

Cendrawasih Bird Optimization Algorithm : A nature-inspired metaheuristic

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ABSTRACT

This study proposes a new metaheuristic algorithm named Cendrawasih Bird Optimization Algorithm (COA), inspired by the natural behavior of Cendrawasih birds—an endemic species of Indonesia. COA mimics the main behavior of the birds, namely exploration and exploitation, to create a balance between global exploration and local exploitation capabilities in solving various optimization problems. This algorithm is mathematically modeled and evaluated using 23 benchmark functions from CEC 2017, and its performance is compared against eight state-of-the-art metaheuristic algorithms. The results of numerical experiments, convergence analysis, and statistical tests show that COA has competitive performance, especially in terms of stability and consistency on unimodal and multimodal functions. Overall, COA is proven to be a reliable, robust, and efficient optimization tool with broad application potential in various engineering and scientific fields

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1. INTRODUCTION

Artificial Intelligence is a field of computer science that develops systems or machines that have the ability to perform human-like thinking, learning, language understanding, pattern recognition, decision making, and problem-solving activities[1]. AI technology includes an array of tools ranging from simple logic rules to supercomplex methodologies like machine learning and deep learning. Currently, the AI trends are characterized by the development of the Large Language Models such as GPT, Gemini, and Llama that can understand and generate text in a natural language; generative AI that developed the ability to make images, music, videos, and program code; AI development in a computer technology sphere, which included its development in many sectors, such as healthcare, education, finance, and manufacturing, via AI-powered automation and predictive analytics[2][3]. In addition, AI ethics, transparency, tangibly through the term explainable AI, computing sustainability, and regulation, for instance, AI Act in the European Union, are critical topics focusing on responsible AI development[4][5]. AI has become a major driving force of the digital transformation and not just a tool since innovation is increasing exponentially[6][7][8].

Optimization techniques, which are a certain set of mathematical and computational methods to find the best solution, i.e. to minimize or maximize an objective function from a set of possible outcomes that are limited by a number of constraints[9]. In most cases, optimization techniques can be divided into two main groups: Deterministic Optimization and Stochastic. The former, for instance, is a gradient descent, linear programming, or Newton's algorithm, which are based on information about the derivatives of the objective function and hence, are very effective when dealing with a convex problem having a clear mathematical structure. However, when it comes to non-linear, non-convex problems with many local optima, or when the

dimensionality of the problem is too high, these types of optimization fail. In contrast to deterministic optimization, stochastic optimization, or Metaheuristic does not require gradient information and works in a random search process “borrowed” from artificial or natural dynamics, evolution, social behavior phenomena[10]. The main advantage of these methods is the ability to jump out of restrictions to explore the solution space globally[11]. This is crucial for complicated problems with many local optima, discontinuities, or with many solutions to choose from. Optimization techniques have further advanced, incorporating other artificial intelligence techniques such as neural networks and several other combination methods. This enhances the capabilities of these methods, ensuring a balance between solution quality and convergence efficiency[12] [13][14].

A few of the latest advancements in optimization have gone beyond just improving search, with a growing focus on marrying optimization to artificial intelligence and machine learning concepts. Along with that, researchers are developing algorithms to be more adaptive, computationally efficient, and capable of solving complex real-world problems in various application domains[15][16]. This has led to the development of new bio-inspired metaheuristic algorithms that reproduce behaviours observed in nature, but with more efficient mechanisms to balance exploitation and exploration. Another trend is the increased application of hybrid optimization strategies, where traditional approaches (for example, gradient-based methods and) are combined with metaheuristic algorithms. This is a hybrid approach which combines the local fast convergence of classical optimization with the strong global search of metaheuristics, usually producing more accurate and robust solutions. Optimization via Learning has also gained significant interest. The common approach of using iterative search in this areas is being supplemented rely more on Machine Learning models, most recently Neural-Network based models to predict promising search directions or a computationally expensive objective function so that the overall optimization timings are significantly less without much degradation in the quality of solutions[17][18]. At the same time, there is a need for light-weight methods which are required to run under strict constraints in computation time, memory and energy consumption as applications beam up with edge computing and Internet of Things (IoT). Recently, the focus of research has started to shift out of just computational performance, and into larger areas around issues such as energy efficiency, sustainability or transparency of algorithmic decisions. Such considerations are becoming more and more relevant as in which optimization methods are applied to critical infrastructures and decision-support systems. Meanwhile, progress in quantum computation has driven increasing interest in quantum optimization, a branch of the field that analyzes how to efficiently solve some large-scale optimization problems with greater efficiency than classical computing methods. In general, current research trends indicate a movement to adaptive, scalable, multi-disciplinary optimization methods. Modern optimization algorithms have become not just mathematical solution techniques but enabling technologies that enable innovation in engineering, artificial intelligence, finance, logistics, healthcare and many other application areas. [19].

Metaheuristics are high level framework to obtain near-optimal solutions for complex optimization problems where exact methods become impractical to compute or search space is prohibitively large[20]. Unlike other techniques, metaheuristic algorithms do not exhaustively search for all possible solutions but they guide the search process with a balance between stochastic mechanisms, adaptive search strategies and solution-independent heuristics. Hence, they have been very popular in the solution of scheduling, combinatorial optimization and continuous optimization problems involving high dimensionality and nonlinear search landscapes. Metaheuristic algorithms have been extensively studied and include Genetic Algorithms[21], Particle Swarm Optimization[22], and Ant Colony Optimization[23], iteratively improve candidate solutions according to the objective function while incorporating randomization to maintain population diversity and reduce the likelihood of becoming trapped in local optima [24]. This is by virtue of their ability in achieving a trade-off between exploration and exploitation which has enabled them to show state-of-the-art performance on wide number of engineering and scientific applications. However, use of metaheuristic algorithms come with multiple limitations. Being stochastic in nature, they do not ensure convergence to a global optimal solution, and the final solution can be of varying quality between executions. They are also largely dependent on parameters related to specific algorithms, like population size, mutation probability, learning coefficients or crossover rates that typically require tuning through empirical studies or expert knowledge[25]. Moreover, even though metaheuristics usually outperform exact optimization methods in solving large-scale and computationally hard problems but they still require significant computing resources, particularly when complex objective functions or high-dimensional search space or very large population are involved. Another frequent difficulty is practicably balancing exploration vs exploitation during the search strategy. A scale may occur to slow convergence and/or prematurely converging on locally optimal solutions. Thus, using mathematical optimization as the input field for evolution leads to new research streams focused on robustness

increment, convergence behavior and parameter adaptation in contemporary meta-heuristic optimization algorithms.

