each problem and algorithms. The quality of the optimum design of each algorithm is one of the most important factors.

The best optimum result of all algorithm with the effect of this operator is almost near to the best-achieved answer. In other words, the difference between all optimum results with the effect of the MDM operator, have not great values. In Figs. 7, 8 and 9, the weight difference of each best, mean and mean of the first the first quarter of the best answers relative to the case without the effect of MDM operator are presented for all 3 problems and all utilized algorithms. Figure 10 is similar to Figs. 7, 8 and 9, with a different that in this figure the population size and iteration number are considered as 30 and 500, respectively. It can be observed that when the population size and iteration number have lower values, the effect of the MDM operator becomes more tangible.

These figures show the efficiency of the MDM operator for the best, mean and mean weight of the first quarter of the best answers for all the considered methods. These figures illustrate that all results are improved. Also, the results show that this operator improved the behavior of all the algorithms for all three problems. In another word, according to figures and tables, this operator causes to reach more reliable answers for all algorithms and problems.

All problems and algorithms were performed in 30 independent runs and the number of populations and iterations were taken 60 and 1000, respectively. Thus, with respect to these cases, each algorithm is expected to provide a very satisfactory answer. Therefore, the mean weight, mean weight of the first quarter of the best answers and the worst answers were presented for better comparison. Some of the results, with and without the MDM operator, were not significantly different, which can be attributed to the suitable performances of the algorithm for a specific problem and also the correct tuning of the algorithm's parameters. When an algorithm presents a suitable answer, it is clear that the performance of the MDM operator will not very tangible. When an algorithm does not present a suitable answer for a specific problem the effect of using the operator will more apparent. The operator's impact is quite obvious for the following problems:

- PSO, GA, VPS and CBO algorithms in the first problem.
- VPS and HS algorithms in the second problem.
- GA and VPS in the last problem.

6 Conclusions

In this study, the MDM operator is used to improve the behavior of seven algorithms consisting of DE, PSO, GA, VPS, EVPS, CBO and HS algorithms. The MDM operator does not cause any change in the main steps of the metaheuristic algorithms and controls the population dispersion and enhances the searchability of the algorithms and for the most of the problems, this operator improves the speed of convergence. The results show the efficiency of this operator for three optimization problems consisting of two trusses and one frame structures. All of the considered problems are well-known problems in structural optimization literature. Almost all of the results are for the best optimal design, mean weight and mean weight of the first quarter of the best answers are improved in comparison to the

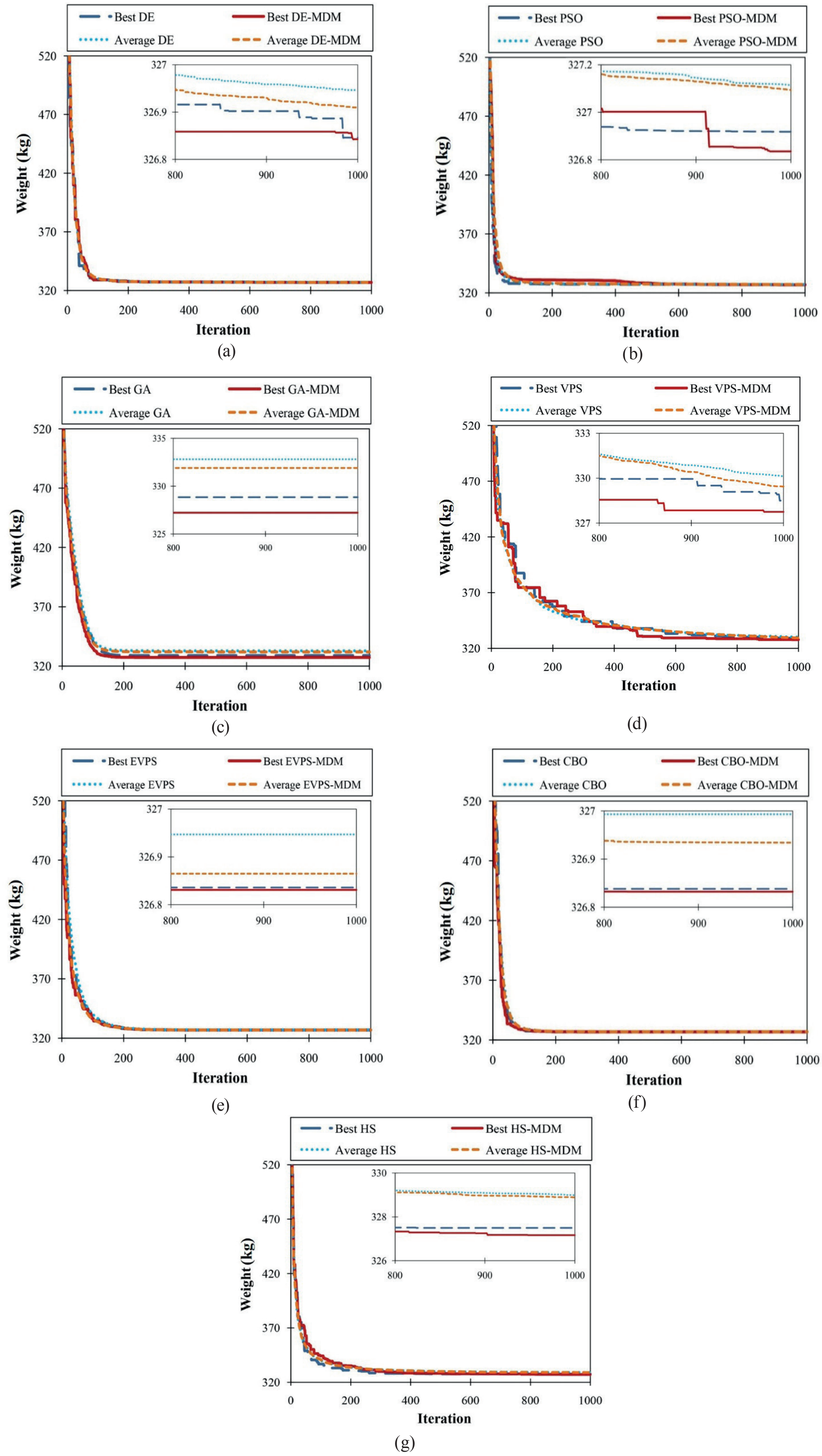

Fig. 6 Convergence curves of the seven algorithms with and without the effect of the MDM operator for the best optimal design and average answer for the 72-bar spatial truss

