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Investigating the actual performance of recent meta-heuristic algorithms in solving different optimization problems

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Abstract

In this paper, the Egret Swarm Optimization Algorithm (ESOA) and Zebra Optimization Algorithm (ZOA) are executed to solve different optimization problems. The results achieved by the two algorithms are evaluated using different criteria, such as stability, minimum, average, and maximum convergence. The evaluation of the results indicates that ESOA not only maintains a surprising stability through its execution but also provides a faster response time compared to ZOA. ESOA requires at most 20 iterations to reach the best value of the main objective functions of the first two selected optimization problems, while ZOA cannot. In the last two selected optimization problems, ESOA continuously shows its superiority over ZOA with its high stability and low utilization of iterations to reach the best value of the main objective functions. Considering these results, ESOA deserves powerful search methods, and the method is strongly recommended to optimize such optimization problems.

Keywords*:* Egret Swarm Optimization Algorithm (ESOA); Zebra Optimization Algorithm (ZOA); Optimization problem; Convergence Speed; Stability; Objective Function; Constraints

1. Introduction

Nowadays, optimization problems become very popular and often seen in different fields, primarily economics and engineering. Achieving the optimal solution in solving any optimization problem is the highest priority because an optimal solution can benefit both the engineering and economic aspects. An optimal solution must result in the minimum or maximum value of the main objective function featured by the given optimization problem and satisfy all the constraints involved. The importance of finding the optimal solution has led to the invention of different optimization methods that are soon known as Cuckoo search algorithms [1], constraint method [2], Krill Herd Algorithm [3], Multi-Objective Genetic Algorithm [4], Multi-Stage Hybrid Open-Circuit Fault Diagnosis Approach [5], Newton-Raphson methods [6-7], etc. Next, meta-heuristic methods have been proposed, and almost all the mentioned downsides have been removed from the old-fashioned ones in term of efficiency and responding time while dealing with the large-scale and complex optimization problems. These problems can feasibly handle by different meta-heuristic methods and results in the high quality of solution. Moreover, meta-heuristic methods also provide a faster response time and a much higher success rate in solving optimization problems.

Due to the high effectiveness as mentioned while dealing with optimization problems, a vast number of meta-heuristic methods have been introduced and developed, such as evolutionary programming (EP) [8], genetic algorithm (GA) [9], particle swarm optimization (PSO) [10], bat algorithm (BA) [11], ant colony optimization (ACO) [12], Social Learning Optimization (SLO) [13], Quantum-inspired Algorithm for Resource Optimization (QARO) [14], Chaotic Harmony Search (CHS) [15], Fruit Fly Optimization Algorithm (FOA) [16], Ant Lion Optimizer (ALO) [17], Archimedes Optimization Algorithm (AOA) [18], Sine Cosine Algorithm (SCA) [19], Pathfinder algorithm (PFA) [20], Gravitational Search

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Algorithm (GSA) [21], Bacterial Foraging Optimization (BFO) [22], whale optimization algorithm (WOA) [23], water cycle algorithm (WCA) [24], Walrus Optimization Algorithm (WaOA) [25], Lyrebird Optimization Algorithm (LOA) [26], Green Anaconda Optimization (GAO) [27], and Harris hawks optimization (HHO) [28].

In this study, two relatively new meta-heuristic methods, including the Egret Swarm Optimization Algorithm (ESOA) [29] and the Zebra Optimization Algorithm (ZOA) [30], are applied to investigate their actual performance while dealing with different optimization problems. Both ESOA and ZOA are proposed at the end of 2022. They are reported to surpass many other previous meta-heuristic methods in solving various optimization problems. ESOA is inspired by the hunting behavior of two egret species, the Great Egret and the Snowy Egret. ZOA is developed based on the living behavior of zebras, particularly their foraging and defense strategies.

