Improved Pelican Optimization Algorithm Based on African Vulture Satiety Rate and Mathematical Distributions

Hao-Ming Song, Cheng Xing*, Jie-Sheng Wang, Xin-Yi Guan

Abstract—**This study proposes an improved Pelican Optimization Algorithm (POA) based on the satiation strategy of African vultures and mathematical distributions. Inspired by the African Vulture Optimization Algorithm (AVOA), we incorporate the satiation strategy of African vultures into the exploration and exploitation phases of POA to enhance population search capability and balance global exploration with local exploitation. Additionally, eight different mathematical distributions are embedded into the exploration phase of POA to improve the diversity and randomness of the search behavior, thereby preventing premature convergence to local optima. The experimental evaluation employs 30 benchmark functions from CEC-BC-2017 and 12 benchmark functions from CEC-BC-2022 to assess the performance of the improved POA based on the satiation strategy and its further enhancement incorporating mathematical distributions. The validation across these two benchmark sets demonstrates the effectiveness of the proposed improvements to POA.**

Index Terms—**Pelican optimization algorithm, African bald eagle satiety rate, Mathematical distribution, Function optimization**

I. Introduction

In recent years, nature-inspired metaheuristic algorithms have gained significant attention in solving complex optimization problems due to their adaptability, robustness, and high efficiency. These algorithms, inspired by biological, physical, and social phenomena, mimic natural processes to achieve an optimal balance between exploration and exploitation. Among them, swarm intelligence-based algorithms, such as Particle Swarm Optimization (PSO) [1], Grey Wolf Optimizer (GWO) [2], and Pelican Optimization Algorithm (POA) [3], have demonstrated remarkable performance in various optimization tasks.

Manuscript received March 24, 2025; revised June 2, 2025. This work was supported by the Basic Scientific Research Project of Institution of Higher Learning of Liaoning Province (Grant No. LJ222410146054), and Postgraduate Education Reform Project of Liaoning Province (Grant No. LNYJG2022137).

Hao-Ming Song is a Ph. D. student of School of Electronic and Information Engineering, University of Science and Technology Liaoning, Anshan, 114051, P. R. China (e-mail: shm@stu.ustl.edu.cn).

Cheng Xing is an associate professor in School of Electronic and Information Engineering, University of Science and Technology Liaoning, Anshan, 114051, P. R. China (Corresponding author, phone: 86-0412-2538246; fax: 86-0412-2538244; e-mail: xingcheng@ustl.edu.cn).

Jie-Sheng Wang is a professor of School of Electronic and Information Engineering, University of Science and Technology Liaoning, Anshan, 114051, P. R. China (e-mail: wjs@ustl.edu.cn).

Xin-Yi Guan is a postgraduate student at School of Electronic and Information Engineering, University of Science and Technology Liaoning, Anshan 114051, China (E-mail: gxy@stu.ustl.edu.cn).

The pursuit of improved search efficiency and optimization performance has driven extensive research in meta-heuristic algorithm development. Common enhancement strategies include adaptive mechanisms [4], chaotic mapping [5], dynamic weight adjustment [6] and hybrid search techniques [7], all aimed at achieving a balance between global exploration and local exploitation, accelerating convergence, and mitigating premature stagnation. Several advanced optimization algorithms have integrated these strategies to enhance performance. For instance, Ye et al. proposed the multi-strategy enhanced dung beetle optimization algorithm (MDBO), incorporating Latin hypercube sampling and a differential mechanism to improve search diversity and escape local optima [8]. Qian et al. introduced six spiral functions and two hybrid variants (SEB-CHOA) to address slow convergence [9], while Chaib et al. enhanced the Crayfish Optimization Algorithm (COA) using fractional chaotic maps and dimension learning-based search techniques [10]. Other notable contributions include the improved Atom Search Optimization (IASO) [11], the enhanced Whale Optimization Algorithm (IWOA) [12], and the Cauchy-Gaussian mutation-based Grey Wolf Optimization algorithm (CG-GWO) [13], all demonstrating significant performance improvements.

The Pelican Optimization Algorithm (POA) [3], a recently introduced bio-inspired metaheuristic based on pelican foraging behavior, has shown promising results in optimization tasks. However, POA still suffers from challenges such as premature convergence and an imbalance between exploration and exploitation. To address these limitations, various improvement strategies, including adaptive mechanisms, chaotic mapping, and biologically inspired modifications, have been explored to enhance its search efficiency and robustness [14].

Motivated by the success of the African Vulture Optimization Algorithm (AVOA) [15], which effectively utilizes the satiety strategy of African vultures to regulate search behavior, this study introduces an improved POA by integrating the African vulture satiety strategy and mathematical distributions. The satiety strategy enhances the exploration and exploitation phases of POA, improving population diversity and search efficiency. Additionally, eight different mathematical distributions are embedded in the exploration phase to increase search randomness and diversity, thereby preventing premature convergence to local optima.

To rigorously evaluate the effectiveness of the enhanced Pelican Optimization Algorithm (POA), extensive computational experiments were conducted using two widely recognized benchmark test suites: the CEC-BC-2017 [16] and CEC-BC-2022 [17] benchmark functions. Specifically, 30 benchmark functions from CEC-BC-2017 and 12 benchmark functions from CEC-BC-2022 were employed to assess the algorithm's performance across diverse optimization landscapes, including unimodal, multimodal and composite functions. These benchmark functions are designed to simulate real-world optimization challenges by incorporating features such as complex landscapes, deceptive local minima, and varying degrees of separability.

The experimental results demonstrate that the proposed enhancements significantly improve POA's optimization capability, effectively mitigating premature convergence while achieving a well-balanced trade-off between global exploration and local exploitation. Additionally, the modified algorithm exhibits accelerated convergence rates and enhanced solution accuracy, highlighting its robustness in solving both high-dimensional and complex optimization problems. These findings provide strong empirical evidence supporting the efficacy of the improved POA in comparison to its original counterpart, reinforcing its potential applicability to a wide range of optimization tasks.

II. Pelican Optimization Algorithm (POA)

Pelican Optimization Algorithm (POA) [3] is an emerging computational method inspired by the hunting behaviors of pelicans in the natural environment. Recent studies indicate that POA emulates the efficient strategies these birds employ when searching for and capturing prey, reflecting a unique dynamic balance between exploration and exploitation. This algorithm is designed to adaptively adjust these two critical components, thereby significantly enhancing its navigation capabilities in complex optimization landscapes.

The operational mechanism of POA simulates a group of pelicans foraging in their environment. In this model, each pelican represents a potential solution to the optimization problem, while the collective behavior of the group contributes to the identification of the optimal solution. A notable advantage of this algorithm is its ability to dynamically adjust search parameters based on the fitness of solutions, establishing a robust search mechanism that effectively avoids local optima while converging toward global optimality.

Compared to traditional optimization algorithms, the Pelican Optimization Algorithm (POA) exhibits significant advantages in both efficiency and solution quality, demonstrating competitive performance across various optimization tasks and attracting considerable research interest. Its innovative framework enriches the field of swarm intelligence and paves the way for its application and further development in diverse domains such as engineering, data analysis, and machine learning.

A. Population Initialization

During the population initialization phase, POA generates an initial set of solutions randomly distributed within the search space. The process is mathematically represented as follows:

$$x_{i,j} = l_j + rand \cdot (u_j - l_j), i = 1,2,\cdots,N, j = 1, 2,\cdots,m \quad (1)$$

In POA, the pelican population is represented by the following matrix of individuals:

$$X = \begin{bmatrix} X_1 \\ \vdots \\ X_i \\ \vdots \\ X_N \end{bmatrix}_{N\times m} = \begin{bmatrix} x_{1,1} \cdots x_{1,j} \cdots x_{1,m} \\ \vdots \quad \ddots \quad \vdots \\ x_{i,1} \cdots x_{i,j} \cdots x_{i,m} \\ \vdots \quad\quad \vdots \quad \ddots \\ x_{N,1} \cdots x_{N,j} \ \cdots x_{N,m} \end{bmatrix}_{N\times m} \quad (2)$$

where, X denotes the population matrix of pelicans, with X_i representing the i-th pelican.

The objective function values for the pelican population are expressed through the objective function vector, as shown in Eq. (3).

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

where, F represents the objective function vector for the pelican population, with F_i denoting the objective function value of the i-th pelican.

B. Phase 1: Approaching Prey

In the exploration phase, pelicans identify the location of their prey and subsequently move towards it. The movement towards the prey position is modeled by Eq. (4).

$$x_{i,j}^{p1} = \begin{cases} x_{i,j} + rand \cdot (p_j - I \cdot x_{i,j}) & F_p < F_j \\ x_{i,j} + rand \cdot (x_{i,j} - p_j) & else \end{cases} \quad (4)$$

where, $x_{i,j}^{P1}$ is the new state of the i-th pelican in the j-th dimension based on the first stage. I is a random number equal to 1 or 2.

In POA, if the objective function value at a given position improves, the pelican's new position is accepted for a valid update. This update process is represented by Eq. (5).

$$X_{\text{i}} = \begin{cases} X_i^{P1} & F_i^{P1} < F_j \\ X_{\text{i}} & else \end{cases} \quad (5)$$

where, F_i^{P1} is the objective function value based on the new position X_i^{P1} of the i-th pelican after the update in the first stage.

C. Phase II: Surface Flight

In the developmental phase, the hunting behavior of pelicans is modeled to enhance the local search and exploitation capabilities of the POA. The mathematical representation of this process is given by Eq. (6), where (R = 0.2).

$$x_{i,j}^{p2} = x_{i,j} + R \cdot \left(1 - \frac{t}{T}\right) \cdot (2 \cdot rand - 1) \cdot x_{i,j} \quad (6)$$

At this stage, valid updates are employed to either accept or reject the new pelican positions, as described by Eq. (7).

$$X_{\text{i}} = \begin{cases} X_i^{P2} & F_i^{P2} < F_j \\ X_{\text{i}} & else \end{cases} \quad (7)$$

where, X_i^{P2} is the new position of the i-th pelican.

