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Improved Coot optimization algorithm with Levy flight for shape and size optimization of truss structures

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Abstract

The convergence issues and getting trapped in local optimal points are two of the major concerns in the field of optimization. For this purpose, improving the standard algorithms to reach better performance in facing complex optimization problems is considered as one of the main challenges in the field of optimization. In this paper, the performance improvement of metaheuristic algorithms is considered while the applicability of the improved and standard algorithms is evaluated through the weight optimization problem of truss structures. For this purpose, the recently proposed Coot optimization algorithm is utilized as the main algorithm which is inspired by different movement types of Coot birds in the water in order to reach food supplies. Regarding the fact that the standard Coot algorithm utilizes random movement in the main search loop, a new improving methodology is utilized in this paper by replacing these random movements with Levy flight as a stochastic procedure with step length defined by levy distribution. The performance of the standard and improved Coot optimization algorithms is investigated in dealing with the problem of optimizing the shape and size of truss structures. Based on the best and statistical results, it is concluded that the improved Coot algorithm is capable of providing better results that the standard Coot algorithm while the capability of the improving methods in increasing the overall performance of the standard algorithm is demonstrated.

Keywords: coot optimization algorithm, truss structure, metaheuristic algorithm, Levy flight, optimization
2020 MSC: 49Q10, 68Q87

1 Introduction

Optimization which has been discussed and investigated in recent years in engineering, mathematics, economics, management and other scientific trends as well as practical use, refers to choosing the best solution from a set of achievable solutions. In the simplest form, the optimization process tries to obtain the maximum or minimum values of an objective function which is defined by means of a set of decision variables and depends on the nature of the problem. In fact, optimizing a system means minimizing or maximizing a function, which is a detailed function of the system's performance, by systematically selecting data from an accessible dataset while this action ultimately leads to improving the efficiency of the system. The goal of the optimization process is to find the best acceptable solution, according to the constraints of the problem.

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In recent decades, the optimal design of engineering structures has received much attention due to the requirements of industrial companies to provide economic designs. In the field of engineering design, it is very important to determine the design variables with the lowest possible cost that satisfies all the design requirements. Nowadays, engineering problems have become more complex in such a way that many design variables and constraints need to be managed and dealt with simultaneously. Some of the methods used in optimization, including gradient methods, have faced problems in determining the starting point, dealing with complex search space, and also getting trapped in local optima. In this regard, many approaches inspired by nature, including metaheuristic algorithms, have been developed in recent decades to optimize engineering design problems, which can solve difficult engineering problems and overcome the shortcomings of classical methods. Therefore, with the progress of science, metaheuristic optimization algorithms were introduced, which are fruitful by providing better solutions for complex real-world problems. Various metaheuristic algorithms have been introduced in the past years, which have different advantages and disadvantages according to different optimization problems.

Due to the widespread use of truss structures in industries, aerospace, transportation, construction etc., the design and optimization of these structures is one of the main challenges of experts in this fields. Trusses are an integral part of modern architecture which enables the builders to reduce the costs as much as possible, easily cover large spans with the trusses, evenly transfer the load on the structure, by saving the consumption of additional materials and build structures that are easy to maintain. The use of optimization algorithms in structural applications has been investigated frequently in the past years. Jawad et al [9] discussed the optimal design of truss structures using the dragonfly algorithm with discrete variables. Adil and Cengiz [1] developed weighted superposition attraction algorithm for optimal design of large-scale truss structures. Sun et al [27] used the PSO algorithm for the optimal design of truss structures. Mortazavi and Togan [22] used different metaheuristic algorithms for the optimal design of truss structures. Prayogo et al [25] used the symbiotic organism search algorithm for reliability-based design of truss structures. Kooshkbaghi et al [18] discussed the optimal design of truss structure using cuckoo search algorithm. Jalili and Husseinzadeh Kashan [8] presented an optics inspired optimization method for the optimization and design of truss structures. Ye [30] discussed the optimal design of truss structures using the improved neutrosophic number optimization method. Wang and Xu [28] discussed the weight optimization of truss structure using frequency constraint functions and metaheuristic algorithms. Artar and Daloglu [2] used Jaya optimization algorithm for optimal design of steel space truss towers considering seismic effects. Fenu et al [5] investigated the optimal design of an arched truss by applying combined horizontal and vertical loads. Kok et al [17] used genetic algorithm for the optimal design of a steel truss residential roof with cold-formed sections. Yan-Cang and Pei-Dong [29] applied the wolf pack algorithm for the optimal design of truss structures. The optimal design of truss structures under different loadings with displacement constraints was done by Farajpour [4]. Karkauskas and Norkus [11] investigated the optimization of trusses with constraints of stiffness and stability against different loading scenarios. Pan and Wang [24] carried out the optimization of truss structures using adaptive genetic algorithm and considered the frequency and displacement of the structure as design constraints against dynamic loadings. Cazacu and Grama [3] investigated the optimum design of truss structures by genetic algorithm and finite element method. Kaveh et al [13] have optimized truss structures with continuous and discrete design variables by using magnetic charge search system algorithm. Kaveh and Seddighian [14] studied multi-material layout alongside connectivity optimum desgin of truss structures by an enriched firefly algorithm. Mortazavi [21] introduced a new fuzzy decision support mechanism to increase the capability of optimization methods in structure size and topology optimization problems. Jawad et al [10] used a swarm intelligence-based optimization technique called artificial bee colony algorithm in combinatorial optimization of truss structures.

In recent decade, the convergence issues and getting trapped in local optimal points are two of the major concerns in the field of optimization. In this regard, improving the standard algorithms to have better performance in facing complex optimization problems is considered as one of the main challenges in the field of optimization. In this paper, the performance improvement of metaheuristic algorithms is considered while applicability of the improved and standard algorithms is evaluated through the weight optimization problem of truss structures. For this purpose, the recently proposed Coot optimization algorithm (COOT) [23] is utilized as the main algorithm which is inspired by the swarm lifestyle of birds called Coot. This algorithm is developed based on the different movement types of Coot birds in the water in order to reach food supplies. Regarding the fact that the standard Coot algorithm utilizes random movement in the main search loop, a new improving methodology is utilized in this paper by replacing these random movements by Levy flight as a stochastic procedure with step length defined by levy distribution. The performance of the standard and improved Coot optimization algorithms (ICOOT) in dealing with the problem of optimizing the shape and size of truss structures are investigated. Based on the best and statistical results, it is concluded that the ICOOT is capable of providing better results that the COOT while the capability of the improving methods in increasing the overall performance of the standard algorithm is demonstrated.