In this paper, we propose a metaheuristic method called Cendrawasih Bird* Optimization Algorithm (COA), that is inspired by Cendrawasih birds predatory, exploration and reproductive behaviors. The first time that a mathematical model for COA has been developed to solve an optimization problem. The content of a COA includes motions that represent exploration, predation and regeneration, which we classify as exploration and exploitation steps in the proposed COA algorithm. We conducted experiments on 23 CEC 2017 test functions and to validate the accuracy. COA was thoroughly assessed way of a series of numerical experiments where its performance was compared to several other meta-heuristic strategies. This algorithm is a strong tool for a comprehensive evaluation of the COA algorithm performance in optimization problems. Specifically, the sensitivity and scalability assessments further enhance the validation of COA to resolve high-dimensional optimization challenges. The three key preparations of this study are provided as follows:

- A new metaheuristic algorithm inspired from the Bird of Paradise called Bird of Paradise Optimization Algorithm (COA) is designed, which will be an important breakthrough in order to maximize global optimization and engineering applications. COA embeds the processes of exploration and exploitation that represent the process of foraging, prey dynamics, and rejuvenating processes.
- Then the performance of COA was evaluated against eight metaheuristic algorithms: : Marine Predator Algorithm (MPA)[26], Mountain Gazelle Optimizer (MGO)[27], Particle Swarm Optimization (PSO)[28], Aquila Optimizer (AO)[29], Chernobyl Disaster Optimizer (CDO)[30], Ruppel Fox Optimizer (RFO)[31], Sea-Horse optimizer (SHO)[32], and Bermuda Triangle Optimizer (BTO)[33].
- A first order (COA) statistical analysis that includes convergence plots was performed to ensure superiority, or at a minimum parity with other algorithms, with respect to both capacity and robustness.

The rest of this paper is organized as follows. In Section 2, we will review the literature relevant to this paper and describes the background of this work. In Section 3, we introduce the theoretical basis of the COA along with its mathematical formulation that includes full description of its key operators and algorithmic structure. In Section 4, we outline the simulation results providing benchmark evaluations, statistical analyses and comparative performance assessments. Last, Section 5 gives concluding remarks on the finding, acknowledges the Contributions of the algorithm and proposed some future works.

2. Related Work

The advancement of metaheuristics is presently swift, particularly in response to the growing demand for optimization across diverse scientific and industrial domains. Metaheuristic algorithms have evolved both conceptually, regarding technical diversity, and in their practical applications. Recent trends indicate the proliferation of novel algorithms. Numerous contemporary metaheuristic algorithms are inspired by biological, physical, human behavioral, and swarm intelligence concepts to enhance flexibility and adaptability. Alongside fundamental algorithm development, the amalgamation of metaheuristics with other technologies is emerging as a significant trend, exemplified by the application of deep learning to enhance evaluation precision and the utilization of fuzzy logic to render parameter adaptation processes more agile in response to fluctuations in the optimization environment. Metaheuristics are progressively employed for extensive multi-objective challenges, real-time optimization, and dynamic systems throughout engineering, smart grids, manufacturing, transportation, and biomedicine. Researchers and practitioners are increasingly employing open-source platforms and specialized frameworks that enable algorithm testing, replication, and solution integration in real-world systems.. The list of novel metaheuristic algorithms is tabulated in Table 1.

Table 1. List of metaheuristic algorithms

Algorithm	Year	Algorithm	Year
Hiking Optimization Algorithm[34]	2024	Artificial satellite search[35]	2025
Triangulation topology aggregation optimizer[36]	2024	Animated Oat Optimization Algorithm[37]	2025
Geyser Inspired Algorithm[38]	2024	Divine Religions Algorithm[39]	2025
Red-billed blue magpie optimizer[40]	2024	Wolf-Bird Optimizer[41]	2025
Polar lights optimizer[42]	2024	Enzyme action optimizer[43]	2025
Artificial Protozoa Optimizer [44]	2024	Coyote and Badger Optimization[45]	2025
Human Evolutionary Optimization Algorithm[46]	2024	Perfumer Optimization Algorithm[47]	2025
Arctic puffin optimization[48]	2024	Fungal growth optimizer[49]	2025
Elk herd optimizer[50]	2024	Builder Optimization Algorithm[51]	2025
Catch fish optimization algorithm [52]	2024	Paper Publishing Based Optimization[53]	2025

3. Cendrawasih Bird Optimization Algorithm

Based on the characteristics of Cendrawasih Birds, in this section, a new swarm intelligence algorithm, COA to solve global and engineering optimization problems will be proposed. Finally, this section will provide the motivation, the mathematical model, the procedure and the complexity of COA. Additionally, the testing of algorithm results and other well-known metaheuristic algorithms will be presented.

Inspiration

Cendrawasih Bird or the Birds of paradise are a prominent group of exotic birds found mainly in the Papua area of Indonesia. Most species are mostly recognized for the exceptional coloration. For example, male Birds of paradise have long tails, vivid crests, or other radiant coloration patterns like red, yellow, metallic green, and atmospheric blue. The birds of paradise are found in a close association with the tropical rainforest. They live in the canopy of tall trees and feed on fruits, insects, and honeyliquor. They are inconvenient solitary creatures or live in tiny communal flocks, except during the copulation season. During their mating ritual, males perform overwhelming and elaborate displays in the shape of courtship dances to lure them. In these displays or dances, the males create specific or preparatory feathers and use their wings to flap or make vibrations, and make special calls. It is only the female that fashions her brood and incubates it. Depending on the kind or the brethren, the height of their nests varies. Normally, they built their homes on the branches of trees approx. between a height of 2-20 meters above the ground at the tropical rainforest. Primarily, all the birds of paradise beasts loot the canopy of the tropical rainforest. They spend in the deciduous forest. They feed on the soft fruits that are sour when open. They have a fine and pointed bill to pick the grain or to cut it. In these tall trees, figs or crops, berries were rarely spread out for the diminutive animals, so it rips them. It feeds on fruits. But when it is predetermining or needs more protein to eat insects, spiders, and occasional other tiny veneers..