III. POA Based on African Vulture Satiety Rate Strategy and Mathematical Distribution

A. African Vulture Satiety Rate Strategy

In this study, the satiety rate strategy of the African vulture from AVOA was incorporated into the optimization process of the pelican optimization algorithm, leading to the development of a new variant, the Adaptive Pelican Optimization Algorithm (APOA).

To align with the proposed enhancement, the original African vulture satiety rate formula was modified. The updated formula and its variation with the number of iterations are presented as follows:

$$a = h \times \left(sin^2(\frac{\pi}{2} \times \frac{it}{maxit}) + cos\left(\frac{\pi}{2} \times \frac{it}{maxit}\right) - 1 \right) \quad (8)$$

$$A = (2 \times rand) \times z \times (1 - \frac{it}{maxit}) + a \quad (9)$$

where, A represents the satiety rate of African vultures, t denotes the current iteration number, and $maxitt$ is the maximum number of iterations.

The variables z and h are randomly generated within the ranges [-1,1] and [-2,2], respectively, while rand is a random number between 0 and 1. When the absolute value of A exceeds or equals 0.5, it is incorporated into the exploration phase of POA, enhancing the balance between exploration and exploitation. After normalization, the formulation is given as follows:

$$x_{i,j}^{p1} = \begin{cases} x_{i,j} + rand \cdot \left(p_j - (A + 0.5) \cdot x_{i,j}\right), & F_p < F_j \\ x_{i,j} + rand \cdot \left(x_{i,j} - p_j\right) & else \end{cases} \quad (10)$$

When the absolute value of vulture satiety rate A is less than 0.5, it is introduced into the development stage of POA. The value (1-t/T) in the original algorithm decreases with the increase of iteration times. In this paper, the (1-t/T) parameter is changed to nonlinear decrease and random disturbance caused by vulture satiety is added in the decreasing process, so it balances the exploration and development of the algorithm and speeds up the convergence speed. The improved formula after normalization is as follows:

$$x_{i,j}^{p2} = x_{i,j} + R \cdot 2 \cdot |A| \cdot (2 \cdot rand - 1) \cdot x_{i,j} \quad (11)$$

B. POA Based on Mathematical Distribution

The application of mathematical distribution is extensive across various domains, with the uniform distribution being a prevalent type that has been extensively researched and analyzed by numerous academics. Beyond the uniform distribution, there exists a plethora of other mathematical distribution forms. This study focuses on a selection of well-known and frequently utilized distributions to enhance APOA further.

The distribution of these mathematical distributions within the range (0,1) is depicted in Fig. 2. TABLE I provides the specific expressions for these distributions. These distributions were employed as substitutes for the random distribution in the position update equation during the exploration phase. The modified equation is presented below. Eq. (12) represents the position update equation post the incorporation of mathematical distribution; Eq. (13) signifies the position update equation post the integration of the African vulture satiety rate and mathematical distribution.

$$x_{i,j}^{p1} = \begin{cases} x_{i,j} + M \cdot \left(p_j - I \cdot x_{i,j}\right), & F_p < F_j \\ x_{i,j} + M \cdot \left(x_{i,j} - p_j\right) & else \end{cases} \quad (12)$$

$$x_{i,j}^{p1} = \begin{cases} x_{i,j} + M \cdot \left(p_j - (A + 0.5) \cdot x_{i,j}\right), & F_p < F_j \\ x_{i,j} + M \cdot \left(x_{i,j} - p_j\right) & else \end{cases} \quad (13)$$

where, M represents different mathematical distributions.

The POA flow chart based on African vulture satiety rate and Mathematical Distribution (AMPOA) is shown in Fig. 3.

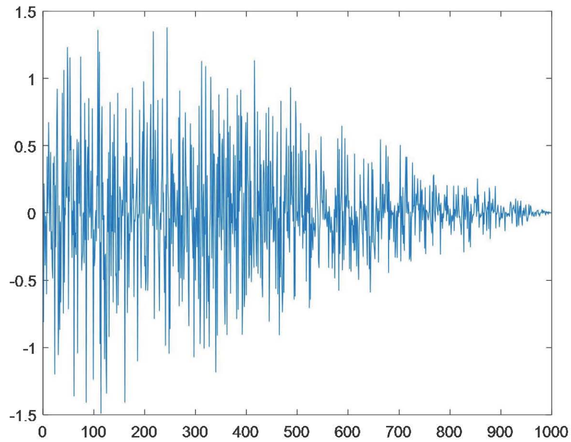
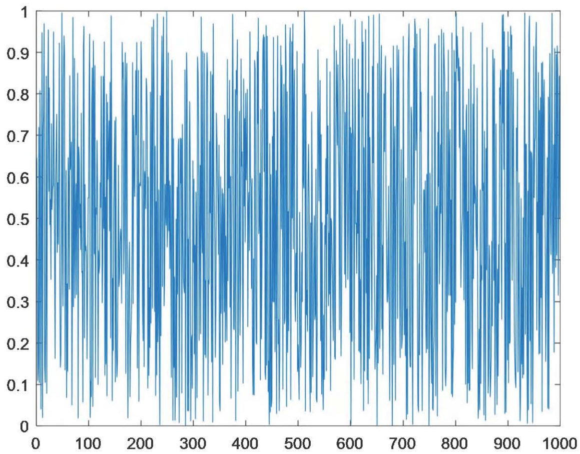
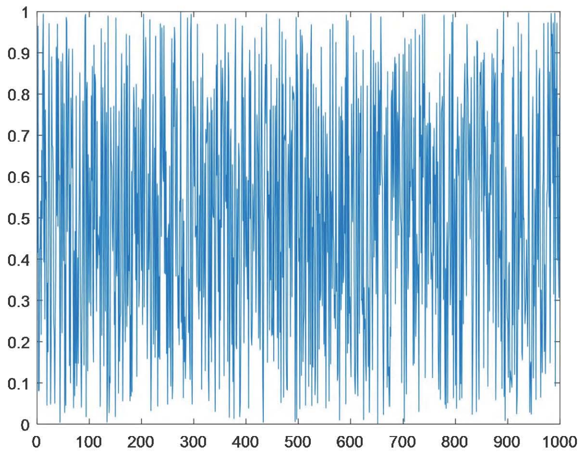


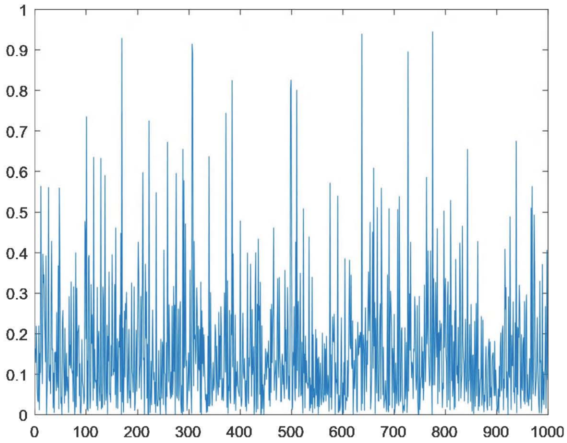
Fig. 1 African Vulture Satiety Rate trend with the number of iterations.