2 Problem Statement

The general formulation of structural shape and size optimization problem regarding truss structures is presented in this section while the main concern is to reduce the overall weight of the structures. In other words, the weight of the truss structure is considered as the objective function while the frequency constraints as also considered during the optimization process. The cross-sectional areas of the truss structure's members are considered as the design variables while the shape optimization is dealt with by means of the nodal coordinates of structure as design variables. These aspects are mathematically presented in the following:

$$\text{Weight } (\boldsymbol{A}, \boldsymbol{X}) = \sum_{i=1}^{e} \rho_i L_i(x_i) A_i \qquad i = 1, 2, \ldots, n. \tag{2.1}$$

$$\omega_j \geq \omega_j^\star \qquad j = 1, 2, \ldots, p. \tag{2.2}$$

$$\omega_k \leq \omega_k^\star, \qquad k = 1, 2, \ldots, p. \tag{2.3}$$

$$A_l^{low} \leq A_l \leq A_l^{up}, \qquad l = 1, 2, \ldots, n. \tag{2.4}$$

$$x_m^{low} \leq x_m \leq x_m^{up}, \qquad m = 1, 2, \ldots, r. \tag{2.5}$$

where $\boldsymbol{X}$ is the design variables' vector for the nodal coordinates of the truss structure; r is the number of structural nodes; $\boldsymbol{A}$ is the design variables' vector for structural members' cross sectional areas; ρ_i and L_i are the material's density and the length of the structural members respectively; the jth and kth natural frequencies of the truss structure is represented by ω_j and ω_k while $\omega_k^\star$ and $\omega_j^\star$ represent the upper and lower bounds of these frequencies; p is the total number of truss structure's frequencies; A_l^{up} and A_l^{low} are the upper and lower bounds for the cross sectional area as design variables considering the lth truss structural element respectively; x_m^{up} and x_m^{low} are the upper and lower bounds for the nodal coordinates as design variables considering the mth node respectively.

Since the truss optimization problem is a kind of constraint optimization problem, a proper handling process should be determined to deal with design constraints. The well-known penalty constraint handling approach is utilized in this paper with mathematical details as follows:

$$f_{penalty}(\boldsymbol{A}) = (1 + \varepsilon_1 \cdot v)^{\varepsilon_2} \times \text{Weigth}(\boldsymbol{A}, \boldsymbol{X}) \tag{2.6}$$

$$v = \sum_{i=1}^{q} \max\{0, g_i(\boldsymbol{A}, \boldsymbol{X})\} \tag{2.7}$$

where q is the overall number of constraints; v demonstrates the sum of constraints which violates the boundary limits; $g_i(\boldsymbol{A})$ is the ith constraint; ε_1 and ε_2 are the parameters for evaluation of through the optimization procedure.

3 Coot optimization algorithm

Coot birds are some kids of water birds which are categorized into Rail or Rallidae family. By means of a decorated forehead, these animals have different looks than other birds by having colored bills and red dark eyes. The behavior of these birds over the surface of water is the main key point which is used to develop an optimization algorithm. These birds try to move at angles toward the direction of their motion or the zone of repulsion. Based on Fig. 1, two types of movement as synchronized movement and disordered movement are demonstrated while the Coots try to have a chain movement over the surface of water while the other follows them accordingly (Fig. 2). In addition, the collective behaviors of Coots are demonstrated through their regular and irregular movements toward the target which is determined as food by including some coots in front of the crowd as leaders. Four different coots' movements are as random motion between deferent sides, chain movement, position adjustment regarding the leaders, and the leader movements.

The mathematical model of the Coot algorithm is developed by unitization of random initial position vectors as $(\rightarrow x) = \{\rightarrow x1, \rightarrow x2, \cdots \rightarrow xn\}$ while for each vector, the objective function is evaluated as $(\rightarrow O) = \{O1, O2, \cdots On\}$. The randomization process is conducted as follows:

$$\text{CootPos}(i) = \text{rand}(1, d) \cdot \star(ub - lb) + lb \tag{3.1}$$

$$O_i = f(\text{CootPos}(i)) \tag{3.2}$$

where $\text{rand}(1, d)$ is a random number in the range of $[0, 1]$ while d is the dimension of the problem; $\text{CootPos}(i)$ is the ith coot's position vector; lb and ub are the lower and upper bounds; O_i is the objective function value for the ith coot.

Figure 1: (a) Synchronized movement, (b) Disordered movement [23]

Figure 2: Chain of coots over the surface of water [23]

By means of a randomization, a number of NL leaders are selected based on the objective function values. In this stage, the four types of coots' movements are modeled mathematically. For random motion between deferent sides (Fig. 3), the following formulation is utilized which is a solution to get away from local optima:

$$Q = \mathrm{rand}(1, d) \cdot \star (ub - lb) + lb \tag{3.3}$$

$$CootPos(i) = CootPos(i) + A \times R2 \times (Q - CootPos(i)) \tag{3.4}$$

$$A = 1 - L \times (1/\mathrm{Iter}) \tag{3.5}$$

$$\tag{3.6}$$

where L denotes on the current iteration; $R2$ represents a randomly generated number in the range $[0, 1]$; $Iter$ demonstrates the maximum considered number of iterations.

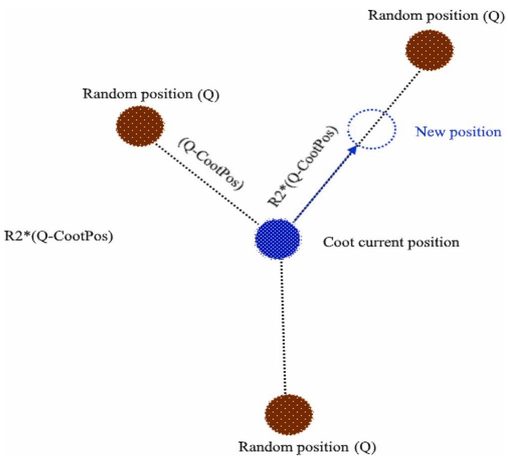

Figure 3: Random motion between deferent sides [23].

For the chain movement (Fig. 4), the average of two coots are utilized as follows:

$$\text{CootPos}(i) = 0 \cdot 5 \times (\text{CootPos}(i-1) + \text{CootPos}(i)) \tag{3.7}$$

where $\text{CootPos}(i)$ and $\text{CootPos}(i-1)$ are two different coots in the search space.

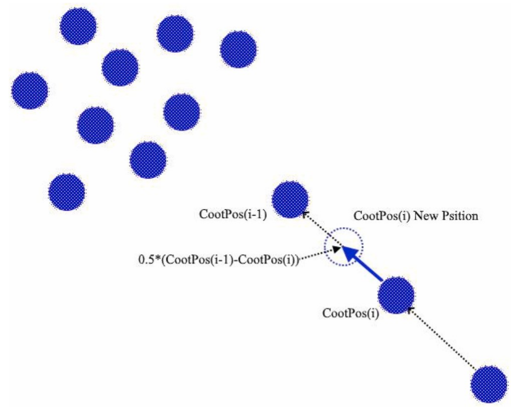

Figure 4: Chain movement of the coots [23].