The main novelties and contributions of the whole study can be summarized as follows:

- Apply two novel meta-heuristic algorithms, including ESOA and ZOA to solve different optimization problem.
- Provide a detailed comparison between the two algorithms about their actual performance on each considered optimization problem using different criteria.
- Indicated the best algorithm for solving the considered optimization problems between the two algorithms.

2. Problem description

Most optimization problems are constructed by two essential elements: an objective function and related constraints. The objective function is usually formulated as a mathematical expression showing the relationship among the variables. The related constraints are mainly about the allowed ranges of the variables. Note that a solution is considered legal if only all the variables are within their allowed ranges and the primary objective function reaches the desired value.

2.1. The main objective function

Generally, the main objective function of a typical optimization algorithm is established using the as below:

$$OF(x_1, x_2, \ldots, x_n) \quad (1)$$

Where, OF is the value the main objective function; $x_1, x_2, \ldots, x_n$ are the variables that constituted the main objective function, and n is the number of variables needed to be found.

2.2. The related constraints

As mentioned above, relative constraints are the essential aspects that must be strictly imposed while solving any optimization problems. Related constraints include equal constraints and unequal constraints as follows:

2.2.1. The equal constraints.

The equal constraints are mostly used to determine the value of the dependent variable (if any) when solving a particular optimization problem. Assumed that x_1 is selected the only dependent valriable, and x_2, x_3, ..., x_n are the control variables. The mathematical expression of an equal constraint is typically formulated as follows:

$$\gamma x_1 + \mu x_2 + \delta x_3 + \ldots - \omega x_n = \varepsilon \quad (2)$$

Where, γ, μ, δ, ω, and ε are the given factors featured by the considered opimization problem; y is the dependent variable.

Note that the value of the dependent variable can be calculated if only all the control variables are entirely determined and satisfy their allowed ranges, as shown in the next subjection:

2.2.2. The unequal constraints

Normally, the unequal constraints are used to generate the control variables at the beginning of the optimization process by the meta-heuristic algorithms as follows:

$$x_2^{min} \le x_2 \le x_2^{max} \quad (3)$$

$$x_3^{min} \le x_3 \le x_4^{max} \quad (4)$$

$$\ldots$$

$$x_n^{min} \leq x_n \leq x_n^{max} \quad (5)$$

In Equations (3) – (5), x_2^{min}, x_3^{min}, ..., x_n^{min} are, respectively, the minimum values of x_2, x_3, ..., x_n, while x_2^{max}, x_4^{max}, ..., x_n^{max} are, respectively, the maximum values.

2.2.3. The considered optimization problem in the paper

The first optimization problem

The mathematical expressions of the main objective function and other related constraints of the first optimization problem are given as below:

$$F_1 = \sum_{n=1}^{x_n} x_n^2 \ with\ n = 1,2,...,30 \quad (6)$$

And

$$x_{F1}^{min} \leq x_1, x_2, ..., x_n \leq x_{F1}^{max} \quad (7)$$

In Equations (6) and (7), F_1 is the value of the main objective function; n is the number of variables that needed to be found for establishing a optimal solution corresponding to the best value of the main objective function; x_{F1}^{min} and x_{F1}^{max} are the minimum and maximum value of variables

The second optimization problem

Similar to the first one, the second optimization problem is also described using the objective function and the involved constrained using specific equations as follows:

$$F_2 = \sum_{n=1}^{x_n} |x_n| + \prod_{n=1}^{x_n} |x_n| \quad with\ n = 1,2,...,30 \quad (8)$$

And

$$x_{F2}^{min} \leq x_1, x_2, ..., x_n \leq x_{F2}^{max} \quad (9)$$

In Equation (10), x_{F2}^{min} and x_{F2}^{max} are the minimum and maximum values of the variables that needed to be found for establishing an optimal solution.

The third optimization problem

Similar to the two optimization problems presented above, the mathematical expression of the objective function and the constraints of variables are given as follows:

$$F_3 = \left| \left\{ (x_1, x_2, ..., x_n): \sum_{n=1}^{x_n} x_n^2 = n \right\} \right| \quad with\ n = 1,2,...,30 \quad (10)$$

And

$$x_{F3}^{min} \leq x_1, x_2, ..., x_n \leq x_{F3}^{max} \quad (11)$$

The fourth optimization problem.