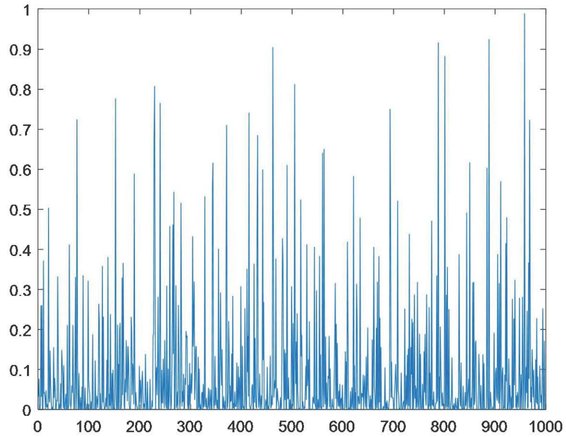
(a) Rand Distribution



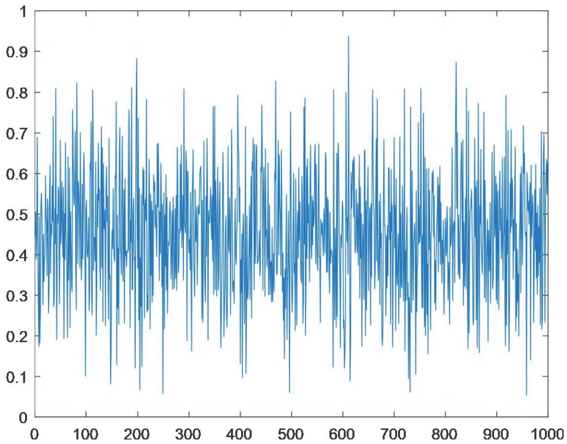
(b) Beta Distribution



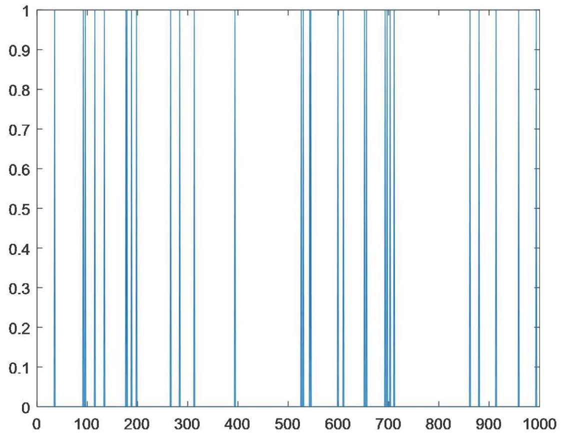
(c) Exponential Distribution



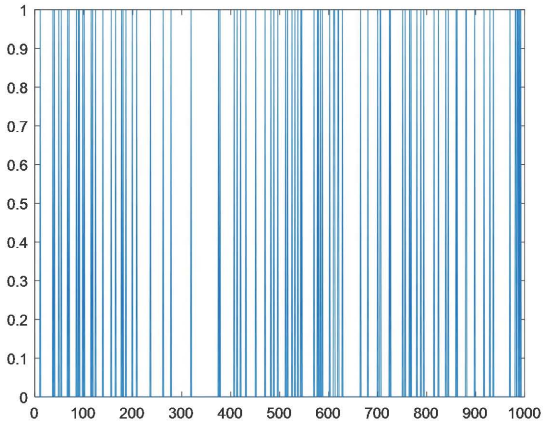
(d) Gamma Distribution



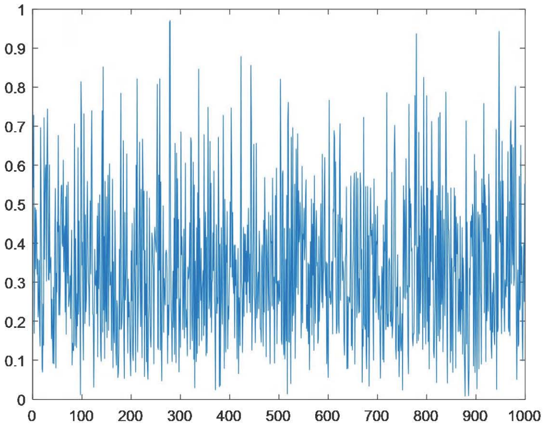
(e) Gaussian Distribution



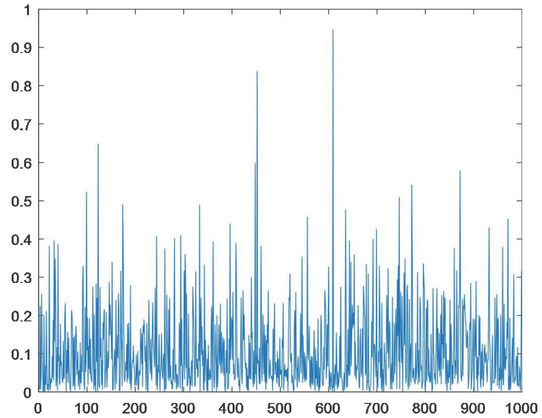
(f) Geometric Distribution



(g) Poisson Distribution



(h) Rayleigh Distribution



(i) Weber Distribution

Fig. 2 Different mathematical distributions between (0, 1).

TABLE I. EXPRESSION OF MATHEMATICAL DISTRIBUTION

Name	Expression
Beta	$f(x) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} x^{\alpha-1}(1-x)^{\beta-1}$
Exponential	$f(x) = \lambda e^{-\lambda x}$
Gamma	$f(x) = \frac{\beta^{\alpha} x^{\alpha-1} e^{-\beta x}}{\Gamma(\alpha)}$
Gaussian	$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$
Geometric	$f(x) = (1-p)^{k-1} p$
Poisson	$f(x) = \frac{\lambda^k}{k!} e^{-\lambda}$
Rayleigh	$f(x) = \frac{x}{\sigma^2} e^{-\frac{x^2}{2\sigma^2}}$
Weber	$f(x) = \frac{k}{\lambda} (\frac{x}{\lambda})^{k-1} e^{-(\frac{x}{\lambda})^k}$

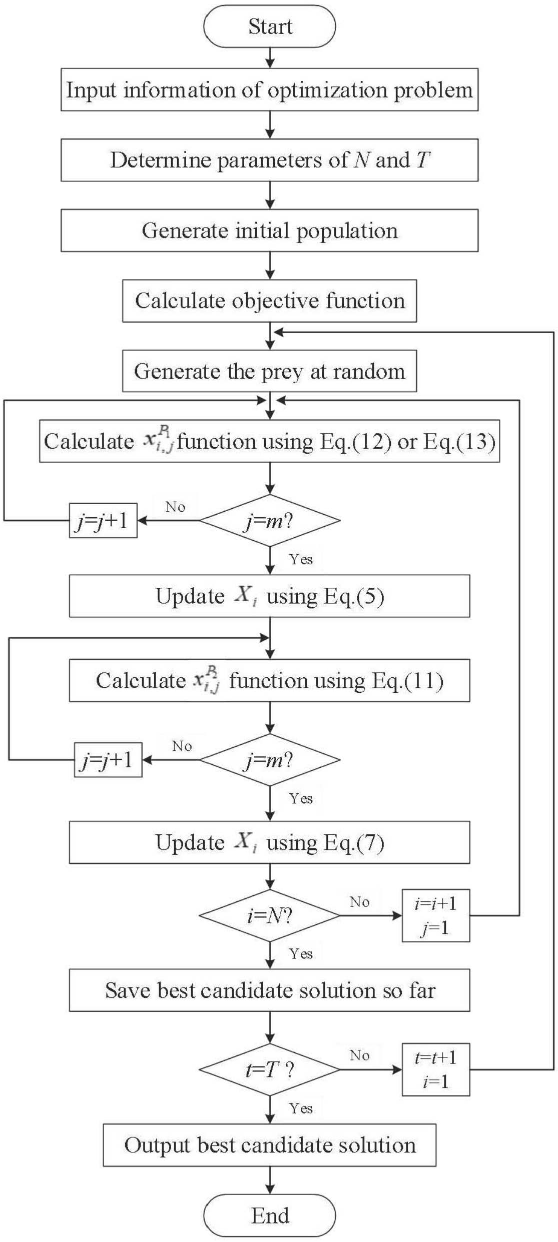


Fig.3 Flow chart of AMPOA.

IV. Simulation Experiments and Result Analysis

This section evaluates the proposed enhanced algorithm through two comparative experiments. First, the improved POA is tested on 30 benchmark functions from the CEC-BC-2017 test suite, followed by validation on 12 benchmark functions from the CEC-BC-2022 test suite. Section A presents the results for CEC-BC-2017, while Section B analyzes the outcomes for CEC-BC-2022.

A. Improved POA to Solve CEC-BC-2017 Test Functions

To demonstrate the superiority of the POA after incorporating the African condor satiety rate and mathematical distribution, we utilized 30 benchmark functions from the CEC-BC-2017 test suite [16]. All test functions had a dimension of 30, with a maximum iteration limit of 1000 and a population size of 30. The function range for all tests was set to [-100, 100]. The selected functions cover four categories: unimodal, multimodal, mixed and compound functions.

To rigorously assess the performance of the improved Pelican Optimization Algorithm (POA) incorporating the African condor satiety rate and mathematical distributions, a comprehensive set of comparative experiments was conducted. The objective was to evaluate the effectiveness of the proposed modifications relative to both the standard POA and a variant that solely integrated the African condor's satiety rate. The experimental setup involved testing each algorithm on a set of benchmark functions, where each function was configured with a dimensionality of 30. A maximum of 1000 iterations per run was allowed, and each algorithm underwent 30 independent runs to ensure statistical reliability. The optimal solution obtained in each run was recorded, and statistical analyses were subsequently performed to facilitate a rigorous comparative evaluation of the different POA variants. To ensure an objective and comprehensive assessment, performance comparisons were primarily based on two key statistical metrics: the mean and variance of the obtained solutions. These statistical indicators provide insights into both the stability and efficiency of the optimization process. The detailed statistical outcomes are summarized in Table II, while Fig. 4 illustrates the convergence behavior of the different algorithms. The empirical results clearly demonstrate that the enhanced POA exhibits superior convergence characteristics across the majority of test functions, highlighting its robustness in solving complex optimization problems.

Through an in-depth analysis of the data from the simulation charts and tables, several key observations can be made. First and foremost, the adaptive POA (APOA) incorporating the African condor's satiety rate consistently outperforms the standard POA across all tested benchmark functions. Furthermore, when mathematical distributions are integrated into APOA, an additional performance boost is observed, affirming the efficacy of these enhancements in improving the algorithm's optimization capabilities.

Among all APOA variants incorporating mathematical distributions, the version utilizing the Gamma distribution emerges as the most effective. This variant consistently achieves superior results in terms of mean and variance, yielding the lowest values across optimization functions 4, 13, 14, 18, 25 and 30. Additionally, in terms of mean values, it also demonstrates the best performance for test functions 1, 2, 7, 15, 19 and 26. These findings provide compelling evidence of its strong competitiveness and superior optimization efficiency. The effectiveness of the Gamma distribution in balancing exploration and exploitation contributes significantly to the algorithm's ability to achieve faster convergence while maintaining solution accuracy. The APOA variant enhanced with the Exponential distribution also demonstrates commendable overall performance. Although its effectiveness does not surpass that of the Gamma-enhanced variant, it consistently ranks highly across multiple benchmark functions. Notably, this variant achieves the smallest mean and variance in optimization function 28, as well as the smallest mean value in function 22. These results indicate that the Exponential distribution plays a vital role in maintaining stability and achieving efficient convergence. In the second performance tier, the APOA variants incorporating the Rayleigh and Weber distributions exhibit notable improvements over the standard POA. These two modifications contribute to enhanced convergence precision and acceleration. Specifically, the Rayleigh-enhanced APOA attains the smallest mean values in optimization functions 3 and 23, while the Weber-enhanced variant achieves the lowest mean and variance in functions 11 and 12. Although these two variants do not reach the optimization level of the Gamma-enhanced APOA, they nonetheless provide significant performance gains, reinforcing the utility of mathematical distributions in further refining optimization algorithms. The third tier of improvements includes APOA variants integrating Gaussian and Poisson distributions. Although these variants offer better convergence performance compared to the standard POA, their overall effectiveness is relatively inferior to that of the higher-ranked distribution-based enhancements. The Gaussian-enhanced APOA achieves the smallest mean values in optimization functions 5, 16, 24 and 29, while the Poisson-enhanced variant attains the lowest mean value for function 20. While these results suggest moderate improvements, the Gaussian and Poisson distributions appear to be less effective in significantly enhancing the optimization process when compared to the Gamma, Exponential, Rayleigh, and Weber distributions. The final tier consists of APOA variants incorporating Beta and Geometric distributions. While these variants still exhibit superior performance compared to the original POA and the standard APOA, their overall optimization effectiveness remains limited when compared to the other mathematical distribution-based enhancements. In particular, for test functions such as 8 and 21, their performance is even worse than that of the original POA. These results suggest that Beta and Geometric distributions may not be optimal for enhancing the search and convergence capabilities of APOA.