For position adjustment regarding the leaders (Fig. 5), a few coots are elected to go in front of the groups while the coots adjust their position by means of the leaders of each group as follows:

$$K = 1 + (\text{iMODNL}) \tag{3.8}$$

$$\text{CootPos}(i) = \text{LeaderPos}(k) + 2 \times R1 \times \cos(2R\pi) \times (\text{LeaderPos}(k) - \text{CootPos}(i)) \tag{3.9}$$

where NL shows the total number of leaders; K represents the index number of leaders; i shows the current coot's ($\text{CootPos}(i)$) index number; $\text{LeaderPos}(k)$ demonstrate the leader's position; $R1$ and R represent a randomly generated number in the ranges of $[0, 1]$ and $[-1, 1]$ respectively.

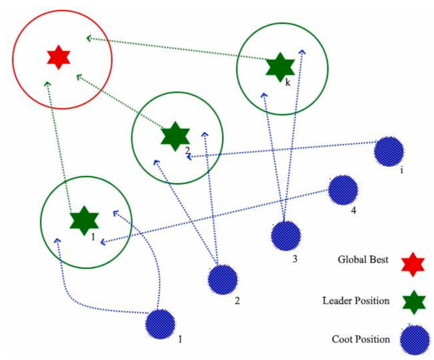

Figure 5: Leaders' selection mechanism [23].

For leader's movement (Fig. 6), the coots in each group have to move toward the optimal area, so leaders have to be directed toward the goal as follows:

$$\text{For } R4 < 0 \cdot 5 : B \times R3 \times \cos(2R\pi) \times (\text{gBest} - \text{LeaderPos}(i)) + \text{gBest} \tag{3.10}$$

$$\text{For} R4 >= 0 \cdot 5 : B \times R3 \times \cos(2R\pi) \times (\text{gBest} - \text{LeaderPos}(i)) - gBest \tag{3.11}$$

$$B = 2 - L \times (\text{Iter}) \tag{3.12}$$

where $R3$ and $R4$ are two randomly generated numbers in the range of $[0, 1]$; gBest represents the global best solution so far found; R determines a randomly created number in the range of $[-1, 1]$; L shows the current iteration.

In Fig. 7, the pseudo code of the Coot optimization algorithm is presented.

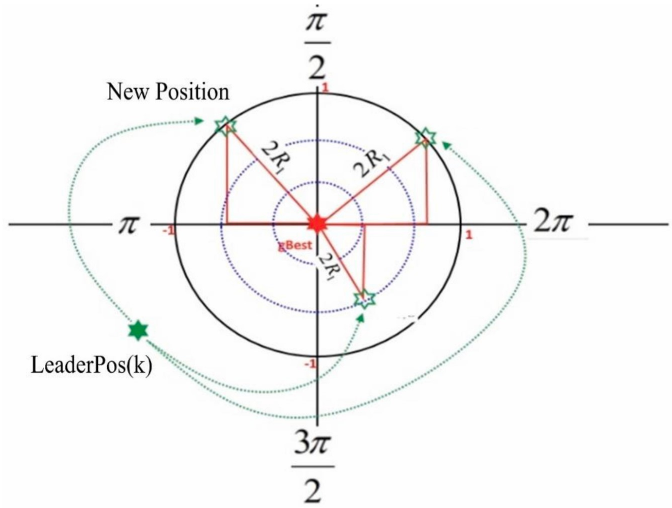

Figure 6: Leaders' position update process [23].

```
Initialize the first population of coots randomly by Eq 1 and
Eq 2
Initialize the  parameters of P=0.5, NL (number of leaders),
Ncoot(number of coots).
Ncoot=Npop-Nl;
Random selection of leaders from the coots
Calculate the fitness of coots and leaders
Find the best coot or leader as the Globa optimum (gBest)
while the end criterion is not satisfied
Calculate A, B parameters by Eq 5 and Eq 10
  If rand< P
    R, R1, and R3 are random vectors along the dimensions of
the problem
  Else
    R, R1, and R3 are  random number
  End
    For i=1 to the number of the coots
        Calculate the  parameter of K by Eq 7
        If  rand>0.5
            Update the position of the coot by Eq 8
        Else
            If rand<0.5 i~=1
                Update the position of the coot by Eq 6
            Else
                Update the position of the coot by Eq 4
            End
        End
        Calculate the fitness of coot
        If  the fitness of coot < the fitness of leader(k)
        Temp=leader(k); leader(k)=coot; coot=Temp;
        end
    End
    For number of Leaders
        If  rand <0.5
          Update the position of the Leader by Eq 9.1
       Else
          Update the position of the Leader by Eq 9.2
       End
       If  the fitness of leader < gBest
        Temp= gBest; gBest =leader; leader=Temp;  (update
Global optimum)
        end
    End
Iter=iter+1;
end
```

Figure 7: Pseudo-code of the Coot algorithm [23].

4 Improved Coot algorithm (ICOOT)

Using random movements in metaheuristic optimization algorithms is one of the frequent actions in creating new solution candidates. This actions leads the algorithms to perform stochastic procedures in order to direct the solution candidates toward the random trajectories. The Brownian random motion was first determined by referring to simple physical phenomenon such as the heat, light and sound transportations. The consecutive random steps with multiple series are used in this process for random movements. In the COOT algorithm, random numbers are frequently included in the position updating process of the algorithm which alters the position of the considered solution candidate by means of random steps (Eqs. 15, 16 and 17) by means of R1 and R3. Entrapment in local optima and poor convergence behavior are two of the main deficiencies of using random distributions, so the Improved COOT (ICOOT) algorithm is proposed while a new improvement methodology is conducted in for position updating process of the standard COOT algorithm. The well-known Levy flight is implemented into the main loop of the COOT algorithm which is a stochastic process with step length defined by levy distribution as a continuous probability distribution determined for non-negative variables. In the Levy flight, the jumping size follows the Levy distribution function in each step and is mathematically presented as follow while the Levy distribution is displayed through the Fourier transform (α is a scale parameter):

$$L(s) \sim |s|^{-1-\beta} \qquad 0 < \beta \leq 2 \tag{4.1}$$

$$F(k) = \exp\left[-\alpha\, |k|^{\beta}\right], \qquad 0 < \beta \leq 2. \tag{4.2}$$

For $\beta = 2$, a Gaussian distribution is resulted while for $\beta = 1$, a Cauchy distribution is satisfied. The inverse integral for the general case is as follows:

$$L(s) = \frac{1}{\pi} \int_0^{\infty} \cos(ks) \exp\left[-\alpha\, |k|^{\beta}\right] dk. \tag{4.3}$$

For s as a large value:

$$L(s) \to \frac{\alpha\beta\tau(\beta)\sin\left(\frac{\pi\beta}{2}\right)}{\pi\, |s|^{1+\beta}}, \qquad s \to \infty. \tag{4.4}$$

where $\tau(z)$ represents the Gamma function.

$$\tau(z) = \int_0^{\infty} t^{z-1} e^{-t} dt \tag{4.5}$$

By referring to Fig. 8 which is the Brownian motion and Levy flight presentation for are 1000 steps, it is obvious that Levy flight can enhance the performance of the searching algorithms in dealing with uncertain complex search spaces.