Similar to above, the mathematical expressions of the main objective function and the involved constraint are expressed as follows:

$$F_4 = -20exp\left[-0.2\sqrt{0.5 \times sum(x_n^2)/n} - exp[sum(cos2\pi x)/n] + 20 + exp(1)\right] \quad with\ n = 1,2,...,30 \quad (12)$$

And

$$x_{F4}^{min} \leq x_1, x_2, ..., x_n \leq x_{F4}^{max} \quad (13)$$

3. The applied algorithms

3.1. The Egret Swarm Optimization Algorithm (ESOA)

The update method of ESOA is based on the sit-and-wait and the Aggressive strategies. The specific mathematical expression of these two strategies will be given as follows:

3.1.1. The Sit and wait strategy

$$X_i^{new\_1} = X_i + ST \times exp(CI/0.1 \times MI) \times G \times IG \quad (14)$$

Where $X_i^{new\_1}$ and X_i are the new and the current location of the individual i of the population and i = 1, 2, ..., Ps with Ps is the population size; ST is the length of step; CI and MI are the current and the maximum index of iteration number; G is the gap between the lowest and highest boundaries of the search space; IG is the integrated gradient calculated by the difference between the best solar individual and the considered one.

3.1.2. The Aggressive strategy

This strategy uses two phases, including the searching and encircling phases, while the Egret bird is hunting for its prey. The two phases are formulated by the two expressions as follows:

$$X_i^{new\_p1} = X_i + ST \times tan(\gamma) \times \frac{G}{1 + CI} \quad (15)$$

$$X_i^{new\_p2} = (1 - \gamma - Rnd2) \times X_i + Rand1 \times DF1 + Rand2 \times DF2 \quad (16)$$

Where, $X_i^{new\_p1}$ and $X_i^{new\_p2}$ ar the new location of the individual i in phase 1 and phase 2; γ is the random value between $\frac{-\pi}{2}$ and $\frac{\pi}{2}$; Rnd1 and Rnd2 are the random values between 0 and 1; $DF1$ and $DF2$ are the differences between the best so far and the considered individual and the global best and the considered individual.

3.2. Zebra Optimization algorithm (ZOA)

The update process of ZOA is described by the stages as follows:

3.2.1. Phase 1:

In the first phase, each zebra is updated its new location using the equation below:

$$X_i^{new\_p1} = X_i + EF \times (X_{Best} - ST_1 X_i) \; with \; i = 1 \ldots Ps \quad (17)$$

Where $X_i^{new,S1}$ is the new position of the zebra m in Stage 1; X_m is the old location of the zebra i;; X_{Best} is the best location in population; ST_1 is the first step length and its value is set by 2; Ps is population size.

3.2.2. Phase 2:

In Phase 2, each zebra will be updated for new location using the following equation:

$$X_i^{new,p2} = \begin{cases} X_i + ST_2 \times (2ST_2 - 1) \times \left(1 - \frac{CI}{MI}\right) X_i, & \text{if} \quad \varepsilon \leq 0.5 \\ X_i + AT \times (Z_{UT} - ST_1 X_i), & \text{otherwise} \end{cases} \quad (18)$$

Where $X_i^{new,S2}$ is the new location of the zebra i in Stage 2; ST_2 is the second step length and its value is set by 0.01; CI and MI are the current and the maximum index of iteration; Z_{UB} is zebra under threaten; ε is the probability deciding which method are used in in Phase 2.

4. Results and discussions

This section will apply both ESOA and ZOA to solve the four optimization problems, as shown in Section 2. The results achieved by the two algorithms are presented in the following subsections, each accompanied by a detailed analysis.