The data presented in Table II unequivocally demonstrate that the incorporation of the African condor satiety rate, combined with mathematical distributions, significantly enhances the optimization performance of the improved POA compared to the original algorithm. This validates the effectiveness and feasibility of the proposed enhancement strategies. Furthermore, among all tested variants, the combination of the African condor satiety rate with the Gamma distribution yields the best overall performance. Given its demonstrated superiority in achieving both enhanced convergence speed and solution accuracy, the AMPOA (Adaptive POA with Gamma Distribution) variant was selected for further experimentation, as it exhibits the most promising potential for solving complex optimization problems efficiently.

B. Improved POA to Solve CEC-BC-2022 Test Functions

To validate the enhanced POA's effectiveness, we assess its performance on 12 benchmark functions from the CEC-BC-2022 test suite [17], a widely used framework for evaluating optimization algorithms. These functions are categorized into unimodal, multimodal, hybrid and composition functions, providing a comprehensive performance assessment. To further substantiate the advantages of incorporating the enhanced Pelican Optimization Algorithm (POA) with the African vultures satiety rate and mathematical distribution, a series of rigorous experiments were conducted using 12 benchmark functions from the CEC-BC-2022 test suite, each with a dimensionality of 20. In each experiment, the maximum iteration limit was set to 1000 generations, with each algorithm being run 30 independent times to obtain reliable and consistent results. The primary objective of these experiments was to capture the optimal solutions achieved by each algorithm and to perform a detailed statistical analysis for a robust comparison. Specifically, we compared the original POA, the Adaptive Pelican Optimization Algorithm (APOA) with the African vultures satiety rate, and the APOA variants based on mathematical distributions. To ensure a thorough and objective evaluation, mathematical statistics were applied to the experimental results, and the analysis focused on key metrics such as the mean values and variances. This allowed for a comprehensive understanding of the relative performance of the algorithms across all test functions. The results are summarized in Table III, and the convergence behavior of each algorithm is visually represented in Fig. 5, providing a clear comparison of the optimization processes.

In order to compare the differences between different algorithms more intuitively, the stacked graph (Figure 6) is introduced to show the average fitness value ranking of each algorithm in all test functions. Each algorithm corresponds to a graph, and the smaller the area in the graph represents the greater the overall effect. From Fig. 6, it can be seen that the improved POA has better convergence performance, especially for most of the test functions. Notably, the APOA variant based on the satiation rate of African vultures consistently outperforms the original POA across all 12 tested functions, reinforcing the proposed enhancement. In addition, the APOA variant combined with the mathematical distribution method shows more significant improvement, which further validates the effectiveness of the satiety rate combined with the mathematical distribution strategy

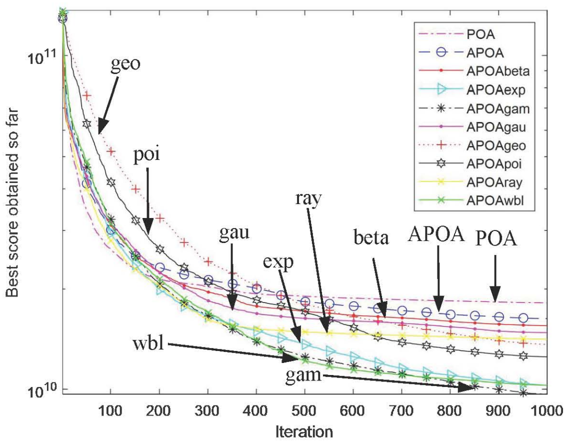
Among all APOA variants incorporating mathematical distributions, the version that integrates the Rayleigh distribution emerged as the most effective enhancement. It not only demonstrated the best performance in terms of both mean and variance but also achieved the minimum values for all three key metrics in test function 12. This variant also delivered superior results in test functions 4, 5 and 7, proving its robustness across a wide range of optimization tasks. The APOA variant incorporating exponential distribution showed commendable performance, achieving the minimum optimal values for functions 1, 4 and 7, and the smallest mean values for functions 2 and 8. While it did not surpass the Rayleigh distribution variant in overall performance, it still demonstrated a competitive edge. The second tier of improvements involved variants that integrated Gaussian and Gamma distributions.

Both of these variants achieved more precise convergence and faster convergence speeds compared to the original POA. While the Gaussian distribution variant did not outperform the other variants in every test function, it consistently ranked highly, reflecting its good stability across all benchmarks. The Gamma distribution variant was particularly notable for achieving the minimum mean and variance values in optimization functions 1 and 6, highlighting its potential in specific optimization scenarios. The third tier comprised variants that incorporated Poisson and Weibull distributions. While these variants showed relatively stable performance, they generally ranked in the middle of the overall performance spectrum. The Poisson distribution variant only achieved the minimum mean value in optimization function 11, whereas the Weibull distribution variant excelled in optimization function 9, obtaining both the minimum mean and optimal values. Despite these improvements, the Poisson and Weibull variants were outperformed by several other distributions in terms of overall effectiveness.

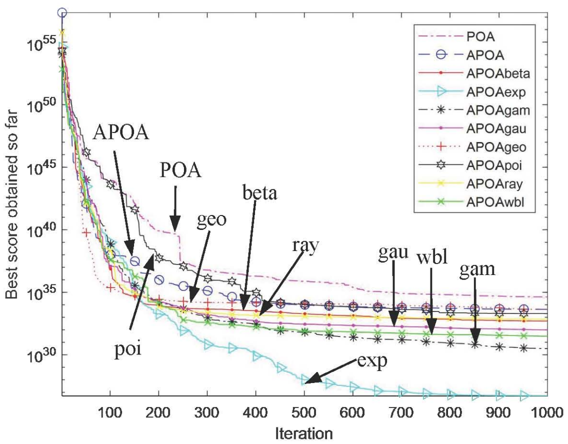
In conclusion, the data presented in Table III clearly demonstrate that integrating mathematical distributions into the POA, particularly when paired with the African vultures satiety rate, results in a substantial improvement in optimization performance. The Rayleigh distribution-based APOA variant outperformed all other algorithms, showcasing the best balance between exploration and exploitation, and proving the feasibility and effectiveness of the proposed improvement methods. Based on these findings, the Rayleigh distribution-based APOA variant was selected for further experiments, confirming its potential as the most effective approach for solving complex optimization problems.

C. Time Complexity Analysis of RAMBPOA

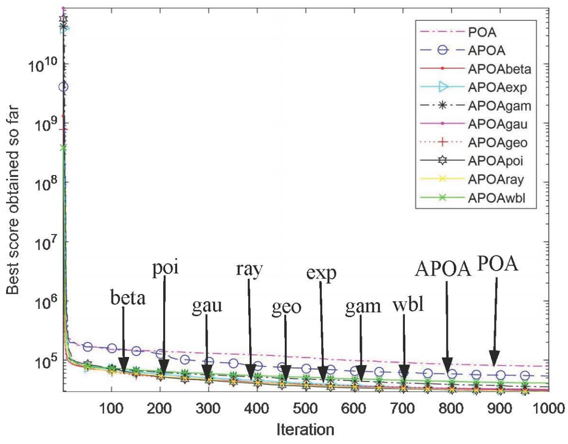
In the RAMBPOA, the overall time complexity consists of two main parts: the initialization phase and the iterative optimization phase. The initialization phase involves generating and binarizing an $N \times d$ population matrix and evaluating the fitness of each individual once, for a cost of $O(Nd + Nt)$. The optimization phase then runs for T iterations; each iteration scans the population to find the current best solution in $O(N)$ and updates every individual through feature selection, exploration, and exploitation steps.