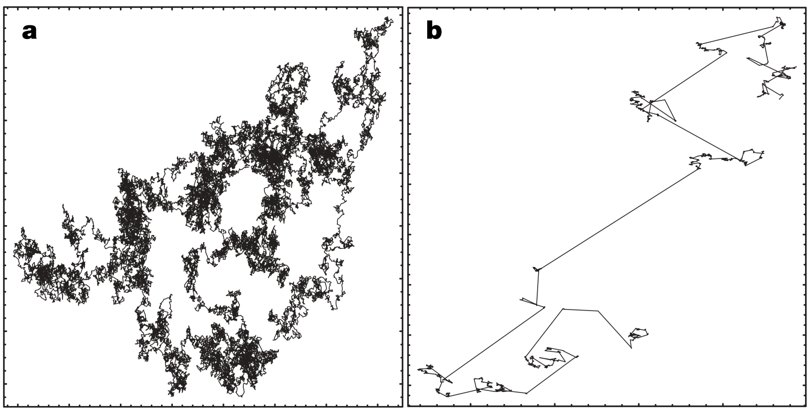

Figure 8: Comparing the Brownian motion (a) and Levy flight (b).

In the ICOOT algorithm, the Levy flight is implemented in the mathematical model of the standard COOT algorithm in which the Levy flight is utilized instead of random numbers ($R1$ and $R3$) as presented in the following:

$$\text{CootPos}(i) = \text{LeaderPos}(k) + 2 \times \text{Levy} \times \cos(2R\pi) \times (\text{LeaderPos}(k) - \text{CootPos}(i)) \tag{4.6}$$

$$\text{For } R4 < 0 \cdot 5 : B \times \text{Levy} \times \cos(2R\pi) \times (\text{gBest} - \text{LeaderPos}(i)) + \text{gBest} \tag{4.7}$$

$$\text{For } R4 >= 0 \cdot 5 : B \times \text{Levy} \times \cos(2R\pi) \times (\text{gBest} - \text{LeaderPos}(i)) - gBest \tag{4.8}$$

where the Levy represent a number generated through Levy distribution.

5 Truss Design Examples

In this section, the basic details of the considered truss structures are presented while the 10-bar truss structure has 10 members and 6 nodes with 10 size optimization variables (Fig. 9). The 37-bar truss structure has 37 members and 20 nodes while 14 design variables for size and 5 for shape optimization are considered (Fig. 10). The 52-bar truss structure has 52 members and 21 nodes with 8 size and 5 shape optimization variables (Fig. 11). The 72-bar truss structure has 72 members and 20 nodes with 16 size variables (Fig. 12) while the 120-bar truss structure has 120 members and 7 size variables (Fig. 13). The other details are presented in Table **??**.

Table 1: The details of the considered truss design examples.

Truss Structure	**Frequency Constraint Limitation**	**Modulus of elasticity**	**Density of steel material**	**lower and upper bounds for the cross-sectional area**	**added mass to the free nodes**
10-bar Truss Structure	7, 15 and 20 Hz	6.89×1010 N/m2	2770 kg/m3	0.645×10-4 and 50×10-4 m2	454 kg
37-bar Truss Structure	20, 40 and 60 Hz	2.1×1011 N/m2	7800 kg/m3	0.0001 and 0.001 m2	10 kg
52-bar Truss Structure	15.961 and 28.648 Hz	2.1×1011 N/m2	7800 kg/m3	0.0001 and 0.001 m2	50 kg
72-bar Truss Structure	4 and 6 Hz	6.89×1010 N/m2	2770 kg/m3	0.645×10-4 and 20×10-4 m2	2270 kg
120-bar Truss Structure	9 and 11 Hz	2.1×1011 N/m2	7971.81 kg/m3	0.0001 and 0.01293 m2	3000 kg (node 1), 1500 kg (nodes 2 to 13) and 100 kg (rest)

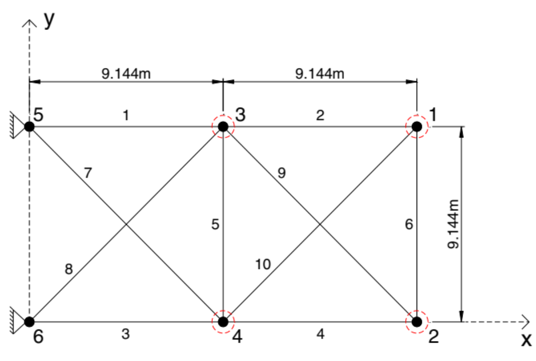

Figure 9: 10-bar truss structure [7].

6 Numerical Investigations

In this section, the results of the numerical investigations are provided in which the optimum design of 5 truss structures with different characteristics are investigated by means of Coot algorithm and the proposed ICOOT algorithm. For statistical purposes, 30 independent runs for each algorithm is conducted regarding each truss structures so

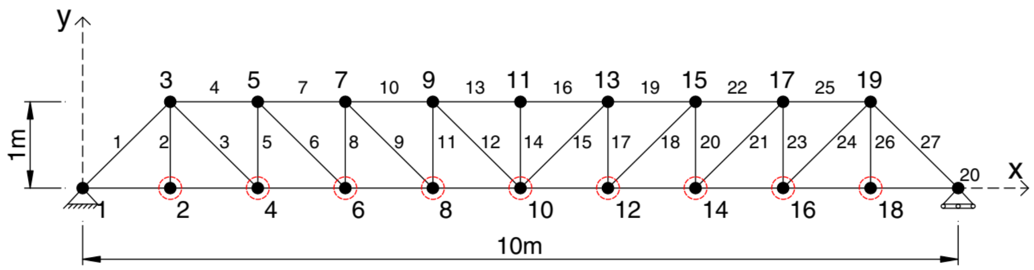

Figure 10: 37-bar truss structure [7].