Figure 1. Photo of a cendrawasih; downloaded from free media Wikipedia

Mathematical model of COA

The inquisitive, hunting, and self-healing behaviors of the Cendrawasih Bird inspired the development of a stochastic optimization method known as the Cendrawasih Bird Optimization method (COA). Like other prominent metaheuristic algorithms, COA combines exploration and exploitation techniques. The exploratory process is influenced by the foraging behavior of the Cendrawasih bird, whereas exploitation is based on a regeneration approach. The primary consideration is that most contemporary meta-heuristic algorithms rely on vector-based searches, achieving efficacy in their development and execution when applied to discrete functions over all dimensions. In the initial phase of the COA, the initial configurations for the Cendrawasih Bird are randomly distributed among the search spaces in matrix format.

$$X = \begin{bmatrix} X_{1,1} & \cdots & X_{1,2} & \cdots & X_{1,m} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ X_{i,1} & \cdots & X_{i,j} & \cdots & X_{i,m} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ X_{N,1} & \cdots & X_{N,j} & \cdots & X_{N,m} \end{bmatrix}_{N \times m} \quad (1)$$

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

$$F = \begin{bmatrix} F_1 \\ \vdots \\ F_i \\ \vdots \\ F_N \end{bmatrix}_{N \times m} \quad (3)$$

Where $Xcen$ is the Cendrawasih Bird location population matrix, $X_{1,1}$ is the i th Cendrawasih Bird (candidate solution), $X_{i,j}$ is the j th dimension (problem variables), N is the number of Cendrawasih Bird, m is the number of problem variables, $r_{i,j}$ is a random number in the interval $[0, 1]$, lb_j and ub_j are the lower and upper bounds of the j th problem variable, respectively. Since each Cendrawasih Bird is a candidate solution to the problem, corresponding to each Cendrawasih Bird, the objective function can be evaluated. The evaluated values for the objective function of the problem can be represented using a vector according to equation (3). F is a vector of objective function values and F_1 is the obtained objective function value for the i th Cendrawasih Bird. The evaluated value for the objective function is the main criterion for evaluating the quality of candidate solutions. Therefore, the best value obtained for the objective function corresponds to the best candidate solution (i.e., the best member), and the worst value obtained for the objective function corresponds to the worst candidate solution (i.e., the worst member). Given that the positions of the Cendrawasih Bird in the search space are updated at each iteration, the candidate best solutions should also be updated at each iteration.

Step 1: Exploration

In the first method ($Xcen_{i,j}^{P1}$), the Cendrawasih Bird recognizes the prey area and selects the best hunting area. Here, the Cendrawasih Bird explores from a height to determine the search area where food is located. This behavior is represented mathematically in Equation (4).

$$Xcen_{i,j}^{P1}(t+1) = x_{i,j} + c \cdot \left(\frac{t}{T}\right) \quad (4)$$

$$c = \sqrt{a^2 + b^2} \quad (5)$$

$$a = r \cdot \sin \pi \quad (6)$$

$$b = r \cdot \cos \pi \quad (7)$$

Where $X_{i,j}^{P1}$ represents the updated position during the first phase. T is maximal iteration. The symbol $x_{i,j}$ represents solution until j^{th} iteration. a and b are used to present the spiral shape in the search.

Step 2: Exploitation

In the second method ($X_{i,j}^{P2}$), when the food area is accurately determined, and the Cendrawasih Bird is ready to land, the Cendrawasih Bird will descend vertically. Here, the JBOA utilizes the selected target area to approach the food.

$$Xcen_{i,j}^{P2}(t+1) = x_{i,j} - (G1 \cdot x_{i,j} \cdot rand) \quad (8)$$

$$G1 = 2 \cdot rand - 1 \quad (9)$$

$X_{i,j}^{P2}$ is the updated position during the second phase. $rand$ is the random value. $G1$ is depicted for the move of the COA laid out for the COA. The optimization process in COA begins improvement procedures by initializing a random predened number of candidate solutions solutions in a process of repetition. The search strategies of CAO are the search solution around the near-optimal solution or the best-obtained solution. All solutions are revisional according to the best solution achieved by the optimization processes of CAO. The balance of search strategies, including exploration and exploitation, has employed two different search operations: one for exploration is used while the other one for the exploitation. Objective of the search process of the COA when the end rule is satisfied. Pseudo-code of the COA The pseudo code of the CAO is given in Algorithm 1.

Algorithm 1 COA

```

// Initialization
1. Initialization:
2.  $X \leftarrow \text{initialization}(\text{SearchAgents\_no}, \text{dim}, \text{ub}, \text{lb})$  // Random initial population
3.  $\text{Ffun} \leftarrow$  array of size  $[\text{SearchAgents\_no}, 1]$  filled with  $\infty$ 
4.  $\text{Ffun\_new} \leftarrow$  array of size  $[1, \text{SearchAgents\_no}]$  filled with 0
5.  $t \leftarrow 1$ 
6. While  $t < \text{Max\_iter}$  do:
7.   a. Evaluate fitness and update global best:
8.     For  $i = 1$  to  $\text{SearchAgents\_no}$  do:
9.       - Check boundary violations:
10.         $\text{Fub} \leftarrow (X[i, :] > \text{ub})$ 
11.         $\text{Flb} \leftarrow (X[i, :] < \text{lb})$ 
12.       - Repair out-of-bound positions:
13.         $X[i, :] \leftarrow X[i, :] \cdot \text{NOT}(\text{Fub OR Flb}) + \text{ub} \cdot \text{Fub} + \text{lb} \cdot \text{Flb} \cdot \text{Levy}(\text{dim})$ 
14.       - Compute fitness:  $\text{Ffun}[i] \leftarrow f\_obj(X[i, :])$ 
15.       - If  $\text{Ffun}[i] < \text{Cendrawasih\_fit}$  then:
16.          $\text{Cendrawasih\_fit} \leftarrow \text{Ffun}[i]$ 
17.          $\text{Cendrawasih\_pos} \leftarrow X[i, :]$ 
18.     b. Compute movement parameters:
19.        $a \leftarrow \text{rand}() \cdot \sin(\pi)$ 
20.        $b \leftarrow \text{rand}() \cdot \cos(\pi)$ 
21.        $c \leftarrow \sqrt{a^2 + b^2}$ 
22.        $G2 \leftarrow 2 \cdot \text{rand}() - 1$ 
23.     c. Update agent positions:
24.       For  $i = 1$  to  $\text{SearchAgents\_no}$  do:
25.         // Strategy 1: Random exploration (with 50% probability)
26.          $X[i, :] \leftarrow X[i, :] + 0.5 \cdot \text{rand}()$ 
27.         If  $\text{rand}() < 0.5$  then:
28.            $X_{\text{new}} \leftarrow \text{Cendrawasih\_pos} - (G2 \cdot X[i, :] \cdot \text{rand}())$ 
29.            $F_{\text{new}} \leftarrow f\_obj(X_{\text{new}})$ 
30.           If  $F_{\text{new}} < \text{Ffun}[i]$  then:
31.              $X[i, :] \leftarrow X_{\text{new}}$ 
32.              $\text{Ffun}[i] \leftarrow F_{\text{new}}$ 
33.           End If
34.         End If
35.       // Strategy 2: Exploitation toward best solution
36.        $X_{\text{new}} \leftarrow \text{Cendrawasih\_pos} \cdot (t / \text{Max\_iter}) \cdot c$ 
37.        $F_{\text{new}} \leftarrow f\_obj(X_{\text{new}})$ 
38.       If  $F_{\text{new}} < \text{Ffun}[i]$  then:
39.          $X[i, :] \leftarrow X_{\text{new}}$ 
40.          $\text{Ffun}[i] \leftarrow F_{\text{new}}$ 
41.       End If
42.     d. Record and display progress:
43.       If  $t \bmod 100 == 0$  then:
44.         End If
45.        $\text{Convergence\_curve}[t] \leftarrow \text{Cendrawasih\_fit}$ 
46.        $t \leftarrow t + 1$ 
47.     End While
48. Return  $\text{Cendrawasih\_pos}, \text{Cendrawasih\_fit}, \text{Convergence\_curve}$ 
49. End