This analysis is crucial for understanding the performance of each algorithm and for making a fair comparison. To ensure this fairness, both ESOA and ZOA are initialized with the same parameters, including the population size and maximum number of iterations, which are set at 20 and 50, respectively, for all the optimization problems. Moreover, both algorithms are executed with 50 trial runs to obtain the best solutions.

The whole study is implemented on a desktop with the following specifications: central processing units with 2.54 GHz of clock speed and 8 GB of random accessing memory (RAM). Additionally, all the related coding and simulation are employed by MATLAB programming language version 2019a.

4.1. The results achieved at the first optimization problem

For the first optimization problem, the effectiveness of the ESOA and ZOA is evaluated on different criteria, including the stability after 50 trial runs and the convergence speed to the optimal value, which can be observed through the minimum, average, and maximum convergences. Figure 1 shows the results of ESOA and ZOA after 50 trial runs. It is straightforward to see that ESOA provides higher stability than ZOA during 50 trial runs.

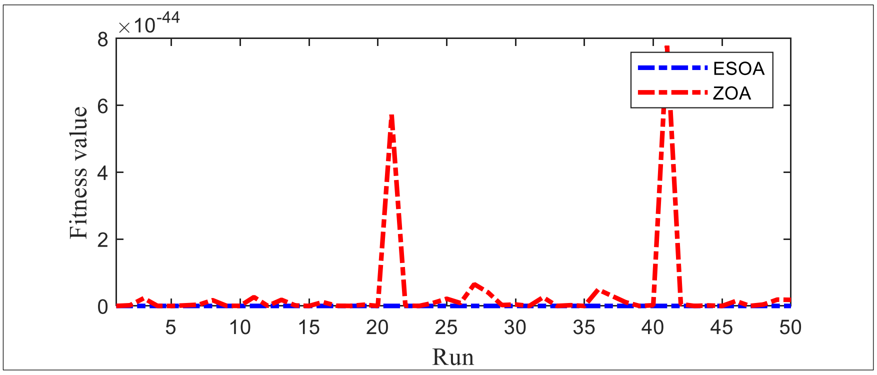

Figure 1 The results achieved by the two algorithms after 50 trial runs while solving the first optimization problem.

Figure 2a shows the maximum convergence, while Figures 2b and 2c show the average and the maximum convergence, respectively. Although the two algorithms can achieve the optimal value of the primary objective function in their best run, ESOA has shown a higher capability. At the same time, the method can reach the optimal value much faster than ZOA in all three convergences. Specifically, ESOA requires less than 20 iterations to reach all the best values of the three convergences, while ZOA can provide a different performance. This means ESOA can provide the same degree of effectiveness as ZOA but uses fewer computing resources and a much shorter response time.

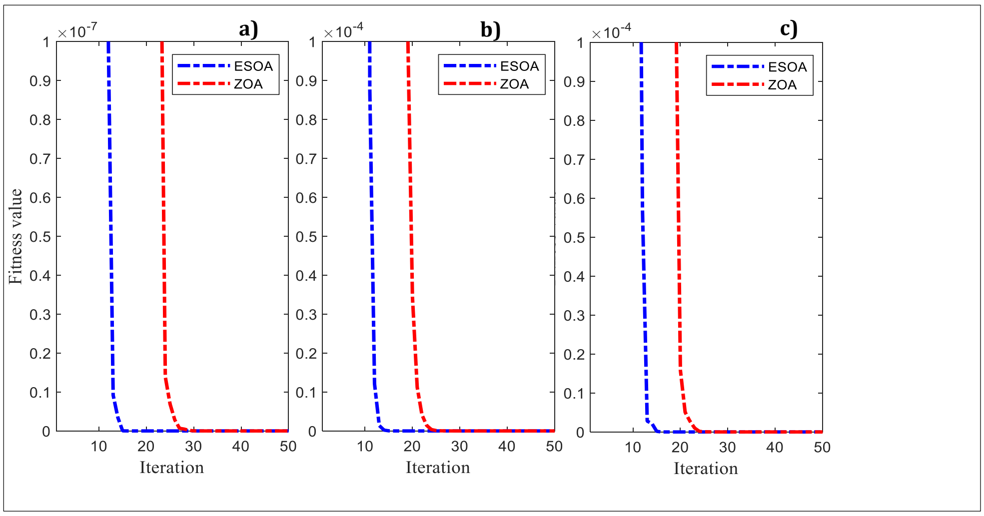

Figure 2 The minimum, average, and maximum convergences achieved by the two algorithms while solving the first optimization problem.