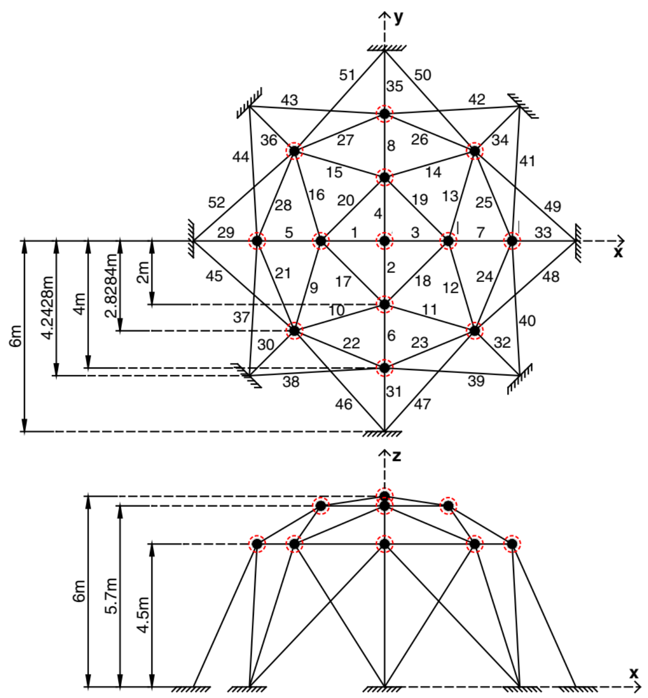

Figure 11: 52-bar truss structure [7].

the best, mean, worst and standard deviation (Std.) of the runs are calculated accordingly. The convergence history for the considered algorithms alongside the competitive results of other algorithms from the literature are all presented for comparison purposes.

6.1 10-bar Truss Structure

Considering the truss structure with 10 structural members, the convergence history of the developed ICOOT and the standard COOT algorithms are presented in Fig. 14 in which the capability of the improved algorithm by Levy flight concept as ICOOT is demonstrated in providing better results.

In Table 2, the optimum results of the best optimization run among the conducted 30 runs are presented by means of optimum design variables in dealing with the 10-bar truss design example. The ICOOT is capable of reaching to 524.93 kg which is better than the 525.28 of the COOT and the previously calculated weights by other algorithms in the literature. Except for the worst run, the ICOOT is superior in regarding the statistical results.

Regarding the frequency constraints that have to be fulfilled by the algorithm, the constraints' values for the ICOOT and COOT algorithms are provide in Table 3 while the both algorithms are capable of providing feasible results in dealing with the 10-bar truss problem based on the constraints' limitations in Table 1.

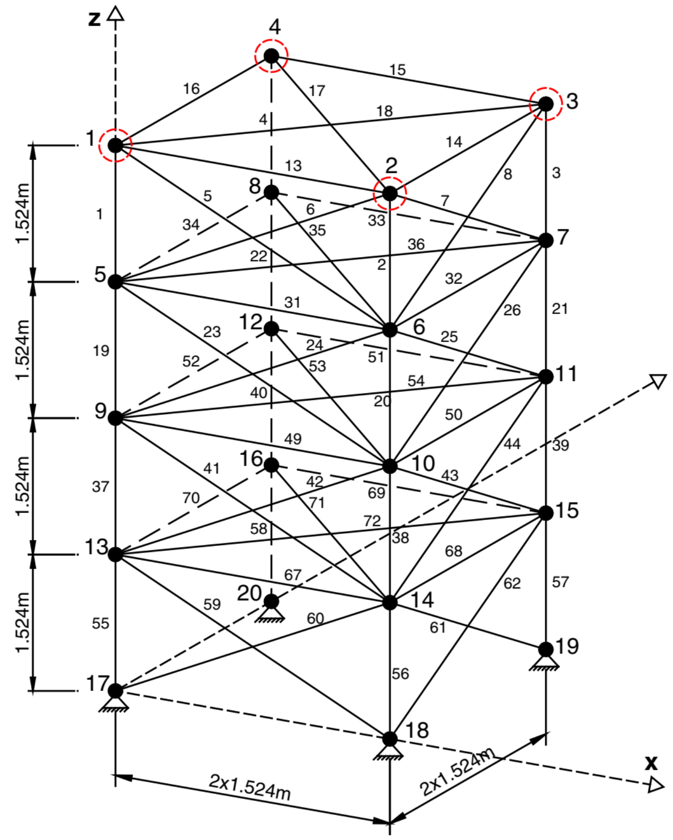

Figure 12: 72-bar truss structure [7].

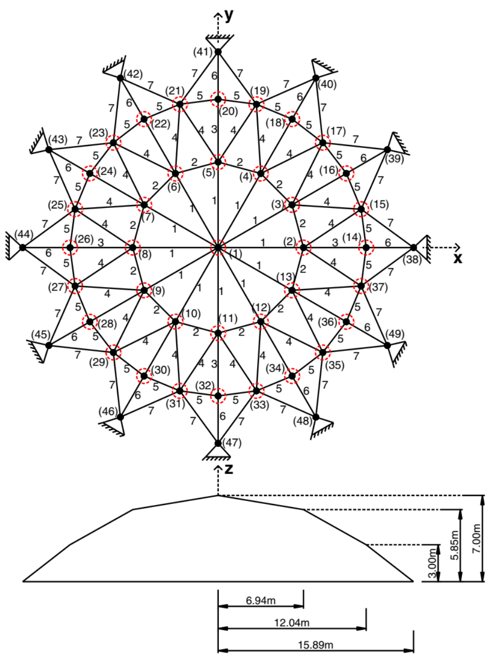

Figure 13: 120-bar truss structure [7].

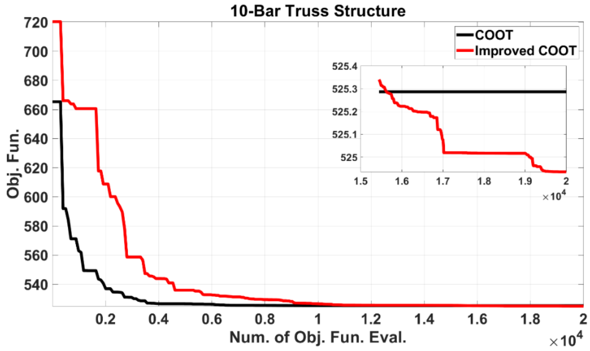

Figure 14: Convergence history of the ICOOT and COOT algorithms for 10-bar truss structure.

Table 2: Results of the ICOOT, COOT and other approaches in dealing with 10-bar truss problem.