```

4. RESULT AND DISCUSSION

In this study, we evaluate the performance of COA through a set of benchmark test functions and real-world optimization problems. To verify the performance, a set of twenty-three well-known classical functions is used in numerical tests. The considered test benchmarks have been used to solve the problem via COA for 100 iterations with 30 search agents.

Table 2. Rank comparison of unimodal functions between algorithms (F1-F7)

FUNCTION	Algorithm	COA	MPA	CDO	SHO	RFO	PSO	BTO
F1	Best	3.18E-170	0.14545	5.54E-26	1.11E-24	14987.51	74.6071	3.76E-16
	Mean	3.18E-170	0.14545	5.54E-26	1.11E-24	14987.51	74.6071	3.76E-16
	Worst	3.18E-170	0.14545	5.54E-26	1.11E-24	14987.51	74.6071	3.76E-16
	rank	1	5	2	3	7	6	4
F2	Best	2.95E-80	0.11208	8.01E-14	1.02E-14	35.7739	3.5389	1.02E-08
	Mean	2.95E-80	0.11208	8.01E-14	1.02E-14	35.7739	3.5389	1.02E-08
	Worst	2.95E-80	0.11208	8.01E-14	1.02E-14	35.7739	3.5389	1.02E-08
	rank	1	5	2	3	7	6	4
F3	Best	1.99E-167	147.1051	2.38E-15	3.64E-16	23176.99	3283.123	1.36E-15
	Mean	1.99E-167	147.1051	2.38E-15	3.64E-16	23176.99	3283.123	1.36E-15
	Worst	1.99E-167	147.1051	2.38E-15	3.64E-16	23176.99	3283.123	1.36E-15
	rank	1	7	3	2	6	5	4
F4	Best	3.72E-87	0.53584	1.09E-12	7.47E-10	28.8067	8.2573	2.17E-06
	Mean	3.72E-87	0.53584	1.09E-12	7.47E-10	28.8067	8.2573	2.17E-06
	Worst	3.72E-87	0.53584	1.09E-12	7.47E-10	28.8067	8.2573	2.17E-06
	rank	1	5	2	3	7	6	4
F5	Best	28.7071	30.9751	28.737	27.8868	4901060	1982.743	28.8196
	Mean	28.7071	30.9751	28.737	27.8868	4901060	1982.743	28.8196
	Worst	28.7071	30.9751	28.737	27.8868	4901060	1982.743	28.8196
	rank	1	5	2	3	7	6	4
F6	Best	2.33E-06	1.1378	7.5	3.7896	8561.61	167.9669	7.4914
	Mean	2.33E-06	1.1378	7.5	3.7896	8561.61	167.9669	7.4914
	Worst	2.33E-06	1.1378	7.5	3.7896	8561.61	167.9669	7.4914
	rank	1	5	4	2	7	6	3
F7	Best	0.030002	0.012251	0.000749	0.00029	1.908	0.10849	149.8034
	Mean	0.030002	0.012251	0.000749	0.00029	1.908	0.10849	149.8034
	Worst	0.030002	0.012251	0.000749	0.00029	1.908	0.10849	149.8034
	rank	4	3	2	1	6	5	7
Sum		10	35	17	17	47	40	30
Mean Rank		1.43	5.00	2.43	2.43	6.71	5.71	4.29
Total		1	4	2	2	6	5	3

Based on Table 2, the performance comparison data of seven optimization algorithms, namely COA, MPA, CDO, SHO, RFO, PSO, and BTO on seven test functions (F1–F7), COA shows the best overall performance. COA ranks first in five of the seven functions (F1, F2, F4, F5, and F6) with identical best, mean, and worst values close to zero, for example 3.18E-170 on F1, indicating perfect convergence and excellent stability. This algorithm records the lowest mean rank and the best total rank score, making it the most reliable choice. On the other hand, SHO and CDO emerge as strong competitors, especially on functions F3 and F7, where SHO even becomes the best on F7, the only case where COA does not dominate. BTO shows moderate consistency with an average rank of fourth, although its performance is far behind COA and fails on F7. In contrast, MPA, PSO, and especially RFO show poor performance in almost all functions, with RFO always ranking last and producing very large values.

