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Improved Chef-Based Optimization Algorithm with Chaos-Based Fitness Distance Balance for Frequency-Constrained Truss Structures

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Keywords

Chaotic Maps

Fitness Distance Balance

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Abstract

Chef-based optimization algorithm (CBOA), one of the recently proposed metaheuristic algorithms, is a population-based optimization algorithm inspired by the process of students becoming skilled chefs after receiving training from chef instructors in a culinary academy. In order to improve the performance of CBOA, seven different CBOA variants are proposed in this study, which are improved with three different chaotic maps, fitness distance balance strategy and their combinations. The effectiveness of the proposed CBOA variants is first evaluated by testing them on 16 different benchmark functions. Then, the proposed CBOA variants are applied to frequency constrained 37-bar and 52-bar truss problems to evaluate their performance on engineering problems. Thus, the success of the proposed CBOA variants on different problems was extensively investigated in three different experimental studies. Among these variants, while FC2-CBOA and FC3-CBOA variants performed well on benchmark functions, FC3-CBOA and C3-CBOA variants performed well on 37-bar and 52-bar truss problems, respectively. The results obtained from these three different experimental studies have shown that each proposed CBOA variant is able to produce effective results depending on the problem type.

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1. INTRODUCTION

In recent years, there has been a growing interest in using metaheuristic algorithms to solve real-world engineering problems (Kiran & Beskirli, 2024). In this direction, there are many new metaheuristic algorithms inspired by natural processes and the behavior of living things. Some of these metaheuristic algorithms are methods such as coati optimization algorithm (COA) (Dehghani et al., 2023), atom search algorithm (ASO) (Zhao et al., 2019), tree-seed algorithm (TSA) (Kiran, 2015), whale optimization algorithm (WOA) (Mirjalili & Lewis, 2016), gorilla troops optimizer (GTO) (Abdollahzadeh et al., 2021), honey badger algorithm (HBA) (Hashim et al., 2022), cleaner fish optimization algorithm (CFO) (Zhang et al., 2024), preschool education optimization algorithm (PEOA) (Trojovský, 2023), secretary bird optimization algorithm (SBOA) (Fu et al., 2024), pelican optimization algorithm (POA) (Trojovský & Dehghani, 2022), fungal growth optimizer (FGO) (Abdel-Basset et al., 2025), zebra optimization algorithm (ZOA) (Trojovská et al., 2022), geyser inspired algorithm (GEA) (Ghasemi et al., 2024), and chef-based optimization algorithm (CBOA) (Trojovská & Dehghani, 2022). Among these methods, CBOA (Trojovská & Dehghani, 2022) is an optimization algorithm

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inspired by the process of becoming a skilled chef by improving the cooking skills of students and young chefs who attend a culinary academy for cooking. CBOA algorithm has been effectively used in the literature to solve many problems. Some of these studies are as follows: Kutlu Onay (2023), proposed a new CBOA method equipped with various strategies to improve the performance of CBOA in engineering design problems with CEC2019 and CEC2022 test functions. They named their proposed method as CBOADP. They compared the results of CBOADP with the results of various metaheuristic algorithms. As a result of the comparison, they said that CBOADP achieved success in most of the engineering design problems solved with CBOADP. They also performed various statistical analyses to support these results. In their statistical analysis, they stated that CBOADP produced significant results and the proposed algorithm achieved success. Huang et al. (2024) proposed a method based on a hybrid SqueezeNet model and an improved CBOA algorithm for breast cancer detection from mammography images. They developed the CBOA algorithm using the sinusoidal chaotic map. They named the improved CBOA as ICBOA. They first tested the performance of their proposed ICBOA on benchmark functions. After verifying its efficiency, ICBOA was then used together with the hybrid SqueezeNet model for breast cancer detection from images. When they compared the results obtained here with the results of various state-of-the-art methods, they stated that their proposed method has a superior performance. Rajesh Kumar et al. (2024) stated that cardiovascular disease is the main cause of disability and mortality in developing countries and it is very difficult to diagnose it according to the initial determinations. For this reason, they proposed a deep learning method trained with fractional CBOA for cardiovascular risk prediction from retinal fundus images. Balasubramaniam et al. (2024) in their study, they used retinal fundus images to predict blood segmentation and cardiovascular disease with a deep residual network-based Res-Unet model trained with chronological CBOA. Aribowo et al. (2023) in his study, they performed proportional-integral-derivative (PID) parameter tuning on an automatic voltage regulator (AVR) using the CBOA algorithm. When they compared the obtained results with the results of some metaheuristic algorithms, they reported that CBOA performed better.

In the literature, the performance of metaheuristic algorithms is improved by using various strategies to produce effective results in engineering problems. Some of the studies in this direction are as follows: Joni (2024) added both chaotic and elite strategies to the mountain gazelle optimizer (MGO) algorithm for parameter estimation of photovoltaic models. They named the proposed method called CEMGO. According to the experimental results, they said that their proposed CEMGO method is better than the original MGO. Prapanca et al. (2025) added the levy flight strategy to the fata morgana algorithm in their study. They named the proposed method called MFATA. They evaluated the performance of their proposed MFATA on benchmark functions. As a result of the evaluation, they said that their proposed method is competitive. Aribowo et al. (2024) optimized the proportional integral derivative (PID) parameters using the frilled lizard optimization algorithm. Liu et al. (2024) proposed an improved marine predators algorithm (FDBCMPA) with six different chaotic maps and fitness distance balance strategy for optimization of camera calibration. They compared the results of their proposed FDBCMPA with existing methods. As a result of the comparison, they stated that the performance of their proposed FDBCMPA improved in the optimization of camera calibration. Demirbas et al. (2025) proposed a coati optimization algorithm with opposition-based learning and fitness distance balance strategies (FDBCOA-OBL) for solving the transmission network expansion problem. As a result of the experimental results, they stated that their proposed FDBCOA-OBL has a robust performance.

In this study, seven different CBOA variants improved with three different chaotic maps, fitness distance balance strategy and their combinations are proposed to improve the performance of CBOA. The performance of the proposed CBOA variants is evaluated both on 16 different benchmark functions and on the optimization of 37-bar and 52-bar truss structures, which are real-world engineering problems.

The following sections of this paper are as follows: Section two describes the general structure of CBOA and the general operation of the algorithm. The third section describes the strategies applied to improve the performance of CBOA. Section four comparatively analyzes the performance of the proposed CBOA variants on benchmark functions. Also, the performance of the proposed CBOA variants on both 37-bar and 52-bar truss problems is evaluated. In the last section, the results of the study are summarized and suggestions for future work are given.

2. CHEF-BASED OPTIMIZATION ALGORITHM (CBOA)

Chef-based optimization algorithm (CBOA) is a population-based optimization algorithm inspired by the process of becoming a skilled chef by improving the cooking skills of students and young chefs who attend a culinary academy for cooking (Trojovská & Dehghani, 2022). In a culinary academy, which is assumed to have a certain number of chef instructors, each chef instructor is responsible for running a course. Culinary students can choose which courses to attend based on their interests. Throughout the training, chef instructors teach cooking skills and techniques to the culinary students, while at the same time developing their own skills through individual skills and instruction from the best chef instructor of the culinary academy. The culinary students, in turn, try to learn and imitate the knowledge and skills of the chef instructors and improve what they have learned through practical applications. Thus, thanks to the training they receive during the training period, each culinary student graduates from the culinary academy as a skilled chef. In this context, the mathematical modeling that played a role in the initiation and design process of CBOA is presented under the relevant headings.

