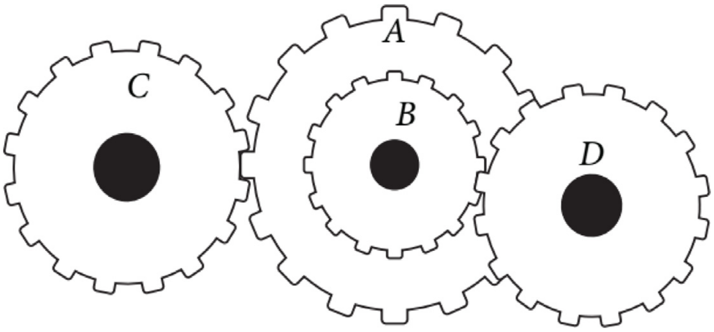

Fig. 15. Schematic illustration of GTD.

Table 10
Comparative result for GTD.

	x1	x2	x3	x4	Best	Worst	Average	SD	Median	Z	p-values
DMO	42.52951	18.7647	15.82212	48.80761	2.70E−12	2.31E−11	6.78E−12	8.59E−12	2.70E−12	na	na
AOA	59.28158	22.04586	12	30.95616	3.82E−09	3.82E−09	3.82E−09	0	3.82E−09	−1.539[a]	0.118
CPSOGSA	48.8906	12.68629	31.35636	56.73214	9.94E−11	2.61E−08	6.46E−09	7.94E−09	3.09E−09	−1.631[a]	0.139
PSO	43.40974	19.24739	15.58414	49.22114	2.70E−12	2.36E−09	1.25E−09	1.04E−09	9.92E−10	−2.172[a]	0.025
ACO	4	2	3	1	0.00050119	0.000501	0.000501	1.14E−19	0.000501	−1.612[a]	0.092
SSA	31.04464	21.71801	12	58.50366	2.70E−12	3.82E−09	1.02E−09	1.08E−09	9.32E−10	−1.750[a]	0.118
SCA	48.133	16.91795	22.05597	53.89677	1.17E−10	2.36E−09	1.24E−09	7.05E−10	1.36E−09	−1.852[a]	0.060
GWO	53.17972	26.05225	15.05245	50.96482	2.70E−12	2.31E−11	1.70E−11	9.84E−12	2.31E−11	−1.523[a]	0.324

[a]Based on negative ranks.
[b]Based on positive ranks.

velocity. The design variables are the number of teeth of gears given as $n_A\,(=x_1)\,, n_B\,(=x_2)\,, n_C\,(=x_3)\,, n_D(=x_4)$ as shown in Fig. 15. The GTD is mathematically formulated as given in Eq. (13).

$$\min f\,(X) = \left(\frac{1}{6.931} - \frac{x_3 x_2}{x_1 x_4}\right)^2 \tag{13}$$

where

$$x_1, x_2, x_3, x_4 \in \{12, 13, 14, \ldots, 60\}$$

The best results of DMO and seven other algorithms are presented in Table 10. Though DMO, SSA, PSO, and GWO all found the optimum solution, the average value and standard deviation of DMO are far superior to the other algorithms. In addition, the Wilcoxson signed test statistics returned negative ranks for all except SSA, PSO, and GWO. The superiority of DMO is also clear, as seen in Fig. 16, converging early toward the optimal cost of the objective function.

4.4.7. The cantilever beam design problem (CBD)

The cantilever beam design problem aims to minimize a cantilever beam's weight with a square cross-section, as shown in Fig. 17 [73]. The decision variables are the height or width of the five hollow square blocks whose thickness is constant. The mathematical model of the CBD is given in Eq. (14).

$$\min f\,(X) = 0.0624\,(x_1 + x_2 + x_3 + x_4 + x_5) \tag{14}$$

Subject to

$$g\,(X) = \frac{61}{x_1^3} + \frac{37}{x_2^3} + \frac{19}{x_3^3} + \frac{7}{x_4^3} + \frac{1}{x_5^3} - 1 \le 0 \qquad 0.01 \le x_i \le 100\ \forall\ 1 = 1, \ldots, 5$$

Looking at Table 11, we see that the best solutions for solving the CBD problem obtained are DMO, CPSOGSA, PSO, SSA, and GWO. They returned the same average values; however, the superiority of DMO is confirmed by

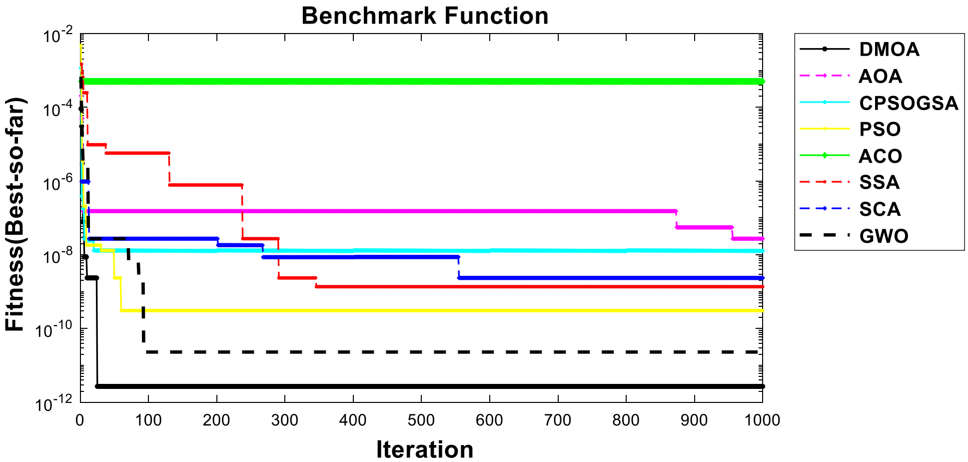

Fig. 16. Convergence rate for GTD.