Element Number	**Gomes [6]**	**Miguel and Fadel Miguel [20]**	**Kaveh and Zolghadr [15]**	**Zuo et al. [31]**	**COOT**	**ICOOT**
1	37.712	36.198	35.944	37.284	34.3313	36.1909
2	9.959	14.030	15.530	9.445	13.8543	15.1468
3	40.265	34.754	35.285	35.051	36.1567	35.3876
4	16.788	14.900	15.385	19.262	14.9984	15.0468
5	11.576	0.654	0.648	2.783	0.6460	0.6450
6	3.955	4.672	4.583	5.450	4.7162	4.5017
7	25.308	23.467	23.610	19.041	22.8217	23.4140
8	21.613	25.508	23.599	27.939	25.0953	23.5175
9	11.576	12.707	13.135	14.95	12.4791	12.6013
10	11.186	12.351	12.357	10.361	12.2119	11.4105
Weight (kg)	537.98	531.28	532.39	535.73	525.2864	524.9352
Worst (kg)	–	–	–	–	535.0304	538.3653
Mean (kg)	540.89	535.07	537.8	–	528.6989	529.4806
Std.	6.84	3.64	4.02	–	3.2425	3.5459

Table 3: First five natural frequencies of different approaches for 10-bar truss problem.

Frequency Number	**Gomes [6]**	**Miguel and Fadel Miguel [20]**	**Kaveh and Zolghadr [15]**	**Zuo et al. [31]**	**COOT**	**ICOOT**
1	7.0000	7.0002	7.0000	7.0007	7.0000	7.0000
2	17.7860	16.1640	16.1870	17.030	16.1881	16.2588
3	20.0000	20.0029	20.0000	20.156	20.0000	20.0000
4	20.0630	20.0221	20.0210	-	20.1560	20.0014
5	27.7760	28.5428	28.4700	-	28.5105	28.1327

6.2 37-bar Truss Structure

The convergence curves for the 37-bar truss problem by means of the ICOOT and COOT algorithms are depicted in Fig. 15 while the superiority of the ICOOT is demonstrated.

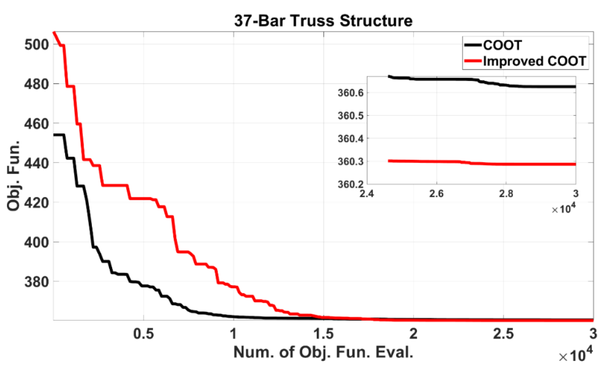

Figure 15: Convergence history of ICOOT and COOT for 37-bar truss structure.

The optimum results of the best optimization run among the conducted 30 runs for the ICOOT, COOT and other algorithms form the literature are presented in Table 4 by means of optimum design variables considering the 37-bar truss design example. The ICOOT is capable of reaching to 360.28 kg which is better than the 360.6252 of the COOT and the previously calculated weights by other algorithms in the literature. The statistical results are only available for the COOT and ICOOT algorithms so the ICOOT is also superior in evaluating the mean and standard deviation.

Table 4: Results of COOT, ICOOT and other approaches in dealing with 37-bar truss problem.

Variables	**Lingyun et al. [19]**	**Gomes [6]**	**Kaveh and Zolghadr [15]**	**COOT**	**ICOOT**
Y3, Y19	1.1998	0.9637	0.9482	1.0656	0.8982
Y5, Y17	1.6553	1.3978	1.3439	1.4737	1.2932
Y7, Y15	1.9652	1.5929	1.5043	1.6519	1.5116
Y9, Y13	2.0737	1.8812	1.6350	1.8081	1.6088
Y11	2.3050	2.0856	1.7182	1.8965	1.6787
A1, A27	2.8932	2.6797	2.6208	2.7521	3.1785
A2, A26	1.1201	1.1568	1.0397	1.0000	1.0664
A3, A24	1.0000	2.3476	1.0464	1.0000	1.0000
A4, A25	1.8655	1.7182	2.7163	2.2373	2.5279
A5, A23	1.5962	1.2751	1.0252	1.4320	1.2467
A6, A21	1.2642	1.4819	1.5081	1.1680	1.2252
A7, A22	1.8254	4.6850	2.3750	2.2877	2.7969
A8, A20	2.0009	1.1246	1.4498	1.3855	1.4324
A9, A18	1.9526	2.1214	1.4499	1.5406	1.5180
A10, A19	1.9705	3.8600	2.5327	2.0291	2.7260
A11, A17	1.8294	2.9817	1.2358	1.4578	1.0000
A12, A15	1.2358	1.2021	1.3528	1.2670	1.4784
A13, A16	1.4049	1.2563	2.9144	2.1628	2.2735
A14	1.0000	3.3276	1.0085	1.0000	1.0000
Weight (kg)	368.84	377.20	360.40	360.6252	360.2870
Worst (kg)	–	–	–	368.3246	369.8363
Mean (kg)	–	–	–	364.6129	362.6334
Std.	–	–	–	2.3101	2.1563

The 37-bar truss problem is an also shape optimization problem so the final optimum shape of the structure is depicted in Fig. 16 while the optimal shape of the 37-bar truss structure is completely different than the initial shape of the structure in Fig. 16.

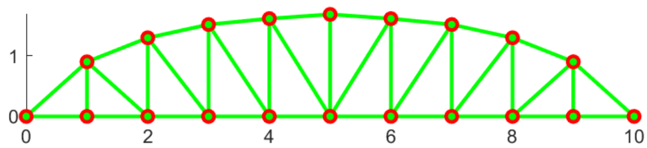

Figure 16: Optimal shape of the 37-bar truss structure.

Regarding the frequency constraints that have to be fulfilled by the algorithm, in Table 5, the constraints' values for the ICOOT and COOT algorithms are provide while the both algorithms are capable of providing feasible results in dealing with the 37-bar truss problem based on the constraints' limitations in Table 5.

Table 5: First five natural frequencies of different approaches for 37-bar truss problem.

Frequency Number	**Lingyun et al. [19]**	**Gomes [6]**	**Kaveh and Zolghadr [15]**	**COOT**	**ICOOT**
1	20.0013	20.0001	20.0194	20.0000	20.0000
2	40.0305	40.0003	40.0113	40.0000	40.0000
3	60.0000	60.0001	60.0082	60.0000	60.0000
4	73.0444	73.0440	76.9896	75.9484	77.7020
5	89.8244	89.8240	97.2222	95.5079	97.3013

6.3 52-bar Truss Structure

Considering the 52-bar truss structure, the convergence history of the ICOOT and the standard COOT algorithms are presented in Fig. 17 in which the capability of the improved algorithm by Levy flight concept as ICOOT is demonstrated in providing better results.