2.1. Initiation of CBOA

The population of CBOA consists of two groups: culinary students and chef instructors. The population process of the algorithm is modeled by the matrix given in Equation 1.

$$X=\begin{bmatrix} X_1 \\ \vdots \\ X_i \\ \vdots \\ X_N \end{bmatrix}_{N\times d} = \begin{bmatrix} x_{1,1} & \cdots & x_{1,j} & \cdots & x_{1,d} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i,1} & \cdots & x_{i,j} & \cdots & x_{i,d} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{N,1} & \cdots & x_{N,j} & \cdots & x_{N,d} \end{bmatrix}_{N\times d} \tag{1}$$

where N is the number of populations and d is the number of dimensions. The starting position of the CBOA is initialized randomly using Equation 2.

$$x_{i,j} = lb_j + r \cdot (ub_j - lb_j) \tag{2}$$

where r is a random number in the range [0,1] ub_j and lb_j are the upper and lower bounds of the jth variable, respectively. The objective function is calculated using the vector given in Equation 3.

$$F = \begin{bmatrix} F_1 \\ \vdots \\ F_i \\ \vdots \\ F_N \end{bmatrix}_{N\times 1} = \begin{bmatrix} F(X_1) \\ \vdots \\ F(X_i) \\ \vdots \\ F(X_N) \end{bmatrix}_{N\times 1} \tag{3}$$

2.2. Mathematical modeling of CBOA

In CBOA, the population consists of two groups: culinary students and chef trainers. The population matrix of CBOA is given in Equations 4 and 5.

$$XS = \begin{bmatrix} XS_1 \\ \vdots \\ XS_{N_C} \\ XS_{N_C+1} \\ \vdots \\ XS_N \end{bmatrix}_{N\times d} = \begin{bmatrix} xs_{1,1} & \cdots & xs_{1,j} & \cdots & xs_{1,d} \\ \vdots & \ddots & \vdots & \dots & \vdots \\ xs_{N_C,1} & \cdots & xs_{N_C,j} & \cdots & xs_{N_C,d} \\ xs_{N_C+1,1} & \cdots & xs_{N_C+1,j} & \cdots & xs_{N_C+1,md} \\ \vdots & \dots & \vdots & \ddots & \vdots \\ xs_{N,1} & \cdots & xs_{N,j} & \cdots & xs_{N,d} \end{bmatrix}_{N\times d} \tag{4}$$

$$FS = \begin{bmatrix} FS_1 \\ \vdots \\ FS_{N_C} \\ FS_{N_C+1} \\ \vdots \\ FS_N \end{bmatrix}_{N\times d} \tag{5}$$

The mathematical modeling and functioning of CBOA is basically based on two phases (Trojovská & Dehghani, 2022). The first phase includes updating processes for chef trainers and the second phase includes updating processes for culinary students.

Phase I Update process for chef trainers

At this phase, a certain number of chef trainers in the culinary academy teach cooking skills to cooking students. Chef trainers develop their cooking skills based on two strategies. The first strategy is to imitate the chef instructor by trying to learn the techniques of the best chef instructor in the culinary academy. The new position of chef trainers is calculated using Equation 6. If this new position improves the objective function, it is accepted. This is expressed in Equation 7.

$$xs_{i,j}^{C/S1} = xs_{i,j} + r.\left(BC_j - I.xs_{i,j}\right) \tag{6}$$

$$XS_i = \begin{cases} XS_i^{C/S1}, & FS_i^{C/S1} < F_i; \\ XS_i, & else, \end{cases} \tag{7}$$

With the second strategy, each chef trainer tries to improve their skills by doing individual activities. This process is described by the mathematical formula in Equation 8. Here a random position is generated. If this randomly generated position improves the objective function, it is accepted. This is expressed in Equation 9.

$$xs_{i,j}^{C/S2} = xs_{i,j} + lb_j^{local} + r \cdot (ub_j^{local} - lb_j^{local}) \tag{8}$$

$$XS_i = \begin{cases} XS_i^{C/S2}, & FS_i^{C/S2} < F_i; \\ XS_i, & else, \end{cases} \tag{9}$$

Phase II Update process for culinary students

In the culinary academy, cooking students learn and improve their cooking skills based on three strategies. According to the first strategy, cooking students randomly choose a course of one of the chef instructors and this chef instructor teaches cooking skills to the students. The aim of this strategy is to have different chef instructors to guide the cooking students and students learn different cooking skills under the guidance of the selected chef instructor. This is done using the formula in Equation 10. New positions are calculated according to Equation 11.

$$xs_{i,j}^{S/S1} = xs_{i,j} + r \cdot (CI_{k_i,j} - I \cdot xs_{i,j}) \tag{10}$$

$$XS_i = \begin{cases} XS_i^{S/S1}, & FS_i^{S/S1} < F_i; \\ XS_i, & else, \end{cases} \tag{11}$$

According to the second strategy, the culinary student imitates the chef instructor by completely learning one of the chef instructor's skills. This situation is modeled as in Equation 12 and positions are calculated according to Equation 13.

$$xs_{i,j}^{S/S2} = \begin{cases} CI_{k_i,j}, & j = l; \\ xs_{i,j}, & else, \end{cases} \tag{12}$$

$$XS_i = \begin{cases} XS_i^{S/S2}, & FS_i^{S/S2} < F_i; \\ XS_i, & else, \end{cases} \tag{13}$$

According to the third strategy, cooking students try to improve their cooking skills through individual studies and activities. This is modeled as in Equations 14 and 15.

$$xs_{i,j}^{S/S3} = \begin{cases} xs_{i,j} + lb_j^{local} + r \cdot (ub_j^{local} - lb_j^{local}), & j = q; \\ xs_{i,j}, & j \neq q, \end{cases} \tag{14}$$

$$XS_i = \begin{cases} XS_i^{S/S3}, & FS_i^{S/S3} < F_i; \\ XS_i, & else, \end{cases} \tag{15}$$

3. STRATEGIES APPLIED FOR VARIANTS OF THE CHEF-BASED OPTIMIZATION ALGORITHM

In this study, various improvement strategies were added to the algorithm to improve the performance of CBOA. These strategies are explained under three subheadings. In the first sub-heading, Fitness distance balance strategy is explained. The second sub-heading describes the chaotic maps added to CBOA. In the third sub-heading, the combination of the fitness distance balance strategy and chaotic maps is explained.

3.1. Fitness distance balance strategy

The fitness distance balance strategy was proposed to the literature by Kahraman et al. (2020). This strategy uses a point system to find the best potential solution in the population. This strategy consists of five basic stages as presented below (Bakır et al., 2023).

1. Stage: When $x_i(i = 1,2,\dots,k)$ P is the population, $x_{ij} = [x_{i1}, x_{i2}, \dots, x_{in}]$, $f_i(i = 1,2,\dots,k)$ is the fitness value. The vectors P and FV are given in Equation 16.

$$P \equiv \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{k1} & \cdots & x_{kn} \end{bmatrix}_{kxn}, FV = \begin{bmatrix} f_1 \\ . \\ . \\ . \\ f_k \end{bmatrix}_{kx1} \tag{16}$$

2. Stage: In this study, the distance is calculated according to Equation 17 using the Euclidean distance if the problem size is n and the number of individuals in the population is k.

$$^{k}_{i=1}\forall x_i \neq x_{best}, D_{x,i} = \sqrt{(x_{i[1]} - x_{best[1]})^2 + (x_{i[2]} - x_{best[2]})^2 + \cdots + (x_{i[n]} - x_{best[n]})^2} \tag{17}$$

3. Stage: The D_x distance vector is given as in Equation 18 below.

$$D_x \equiv \begin{bmatrix} d_1 \\ . \\ . \\ . \\ d_k \end{bmatrix}_{kx1} \tag{18}$$

4. Stage: $normFV$ ve $normD_x$ are the normalized fitness value and distance value, respectively, and the FDB score of individual i. is calculated as in Equation 19 below.