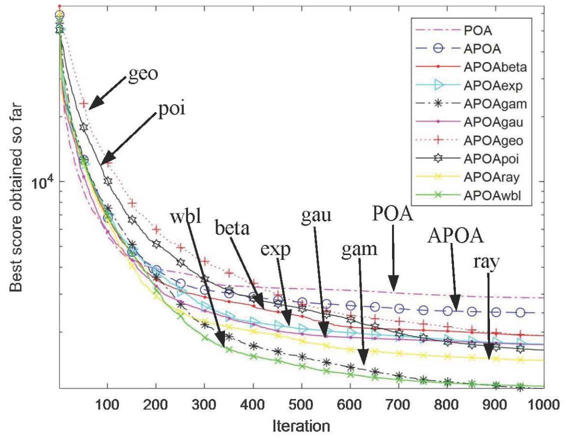
(1) f_1



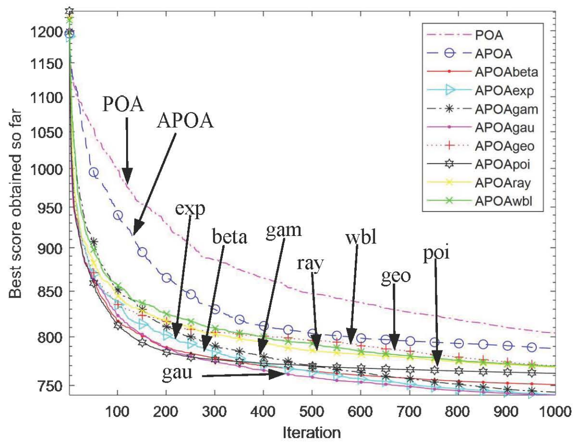
(2) f_2



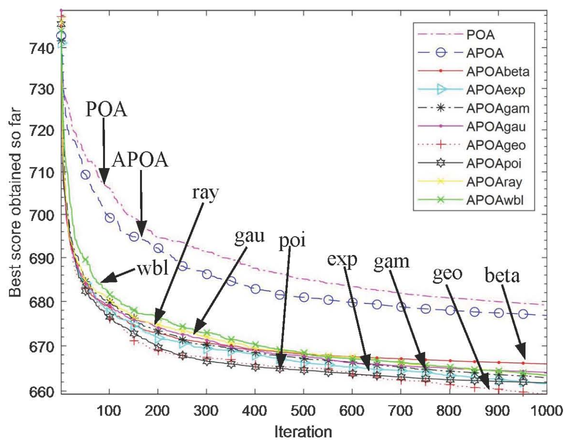
(3) f_3



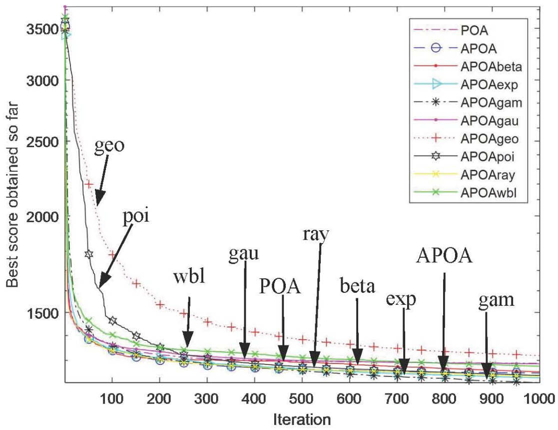
(4) f_4



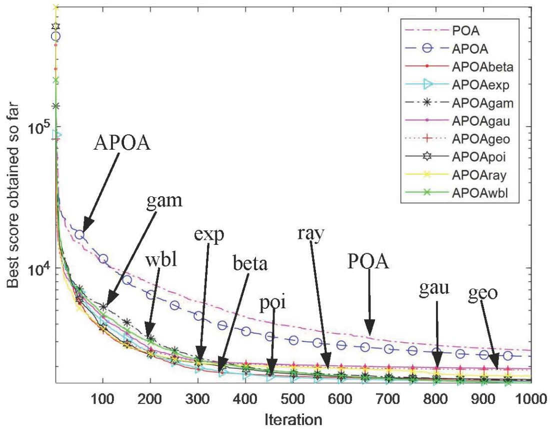
(5) f_5



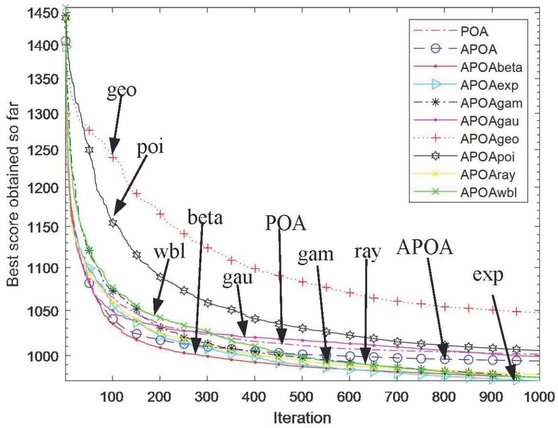
(6) f_6



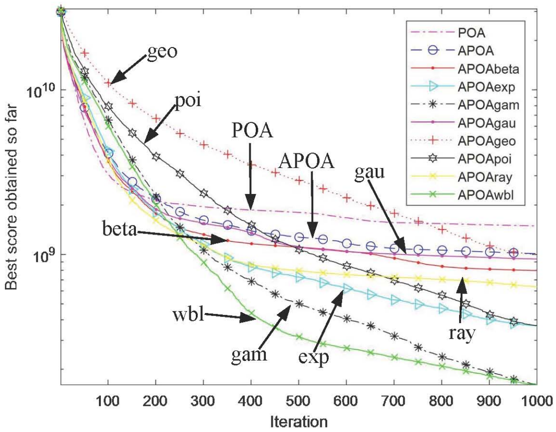
(7) f_7



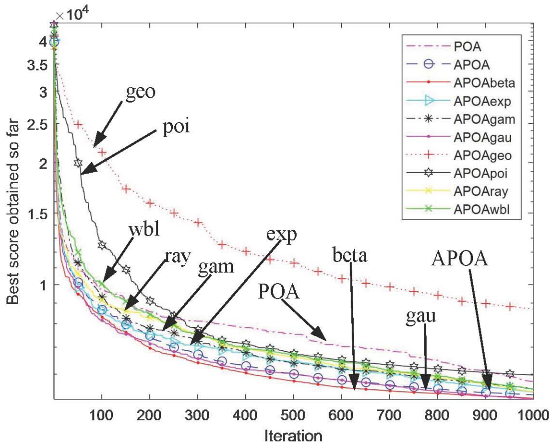
(11) f_{11}



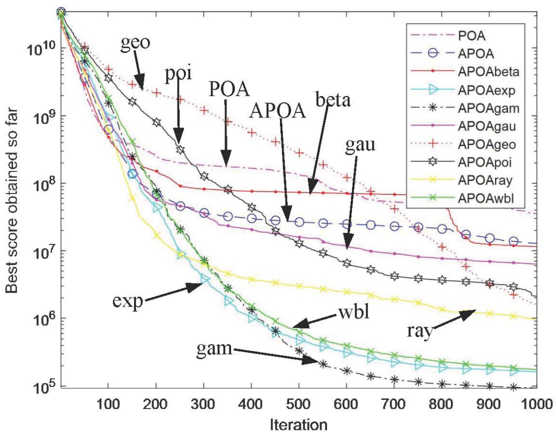
(8) f_8



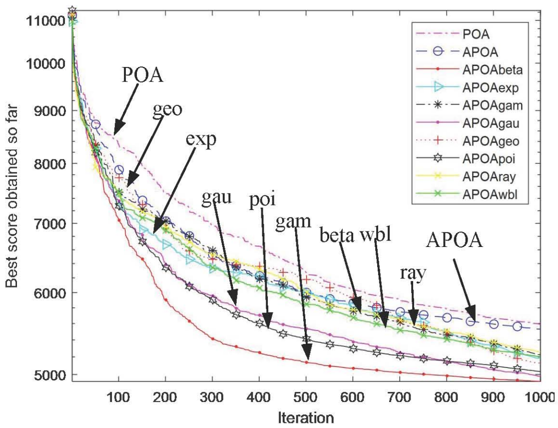
(12) f_{12}



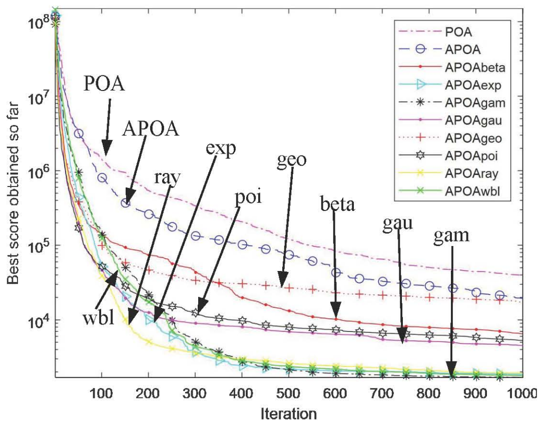