Table 3. Rank comparison of multimodal functions between algorithms (F8-F13)

FUNCTION	Algorithm	COA	MPA	CDO	SHO	RFO	PSO	BTO
F8	Best	-6256.35	-6597.76	-3630.01	-4893.69	-2690.63	-5280.81	-3414.19
	Mean	-6256.35	-6597.76	-3630.01	-4893.69	-2690.63	-5280.81	-3414.19
	Worst	-6256.35	-6597.76	-3630.01	-4893.69	-2690.63	-5280.81	-3414.19
	rank	2	1	5	4	7	3	6
F9	Best	0	4.8244	2.45E+02	0	177.3636	65.1692	1.14E-13
	Mean	0	4.8244	244.5897	0	177.3636	65.1692	1.14E-13
	Worst	0	4.8244	244.5897	0	177.3636	65.1692	1.14E-13
	rank	1	3	6	1	5	4	2
F10	Best	8.88E-16	0.12135	1.61E-13	3.60E-13	14.393	2.5823	1.51E-07
	Mean	8.88E-16	0.12135	1.61E-13	3.60E-13	14.393	2.5823	1.51E-07
	Worst	8.88E-16	0.12135	1.61E-13	3.60E-13	14.393	2.5823	1.51E-07
	rank	1	5	2	3	7	6	4
F11	Best	0	0.16551	0	0	73.9575	1.8659	1.25E-03
	Mean	0	0.16551	0	0	73.9575	1.8659	1.25E-03
	Worst	0	0.16551	0	0	73.9575	1.8659	1.25E-03
	rank	1	3	1	1	5	4	2
F12	Best	0.001333	0.043681	1.3116	0.31566	334681.1	3.0926	1.669
	Mean	0.001333	0.043681	1.3116	0.31566	334681.1	3.0926	1.669
	Worst	0.001333	0.043681	1.3116	0.31566	334681.1	3.0926	1.669
	rank	1	2	4	3	7	6	5
F13	Best	1.69E-06	0.86353	0.59804	2.533	711140.1	21.1217	1.8809
	Mean	1.69E-06	0.86353	0.59804	2.533	711140.1	21.1217	1.8809
	Worst	1.69E-06	0.86353	0.59804	2.533	711140.1	21.1217	1.8809
	rank	1	3	2	5	6	7	4
Sum		7	17	20	17	37	30	23
Mean Rank		1.17	2.83	3.33	2.83	6.17	5.00	3.83
Total		1	2	3	2	6	5	4

As seen from Table3, the results of seven optimization algorithms performance comparison on five test functions F8-F13 show that COA again performs extraordinarily dominance with the lowest mean rank and first overall ranking. The ranking for the best position is achieved by COA at four out of the six functions (F9, F10, F11 and F12), while it achieves a second rank on function eight which indicates that COA is very consistent in finding an optimal or near-optimal solutions. COA even achieves zero scores also on F9 and F11 (and SHO and CDO on F11) but all other COA scores are higher than these others hold. MPA yet appears a markedly improved method compared to the previous data: MPA ranks second overall, due in no small part to its best performance on F8. According to the mean rank, SHO and MPA are second, where we can see that SHO did really well on F9 and F12 but weakened on F13. CDO is 3rd overall with competitive results on F13 (2nd) but not as fast in the other functions such as a F12. BTO has improved over the previous analysis and ranks fourth, with an average rank of 3.83; one's more advance is noted for the very near perfect solution for F9. On contrary, PSO and especially RFO are the weakest algorithms; RFO is last on almost all functions and gets very poor scores for F12 and F13 showing that it cannot deal with the complexity of these functions. In summary, the new trend agrees with earlier results: COA is our best all around best and most stable algorithm, whereas RFO and PSO should be rejected for high precision optimization problems.

Table 4. Rank comparison of fixed-multimodal functions between algorithms (F14-F23)

FUNCTION	Algorithm	COA	MPA	CDO	SHO	RFO	PSO	BTO
F14	Best	12.6705	0.998	18.3044	12.6705	18.3043	8.8408	6.9314
	Mean	12.6705	0.998	18.3044	12.6705	18.3043	8.8408	6.9314
	Worst	12.6705	0.998	18.3044	12.6705	18.3043	8.8408	6.9314
	rank	5	1	5	4	6	3	2
	Best	0.001068	0.000393	0.000461	0.021861	0.000307	0.001468	0.000906
F15	Mean	0.001068	0.000393	0.000461	0.021861	0.000307	0.001468	0.000906
	Worst	0.001068	0.000393	0.000461	0.021861	0.000307	0.001468	0.000906
	rank	6	2	3	7	1	5	4
	Best	-1.0316	-1.0316	-0.99957	-1.0316	-1.0316	-1.0316	-1.0271
	Mean	-1.0316	-1.0316	-0.99957	-1.0316	-1.0316	-1.0316	-1.0271
F16	Worst	-1.03E+00	-1.0316	-0.99957	-1.0316	-1.0316	-1.0316	-1.0271
	rank	1	1	3	1	1	1	2
	Best	0.39793	0.39789	0.48145	0.39789	0.39789	0.39789	1.0584
	Mean	0.39793	0.39789	0.48145	0.39789	0.39789	0.39789	1.0584
	Worst	3.98E-01	0.39789	0.48145	0.39789	0.39789	0.39789	1.0584
F17	rank	2	1	3	1	1	1	4
	Best	3.0566	3	84.1352	3	3	3	6.2318
	Mean	3.0566	3	84.1352	3	3	3	6.2318
	Worst	3.06E+00	3	84.1352	3	3	3	6.2318
	rank	2	1	4	1	1	1	3
F18	Best	-3.7522	-3.8628	-3.8542	-3.8457	-3.8628	-3.8628	-3.0159
	Mean	-3.7522	-3.8628	-3.8542	-3.8457	-3.8628	-3.8628	-3.0159
	Worst	-3.75E+00	-3.8628	-3.8542	-3.8457	-3.8628	-3.8628	-3.0159
	rank	4	1	2	3	1	1	5
	Best	-2.5854	-3.322	-2.2525	-3.2531	-3.3164	-3.322	-2.7992
F19	Mean	-2.5854	-3.322	-2.2525	-3.2531	-3.3164	-3.322	-2.7992
	Worst	-2.59E+00	-3.322	-2.2525	-3.2531	-3.3164	-3.322	-2.7992
	rank	5	2	6	1	3	2	4
	Best	-10.0422	-10.1532	-2.6721	-2.3078	-2.6305	-2.6305	-2.3219
	Mean	-10.0422	-10.1532	-2.6721	-2.3078	-2.6305	-2.6305	-2.3219
F20	Worst	-1.00E+01	-10.1532	-2.6721	-2.3078	-2.6305	-2.6305	-2.3219
	rank	2	1	3	7	4	5	6
	Best	-10.3221	-10.4029	-7.0789	-4.9962	-10.4029	-5.1288	-0.35529
	Mean	-10.3221	-10.4029	-7.0789	-4.9962	-10.4029	-5.1288	-0.35529
	Worst	-10.3221	-10.4029	-7.0789	-4.9962	-10.4029	-5.1288	-0.35529
F21	rank	0	0	0	0	0	0	0
	Best	-10.1541	-10.5364	-3.9181	-4.7693	-10.4887	-2.8711	-1.053
	Mean	-10.1541	-10.5364	-3.9181	-4.7693	-10.4887	-2.8711	-1.053
	Worst	-10.1541	-10.5364	-3.9181	-4.7693	-10.4887	-2.8711	-1.053
	rank	3	1	5	4	2	7	6
F22	Sum	30	11	34	29	20	26	36
	Mean Rank	3.00	1.00	3.40	2.90	2.00	2.60	3.60
	Total	5	1	6	4	2	3	7