$$^{k}_{i=1}\forall x_i, S_{x[i]} = w * normFV_{x[i]} + (1 - w) * normD_{x[i]} \tag{19}$$

5. Stage: Each individual's score vector is presented in Equation 20.

$$S_x \equiv \begin{bmatrix} s_1 \\ . \\ . \\ . \\ s_k \end{bmatrix}_{kx1} \tag{20}$$

The improved CBOA with the fitness distance balance strategy is called F-CBOA. The FDB strategy added to the CBOA algorithm is presented in Equation 21 and the pseudo code of the proposed F-CBOA is given in Algorithm 1.

$$xs_{i,j}^{S/S1} = xs_{F,j} + r \cdot (CI_{k_i,j} - I \cdot xs_{F,j}) \tag{21}$$

Algorithm 1: F-CBOA

Initialize: Set population size of the CBOA(N) and iterations (T)
Randomly generate an initial population matrix X.
Evaluate the given objective function to obtain the vector F.
for t = 1 to T do
Sort the X according to objective function value by Eq. 4 and 5
Start Phase1:
for i=1 to N_C do
Calculate $XS_i^{C/S1}$ using Eq. 6
Update XS_i using Eq. 7
Calculate $XS_i^{C/S2}$ using Eq. 8
Update XS_i using Eq. 9
end for
End Phase1:
Start Phase2:
for t = N_C +1 to N do
Calculate $XS_i^{S/S1}$ using Eq. 20 **with Fitness Distance Balance**
Update XS_i using Eq. 11
Calculate $XS_i^{S/S2}$ using Eq. 12
Update XS_i using Eq. 13
Calculate $XS_i^{S/S3}$ using Eq. 14
Update XS_i using Eq. 15
end for
End Phase2:
end for
Return the best solution

3.2. Chaotic map strategies

Chaotic maps are sensitive to initial parameters and deal with nonlinear systems (Mirjalili & Gandomi, 2017). Chaotic systems can help avoid local minima and are therefore often used to improve the performance of population-based optimization algorithms (Turkoglu et al., 2025). Therefore, chaotic maps are frequently preferred in population-based methods. In this study, duffing map (Dhopavkar et al., 2022), iterative map (Wang et al., 2014) and sinusoidal map (Wang et al., 2014) are used presented in Table 1. These three different chaotic maps were applied to the CBOA algorithm and named C1-CBOA, C2-CBOA and C3-CBOA respectively. The pseudo code of the chaos-based CBOA variants is given in Algorithm 2.

Table 1. *Three different chaotic map strategies and formulas*

Algorithm	Chaotic map	Formula
C1-CBOA	Duffing	$x_{k+1} = y_k$ $y_{k+1} = -bx_k y_k + ay_k - y_k^3$
C2-CBOA	Iterative	$x_{k+1} = \sin\left(\frac{a\pi}{x_k}\right), a \in (0, 1)$
C3-CBOA	Sinusoidal	$x_{k+1} = ax_k^2 \sin(\pi x_k)$

Algorithm 2: C1-CBOA, C2-CBOA, C3-CBOA

Initialize: Set population size of the CBOA(N) and iterations (T)
Generate an initial population matrix X **with chaotic maps**.
Evaluate the given objective function to obtain the vector F.
for t = 1 to T do
Sort the X according to objective function value by Eq. 4 and 5
Start Phase1:
for i=1 to N_C do
Calculate $XS_i^{C/S1}$ using Eq. 6
Update XS_i using Eq. 7
Calculate $XS_i^{C/S2}$ using Eq. 8
Update XS_i using Eq. 9
end for
End Phase1:
Start Phase2:
for t = N_C +1 to N do
Calculate $XS_i^{S/S1}$ using Eq. 10
Update XS_i using Eq. 11
Calculate $XS_i^{S/S2}$ using Eq. 12
Update XS_i using Eq. 13
Calculate $XS_i^{S/S3}$ using Eq. 14
Update XS_i using Eq. 15
end for
End Phase2:
end for
Return the best solution

3.3. Combination of fitness distance balance and chaotic map strategies

In this section, three different approaches, FC1-CBOA, FC2-CBOA and FC3-CBOA, are proposed in combination with the fitness distance balance strategy and chaotic maps to further improve the performance of the CBOA algorithm. The pseudo code of the proposed approach is presented in Algorithm 3.

Algorithm 3: FC1-CBOA, FC2-CBOA, FC3-CBOA

Initialize: Set population size of the CBOA(N) and iterations (T)
Generate an initial population matrix X **with chaotic maps**.
Evaluate the given objective function to obtain the vector F.
for t = 1 to T do
Sort the X according to objective function value by Eq. 4 and 5
Start Phase1:
for i=1 to N_C do
Calculate $XS_i^{C/S1}$ using Eq. 6
Update XS_i using Eq. 7
Calculate $XS_i^{C/S2}$ using Eq. 8
Update XS_i using Eq. 9
end for
End Phase1:
Start Phase2:
for t = N_C +1 to N do
Calculate $XS_i^{S/S1}$ using Eq. 20 **with Fitness Distance Balance**
Update XS_i using Eq. 11
Calculate $XS_i^{S/S2}$ using Eq. 12
Update XS_i using Eq. 13
Calculate $XS_i^{S/S3}$ using Eq. 14
Update XS_i using Eq. 15
end for
End Phase2:
end for
Return the best solution

4. EXPERIMENTAL RESULTS

In this study, the performance of the proposed CBOA variants is first tested on benchmark functions and then its performance on 37-bar and 52-bar truss problems is evaluated. The number of iterations of the original CBOA and the proposed CBOA variants is taken as 250. The benchmark functions and bar truss problems considered in the study were 30 runtimes. According to these conditions, the results obtained with the variants of the proposed CBOA and the original CBOA are presented in tables under the relevant headings.

4.1. Application of the proposed methods to benchmark functions

The names of the 16 different benchmark test functions used in the study and their equations are given in Table 2 (Bai et al., 2021; Beşkirli, 2021).

The comparison of the best, mean, std values of the original CBOA and the best, mean, std values of the proposed CBOA variants are given in Table 3, Table 4, Table 5, Table 6, Table 7, Table 8, Table 9. The results of the original CBOA are compared one by one with the results of the variants of CBOA. Also, according to the results given in the tables, a rank graph between the algorithms was created as shown in Figure 1.

The graph in Figure 1 shows the performance rankings of the original CBOA and the proposed methods on the benchmark functions. When the graph is analyzed, it is seen that the methods compared with the original CBOA show a variable performance on the test functions. When the original CBOA is compared with the F-CBOA method, it is seen that F-CBOA has a better performance ranking. However, when the original CBOA is compared with the C1-CBOA method, it is seen that the original CBOA performs better, while when the original CBOA is compared with the C2-CBOA method, both algorithms perform equally well. When the original CBOA is compared with the C3-CBOA method, it is again observed that the original CBOA has a better success ranking. In addition, when the original CBOA is compared with FC1-CBOA, FC2-CBOA, FC3-CBOA combination algorithms, it is seen that the proposed FC2-CBOA and FC3-CBOA algorithms have a higher success ranking than the original CBOA.

4.2. Application of the proposed methods to 37-bar and 52-bar truss structures

In this section, 37-bar and 52-bar truss problems with frequency constraints, which are real-world engineering problems, are considered to evaluate the performance of the proposed methods.

4.2.1. 37-bar truss structures

One of the optimization problems considered in the study is a 37-bar truss structure with frequency constraints (Öztürk & Kahraman, 2025), the details of which are presented in Figure 2. This structure has a total of 19 design variables. In order to evaluate the effectiveness of the algorithms on the 37-bar truss structure, the best, mean, standard deviation (std.) values obtained by the original CBOA and the proposed CBOA variants are presented comparatively in Table 10.