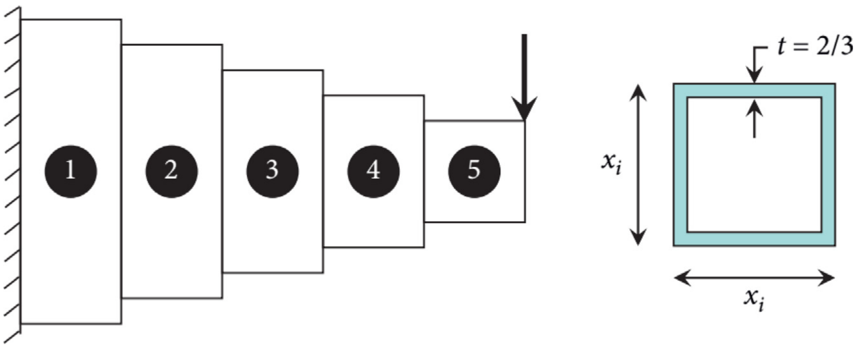

Fig. 17. Schematic illustration of CBD.

Table 11
Comparative result for CBD.

	x1	x2	x3	x4	x5	Best	Worst	Average	SD	Median	Z	p-values
DMO	5.694297	5.025255	4.253986	3.314226	2.037547	1.3004	1.3004	1.3004	2.22E−16	1.3004	na	na
AOA	6.114257	5.352915	4.085839	3.181646	1.72922	1.3866	1.3866	1.3866	0	1.3866	−2.469[a]	0.019
CPSOGSA	5.694297	5.025255	4.253986	3.314226	2.037547	1.3004	1.3004	1.3004	1.65E−16	1.3004	−1.205[b]	0.256
PSO	5.694297	5.025255	4.253986	3.314226	2.037547	1.3004	1.3004	1.3004	2.77E−16	1.3004	−1.205[b]	0.256
ACO	5	4	2	1	3	7.9311	7.9311	7.9311	0	7.9311	−1.275[a]	0.009
SSA	5.694292	5.025255	4.253987	3.314232	2.037549	1.3004	1.3004	1.3004	1.44E−12	1.3004	−2.145[b]	0.141
SCA	5.570738	5.037303	4.561549	3.517433	1.846623	1.3063	1.3364	1.3218	0.008546	1.3228	−2.701[a]	0.007
GWO	5.693828	5.023601	4.254542	3.315875	2.036844	1.3004	1.3004	1.3004	1.60E−07	1.3004	−1.630[b]	0.110

[a]Based on negative ranks.
[b]Based on positive ranks.

the least standard deviation values it returned. ACO and AOA could not escape the local minima, and the Wilcoxon signed test and the convergence rate shown in Fig. 18 support this assertion.

4.4.8. The optimal design of I-shaped beam (IBD)

The I-beam design problem (IBD), formulated in Eq. (15), aims to minimize the vertical deflection of the beam is shown in Fig. 19. The IBD is subject to the load's cross-sectional area and stress constraints. The design variables are as follows: the flange's width $b(= x_1)$, the height of section $h(= x_2)$, the web's thickness $t_w(= x_3)$, and the

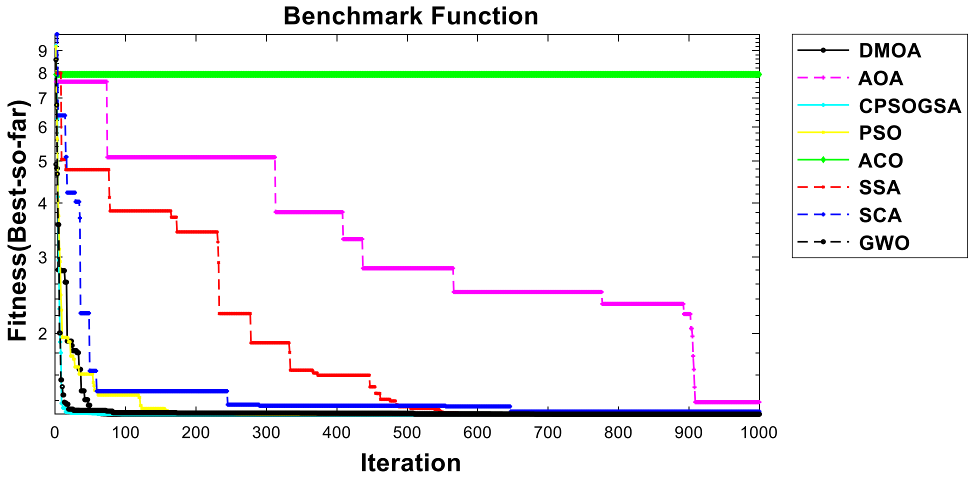

Fig. 18. Convergence rate for CBD.