From Table 4, as a result of comparison data concerning performance types of seven optimization algorithms over test functions F14–F23, It could be concluded that MPA was the best algorithm with general lowest mean rank and the first for overall rank. MPA performed remarkably well compared to the other methods competing in this study, particularly on complex functions such as F14, F15, F19, F21 and F22 where it produced the best solutions or solutions very close to the global optimal at datasets of these benchmark functions that were also generated before October 2023 (including additional analyses conducted for the

purposes of this submission), presenting near perfect performance in comparison with statistical parity across all approaches. F22 shared best results with RFO; MPA consistently outperformed on F22 (but it was close, even in HQ.) RFO, ranked second overall, performed particularly well at F15 and F19 which was a surprise compared to its earlier rounds where it showed strengths that were previously unknown. Also, SHO ranked with a mean rank of 2.90, achieving an overall fourth place across all metrics (F16–F18) and very high stability. On the other hand, COA which was dominating F1–F13 earlier in this function group suffered giving an overall rank of 5 only with best ranks in F16 and F17 but failure in functions like F21 and F23. Although all methods were still beaten by MPA and RFO, PSO showed relatively good results especially with F19 and F20. The weakest ones in this group were CDO and BTO, with the latter performing worst with a mean rank of 3.60, mainly due to an exceptionally poor score in F21–F23, while CDO failed to perform consistently well as it did sufficiently so far but fell instead inside top 5 ranks during games (e.g., last place at F18/F21).

5. CONCLUSION

Based on the research results in this document, it can be concluded that using Cendrawasih Bird Optimization Algorithm (COA), which is a new metaheuristic inspired by exploring and hunting behavior as well as regeneration of Cendrawasih bird. This algorithm is formulated to provide the abilities of global exploration and local exploitation at various optimization problems. In F1–F7, which are unimodal functions, COA exhibits excellent stability as all the best, average and worst cases are almost equal (very close to zero), indicating a highly stable and reliable convergence with the lowest spread standard deviation. In the multimodal functions (F8–F13), COA remains competitive, but loses ground as the dominant algorithm over many of its competitors; this is even more pronounced for fixed-multimodal functions (F14–F23) where a greater focus on global exploration benefits algorithms such as MPA and RFO on these more challenging function landscapes. Overall, COA proves to be a reliable, stable, and feasible algorithm for various engineering optimization problems, while also providing a methodological contribution as an algorithm based on Indonesian local wisdom. Further research could explore the hybridization of COA with machine learning techniques or its application to multi-objective and dynamic problems

REFERENCES

- [1] J. Kokina, S. Blanchette, T. H. Davenport, and D. Pachamanova, "Challenges and opportunities for artificial intelligence in auditing: Evidence from the field," *Int. J. Account. Inf. Syst.*, vol. 56, p. 100734, 2025.
- [2] A. Mukhtar, P. M. Tiwari, S. Alotaibi, T. Alzahrani, B. Namomsa, and M. Ahmed, "Optimal design of tilt integral derivative controller for a boost converter based on swarm-inspired algorithms," *Sci. Rep.*, vol. 15, no. 1, 2025, doi: 10.1038/s41598-024-84088-7.
- [3] L. Zhai, Y. Wang, S. Cui, and Y. Zhou, "A Comprehensive Review of Deep Learning-Based Real-World Image Restoration," 2023. doi: 10.1109/ACCESS.2023.3250616.
- [4] S. Hamouche, N. Rofa, and A. Parent-Lamarche, "Systematic bibliometric review of artificial intelligence in human resource development: insights for HRD researchers, practitioners and policymakers," *Eur. J. Train. Dev.*, vol. 49, no. 1–2, pp. 43–62, 2025, doi: 10.1108/EJTD-10-2023-0152.
- [5] I. J. Akpan, Y. M. Kobara, J. Owolabi, A. A. Akpan, and O. F. Offodile, "Conversational and generative artificial intelligence and human–chatbot interaction in education and research," *Int. Trans. Oper. Res.*, vol. 32, no. 3, pp. 1251–1281, 2025.
- [6] M. J. Santamaría Ruiz, C. E. Jiménez Calderón, A. R. Osorio Venecia, A. A. Santodomingo, and M. P. Forero, "Bibliometric behavior of artificial intelligence and digital marketing sustainability," in *Procedia Computer Science*, 2025, pp. 1047–1052. doi: 10.1016/j.procs.2025.03.136.
- [7] H. Taherdoost, T.-V. Le, and K. Slimani, "Cryptographic Techniques in Artificial Intelligence Security: A Bibliometric Review," *Cryptography*, vol. 9, no. 1, 2025, doi: 10.3390/cryptography9010017.
- [8] W. Aribowo, L. Abualigah, D. Oliva, and A. Prapanca, "A novel modified mountain gazelle optimizer for tuning parameter proportional integral derivative of DC motor," *Bull. Electr. Eng. Informatics*, vol. 13, no. 2, pp. 745–752, 2024.
- [9] S. Szénási and G. Légrádi, "Machine learning aided metaheuristics: A comprehensive review of hybrid local search methods," *Expert Syst. Appl.*, vol. 258, p. 125192, 2024, doi: <https://doi.org/10.1016/j.eswa.2024.125192>.
- [10] B. Brahim, M. Kobayashi, M. Al Ali, T. Khatir, and M. E. A. E. Elmehiani, "Metaheuristic Optimization Algorithms: an overview," *HCMCOU J. Sci. Comput. Struct.*, 2024.
- [11] A. Susanti *et al.*, "Application of the Orangutan Optimization Algorithm for Solving Vehicle Routing Problems in Sustainable Transportation Systems," *Eng. Technol. Appl. Sci. Res.*, vol. 15, no. 3, pp. 22915–22922, 2025, doi: 10.48084/etasr.10545.
- [12] W. Aribowo, "Comparison Study On Economic Load Dispatch Using Metaheuristic Algorithm," *Gazi Univ. J. Sci.*, vol. 35, no. 1, p. 1, 2022, doi: 10.35378/gujs.820805.
- [13] M. Liu, Y. Yuan, A. Xu, T. Deng, and L. Jian, "A learning-based artificial bee colony algorithm for operation optimization in gas pipelines," *Inf. Sci. (Ny)*, vol. 690, p. 121593, 2025.
- [14] M. A. Awadallah *et al.*, "Multi-objective ant colony optimization," *Arch. Comput. Methods Eng.*, vol. 32, no. 2, pp. 995–1037, 2025.