Table 2. *Benchmark functions*

Fn.	Function Name	Search Range	Function
F1	Sphere	$[-100, 100]^D$	$F1(x) = \sum_{i=1}^{N} x_i^2$
F2	Elliptic	$[-100, 100]^D$	$F2(x) = \sum_{i=1}^{n} (10^6)^{(i-1)/(n-1)} x_i^2$
F3	SumSquares	$[-10, 10]^D$	$F3(x) = \sum_{i=1}^{n} ix_i^2$
F4	SumPower	$[-10, 10]^D$	$F4(x) = \sum_{i=1}^{n} \lvert x_i\rvert^{(i+1)}$
F5	Schwefel 2.22	$[-10, 10]^D$	$F5(x) = \sum_{i=1}^{n} \lvert x_i\rvert + \prod_{i=1}^{n} \lvert x_i\rvert$
F6	Schwefel 2.21	$[-100, 100]^D$	$F6(x) = max_i\{\lvert x_i\rvert, 1 \le i \le n\}$
F7	QuarticWN	$[-1.28, 1.28]^D$	$F7(x) = \sum_{i=1}^{n} ix_i^4 + random[0,1)$
F8	Rosenbrock	$[-10, 10]^D$	$F8(x) = \Sigma_{i=1}^{n-1} [100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2]$
F9	Non-Continuous Rastrigin	$[-5.12, 5.12]^D$	$F9(x) = \sum_{i=1}^{n} [y_i^2 - 10cos(2\pi y_i) + 10]\ y_i = \begin{cases} x_i, \lvert x_i\rvert < \frac{1}{2} \\ \frac{round(2x_i)}{2}, \lvert x_i\rvert \ge \frac{1}{2} \end{cases}$
F10	Schwefel 2.26	$[-500, 500]^D$	$F10(x) = 418.98 * n - \sum_{i=1}^{n} x_i sin(\sqrt{\lvert x_i\rvert})$
F11	Ackley	$[-32, 32]^D$	$F11(x) = 20 + e \pm 20\exp(-0.2\sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2}) - \exp(\frac{1}{N}\sum_{i=1}^{N}\cos(2\pi x_i))$
F12	Penalized 1	$[-50, 50]^D$	$F12(x) = \frac{\pi}{n}\left\{10sin^2(\pi y_1) + \sum_{i=1}^{n-1}(y_i - 1)^2[1 + 10sin^2(\pi y_{i+1})] + (y_n - 1)^2\right\} + \sum_{i=1}^{n} u(x_i, 10,100,4)$
F13	Penalized 2	$[-50, 50]^D$	$F13(x) = \frac{1}{10}\left\{sin^2(\pi x_1) + \sum_{i=1}^{n-1}(x_i - 1)^2[1 + sin^2(3\pi x_{i+1})] + (x_n - 1)^2[1 + sin^2(2\pi x_{i+1})]\right\} + \sum_{i=1}^{n} u(x_i, 5,100,4)$
F14	Alpine	$[-10, 10]^D$	$F14(x) = \sum_{i=1}^{n} \lvert x_i sin(x_i) + 0.1x_i\rvert$
F15	Levy	$[-10, 10]^D$	$F15(x) = \sum_{i=1}^{n-1}(x_i - 1)^2[1 + sin^2(3\pi x_{i+1})] + sin^2(3\pi x_1) + \lvert x_n - 1\rvert[1 + sin^2(3\pi x_n)]$
F16	Schwefel 1.20	$[-100, 100]^D$	$F16(x) = \Sigma_{i=1}^{n}\left(\Sigma_{j=1}^{i} x_j\right)^2$

Table 3. *Results of original CBOA and proposed F-CBOA*

Fnc.	CBOA			F-CBOA		
	Best	**Mean**	**Std.**	**Best**	**Mean**	**Std.**
F1	1.5867E-187	4.9473E-170	0.000E+00	**7.6504E-238**	1.0757E-216	0.000E+00
F2	3.7559E-180	4.9385E-169	0.000E+00	**2.1187E-245**	1.0124E-221	0.000E+00
F3	9.2550E-183	7.0487E-172	0.000E+00	**2.8681E-246**	4.6185E-220	0.000E+00
F4	4.1035E-249	1.3305E-228	0.000E+00	**0.000E+00**	0.000E+00	0.000E+00
F5	2.8999E-94	2.1182E-86	1.0822E-85	**3.8192E-122**	5.3787E-109	2.1577E-108
F6	2.9144E-89	5.8790E-84	1.7759E-83	**8.5125E-126**	1.6638E-109	8.9575E-109
F7	**3.3007E-07**	3.3327E-04	2.8540E-04	2.8331E-05	3.6955E-04	2.5055E-04
F8	1.3103E-02	1.4967E+01	1.3918E+01	**7.3961E-03**	1.0237E+01	1.3416E+01
F9	0.000E+00	1.1405E+00	3.5723E+00	0.000E+00	0.000E+00	0.000E+00
F10	**1.3832E+03**	3.4978E+03	9.7996E+02	2.6269E+03	5.0098E+03	1.1986E+03
F11	0.000E+00	1.4803E-16	5.5388E-16	0.000E+00	0.000E+00	0.000E+00
F12	**1.1651E-05**	2.8967E-05	1.1089E-05	1.2016E-05	3.6117E-05	1.5097E-05
F13	**1.8638E-04**	6.6179E-04	3.0371E-04	3.4117E-04	1.4731E-03	3.4799E-03
F14	1.3844E-92	5.0568E-89	1.6277E-88	**9.9461E-122**	2.0300E-110	9.2100E-110
F15	**1.5586E-04**	6.9348E-02	1.9938E-01	1.7356E-04	1.1508E-01	1.6865E-01
F16	3.0926E-166	8.3527E-156	3.5277E-155	**3.4584E-226**	1.3868E-199	0.000E+00

Table 4. Results of original CBOA and proposed C1-CBOA

Fnc.	CBOA			C1-CBOA		
	Best	Mean	Std.	Best	Mean	Std.
F1	**1.5867E-187**	4.9473E-170	0.000E+00	7.0904E-180	1.9737E-168	0.000E+00
F2	**3.7559E-180**	4.9385E-169	0.000E+00	1.1857E-176	2.4599E-141	1.3247E-140
F3	**9.2550E-183**	7.0487E-172	0.000E+00	1.7677E-180	4.7124E-169	0.000E+00
F4	4.1035E-249	1.3305E-228	0.000E+00	**5.3968E-253**	3.5888E-208	0.000E+00
F5	**2.8999E-94**	2.1182E-86	1.0822E-85	1.9829E-91	9.2268E-84	2.4200E-83
F6	**2.9144E-89**	5.8790E-84	1.7759E-83	3.0588E-88	8.7167E-83	3.4520E-82
F7	**3.3007E-07**	3.3327E-04	2.8540E-04	5.5611E-05	3.5300E-04	2.0736E-04
F8	**1.3103E-02**	1.4967E+01	1.3918E+01	3.5078E-02	1.6817E+01	1.3658E+01
F9	0.000E+00	1.1405E+00	3.5723E+00	0.000E+00	2.2988E+00	4.8737E+00
F10	**1.3832E+03**	3.4978E+03	9.7996E+02	2.3605E+03	3.5427E+03	6.6630E+02
F11	0.000E+00	1.4803E-16	5.5388E-16	0.000E+00	0.000E+00	0.000E+00
F12	1.1651E-05	2.8967E-05	1.1089E-05	**7.5952E-06**	3.4825E-03	1.8614E-02
F13	**1.8638E-04**	6.6179E-04	3.0371E-04	2.7630E-04	5.7482E-04	2.2679E-04
F14	1.3844E-92	5.0568E-89	1.6277E-88	**1.4818E-93**	7.4963E-86	3.1492E-85
F15	**1.5586E-04**	6.9348E-02	1.9938E-01	2.8324E-04	3.3956E-02	5.4541E-02
F16	3.0926E-166	8.3527E-156	3.5277E-155	**3.0814E-170**	5.8351E-151	3.1112E-150