4.2. The results achieved at the second optimization problem

In this subsection, the effectiveness of the ESOA and ZOA while dealing with the second optimization problem is also justified through the results of 50 trial runs and the three convergences similar to the previous section. Despite the complexity of the second optimization problem being increased more than the first one, ESOA still maintains its superiority to ZOA. Mainly, ESOA continuously showed surprising stability during the 50 trial runs, as shown in Figure 3. In contrast, ZOA shows a higher fluctuation of the fitness values among the trial runs compared to the first considered problem. The observation of the minimum, average, and maximum convergence in Figures 4a, 4b, and 4c indicated that ESOA can produce the same optimal value as ZOA. However, the method requires fewer iterations and also provides a faster response time. Namely, ESOA also requires less than 20 iterations to reach all the best values of the three convergences.

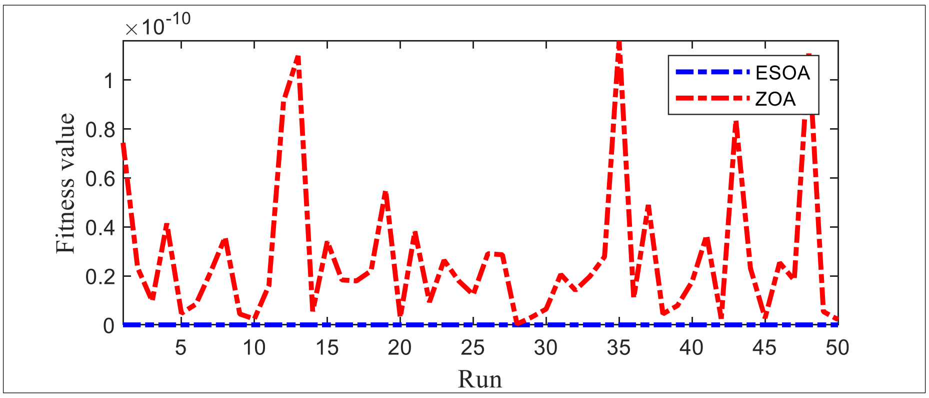

Figure 3 The results achieved by the two algorithms after 50 trial runs while solving the second optimization problem.