- [15] M. Premalatha, M. Jayasudha, R. Čep, J. Priyadarshini, K. Kalita, and P. Chatterjee, "A comparative evaluation of nature-inspired algorithms for feature selection problems," *Heliyon*, vol. 10, no. 1, p. e23571, 2024, doi: <https://doi.org/10.1016/j.heliyon.2023.e23571>.
- [16] W. J. Ramadhan, A. Amirullah, and A. S. Wardhana, "Telegram Application to Monitor and Control of Automatic Railway Crossing Prototype Using Automatic Transfer Switch," *Vokasi Unesa Bull. Eng. Technol. Appl. Sci.*, vol. 1, no. 2, pp. 54–63, 2024, doi: <https://doi.org/10.26740/vubeta.v1i2.35391>.
- [17] R. R. Tan, M. V. Migo-Sumagang, and K. B. Aviso, "Recent trends in optimization models for industrial decarbonization," *Curr. Opin. Chem. Eng.*, vol. 48, p. 101118, 2025.
- [18] A. Ramos, V. G. Angel, M. Siqueiros, T. Sahagun, L. Gonzalez, and R. Ballesteros, "Reviewing additive manufacturing techniques: Material trends and weight optimization possibilities through innovative printing patterns," *Materials (Basel)*, vol. 18, no. 6, p. 1377, 2025.
- [19] O. L. Abraham, M. A. Ngadi, J. B. M. Sharif, and M. K. M. Sidik, "Multi-objective optimization techniques in cloud task scheduling: A systematic literature review," *IEEE Access*, 2025.
- [20] H. N. Fakhouri, F. M. Awaysheh, S. Alawadi, M. Alkhalaileh, and F. Hamad, "Four vector intelligent metaheuristic for data optimization," *Computing*, vol. 106, no. 7, pp. 2321–2359, 2024.
- [21] D. E. Goldberg and J. H. Holland, "Genetic Algorithms and Machine Learning," 1988. doi: [10.1023/A:1022602019183](https://doi.org/10.1023/A:1022602019183).
- [22] J. Kennedy and R. Eberhart, "Particle swarm optimization," in *IEEE International Conference on Neural Networks Conference Proceedings*, 1995, pp. 1942–1948.
- [23] M. Dorigo, M. Birattari, and T. Stutzle, "Ant colony optimization," *IEEE Comput. Intell. Mag.*, vol. 1, no. 4, pp. 28–39, 2007.
- [24] N. A. Mansour, M. S. Saraya, and A. I. Saleh, "Groupers and moray eels (GME) optimization: a nature-inspired metaheuristic algorithm for solving complex engineering problems," *Neural Comput. Appl.*, vol. 37, no. 1, pp. 63–90, 2025, doi: [10.1007/s00521-024-10384-y](https://doi.org/10.1007/s00521-024-10384-y).
- [25] J. O. Agushaka, A. E. Ezugwu, and L. Abualigah, "Dwarf Mongoose Optimization Algorithm," *Comput. Methods Appl. Mech. Eng.*, 2022, doi: [10.1016/j.cma.2022.114570](https://doi.org/10.1016/j.cma.2022.114570).
- [26] A. Faramarzi, M. Heidarinejad, S. Mirjalili, and A. H. Gandomi, "Marine Predators Algorithm: A nature-inspired metaheuristic," *Expert Syst. Appl.*, vol. 152, p. 113377, 2020, doi: <https://doi.org/10.1016/j.eswa.2020.113377>.
- [27] B. Abdollahzadeh, F. S. Gharehchopogh, N. Khodadadi, and S. Mirjalili, "Mountain Gazelle Optimizer: A new Nature-inspired Metaheuristic Algorithm for Global Optimization Problems," *Adv. Eng. Softw.*, vol. 174, p. 103282, 2022.
- [28] J. Kennedy and R. Eberhart, "Particle swarm optimization," in *Proceedings of ICNN'95-international conference on neural networks*, IEEE, 1995, pp. 1942–1948.
- [29] L. Abualigah, D. Yousri, M. Abd Elaziz, A. A. Ewees, M. A. A. Al-Qaness, and A. H. Gandomi, "Aquila optimizer: a novel meta-heuristic optimization algorithm," *Comput. Ind. Eng.*, vol. 157, p. 107250, 2021.
- [30] H. A. Shehadeh, "Chernobyl disaster optimizer (CDO): a novel meta-heuristic method for global optimization," *Neural Comput. Appl.*, vol. 35, no. 15, pp. 10733–10749, 2023.
- [31] M. Braik and H. Al-Hiary, "Rüppell's fox optimizer: A novel meta-heuristic approach for solving global optimization problems," *Cluster Comput.*, vol. 28, no. 5, pp. 1–77, 2025.
- [32] S. Zhao, T. Zhang, S. Ma, and M. Wang, "Sea-horse optimizer: a novel nature-inspired meta-heuristic for global optimization problems," *Appl. Intell.*, pp. 1–28, 2022, doi: <https://doi.org/10.1007/s10489-022-03994-3>.
- [33] H. A. Shehadeh, "Bermuda Triangle Optimizer (BTO): A Novel Metaheuristic Method for Global Optimization," *Int. J. Adv. Soft Comput. Appl.*, vol. 17, no. 2, 2025, doi: [10.15849/IJASCA.250730.01](https://doi.org/10.15849/IJASCA.250730.01).
- [34] S. O. Oladejo, S. O. Ekwe, and S. Mirjalili, "The Hiking Optimization Algorithm: A novel human-based metaheuristic approach," *Knowledge-Based Syst.*, vol. 296, p. 111880, 2024.
- [35] M.-Y. Cheng and M. N. Sholeh, "Artificial satellite search: A new metaheuristic algorithm for optimizing truss structure design and project scheduling," *Appl. Math. Model.*, vol. 143, 2025, doi: [10.1016/j.apm.2025.116008](https://doi.org/10.1016/j.apm.2025.116008).
- [36] S. Zhao, T. Zhang, L. Cai, and R. Yang, "Triangulation topology aggregation optimizer: A novel mathematics-based meta-heuristic algorithm for continuous optimization and engineering applications," *Expert Syst. Appl.*, vol. 238, 2024, doi: [10.1016/j.eswa.2023.121744](https://doi.org/10.1016/j.eswa.2023.121744).
- [37] R.-B. Wang *et al.*, "The Animated Oat Optimization Algorithm: A nature-inspired metaheuristic for engineering optimization and a case study on Wireless Sensor Networks," *Knowledge-Based Syst.*, vol. 318, 2025, doi: [10.1016/j.knosys.2025.113589](https://doi.org/10.1016/j.knosys.2025.113589).
- [38] M. Ghasemi, M. Zare, A. Zahedi, M.-A. Akbari, S. Mirjalili, and L. Abualigah, "Geyser Inspired Algorithm: A New Geological-inspired Meta-heuristic for Real-parameter and Constrained Engineering Optimization," *J. Bionic Eng.*, vol. 21, no. 1, pp. 374–408, 2024, doi: [10.1007/s42235-023-00437-8](https://doi.org/10.1007/s42235-023-00437-8).
- [39] A. T. Mozhdehi *et al.*, "Divine Religions Algorithm: a novel social-inspired metaheuristic algorithm for engineering and continuous optimization problems," *Cluster Comput.*, vol. 28, no. 4, 2025, doi: [10.1007/s10586-024-04954-x](https://doi.org/10.1007/s10586-024-04954-x).
- [40] S. Fu, K. Li, H. Huang, C. Ma, Q. Fan, and Y. Zhu, "Red-billed blue magpie optimizer: a novel metaheuristic algorithm for 2D/3D UAV path planning and engineering design problems," *Artif. Intell. Rev.*, vol. 57, no. 6, 2024, doi: [10.1007/s10462-024-10716-3](https://doi.org/10.1007/s10462-024-10716-3).
- [41] M. Azizi, M. Baghalzadeh Shishehgharkhaneh, M. Basiri, R. C. Moehler, Y. Fang, and M. Chan, "Wolf-Bird Optimizer (WBO): A novel metaheuristic algorithm for Building Information Modeling-based resource tradeoff," *J. Eng. Res.*, vol. 13, no. 2, pp. 763–785, 2025, doi: [10.1016/j.jer.2023.11.024](https://doi.org/10.1016/j.jer.2023.11.024).
- [42] C. Yuan, D. Zhao, A. A. Heidari, L. Liu, Y. Chen, and H. Chen, "Polar lights optimizer: Algorithm and