Table 5. Results of original CBOA and proposed C2-CBOA

Fnc.	CBOA			C2-CBOA		
	Best	Mean	Std.	Best	Mean	Std.
F1	**1.5867E-187**	4.9473E-170	0.000E+00	6.8254E-183	6.5051E-171	0.000E+00
F2	**3.7559E-180**	4.9385E-169	0.000E+00	6.5037E-176	8.4632E-159	4.5130E-158
F3	9.2550E-183	7.0487E-172	0.000E+00	**4.5305E-183**	1.8571E-171	0.000E+00
F4	4.1035E-249	1.3305E-228	0.000E+00	**7.3651E-251**	6.3099E-224	0.000E+00
F5	**2.8999E-94**	2.1182E-86	1.0822E-85	8.1506E-90	1.9933E+00	1.0734E+01
F6	**2.9144E-89**	5.8790E-84	1.7759E-83	6.7089E-89	7.2424E-84	2.7756E-83
F7	**3.3007E-07**	3.3327E-04	2.8540E-04	3.3664E-05	3.4324E-04	2.4912E-04
F8	**1.3103E-02**	1.4967E+01	1.3918E+01	2.5863E-02	2.3347E+01	1.0399E+01
F9	0.000E+00	1.1405E+00	3.5723E+00	0.000E+00	4.4761E+00	6.8436E+00
F10	**1.3832E+03**	3.4978E+03	9.7996E+02	1.9391E+03	3.4671E+03	7.3962E+02
F11	0.000E+00	1.4803E-16	5.5388E-16	0.000E+00	7.4015E-17	3.9858E-16
F12	1.1651E-05	2.8967E-05	1.1089E-05	**1.1085E-05**	2.6678E-05	1.0540E-05
F13	1.8638E-04	6.6179E-04	3.0371E-04	**8.0753E-05**	5.6799E-04	2.7924E-04
F14	1.3844E-92	5.0568E-89	1.6277E-88	**2.0916E-93**	5.3044E-86	2.8111E-85
F15	1.5586E-04	6.9348E-02	1.9938E-01	**8.8292E-05**	3.3667E-02	6.6173E-02
F16	3.0926E-166	8.3527E-156	3.5277E-155	**8.3507E-173**	7.4692E-156	3.9926E-155

__Table 6.__ Results of original CBOA and proposed C3-CBOA

Fnc.	CBOA			C3-CBOA		
	Best	**Mean**	**Std.**	**Best**	**Mean**	**Std.**
F1	**1.5867E-187**	4.9473E-170	0.000E+00	1.1373E-179	7.6474E-171	0.000E+00
F2	**3.7559E-180**	4.9385E-169	0.000E+00	3.5786E-177	7.4605E-166	0.000E+00
F3	9.2550E-183	7.0487E-172	0.000E+00	**3.7614E-183**	2.5247E-169	0.000E+00
F4	**4.1035E-249**	1.3305E-228	0.000E+00	8.3708E-248	5.3006E-228	0.000E+00
F5	**2.8999E-94**	2.1182E-86	1.0822E-85	3.9010E-91	4.0334E-87	1.2177E-86
F6	**2.9144E-89**	5.8790E-84	1.7759E-83	1.3990E-88	8.5179E-83	3.8513E-82
F7	**3.3007E-07**	3.3327E-04	2.8540E-04	1.0677E-04	4.5000E-04	3.1200E-04
F8	**1.3103E-02**	1.4967E+01	1.3918E+01	2.4128E-02	1.6830E+01	1.3667E+01
F9	0.000E+00	1.1405E+00	3.5723E+00	0.000E+00	0.000E+00	0.000E+00
F10	**1.3832E+03**	3.4978E+03	9.7996E+02	2.0216E+03	3.7003E+03	9.7581E+02
F11	0.000E+00	1.4803E-16	5.5388E-16	0.000E+00	0.000E+00	0.000E+00
F12	1.1651E-05	2.8967E-05	1.1089E-05	**6.6017E-06**	2.6277E-05	1.0415E-05
F13	**1.8638E-04**	6.6179E-04	3.0371E-04	2.7074E-04	1.2558E-03	3.4701E-03
F14	1.3844E-92	5.0568E-89	1.6277E-88	**4.1695E-94**	3.3522E-89	7.8233E-89
F15	**1.5586E-04**	6.9348E-02	1.9938E-01	2.9917E-04	6.3434E-02	1.0196E-01
F16	3.0926E-166	8.3527E-156	3.5277E-155	**2.1340E-168**	8.4216E-154	4.2894E-153

Table 7. Results of original CBOA and proposed FC1-CBOA

Fnc.	CBOA			FC1-CBOA		
	Best	Mean	Std.	Best	Mean	Std.
F1	1.5867E-187	4.9473E-170	0.000E+00	**1.2520E-238**	1.7924E-213	0.000E+00
F2	3.7559E-180	4.9385E-169	0.000E+00	**8.1321E-250**	1.1973E-216	0.000E+00
F3	9.2550E-183	7.0487E-172	0.000E+00	**1.9576E-247**	1.4412E-216	0.000E+00
F4	4.1035E-249	1.3305E-228	0.000E+00	**0.000E+00**	1.1979E-316	0.000E+00
F5	2.8999E-94	2.1182E-86	1.0822E-85	**3.1489E-121**	1.5183E-101	8.1762E-101
F6	2.9144E-89	5.8790E-84	1.7759E-83	**4.2720E-125**	1.1834E-111	4.6352E-111
F7	**3.3007E-07**	3.3327E-04	2.8540E-04	2.7930E-05	5.3348E-04	2.8952E-04
F8	1.3103E-02	1.4967E+01	1.3918E+01	**2.4003E-03**	1.5819E+01	1.3808E+01
F9	0.000E+00	1.1405E+00	3.5723E+00	0.000E+00	0.000E+00	0.000E+00
F10	**1.3832E+03**	3.4978E+03	9.7996E+02	3.8382E+03	5.4913E+03	1.0920E+03
F11	0.000E+00	1.4803E-16	5.5388E-16	0.000E+00	0.000E+00	0.000E+00
F12	**1.1651E-05**	2.8967E-05	1.1089E-05	1.6574E-05	4.1278E-05	1.5501E-05
F13	**1.8638E-04**	6.6179E-04	3.0371E-04	2.5477E-04	8.2295E-04	3.1033E-04
F14	1.3844E-92	5.0568E-89	1.6277E-88	**1.7118E-119**	1.4935E-107	8.0154E-107
F15	**1.5586E-04**	6.9348E-02	1.9938E-01	1.8563E-04	4.7129E-02	1.2025E-01
F16	3.0926E-166	8.3527E-156	3.5277E-155	**4.5025E-230**	4.5393E-198	0.000E+00