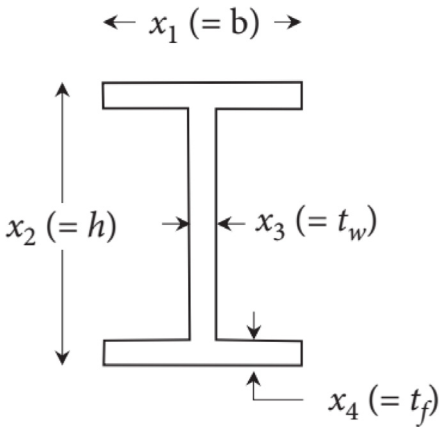

Fig. 19. Schematic illustration of IBD.

flange's thickness $t_f(= x_4)$ [74]

$$\min f(X) = \frac{500}{\frac{x_3(x_2-2x_4)^3}{12} + \left(\frac{x_1 x_4^3}{6}\right) + 2bx_4(x_2 - x_4)^2} \tag{15}$$

Subject to

$$g_1(X) = 2x_1x_3 + x_3(x_2 - 2x_4) \leq 300,$$

$$g_2(X) = \frac{18x_2 \times 10^4}{x_3(x_2 - 2x_4)^3 + 2x_1x_3\left(4x_4^2 + 3x_2(x_2 - 2x_4)\right)} + \frac{15x_1 \times 10^3}{(x_2 - 2x_4)x_3^2 + 2x_3x_1^3} \leq 56$$

Range

$$10 \leq x_1 \leq 50, 10 \leq x_2 \leq 80, 0.9 \leq x_3 \leq 5, 0.9 \leq x_4 \leq 5$$

Many algorithms have been used to solve the IBD, and the comparative result is presented in Table 12. We see that all the algorithms returned optimal solutions except the PSO and ACO. The DMO returned the lowest value for the standard deviation, confirming the proposed algorithm's stability and superiority. This is also seen from the values of the Wilcoxon signed test and convergence rate shown in Fig. 20.

Table 12
Comparative result for IBD.

	x1	x2	x3	x4	Best	Worst	Average	SD	Median	Z	p-values
DMO	80	50	0.9	2.321793	0.013074	0.013074	0.013074	5.95E−13	0.013074	na	na
AOA	80	50	0.9	2.319713	0.013099	0.013099	0.013099	0	0.013099	−2.407[b]	0.213
CPSOGSA	80	42.21398	0.9	2.759357	0.013074	0.013483	0.013197	0.000145	0.013099	−1.355[b]	0.202
PSO	1.151795	1.096731	2.078424	1.173465	−1.88E+20	−1.21E+10	−1.63E+19	3.95E+19	−7.77E+17	−1.272[a]	0.005
ACO	3	1	4	2	−2500	−2500	−2500	0	−2500	−1.250[a]	0.009
SSA	80	50	0.9	2.321792	0.013074	0.013079	0.013074	8.47E−07	0.013074	−2.045[b]	0.141
SCA	80	50	0.9	2.31115	0.013074	0.013155	0.013094	2.00E−05	0.01309	−2.703[b]	0.107
GWO	80	50	0.9	2.321781	0.013074	0.013075	0.013074	1.85E−07	0.013074	−1.601[b]	0.112

[a]Based on negative ranks.
[b]Based on positive ranks.

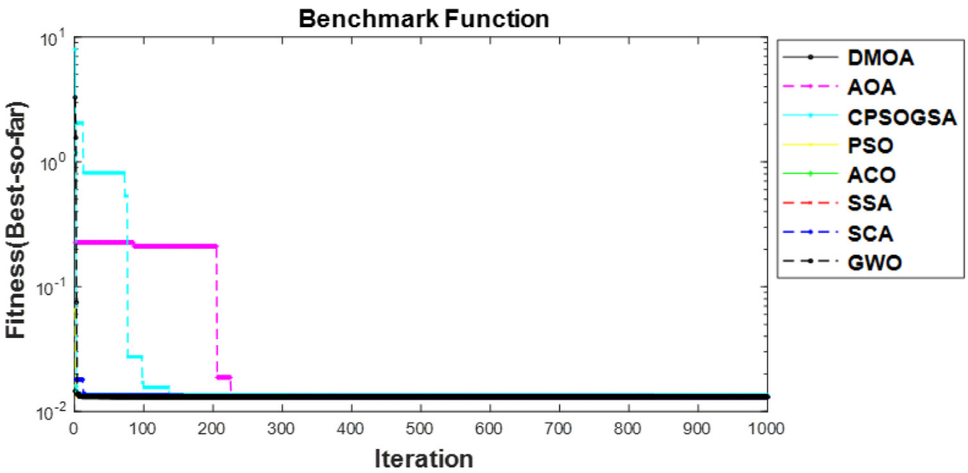

Fig. 20. Convergence rate for IBD.