(9) f_9



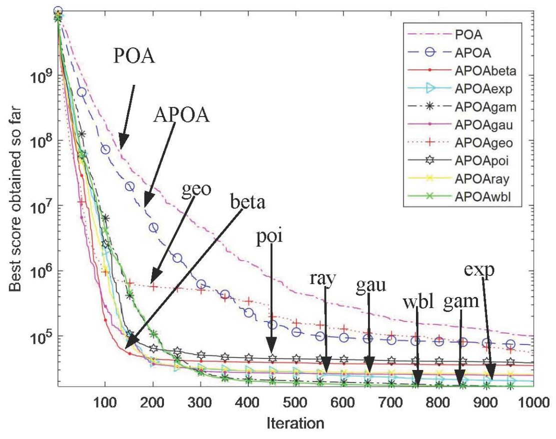
(13) f_{13}



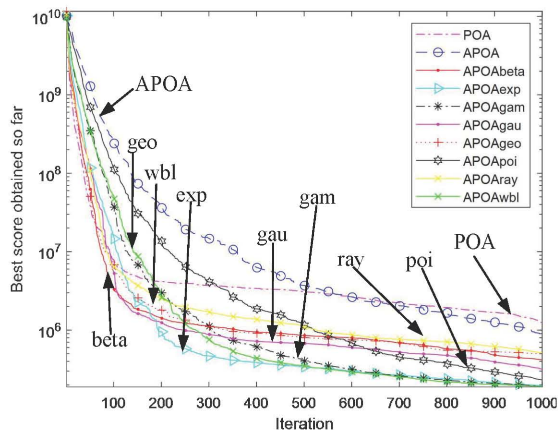
(10) f_{10}



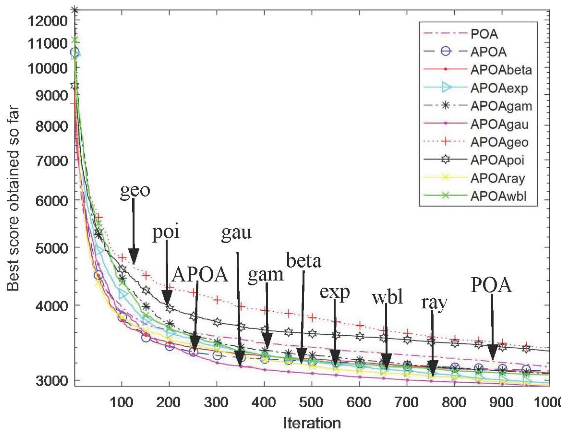
(14) f_{14}



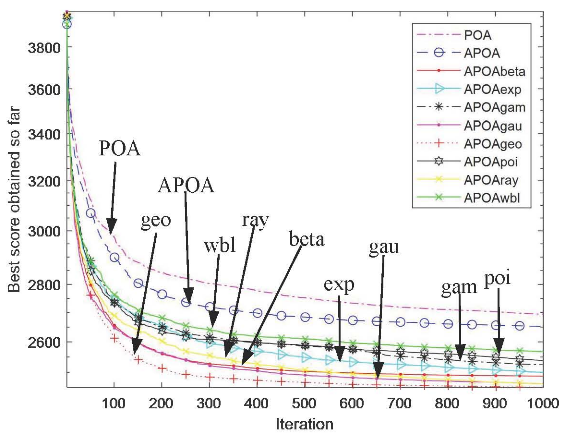
(15) f_{15}



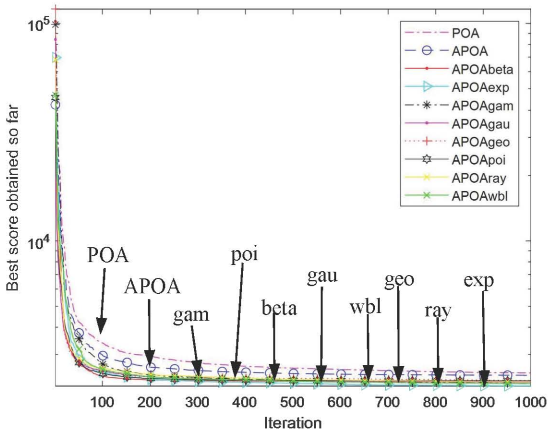
(19) f_{19}



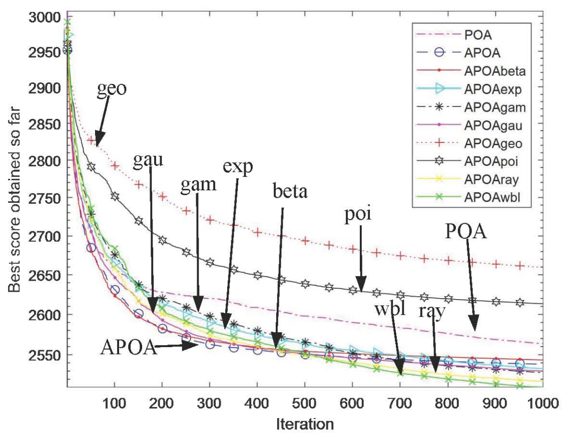
(16) f_{16}



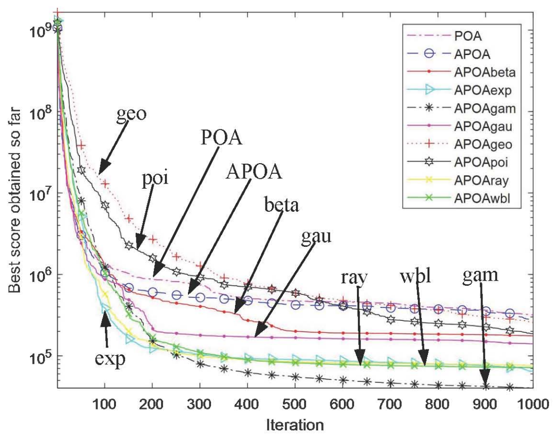
(20) f_{20}



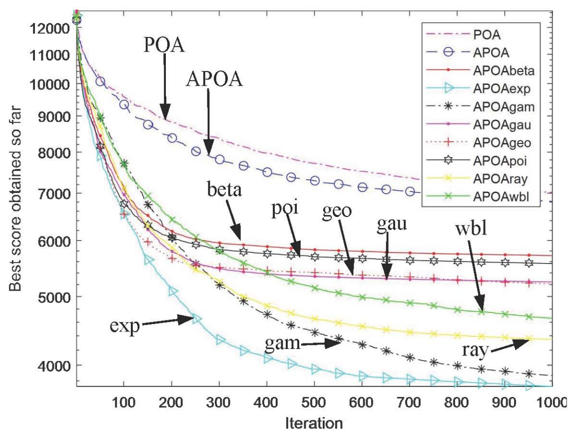
(17) f_{17}



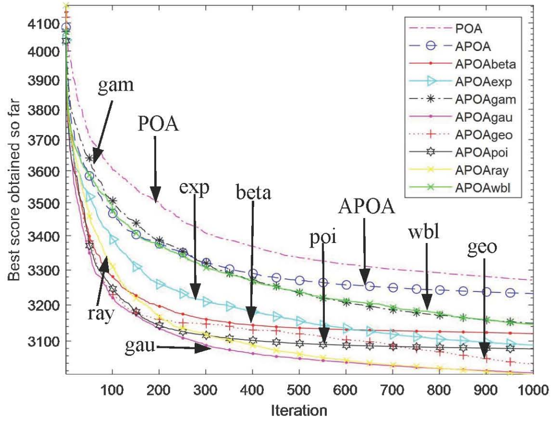
(21) f_{21}



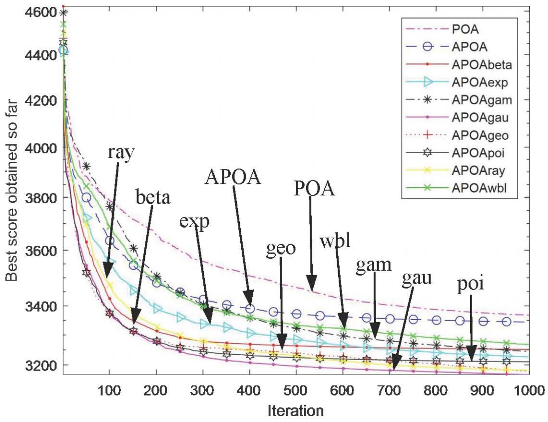
(18) f_{18}