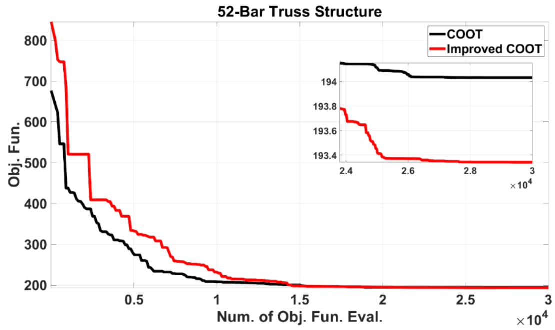

Figure 17: Convergence history of the ICOOT and COOT algorithms for 52-bar truss structure.

Regarding the 30 independent optimization runs, the design variables of the best run alongside the statistical results in dealing with 52-bar truss problem are provided in Table 6 for the ICOOT, COOT and other approaches from the literature. ICOOT is capable of reaching to 193.3448 kg that is the best among other approaches. The ICOOT is also capable of providing better standard division while for the mean and worst, the COOT is superior.

Table 6: Comparative results of ICOOT, COOT and other approaches in dealing with 52-bar truss problem.

Variables	**Lingyun et al. [19]**	**Gomes [6]**	**Kaveh and Ghazan [12]**	**Miguel and Fadel Miguel [20]**	**COOT**	**ICOOT**
Z_A	5.8851	5.5344	5.9362	6.4332	4.8296	4.9899
X_B	1.7623	2.0885	2.2416	2.2208	2.2470	2.3665
Z_B	4.4091	3.9283	3.7309	3.9202	3.0224	3.0048
X_F	3.4406	4.0255	3.963	4.0296	1.9461	1.9996
Z_F	3.1874	2.4575	2.500	2.5200	-1.9999	-2.0000
A_1	1.0000	0.3696	1.0001	1.0050	1.0000	1.0000
A_2	2.1417	4.1912	1.1654	1.3823	1.1665	1.0419
A_3	1.4858	1.5123	1.2323	1.2295	1.1671	1.1780
A_4	1.4018	1.5620	1.4323	1.2662	1.5164	1.4168
A_5	1.9110	1.9154	1.3901	1.4478	1.3835	1.3897
A_6	1.0109	1.1315	1.0001	1.0000	1.0000	1.0000
A_7	1.4693	1.8233	1.6024	1.5728	1.5791	1.5920
A_8	2.1411	1.0904	1.4131	1.4153	1.4375	1.4086
Weight (kg)	236.046	228.381	194.85	197.53	194.0314	193.3448
Worst (kg)	–	–	–	–	397.5422	409.6381
Mean (kg)	–	234.3	196.85	212.8	207.1353	210.1835
Std.	–	5.22	2.38	17.98	36.9269	53.7858

Regarding the frequency constraints, the ICOOT and COOT algorithms are provided in Table 7 while the both algorithms are capable of providing feasible results in dealing with the 52-bar truss problem based on the constraints' limitations in Table 7.

Table 7: First five natural frequencies of different approaches for 52-bar truss problem.

Frequency Number	**Lingyun et al. [19]**	**Gomes [6]**	**Kaveh and Ghazan [12]**	**Miguel and Fadel Miguel [20]**	**COOT**	**ICOOT**
1	12.8100	12.7510	11.4339	11.3119	11.8151	12.0972
2	28.6500	28.6490	28.6480	28.6529	28.6480	28.6480
3	28.6500	28.6490	28.6480	28.6529	28.6480	28.6482
4	29.5400	28.8030	28.6482	28.8030	28.8084	28.6506
5	30.2400	29.2300	28.6848	28.8030	28.8746	28.6701

The 37-bar truss problem is an also shape optimization problem so the final optimum shape of the structure is depicted in Fig. 18 while the optimal shape of the 37-bar truss structure is completely different than the initial shape of the structure in Fig. 18.

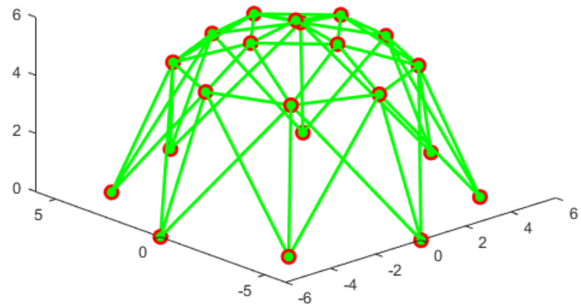

Figure 18: Optimal shape of the 52-bar truss structure.

6.4 72-bar Truss Structure

Convergence history of the ICOOT and COOT algorithms regarding the 72-bar truss structure is depicted in Fig. 19 which is for the best run of 30 independent runs in each algorithm. It is obvious that ICOOT is superior and provides better results than the standard COOT algorithm.

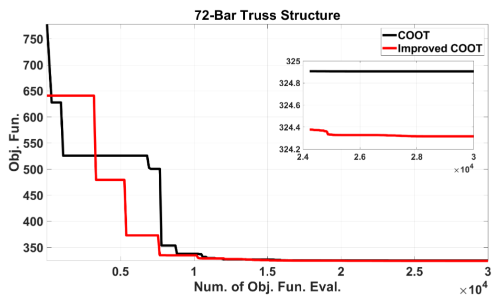

Figure 19: Convergence history of the ICOOT and COOT algorithms for 72-bar truss structure.

Based on the optimum results of the best optimization run among the conducted 30 runs are presented in Table 8 for the 72-bar truss problem, the ICOOT is capable of reaching to 324.31 kg which is better than the 324.90 of the COOT and the previously calculated weights by other algorithms in the literature. Except for the standard deviation, the ICOOT is superior in regarding the statistical results.

Regarding the frequency constraints that have to be fulfilled by the algorithm, the constraints' values for the ICOOT and COOT algorithms are provide in Table 9 while the both algorithms are capable of providing feasible results in dealing with the 72-bar truss problem based on the constraints' limitations in Table 9.

6.5 120-bar Truss Structure

The convergence curves of best runs for the COOT and COOT algorithms are presented in Fig. 20 while the alongside the best and statistical results are provided in Table 10 regarding the 120-bar truss structure. The ICOOT is capable of outranking the COOT and the other approaches from the literature in this case.

Regarding the first five natural frequencies as the design constraint of 120-bar truss problem, the ICOOT and COOT algorithms are capable of satisfying these constraints based on the results of Table 11 and the boundaries of Table 1.

7 Conclusion

The performance improvement of COOT metaheuristic algorithms is considered in this paper while the applicability of the improved algorithm (ICOOT) alongsdei the standard algorithm (COOT) is investigated through the weight optimization problem of truss structures. In the ICOOT algorithm, instead of utilizing random movement in the main search loop, a new improving methodology is utilized by replacing these random movements by Levy flight as a stochastic procedure with step length defined by levy distribution. The performance of the standard and improved

Table 8: Results of ICOOT, COOT and other approaches in dealing with 72-bar truss problem.