4.4.9. The tubular column design (TCD)

The tabular column problem aims to design, at minimum cost, a uniform column of the tubular section to carry a compressive load. The design variables are namely: the column's mean diameter $d(=x_1)$ and the tube's thickness $t(=x_2)$. The schematic illustration of the TCD is shown in Fig. 21. The material used for the column has yield stress ($\sigma_y = 500$ kgf/cm^2) and modulus of elasticity $\left(E = 0.85 \times 10^6 \text{ kgf/cm}^2\right)$. The TCD is mathematically modeled as in Eq. (16) [75]

$$\min f(X) = 9.8x_1x_2 + 2x_1 \tag{16}$$

Subject to

$$g_1(X) = \frac{P}{\pi x_1 x_2 \sigma_y} - 1 \le 0,$$
$$g_2(X) = \frac{8PL^2}{\pi^3 E x_1 x_2 \left(x_1^2 + x_2^2\right)} - 1 \le 0,$$
$$g_3(X) = \frac{2.0}{x_1} - 1 \le 0,$$
$$g_4(X) = \frac{x_1}{14} - 1 \le 0,$$
$$g_5 = \frac{0.2}{x_2} - 1 \le 0, g_6(X) = \frac{x_2}{8} - 1 \le 0,$$

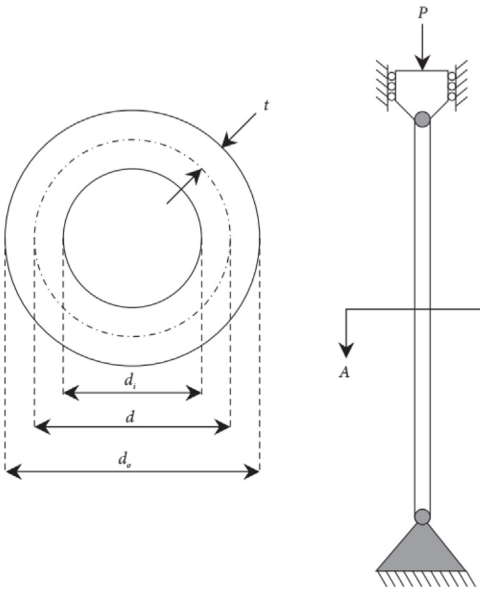

Fig. 21. Schematic illustration of TCD.

Table 13
Comparative results for TCD.

	x1	x2	Best	Worst	Average	SD	Median	Z	p-values
DMO	6.182683	0.2	24.615	24.615	24.615	1.81E−14	24.615	na	na
AOA	6.182704	0.2	24.617	24.617	24.617	0	24.617	−2.497[b]	0.213
CPSOGSA	6.182683	0.2	24.615	24.615	24.615	1.81E−14	24.615	−1.255[b]	0.209
PSO	0.8	0.8	2183	2183	2183	9.25E−13	2183	−1.255[a]	0.009
ACO	2	1	1422.4	1422.4	1422.4	4.63E−13	1422.4	−1.255[a]	0.009
SSA	6.182683	0.2	24.615	24.615	24.615	3.50E−12	24.615	−2.045[b]	0.041
SCA	6.183237	0.2	24.615	24.618	24.616	0.000639	24.615	−2.701[b]	0.007
GWO	6.182661	0.2	24.615	24.615	24.615	2.88E−07	24.615	−1.600[b]	0.11

[a]Based on negative ranks.
[b]Based on positive ranks.

where,

$$2 \leq x_1 \leq 14, \quad 0.2 \leq x_2 \leq 0.8$$

We present the results of solving the TCD using the eight algorithms in Table 13. All the algorithms except for ACO and PSO returned optimal cost. However, the standard deviation value shows that AOA converged early to the optimal cost and was trapped there. The standard deviation value for DMO is the least, meaning its results are stable around the best-obtained cost. Wilcoxon signed test and the convergence curve shown in Fig. 22 corroborate the superiority of the proposed algorithm.

4.4.10. The piston lever design problem (PLD)

The goal of the piston lever design problem is to minimize the volume of oil when the piston's lever is lifted from 0° *to* 45°. The location of the piston's components $H\,(= x_1)\,, B\,(= x_2)\,, D\,(= x_3)\,, and X(= x_4)$ are crucial in the optimization as shown in Fig. 23. The PLD is modeled in Eq. (17) [74].

$$\min f(X) = \frac{1}{4}\pi x_3^2\,(L_2 - L_1) \tag{17}$$

Subject to

$$g_1\,(X) = QLcos\theta - R \times F \leq 0,$$

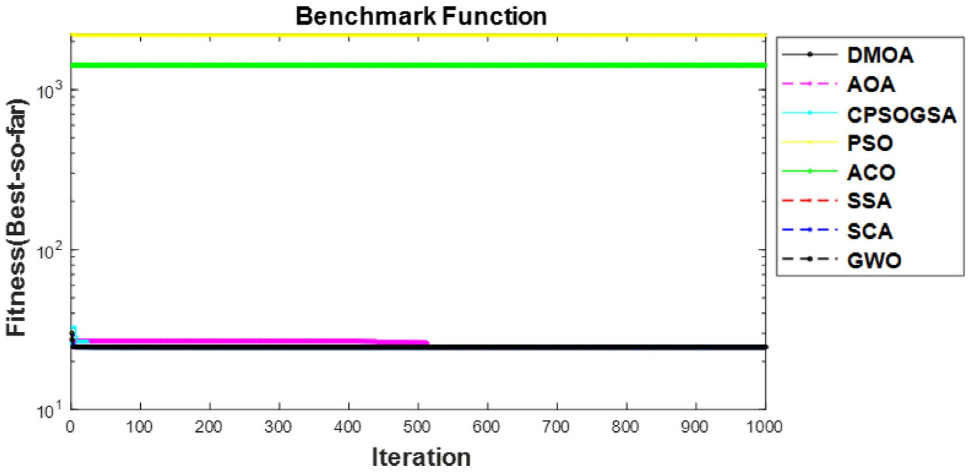

Fig. 22. Convergence rate for TCD.