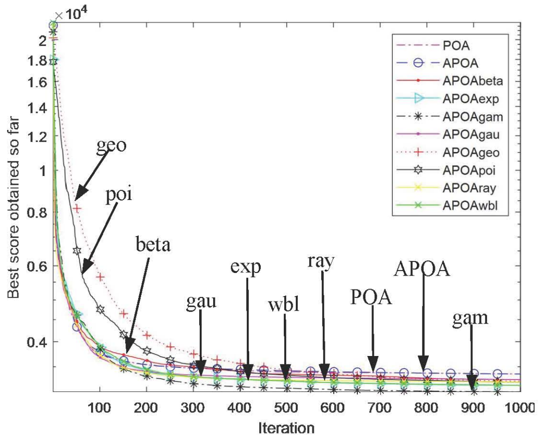
(22) f_{22}



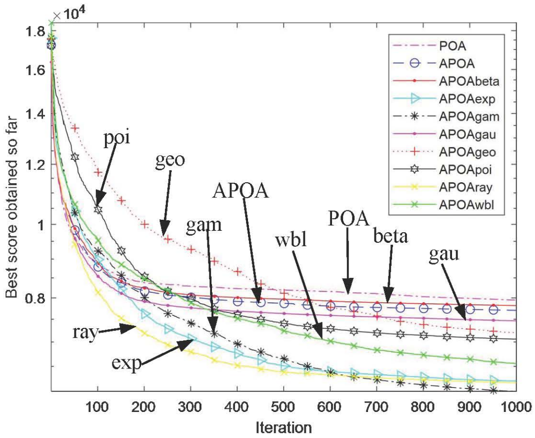
(23) f_{23}



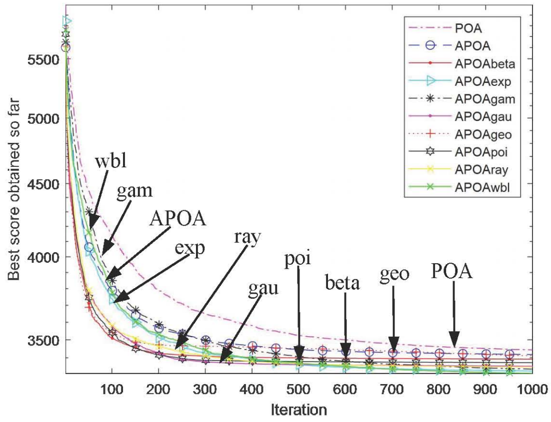
(24) f_{24}



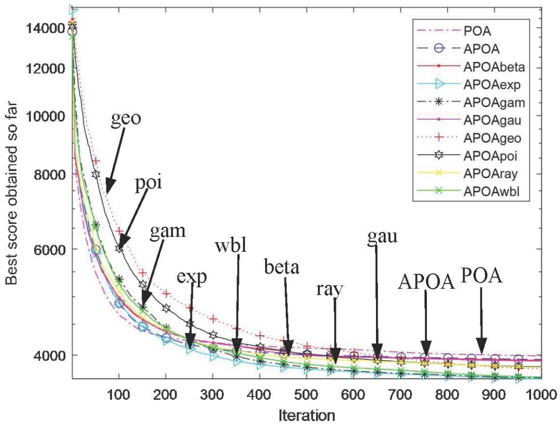
(25) f_{25}



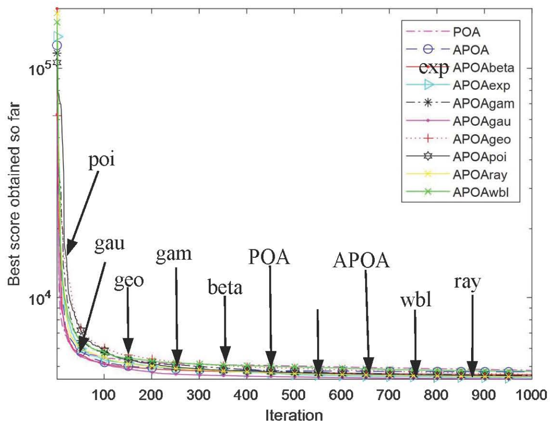
(26) f_{26}



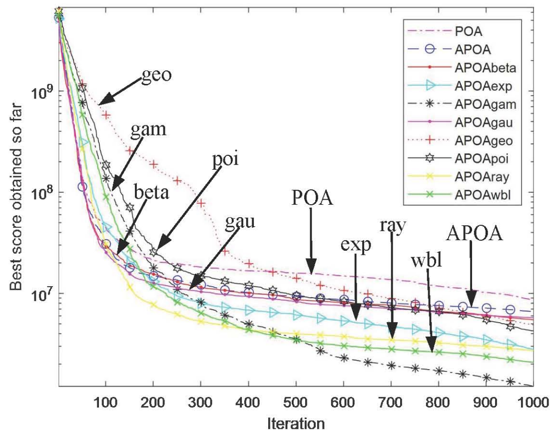
(27) f_{27}



(28) f_{28}

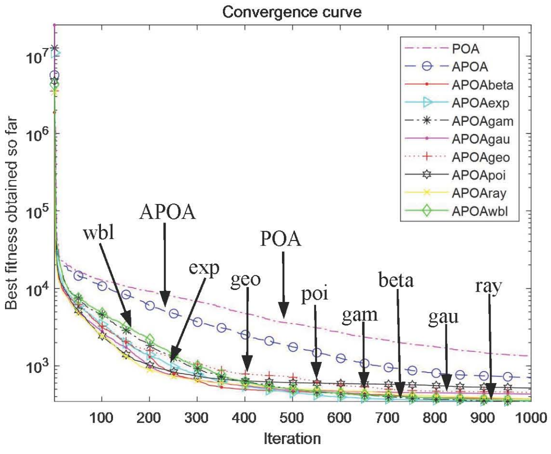


(29) f_{29}

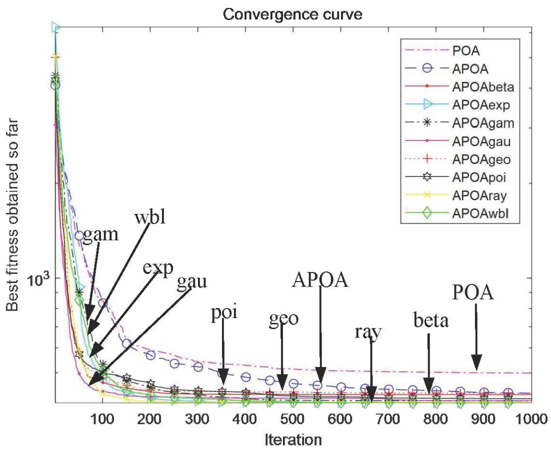


(30) f_{30}

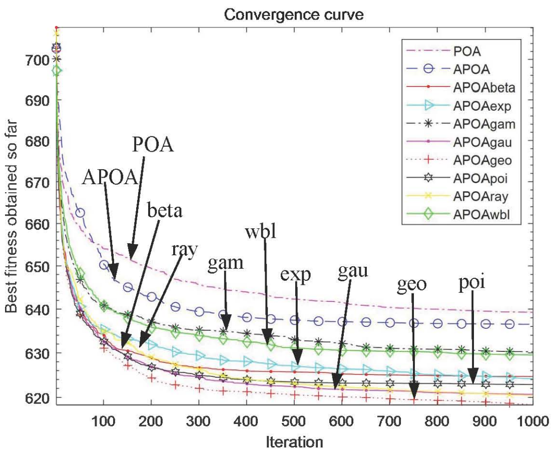
Fig. 4 Convergence curves of POA variants to solve the CEC-2017.