Table 8. *Results of original CBOA and proposed FC2-CBOA*

Fnc.	CBOA			FC2-CBOA		
	Best	**Mean**	**Std.**	**Best**	**Mean**	**Std.**
F1	1.5867E-187	4.9473E-170	0.000E+00	**4.2149E-237**	1.4247E-216	0.000E+00
F2	3.7559E-180	4.9385E-169	0.000E+00	**4.3726E-253**	4.4781E-209	0.000E+00
F3	9.2550E-183	7.0487E-172	0.000E+00	**5.7958E-239**	1.4535E-212	0.000E+00
F4	4.1035E-249	1.3305E-228	0.000E+00	**0.000E+00**	0.000E+00	0.000E+00
F5	2.8999E-94	2.1182E-86	1.0822E-85	**2.8571E-117**	1.8823E+00	1.0136E+01
F6	2.9144E-89	5.8790E-84	1.7759E-83	**8.9505E-127**	2.1396E-107	1.1136E-106
F7	**3.3007E-07**	3.3327E-04	2.8540E-04	4.0916E-05	2.7858E-04	1.7081E-04
F8	1.3103E-02	1.4967E+01	1.3918E+01	**4.0228E-03**	1.2098E+01	1.3790E+01
F9	0.000E+00	1.1405E+00	3.5723E+00	0.000E+00	1.000E+00	5.3852E+00
F10	**1.3832E+03**	3.4978E+03	9.7996E+02	3.5460E+03	5.4033E+03	1.1114E+03
F11	0.000E+00	1.4803E-16	5.5388E-16	0.000E+00	0.000E+00	0.000E+00
F12	**1.1651E-05**	2.8967E-05	1.1089E-05	1.6033E-05	3.4914E-03	1.8612E-02
F13	**1.8638E-04**	6.6179E-04	3.0371E-04	3.7583E-04	2.0549E-03	4.7325E-03
F14	1.3844E-92	5.0568E-89	1.6277E-88	**1.3249E-125**	3.1826E-107	1.7090E-106
F15	1.5586E-04	6.9348E-02	1.9938E-01	**5.9513E-05**	4.8787E-02	8.6617E-02
F16	3.0926E-166	8.3527E-156	3.5277E-155	**1.2857E-225**	3.8665E-206	0.000E+00

Table 9. *Results of original CBOA and proposed FC3-CBOA*

Fnc.	CBOA			FC3-CBOA		
	Best	**Mean**	**Std.**	**Best**	**Mean**	**Std.**
F1	1.5867E-187	4.9473E-170	0.000E+00	**7.0016E-240**	6.2062E-217	0.000E+00
F2	3.7559E-180	4.9385E-169	0.000E+00	**8.2057E-256**	1.5177E-221	0.000E+00
F3	9.2550E-183	7.0487E-172	0.000E+00	**9.3712E-248**	1.3014E-222	0.000E+00
F4	4.1035E-249	1.3305E-228	0.000E+00	**0.000E+00**	2.4227E-314	0.000E+00
F5	2.8999E-94	2.1182E-86	1.0822E-85	**8.8458E-122**	1.5093E-110	4.3088E-110
F6	2.9144E-89	5.8790E-84	1.7759E-83	**4.1242E-125**	5.5322E-113	2.7803E-112
F7	**3.3007E-07**	3.3327E-04	2.8540E-04	2.9603E-05	3.1024E-04	2.1259E-04
F8	1.3103E-02	1.4967E+01	1.3918E+01	**2.9015E-03**	1.0260E+01	1.3423E+01
F9	0.000E+00	1.1405E+00	3.5723E+00	0.000E+00	0.000E+00	0.0000E+00
F10	**1.3832E+03**	3.4978E+03	9.7996E+02	3.0314E+03	5.3814E+03	1.2002E+03
F11	0.000E+00	1.4803E-16	5.5388E-16	0.000E+00	0.000E+00	0.000E+00
F12	1.1651E-05	2.8967E-05	1.1089E-05	**8.6835E-06**	3.4923E-03	1.8624E-02
F13	**1.8638E-04**	6.6179E-04	3.0371E-04	3.8203E-04	8.4733E-04	3.5427E-04
F14	1.3844E-92	5.0568E-89	1.6277E-88	**3.5821E-122**	5.2003E-108	2.4297E-107
F15	**1.5586E-04**	6.9348E-02	1.9938E-01	2.5303E-04	8.1376E-02	1.0959E-01
F16	3.0926E-166	8.3527E-156	3.5277E-155	**1.2284E-236**	1.8165E-208	0.000E+00

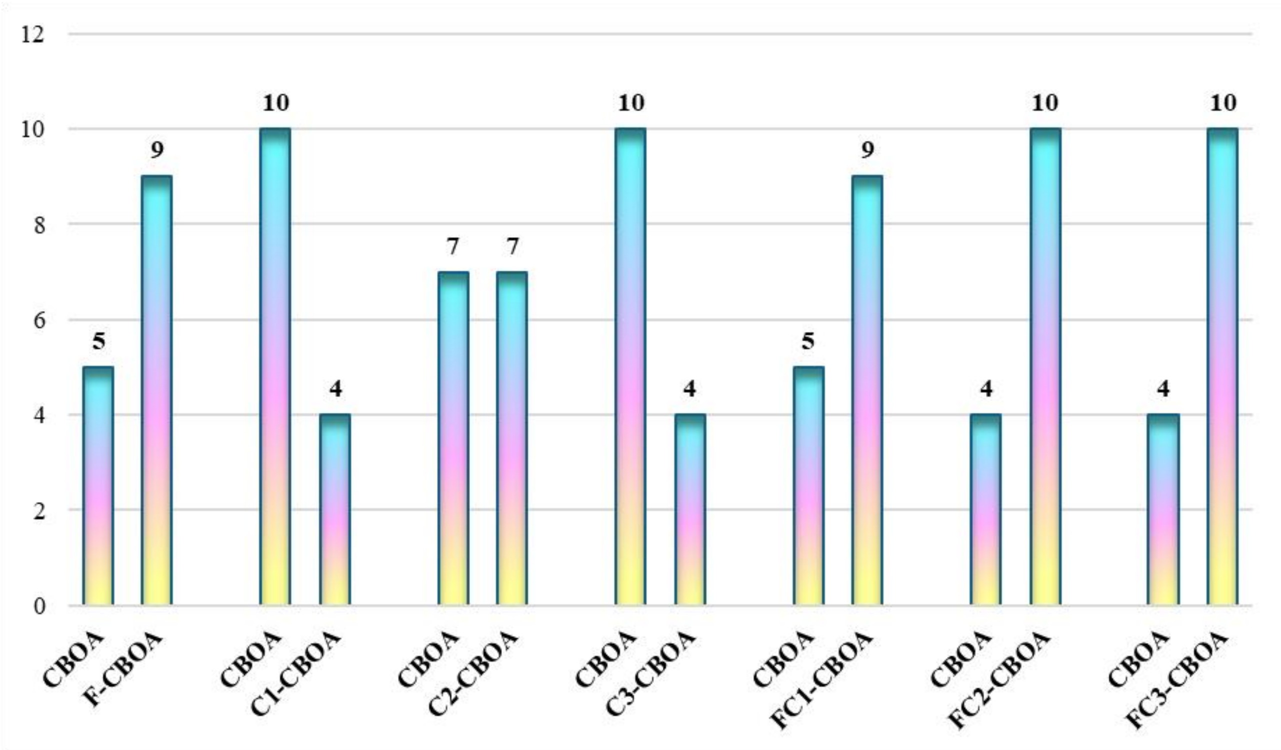

Figure 1. *Success ranking of the algorithms on benchmark functions*

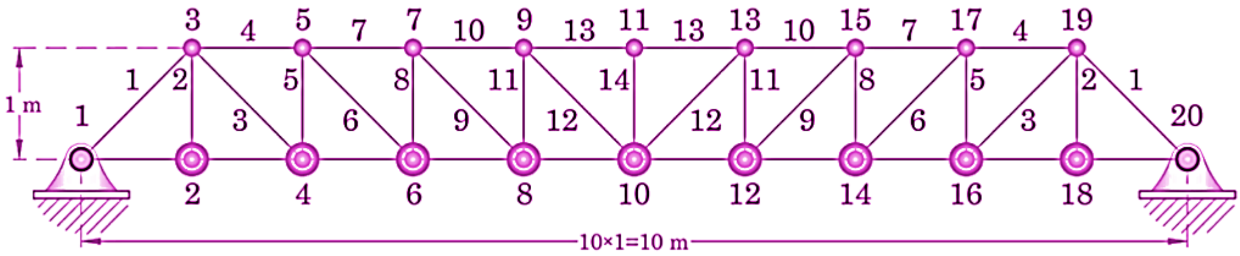

Figure 2. *37-bar truss structure (Kaveh & Mahjoubi, 2019)*

When Table 10 is analyzed in terms of the best values obtained, it is seen that the proposed FC3-CBOA variant produces a better result than the original CBOA. The grouping of the design variables and the values obtained by the algorithms are presented in Table 11.