Table 14
Comparative result for PLD.

	x1	x2	x3	x4	Best	Worst	Average	SD	Median	Z	p-values
DMO	0.05	0.05	4.11733	120	4.6949	4.7006	4.6996	0.002165	4.7006	na	na
AOA	500	500	2.593082	120	481.97	481.97	481.97	0	481.97	−1.599[a]	0.014
CPSOGSA	165.7574	387.4015	3.439238	60	4.6949	571.24	232.81	149.31	220.31	−1.733[b]	0.15
PSO	0.05	0.125143	4.116041	120	4.6949	4.6949	4.6949	2.33E−08	4.6949	−1.614[b]	0.003
ACO	1	4	3	2	2.79E+12	2.79E+12	2.79E+12	0.000497	2.79E+12	−1.972[a]	0.127
SSA	0.05	0.127021	4.122146	119.6422	4.6949	6.5845	5.0255	0.48808	4.8001	−2.023[b]	0.042
SCA	0.05	0.074902	4.117164	120	4.6971	4.7544	4.7112	0.012761	4.7078	−1.963[b]	0.04
GWO	499.5044	500	2.211836	60.01284	4.695	167.67	37.278	66.276	4.6962	−1.125[b]	0.043

[a]Based on negative ranks.
[b]Based on positive ranks.

$$g_2(X) = Q(L - x_4) - M_{max} \leq 0,$$
$$g_3(X) = 1.2(L_2 - L_1) - L_1 \leq 0,$$
$$g_4(X) = \frac{x_3}{2} - x_2 \leq 0$$

where,

$$R = \frac{|-x_4(x_4 sin\theta + x_1) + x_1(x_2 - x_4 cos\theta)|}{\sqrt{(x_4 - x_2)^2 + x_1^2}}, F = \frac{\pi P x_3^2}{4}, L_1 = \sqrt{(x_4 - x_2)^2 + x_1^2},$$
$$L_2 = \sqrt{(x_4 sin\theta + x_1)^2 + (x_2 - x_4 cos\theta)^2}, \theta = 45°, Q = 10{,}000 \text{ lbs}, L = 240 \text{ in},$$
$$M_{max} = 1.8 \times 10^6 \text{ ibs in}, P = 1500 \text{ psi},$$

Range: $0.05 \leq x_1, x_2, x_4 \leq 500, \quad 0.05 \leq x_3 \leq 120$

Looking at Table 14, we see that DMO, CPSOGSA, PSO, SSA, and GWO all returned the optimal cost of the objective function. The standard deviation showed that DMO is second to PSO in the results' stability. Statistical analysis using Wilcoxon signed test, and the convergence rate graph shown in Fig. 24 confirmed the competitiveness of our proposed algorithm.

4.4.11. The corrugated bulkhead design problem (CBhD)

This optimization problem aims to minimize the weight of the chemical tanker's corrugated bulkhead. The design variables are the width ($= x_1$), depth ($= x_2$), length ($= x_3$), and thickness of the plate ($= x_4$). The problem is

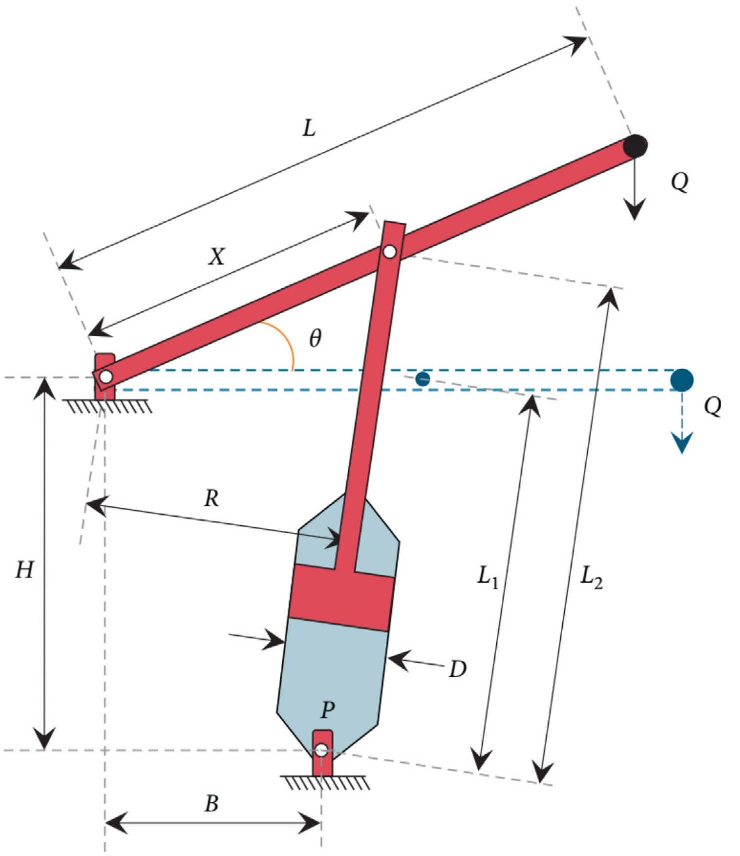

Fig. 23. Schematic illustration of the PLD.