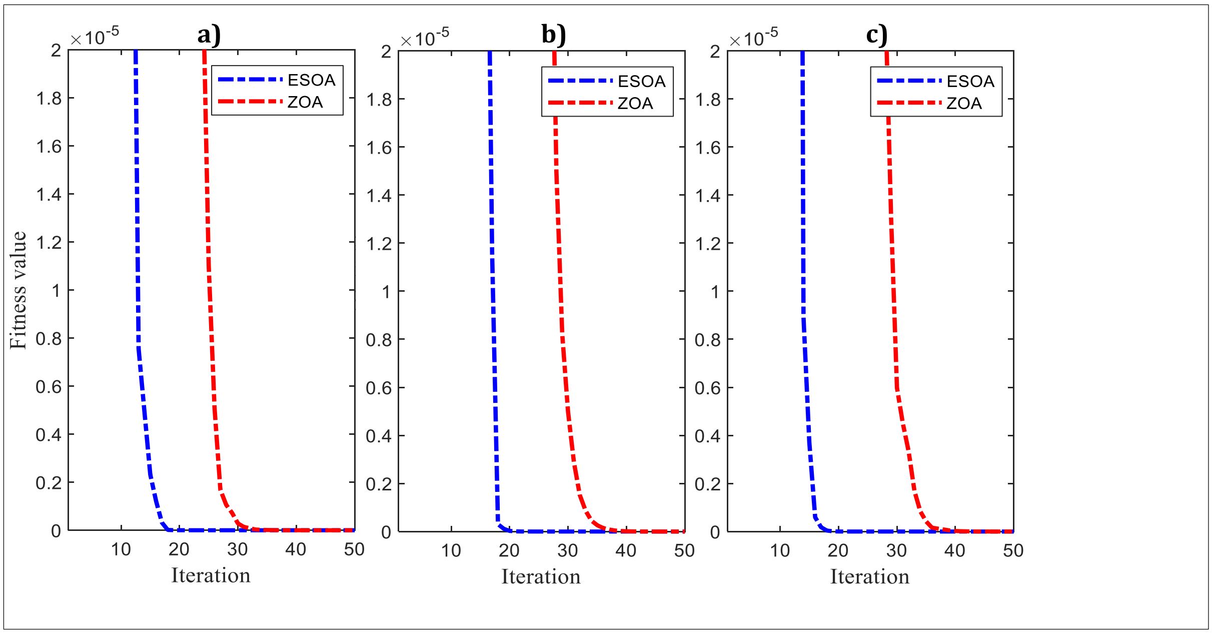

Figure 4 The minimum, average, and maximum convergences achieved by the two algorithms while solving the second optimization problem.

4.3. The results achieved at the third optimization problem

This subsection presents the results achieved by ESOA and ZOA when dealing with the third optimization problem. Similar to the first problem, ESOA still outperforms ZOA regarding stability and convergence speed, as shown in Figures 5, 6a, 6b, and 6c, respectively. For instance, ESOA's stability while dealing with the third optimization problem is excellent compared to ZOA.

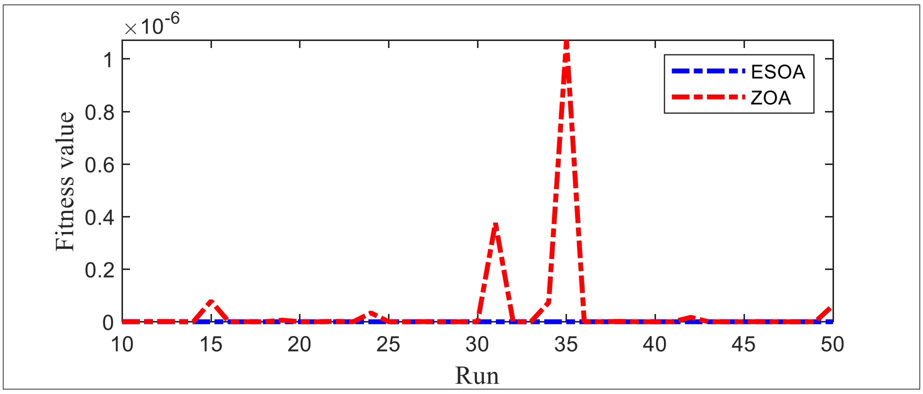

Figure 5 The results achieved by the two algorithms after 50 trial runs while solving the third optimization problem.

Speaking of the minimum convergence in Figure 6a, ESOA only requires approximately 20 iterations to achieve the best value of the considered optimization problem. In comparison, ZOA needs over 40 iterations to do the same. Moreover, the observation also indicates more proof regarding the high efficiency of ESOA compared to ZOA. Specifically, ESOA utilizes over 30 to reach the best value in the average convergence and around 20 iterations in the maximum convergence. The number of iterations that ZOA needs to reach similar results as ESOA in the average convergence is over 45, and up to 48 iterations for the maximum convergence.