4.2.2. 52-bar truss structures

Another optimization problem considered in the study is a 52-bar truss structure with frequency constraints (Öztürk & Kahraman, 2025) as detailed in Figure 3. This structure has a total of 13 design variables. To evaluate the effectiveness of the algorithms on the 52-bar lattice structure, the best, mean, std. values obtained by the original CBOA and the proposed CBOA variants are presented in Table 12.

When Table 12 is analyzed in terms of the best values obtained, it is seen that the proposed C3-CBOA variant produces a better result than the original CBOA. The grouping of the design variables and the values obtained by the algorithms are presented in Table 13. Figure 4 shows the comparison of the best values of the proposed CBOA variants with the original CBOA for 37-bar and 52-bar truss structures. When the figure is analyzed, it is seen that the best value for the 37-bar truss structure is obtained by the F3-CBOA variant, while the best value for the 52-bar truss structure is obtained by the C3-CBOA variant.

Table 10. *Results of original CBOA and proposed CBOA variants for 37-bar truss structure*

37-bar truss			
	Best	Mean	Std.
CBOA	3.7950E+02	3.8946E+02	4.9427E+00
F-CBOA	3.7735E+02	3.9333E+02	7.2335E+00
C1-CBOA	3.7291E+02	3.9117E+02	6.2613E+00
C2-CBOA	3.8613E+02	3.9286E+02	4.0322E+00
C3-CBOA	3.8164E+02	3.9028E+02	5.2331E+00
FC1-CBOA	3.8380E+02	3.9932E+02	7.8299E+00
FC2-CBOA	3.8749E+02	4.0123E+02	6.6931E+00
FC3-CBOA	3.7060E+02	3.9829E+02	7.9865E+00

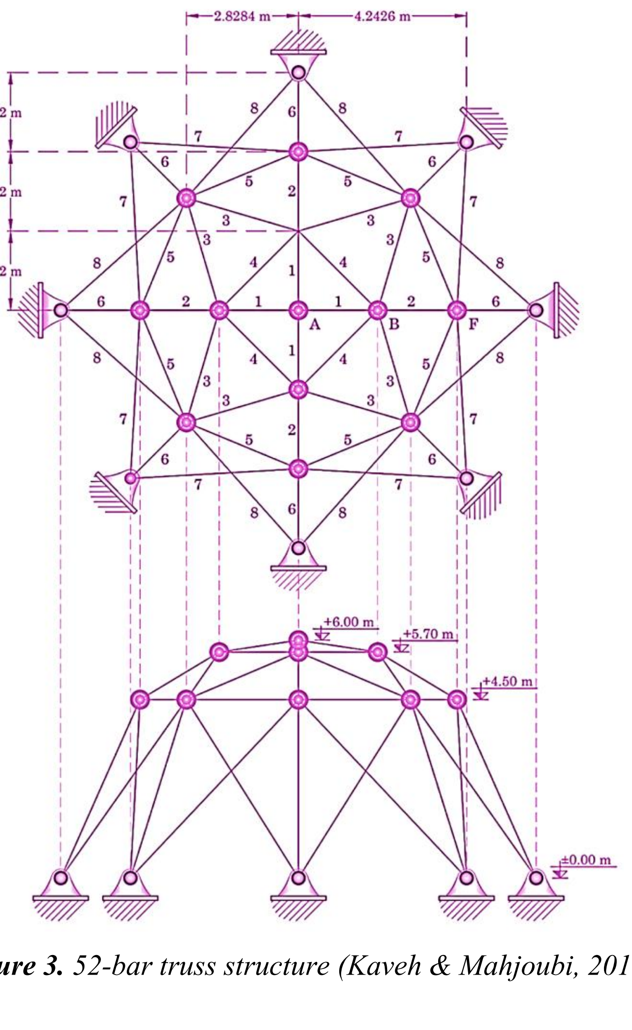

Figure 3. *52-bar truss structure (Kaveh & Mahjoubi, 2019)*

Table 11. *Results of the algorithms according to the grouped design variables*

37–Bar Truss									
Groups	Element Group	Areas (cm^2)							
		CBOA	F-CBOA	C1-CBOA	C2-CBOA	C3-CBOA	FC1-CBOA	FC2-CBOA	FC3-CBOA
1	Y_3, Y_{19}	0.7267	1.0044	0.7462	0.7428	0.6946	0.9207	0.7508	0.7273
2	Y_5, Y_{17}	1.0475	1.1789	1.0779	1.0349	1.0666	1.2232	1.1902	1.1511
3	Y_7, Y_{15}	1.3255	1.3301	1.3199	1.3180	1.2379	1.3749	1.3766	1.4480
4	Y_9, Y_{13}	1.5144	1.4329	1.3956	1.4027	1.3691	1.4671	1.4801	1.6161
5	Y_{11}	1.5762	1.4701	1.4052	1.4215	1.4440	1.4761	1.5000	1.6504
6	1–27	2.8890	2.9156	2.5734	3.0803	3.5238	3.0029	2.8638	2.6414
7	2–26	1.2420	3.5195	1.8876	2.8732	3.6117	3.2491	3.5697	2.2767
8	3–24	3.0044	2.4569	2.5352	3.0345	3.3928	3.0730	2.1645	1.2326
9	4–25	4.2594	3.2962	3.7985	3.1248	3.4259	2.2961	2.8660	2.8704
10	5–23	2.4697	2.2222	1.4959	2.0887	1.7522	3.0260	3.2832	1.0066
11	6–21	1.7674	2.3403	1.8722	2.2548	2.0133	2.8446	4.0986	2.0170
12	7–22	3.4931	2.6690	2.9777	3.1762	3.3955	2.7518	2.5506	2.3355
13	8–20	2.6885	1.8543	2.0791	2.7046	3.3346	2.6668	2.5793	2.5757
14	9–18	1.2856	1.4334	1.8462	3.0770	1.1559	2.1076	2.4470	2.4746
15	10–19	2.8132	4.2369	3.6442	4.0001	3.9096	2.7084	3.9198	2.8620
16	11–17	2.9817	1.4559	1.3142	1.6238	1.9856	1.7962	1.0040	1.7644
17	12–15	2.6678	1.8291	1.4765	3.4702	2.4937	1.3949	2.3830	1.6595
18	13–16	2.6322	3.0505	3.7930	3.7311	3.2573	4.6259	3.2636	3.2535
19	14	1.6276	1.3788	3.1458	1.6152	2.3171	2.2930	3.6779	1.3091
Mass (kg)		379.50	377.35	372.91	386.13	381.64	383.80	387.49	370.60

Table 12. *Results of original CBOA and proposed CBOA variants for 52-bar truss structure*