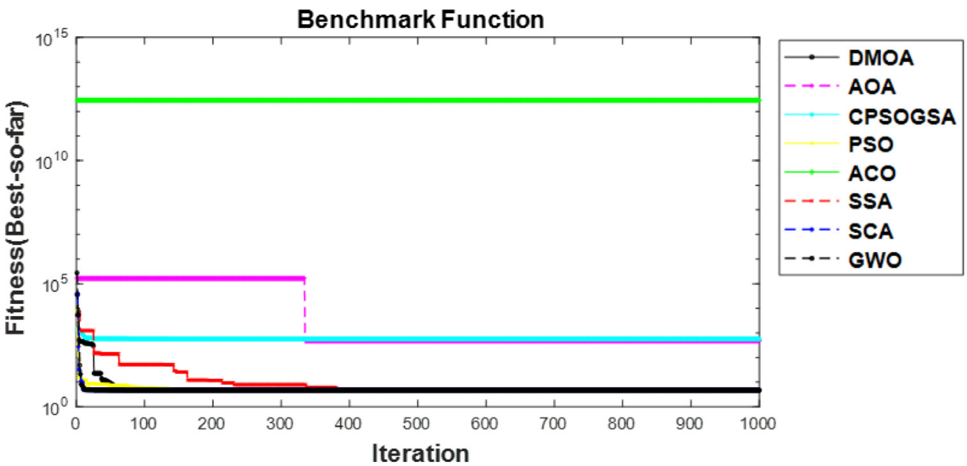

Fig. 24. Convergence rate for PLD.

modeled in Eq. (18), and the schematic illustration is shown in Fig. 25 [76].

$$\min f(X) = \frac{5.885 x_4 (x_1 + x_3)}{x_1 + \sqrt{\left|x_3^2 - x_2^2\right|}} \tag{18}$$

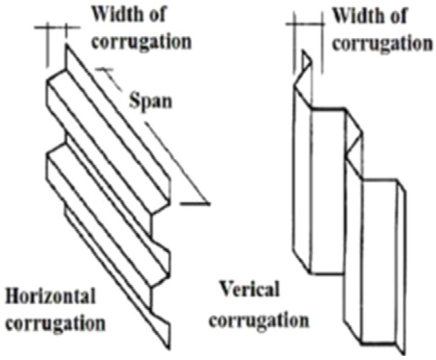

Fig. 25. Schematic illustration of the (CBhD).

Table 15
Comparative result for (CBhD).

	x1	x2	x3	x4	Best	Worst	Average	SD	Median	Z	p-values
DMO	48.31191	54.78270401	61.92983	0.424913	4.6972	1.548	4.6693	4.3569	0.98697	na	na
AOA	43.08666	71.77219383	77.94126	0.324839	4.0019e−322	5.0058	5.0058	5.0058	0	−1.859[a]	0.003
CPSOGSA	52.64682	46.73842696	51.79144	0.482916	5.0058	4.6704	5.1472	4.8077	0.16624	−2.075[a]	0.038
PSO	8.78E−59	2.37E−19	0	1.41379	4.7337	2.90E−42	1.1683	0.11683	0.36944	−2.192[a]	0.028
ACO	1	3	2	4	7.61E−38	33 620	33 620	33 620	0	−2.194[a]	0.028
SSA	49.34138	53.82910853	61.03121	0.433705	1.548	4.6726	3.2716	2.1245	4.6692	−2.023[a]	0.043
SCA	8.57E−15	0	0	0	4.0019e−322	4.7295	1.2878	1.8821	0.57375	−1.400[a]	0.161
GWO	48.26083	54.95290208	62.0196	0.4227	4.669	4.6692	4.6691	8.26E−05	4.6691	−1.014[b]	0.31

[a]Based on negative ranks.
[b]Based on positive ranks.

Subject to

$$g_1(X) = -x_4x_2\left(0.4x_1 + \frac{x_3}{6}\right) + 8.94\left(x_1 + \sqrt{\left|x_3^2 - x_2^2\right|}\right) \le 0,$$

$$g_2(X) = -x_4x_2^2\left(0.2x_1 + \frac{x_3}{12}\right) + 2.2\left(8.94\left(x_1 + \sqrt{\left|x_3^2 - c_2^2\right|}\right)\right)^{\frac{4}{3}},$$

$$g_3(X) = -x_4 + 0.0156x_1 + 0.15 \le 0,$$

$$g_4(X) = -x_4 + 0.0156x_3 + 0.15 \le 0,$$

$$g_5(X) = -x_4 + 1.05 \le 0,$$

$$g_6(X) = -x_3 + x_2 \le 0$$

range: $0 \le x_1, x_2, x_3 \le 100, \quad 0 \le x_4 \le 5$

Table 15 compares the best and statistical results of DMO and seven other algorithms. According to these results, the DMO's performance is second to GWO, which returned the best outcome for this problem. AOA returned poor results, as can be seen as an outlier in the convergence curve (Fig. 26). The Wilcoxon signed test was negative for all pairwise comparisons except GWO.