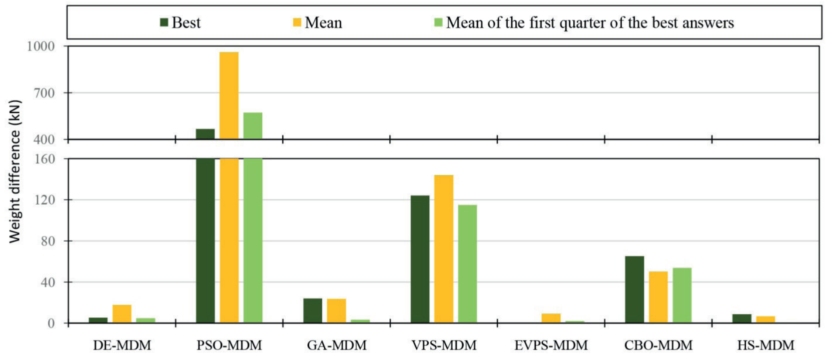

Fig. 7 Comparison of the results according to weight differences for the first problem.

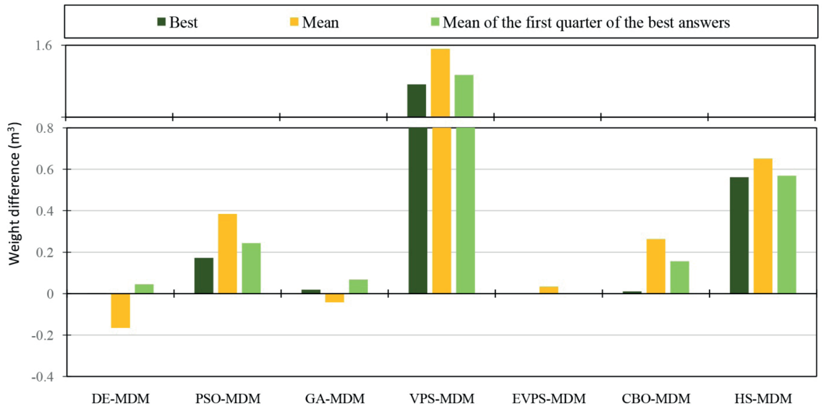

Fig. 8 Comparison of the results according to weight difference for second problem.

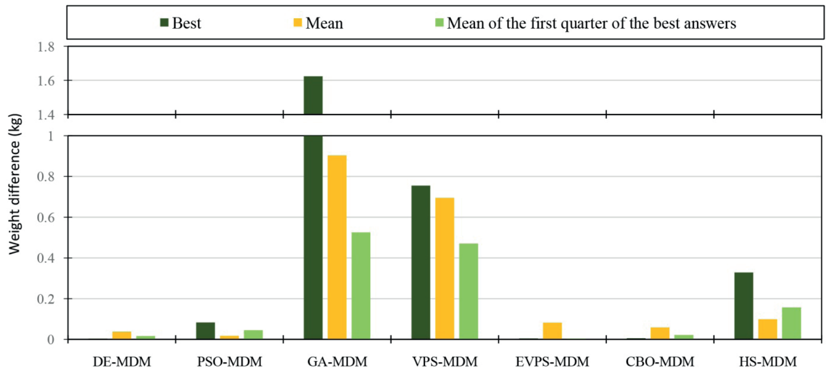

Fig. 9 Comparison of the results according to weight difference for last problem.

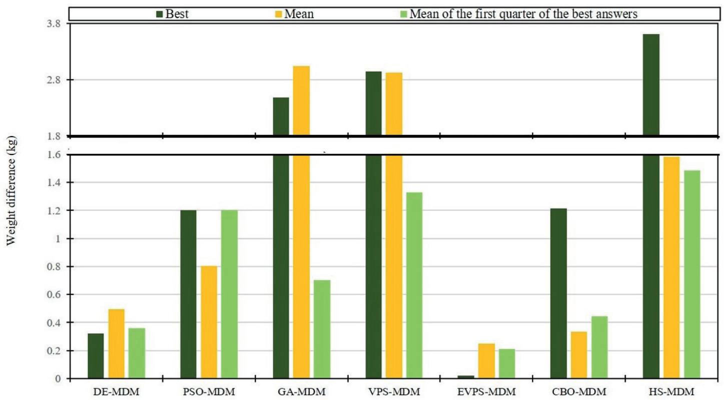

Fig. 10 Comparison of the results according to weight differences for 3rd example with lower population size and iteration.

results of the algorithms without the effect of this operator. Another achievement of this operator, the results show that this operator reduces the dependency of the algorithms to their parameter tuning and the types of the problems. In each iteration, the population within the pre-defined range must be certain. This value (Eq. (1)) will ascend in each iteration, so with the increases in iterations, the population (for each variable) within this range will increase. Thus, the balance between exploration and exploitation will be established. In fact, this balance will be improved by controlling the population within the pre-defined range.

Finally, the authors recommend the use of this operator for other metaheuristic algorithms and for other types of optimization problems.

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