52-bar truss			
	Best	**Mean**	**Std.**
CBOA	2.3845E+02	2.6777E+02	2.1214E+01
F-CBOA	2.2629E+02	2.9764E+02	4.8092E+01
C1-CBOA	2.3579E+02	2.7716E+02	2.1372E+01
C2-CBOA	2.3588E+02	2.8471E+02	2.7742E+01
C3-CBOA	2.2153E+02	2.7540E+02	3.4255E+01
FC1-CBOA	2.4315E+02	3.0878E+02	5.4580E+01
FC2-CBOA	2.3345E+02	3.3966E+02	6.8234E+01
FC3-CBOA	2.4065E+02	3.0027E+02	4.4956E+01

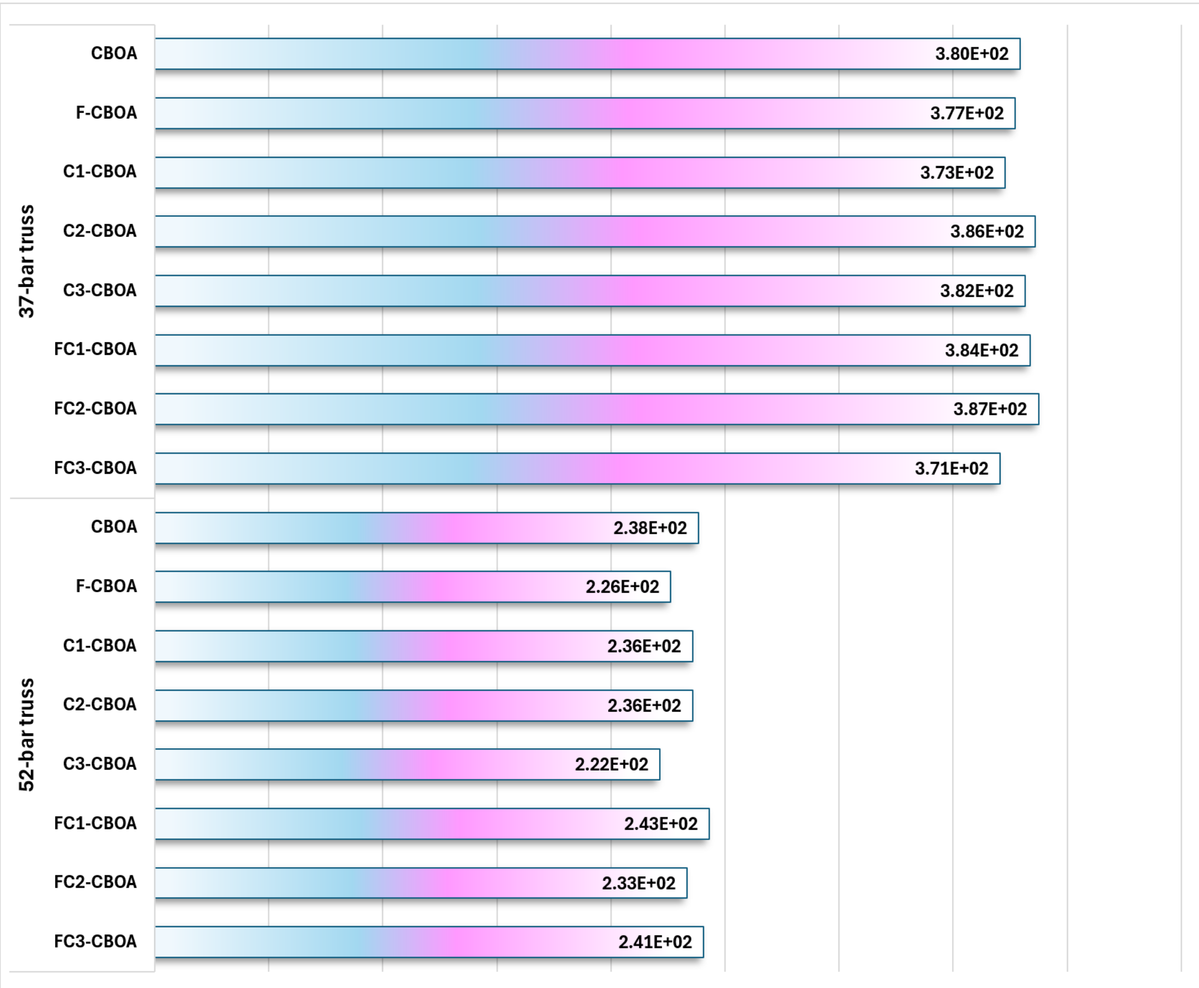

Figure 4. *Ranking of best values for 37-bar and 52-bar truss structures*

Table 13. *Results of the algorithms according to the grouped design variables*

52–Bar Truss									
Groups	**Element Group**	**Areas (cm^2)**							
		CBOA	**F-CBOA**	**C1-CBOA**	**C2-CBOA**	**C3-CBOA**	**FC1-CBOA**	**FC2-CBOA**	**FC3-CBOA**
1	Z_A	4.4145	4.7051	4.0000	4.2358	4.0000	4.0000	4.4820	4.0192
2	X_B	1.4031	1.5554	1.6453	1.0932	1.7827	1.9377	1.1868	1.7807
3	Z_B	3.7000	3.7579	3.8152	3.7473	3.7993	3.7472	3.7908	3.8365
4	X_F	3.1246	3.7467	3.7149	2.8600	3.8071	3.5574	3.0916	3.5422
5	Z_F	2.7652	2.5000	2.6189	2.8672	2.5000	2.6781	2.8157	2.7336
6	1–4	1.0000	1.4285	1.0000	1.0188	1.3863	1.0000	1.2207	1.0000
7	5–8	1.5746	2.4670	1.5030	2.3344	1.3006	1.4505	2.0581	2.6062
8	9–16	1.3901	2.0931	1.9726	1.5614	1.7855	2.0143	1.7702	2.4286
9	17–20	1.2416	1.6589	2.4156	1.9035	1.4057	1.6336	2.4155	1.4155
10	21–28	2.1040	1.9321	1.9937	1.8302	1.2389	1.3876	1.8393	1.3656
11	29–36	1.0245	1.0094	1.4014	1.0000	1.0000	1.1825	1.0000	1.0000
12	37–44	2.5847	1.2938	1.1665	2.1900	1.7038	3.0784	2.3040	1.5464
13	45–52	1.6603	1.6424	1.9847	1.8488	2.0197	1.0000	1.4029	2.1682
Mass (kg)		238.45	226.29	235.79	235.88	221.53	243.15	233.45	240.65

5. CONCLUSION

In this study, seven different variants of CBOA improved with chaos-based fitness distance balance are proposed to improve the performance of CBOA. The performance of the proposed CBOA variants on different problems is evaluated with three different experimental studies. In the improvement process, fitness distance balance is integrated into the algorithm as the first variant of CBOA. Then, duffing, iterative and sinusoidal chaotic maps were added to the CBOA algorithm as three different variants. Finally, a combination of both conformity distance balance and three different chaotic maps is proposed, and the performance of the proposed CBOA variants is investigated comparatively with three different experimental studies. In the first experimental study, the proposed CBOA variants were tested on 16 different benchmark functions. According to the results obtained, it is observed that especially the FC3-CBOA variant performs better than the original CBOA. In the second experimental study, the 37-bar truss problem with frequency constraints was considered and the best results were obtained by the FC3-CBOA variant compared to the original CBOA. In the third and final experimental study, the 52-bar truss problem was evaluated, and the C3-CBOA variant was found to be prominent in this problem. The obtained analysis results show that each proposed CBOA variant is able to produce effective solutions depending on the problem type. In future studies, the effectiveness of the proposed CBOA variants on multi-objective optimization problems can be tested.

CONFLICT OF INTEREST

The author declares no conflict of interest.

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