4.4.12. The reinforced concrete beam design problem (RCB)

The reinforced concrete beam design problem assumed a beam supported by a span of 30ft and subjected to live and dead load of 2000 lbf and 1000 lbf, respectively [77]. Fig. 27 shows the schematic illustration of the RCB. The compressive strength of the concrete ($\sigma_c = 5$ ksi), reinforce steel yield stress ($\sigma_y = 50$ ksi). The design variables are the reinforcement area $A_s(= x_1)$, the beam width $b(= x_2)$, and the depth of the beam $h(= x_3)$. The mathematical model for RCB is given in Eq. (19).

$$\min f(X) = 2.9x_1 + 0.6x_2x_3 \tag{19}$$

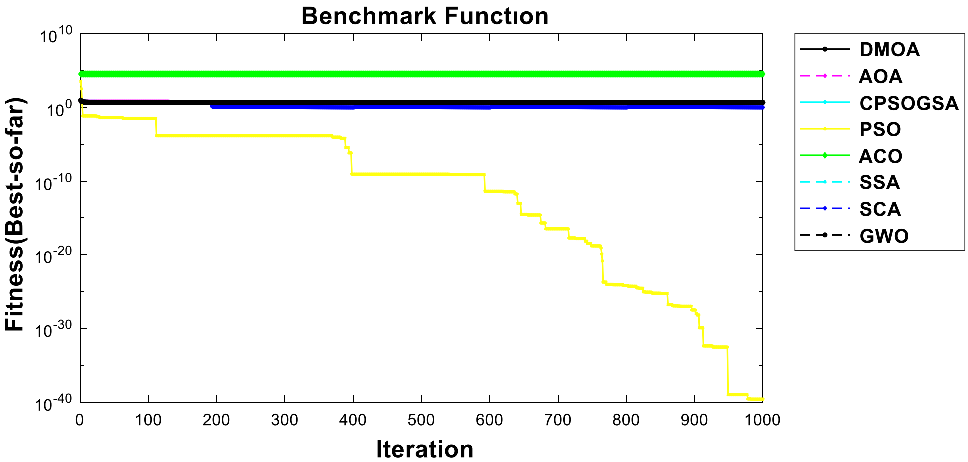

Fig. 26. Convergence rate for CBhD.

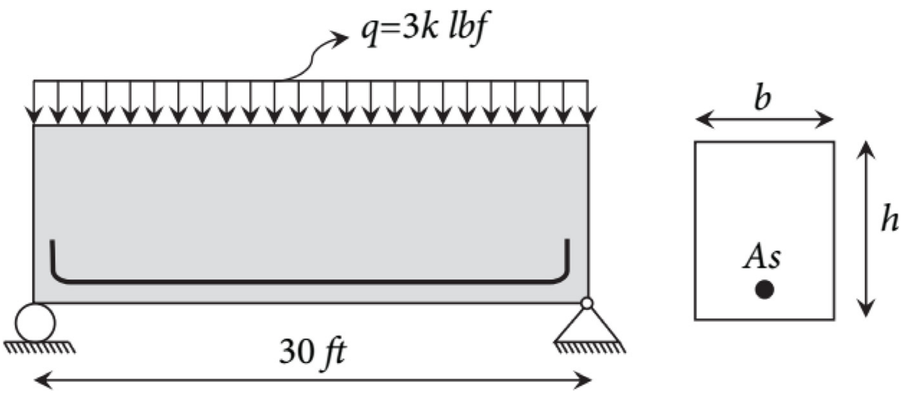

Fig. 27. Schematic illustration of the RCB.

Subject to

$$g_1 = \frac{x_2}{x_3} - 4 \leq 0,$$

$$g_2 = 180 + 7.375\frac{x_1^2}{x_3} - x_1 x_2 \leq 0$$

Range: $x_1 \in \{6, 6.16, 6.32, 6.6, 7, 7.11, 7.2, 7.8, 7.9, 8, 8.4\}$, $x_2 \in \{28, 29, 30, \ldots, 40\}$, $5 \leq x_3 \leq 10$

Looking at Table 16, we see that all the algorithms except for PSO and ACO returned the best minimum cost for the RCB. AOA got trapped in the best solution, and PSO was found near-optimal cost. The convergence curve shown in Fig. 28 confirmed this assertion, as seen from their line position on the graph. Wilcoxon signed test return positive rank for the pairwise comparison except for PSO and ACO.

4.5. Summary of results

The results of experiments on unimodal test functions show that DMO has excellent exploitation capabilities compared to the seven other algorithms. This can be attributed to the selection of the alpha and the way the alpha influences the movement of the remaining members towards the best solutions at every iteration. At the exploitation phase, the alpha ensures continuous neighborhood searching until the babysitter exchange criteria are met, thereby making the current solution more accurate. The results of experiments on multimodal test functions also show that DMO has outstanding exploration capabilities compared to seven other related algorithms. The mongooses do not

Table 16
Comparative result for RCB.

	x1	x2	x3	Best	Worst	Average	SD	Median	Z	p-values
DMO	0.067312	0.849121	5	307.84	307.84	307.84	1.16E−13	307.84	na	na
AOA	0	0.849929	5	307.84	307.84	307.84	0	307.84	−1.540[b]	0.128
CPSOGSA	0.010205	0.862546	5	307.84	307.84	307.84	1.16E−13	307.84	−1.601[b]	0.119
PSO	6.306019	5	5	382.96	382.96	382.96	2.31E−13	382.96	−2.192[a]	0.029
ACO	2	1	3	710.92	710.92	710.92	2.31E−13	710.92	−1.601[a]	0.09
SSA	0	0.918583	5	307.84	307.84	307.84	1.16E−13	307.84	−1.753[b]	0.108
SCA	0	0.871377	5	307.84	307.84	307.84	1.16E−13	307.84	−1.859[b]	0.063
GWO	0	0.4	5	307.84	307.84	307.84	1.16E−13	307.84	−1.521[b]	0.328

[a]Based on negative ranks.
[b]Based on positive ranks.