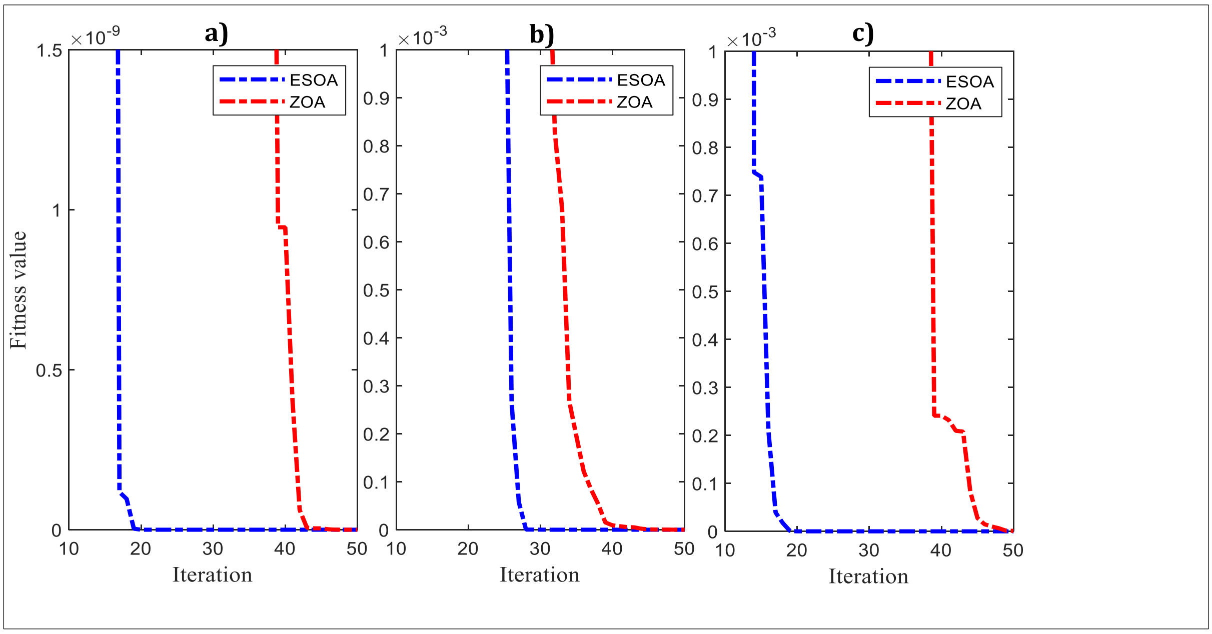

Figure 6 The minimum, average, and maximum convergences achieved by the two algorithms while solving the second optimization problem.

4.4. The results achieved at the fourth optimization problem

This subsection presents and evaluates the results achieved by ESOA and ZOA while dealing with the fourth optimization problem. Similar to the above subsections, the stability and the convergence speed to the optimal values in different convergences of the two algorithms are also given in Figure 7 and Figure 8, respectively. In this last considered optimization problem, ESOA continuously shows higher stability than ZOA after 50 trial runs, as seen in Figure 7.