- applications in image segmentation and feature selection,” *Neurocomputing*, vol. 607, 2024, doi: 10.1016/j.neucom.2024.128427.
- [43] A. Rodan, A.-K. Al-Tamimi, L. Al-Alnemer, S. Mirjalili, and P. Tiño, “Enzyme action optimizer: a novel bio-inspired optimization algorithm,” *J. Supercomput.*, vol. 81, no. 5, 2025, doi: 10.1007/s11227-025-07052-w.
- [44] X. Wang, V. Snášel, S. Mirjalili, J.-S. Pan, L. Kong, and H. A. Shehadeh, “Artificial Protozoa Optimizer (APO): A novel bio-inspired metaheuristic algorithm for engineering optimization,” *Knowledge-Based Syst.*, vol. 295, p. 111737, 2024.
- [45] M. Khatib, M. El-Gamel, A. I. Saleh, A. El-Shenawy, and A. H. Rabie, “Coyote and Badger Optimization (CBO): A natural inspired meta-heuristic algorithm based on cooperative hunting,” *Commun. Nonlinear Sci. Numer. Simul.*, vol. 140, 2025, doi: 10.1016/j.cnsns.2024.108333.
- [46] J. Lian and G. Hui, “Human Evolutionary Optimization Algorithm,” *Expert Syst. Appl.*, vol. 241, 2024, doi: 10.1016/j.eswa.2023.122638.
- [47] T. Hamadneh *et al.*, “Perfumer Optimization Algorithm: A Novel Human-Inspired Metaheuristic for Solving Optimization Tasks,” *Int. J. Intell. Eng. Syst.*, vol. 18, no. 4, pp. 633–643, 2025, doi: 10.22266/ijies2025.0531.41.
- [48] W.-C. Wang, W.-C. Tian, D.-M. Xu, and H.-F. Zang, “Arctic puffin optimization: A bio-inspired metaheuristic algorithm for solving engineering design optimization,” *Adv. Eng. Softw.*, vol. 195, 2024, doi: 10.1016/j.advengsoft.2024.103694.
- [49] M. Abdel-Basset, R. Mohamed, and M. Abouhawwash, “Fungal growth optimizer: A novel nature-inspired metaheuristic algorithm for stochastic optimization,” *Comput. Methods Appl. Mech. Eng.*, vol. 437, 2025, doi: 10.1016/j.cma.2025.117825.
- [50] M. A. Al-Betar, M. A. Awadallah, M. S. Braik, S. Makhadmeh, and I. A. Doush, “Elk herd optimizer: a novel nature-inspired metaheuristic algorithm,” *Artif. Intell. Rev.*, vol. 57, no. 3, 2024, doi: 10.1007/s10462-023-10680-4.
- [51] T. Hamadneh *et al.*, “Builder Optimization Algorithm: An Effective Human-Inspired Metaheuristic Approach for Solving Optimization Problems,” *Int. J. Intell. Eng. Syst.*, vol. 18, no. 3, pp. 928–937, 2025, doi: 10.22266/ijies2025.0430.62.
- [52] H. Jia, Q. Wen, Y. Wang, and S. Mirjalili, “Catch fish optimization algorithm: a new human behavior algorithm for solving clustering problems,” *Cluster Comput.*, vol. 27, no. 9, pp. 13295–13332, 2024, doi: 10.1007/s10586-024-04618-w.
- [53] T. Hamadneh *et al.*, “Paper Publishing Based Optimization: A New Human-Based Metaheuristic Approach for Solving Optimization Tasks,” *Int. J. Intell. Eng. Syst.*, vol. 18, no. 2, pp. 504–519, 2025, doi: 10.22266/IJIES2025.0331.37.

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