Variable	Gomes [6]	Kaveh and Zolghadr [15]	Khatibinia and Nasealavi [16]	Kaveh and Ghazan [12]	Sedaghati [26]	COOT	ICOOT
1–4	2.987	2.854	3.5142	3.3437	3.499	4.6331	3.3723
5–12	7.849	8.301	7.9464	7.8688	7.932	7.9363	7.8956
13–16	0.645	0.645	0.6450	0.6450	0.645	0.6450	0.6450
17–18	0.645	0.645	0.6450	0.6450	0.645	0.6450	0.6450
19–22	8.765	8.202	8.0641	8.1626	8.056	7.9869	7.6022
23–30	8.153	7.043	8.0278	7.9502	8.011	7.8656	8.1161
31–34	0.645	0.645	0.6450	0.6452	0.645	0.6450	0.6450
35–36	0.645	0.645	0.6450	0.6450	0.645	0.6450	0.6450
37–40	13.45	16.328	12.8493	12.2668	12.812	13.0512	12.6891
41–48	8.073	8.299	8.0888	8.1845	8.061	7.9804	7.8725
49–52	0.645	0.645	0.6450	0.6451	0.645	0.6451	0.6450
53–54	0.645	0.645	0.6450	0.6451	0.645	0.6450	0.6450
55–58	16.684	15.048	17.317	17.9632	17.279	15.9059	17.5660
59–66	8.159	8.268	8.1104	8.1292	8.088	7.9757	7.8735
67–70	0.645	0.645	0.6450	0.6450	0.645	0.6450	0.6450
71–72	0.645	0.645	0.6450	0.6450	0.645	0.6450	0.6450
Weight (kg)	328.823	327.507	328.32	327.77	327.605	**324.9052**	**324.3160**
Worst (kg)	–	–	–	–	–	**330.2106**	**328.4660**
Mean (kg)	–	–	329.12	327.99	–	**325.5492**	**325.1554**
Std.	–	–	1.496	0.19	–	**1.0271**	**0.9065**

Table 9: First five natural frequencies of different approaches for 72-bar truss problem.

Frequency Number	Gomes [6]	Kaveh and Zolghadr [15]	Khatibinia and Nasealavi [16]	Kaveh and Ghazan [12]	Sedaghati [26]	COOT	ICOOT
1	4.0000	4.0000	4.0000	4.0000	4.0000	3.9996	3.9996
2	4.0000	4.0000	4.0000	4.0000	4.0000	3.9996	3.9996
3	6.0000	6.0040	6.0000	6.0000	6.0000	6.0000	6.0000
4	6.2190	6.2491	6.2410	6.2300	6.2470	6.3293	6.2529
5	8.9760	8.9726	9.0680	9.0410	9.0740	9.2156	9.0962

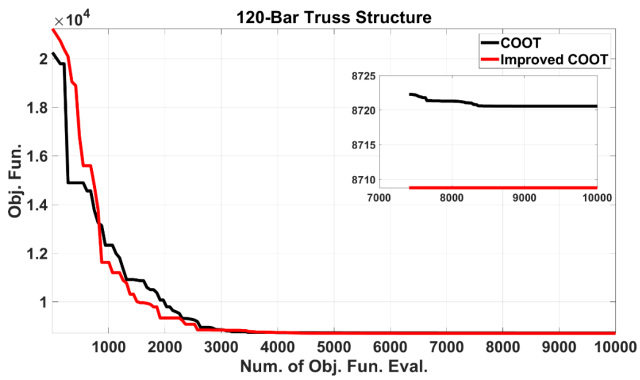

Figure 20: Convergence history of the ICOOT and COOT algorithms for 120-bar truss structure.

COOT optimization algorithms in dealing with the 10-, 37-, 52-, 72- and 120-bar truss problems are investigated. The key findings of this paper are as follows:

- Considering the 10-bar truss, the ICOOT is capable of reaching to 524.93 kg which is better than the 525.28 of the COOT and the previously calculated weights by other algorithms in the literature.
- Except for the worst run, the ICOOT is superior in regarding the statistical results for the 10-bar truss.
- The ICOOT is capable of reaching to 360.28 kg for the 37-bar truss example which is better than the 360.6252 of the COOT and the previously calculated weights by other algorithms in the literature.

Table 10: Results of ICOOT, COOT and other approaches in dealing with 120-bar truss problem.

Element number	**Kaveh and Zolghadr [15]**	**Khatibinia and Naseralavi [16]**	**Kaveh and Ghazaan [12]**	**COOT**	**ICOOT**
1	19.607	20.263	19.8905	20.2205	19.3088
2	41.290	39.294	40.4045	38.3474	41.1233
3	11.136	9.989	11.2057	10.8822	10.6432
4	21.025	20.563	21.3768	21.3384	21.2016
5	10.060	9.603	9.8669	9.5773	9.7864
6	12.758	11.738	12.7200	11.2650	11.8331
7	15.414	15.877	15.2236	15.1133	14.6393
Weight (kg)	8,890.48	8,724.97	8,889.96	**8720.5858**	**8708.7975**
Worst weight (kg)	–	–	–	**9010.7514**	**8911.6952**
Average weight (kg)	–	8,745.58	8,900.39	**8783.0928**	**8768.5720**
Standard deviation	–	1.183	6.38	**61.9963**	**51.0785**

Table 11: First five natural frequencies of different approaches for 120-bar truss problem.

Frequency Number	**Kaveh and Zolghadr [15]**	**Khatibinia and Naseralavi [16]**	**Kaveh and Ghazaan [12]**	**COOT**	**ICOOT**
1	9.0001	9.0020	9.0000	11.0000	11.0000
2	11.0007	11.0030	11.0000	11.0000	11.0000
3	11.0053	11.0030	11.0000	11.0010	11.0000
4	11.0129	11.0070	11.0100	11.0669	11.0663
5	11.0471	11.0760	11.0500	11.0000	11.0000

- For the 52-bar truss problem, the ICOOT is capable of reaching to 193.3448 kg that is the best among other approaches.
- The ICOOT is capable of providing better standard division while for the mean and worst, the COOT is superior regarding the 52-bar truss problem.
- The ICOOT is capable of reaching to 324.31 kg for the 72-bar truss problem, which is better than the 324.90 of the COOT and the previously calculated weights by other algorithms in the literature.
- Regarding the 72-bar truss problem, the ICOOT is superior in regarding the statistical results except for the standard deviation.
- The ICOOT is capable of outranking the COOT and the other approaches from the literature for the 120-bar truss structure.

For the future challenges, the applicability of the COOT and ICOOT can be determined for optimum design of vibration control systems and optimum concrete structural design.

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