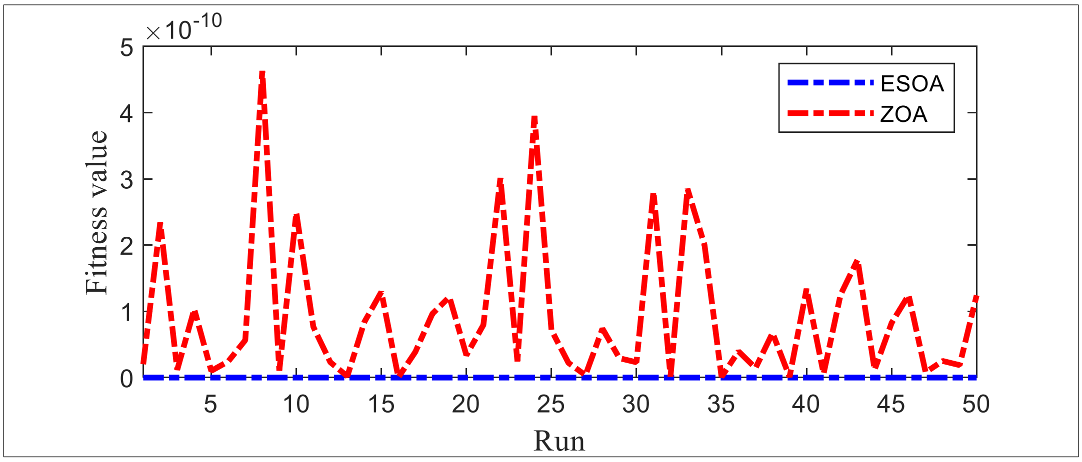

Figure 7 The results achieved by the two algorithms after 50 trial runs while solving the fourth optimization problem.

Regarding the convergence speed, ESOA also provides a faster speed in all three convergences, including the minimum, the average, and the maximum, which can be observed in Figures 8a, 8c, and 8d. ESOA is entirely superior to ZOA in all comparison criteria.

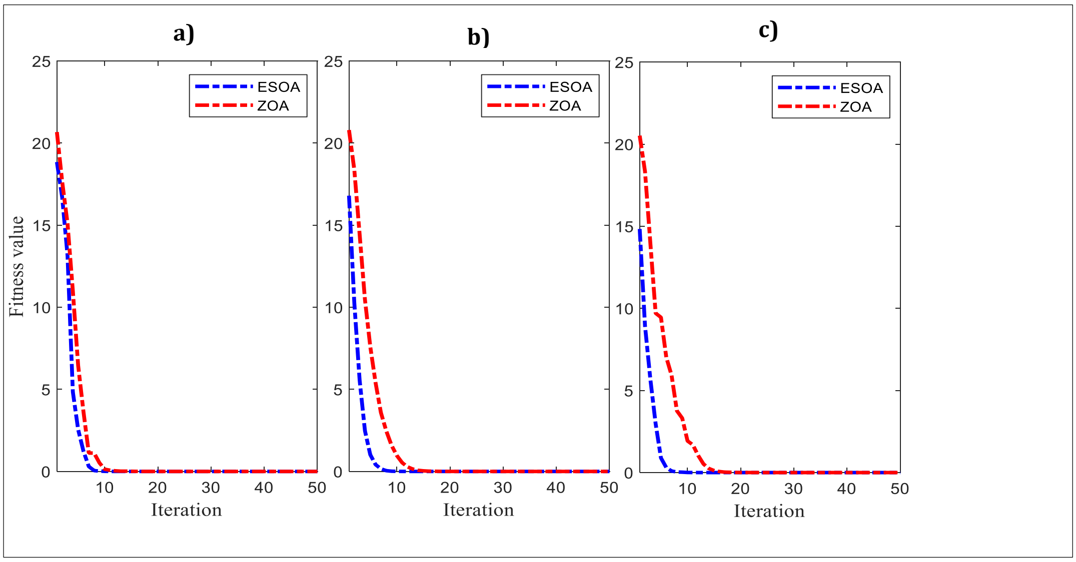

Figure 8 The minimum, average, and maximum convergences achieved by the two algorithms while solving the fourth optimization problem.

5. Conclusions

This study applies Egret Swarm Optimization Algorithm (ESOA) and the Zebra Optimization Algorithm (ZOA) to solve optimization problems and investigate their performances. The results of the two algorithms in each problem are compared using different criteria, such as stability and convergence speed, through minimum, average, and maximum convergence. Despite the complexity increase, ESOA showed surprising stability and convergence speed to the best value while dealing with the four optimization problems. In the first two considered optimization problems, ESOA requires less than 20 iterations to reach all the best values of the three convergences, while ZOA can achieve a different capability. In the last two optimization problems, ESOA still maintains its superiority to ZOA by showing surprising stability and requiring fewer iterations to achieve the best values of given convergences. By analyzing all the results, ESOA is acknowledged as a highly effective and powerful search method for solving different optimization problems.

Compliance with ethical standards

Acknowledgement

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Disclosure of conflict of interest

The authors declare that they have no conflicts of interest.

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