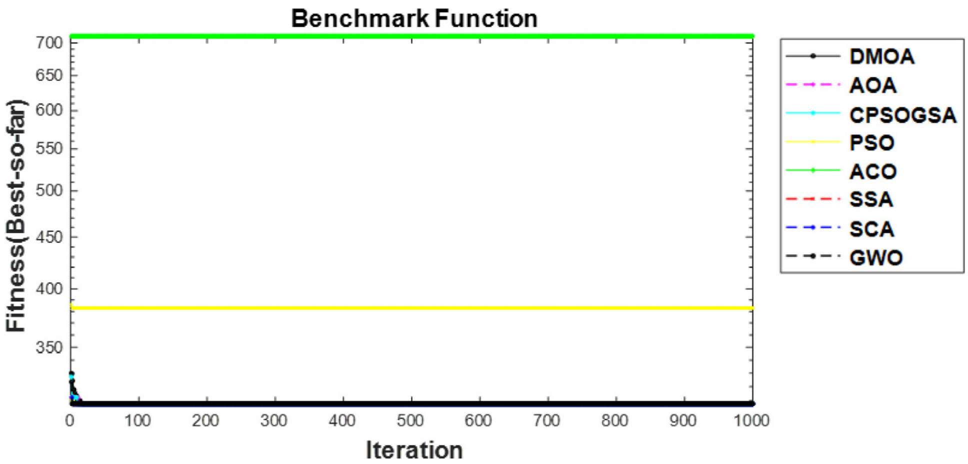

Fig. 28. Convergence rate for RCB.

return to the same sleeping and foraging area; the alpha ensures that a new foraging area is sought every time the babysitters are exchanged.

Also, the uniformity of the initial population, number of iterations, and adequately controlled population size contribute to the general performance of the proposed algorithm. We can see from the convergence plots that DMO converges near the minimum solution early in the iteration phase when the position vectors are close to the global minimum (e.g., F13 in Fig. 3). The final ranking of tested algorithms is based on Friedman's test's general performance. The algorithm with the lowest mean rank is ranked first. The results for the 12 engineering problems showed that the proposed algorithm performed best in all but two of the benchmark functions in the engineering domain.

4.6. Strengths and limitations of DMO

Theoretically, the proposed DMO can find the global optimum solutions of different optimization problems better than some algorithms in the literature. The DMO stochastically creates and improves a set of candidate solutions for a given optimization problem, relying on the exploratory and exploitation capability of DMO, which mimics the seminomadic behavior and compensatory adaptation of the dwarf mongoose. Different regions of the problem search space are explored as the dwarf mongoose move from one food source or sleeping mound to another. Promising regions of the search space are exploited because the DMO is modeled after the dwarf mongoose's inability to capture large prey for family feeding but individually sourcing enough food to satisfy the individual. Moreover, the DMO has only one parameter that can be tuned.

However, there is no guarantee that the DMO's computed solution is optimal like many other proposed algorithms. Specifically, DMO showed a low convergence rate for a situation where the initial solutions are close to the optimum (e.g., F1, F2, F3, F6), the algorithm must wait for the alpha to be small to advance to a better solution meaning more iteration is needed. There is a need to test the DMO on other real-world problems in parallel machine scheduling and others.

5. Conclusion and future work

The dwarf mongoose optimization algorithm (DMO) is a newly developed metaheuristic algorithm that mimics the foraging behavior of the dwarf mongoose. The proposed algorithm was tested using the classical and CEC 2020 benchmark test functions and twelve semi-real constrained engineering optimization problems. From the comparative study, the DMO has shown its potential to handle these optimization problems, and its performance is much better than or competitive with seven other state-of-the-art algorithms in terms of the five selected performance metrics. Also, given the structural complexity of DMO and the few parameter-tuning, this result is very positive. It is important to point out that other recently proposed representative computational intelligence metaheuristic algorithms have been used to solve the problems considered in this study, like monarch butterfly optimization (MBO) [15], earthworm optimization algorithm (EWA) [18], elephant herding optimization (EHO) [16], moth search (MS) algorithm [17], Slime mound algorithm (SMA) [78], and Harris hawks optimization (HHO) [79].

The DMO, however, showed a low convergence rate for a situation where the initial solutions are close to the optimum and must wait for the alpha to be small to advance to a better solution meaning more iteration is needed. We intend in the future to find ways to effectively balance the exploitation with the exploration to overcome this challenge. Hybridizing the proposed algorithm with other popular algorithms is another way of harnessing the advantages of different metaheuristic algorithms to develop a more robust optimization algorithm.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability statements

All data generated or analyzed during this study will be available upon request made directly to the authors.

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