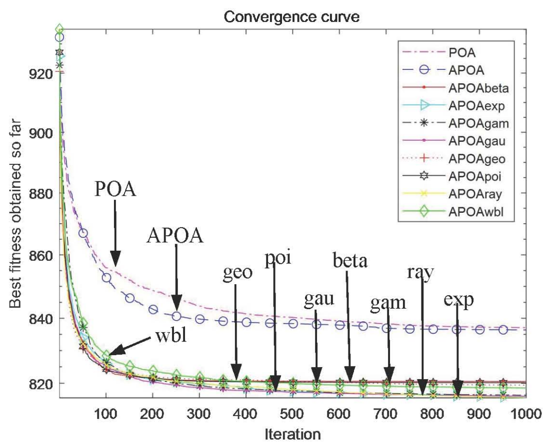
(1) f_1



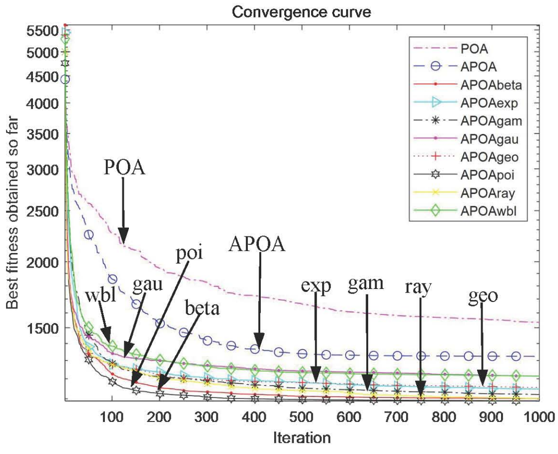
(2) f_2



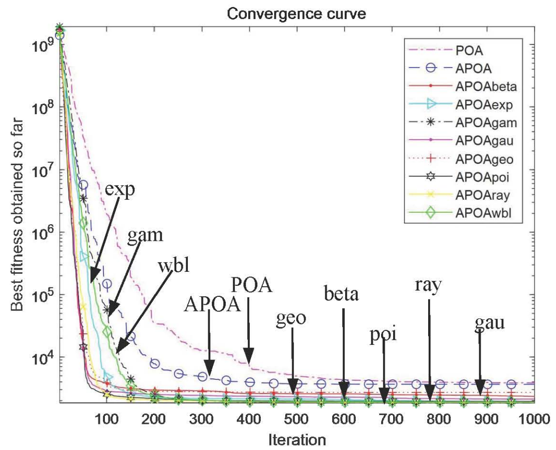
(3) f_3



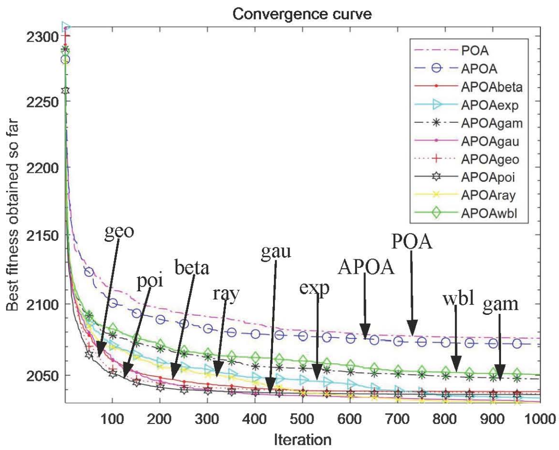
(4) f_4



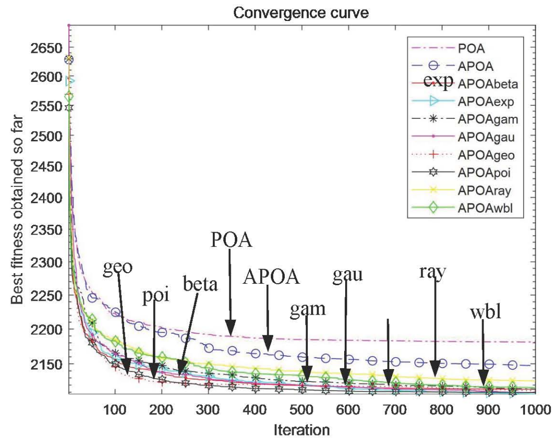
(5) f_5



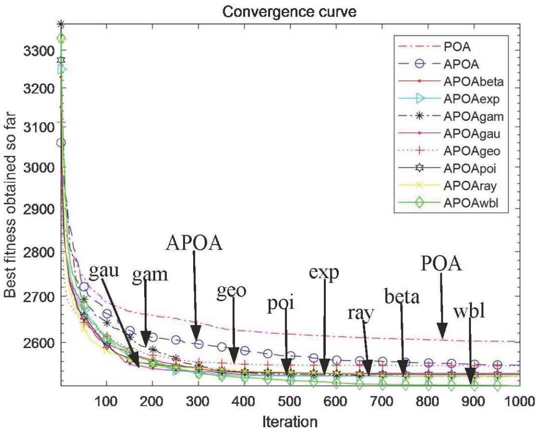
(6) f_6



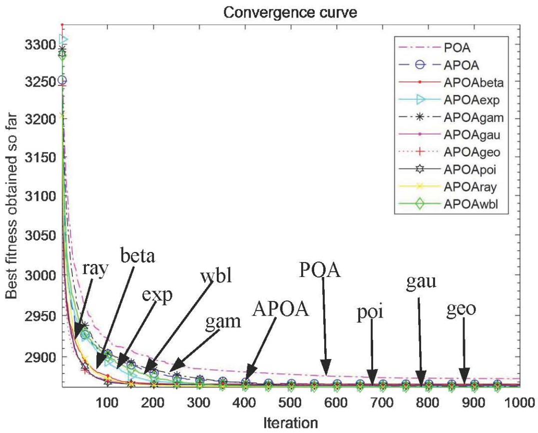
(7) f_7



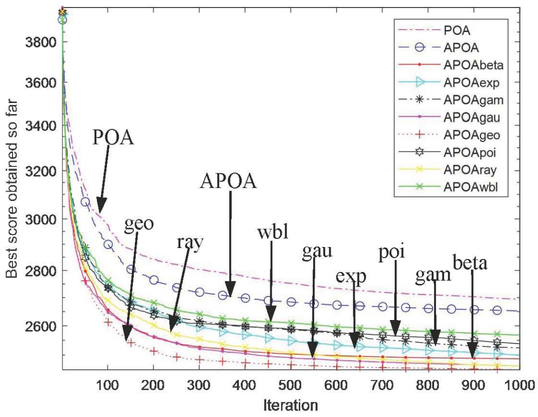
(8) f_8



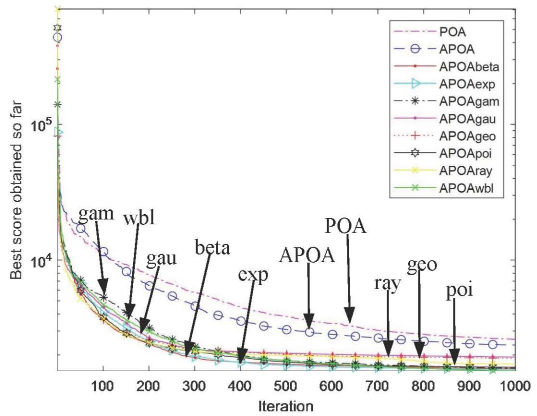
(9) f_9



(10) f_{10}

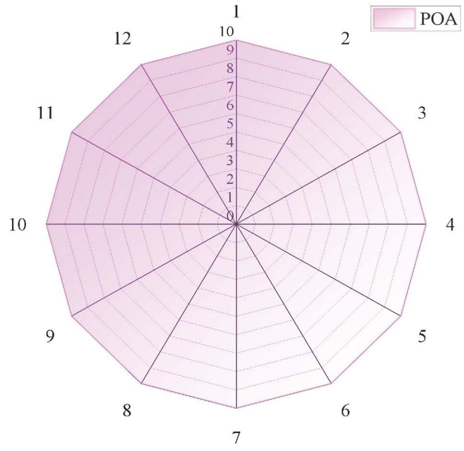


(11) f_{11}

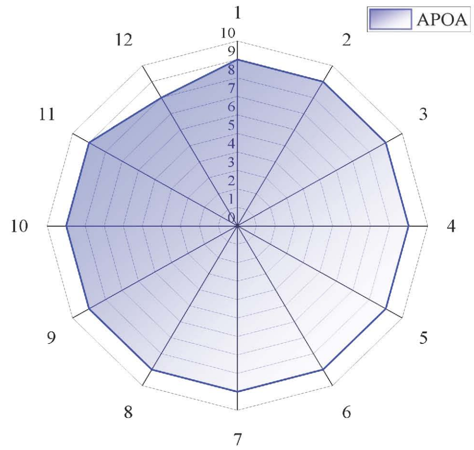


(12) f_{12}

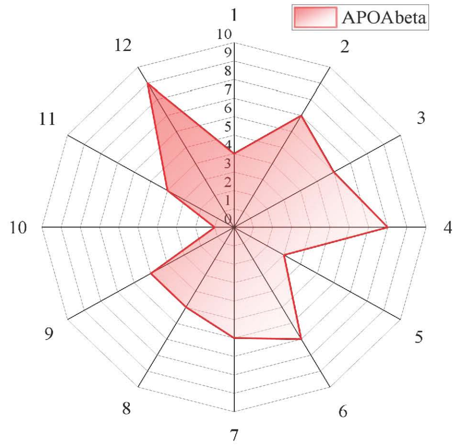
Fig. 5 The convergence curves of adaptive POA based on mathematical distribution to solve the CEC-2022 functions.



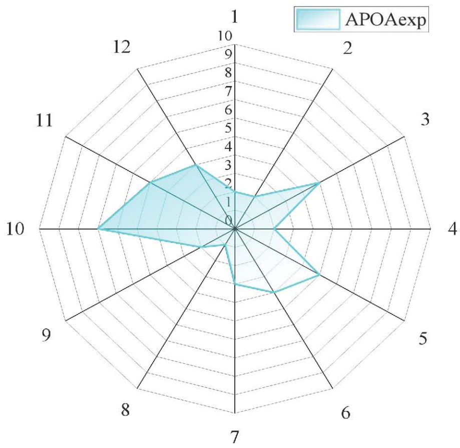
(1) POA



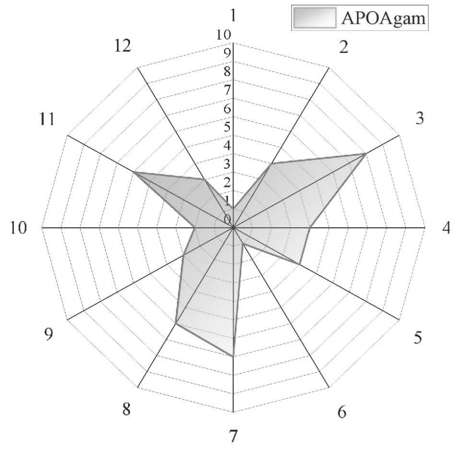
(2) APOA



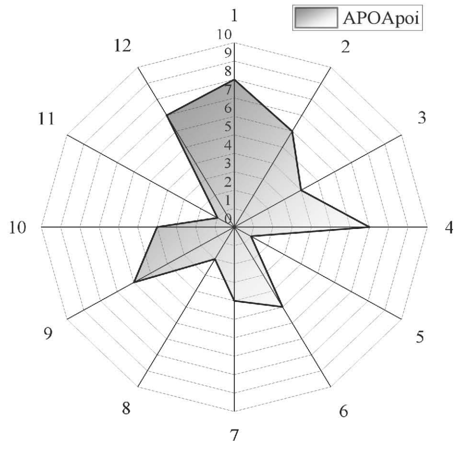
(3) APOA-beta



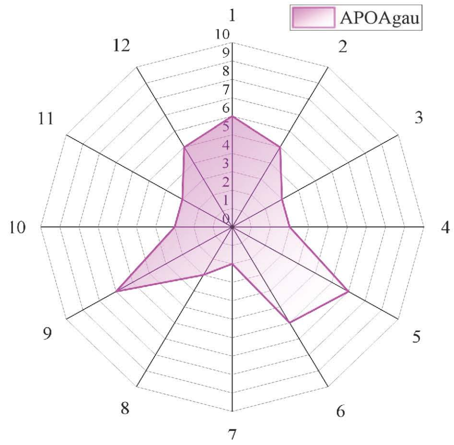
(4) APOA-exponential



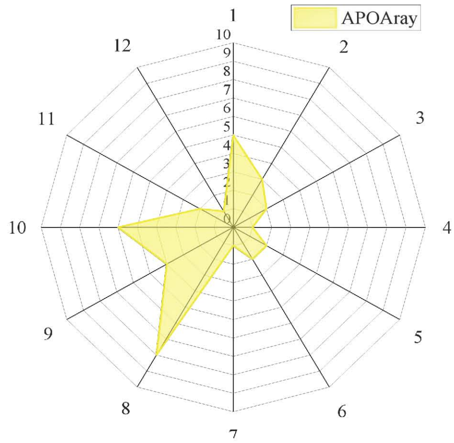
(5) APOA-gamma



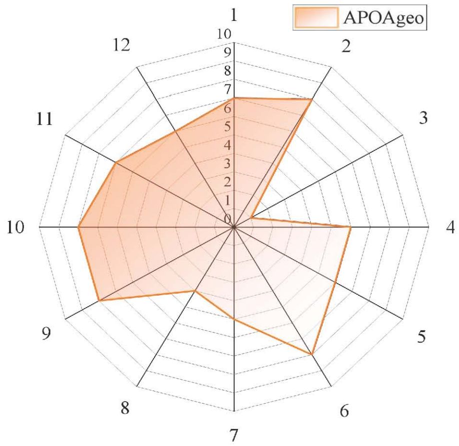
(8) APOA-poisson



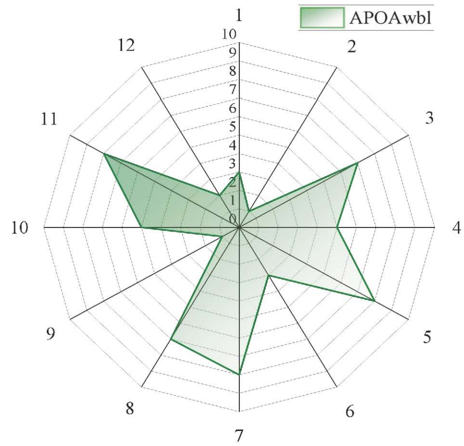
(6) APOA-gaussian



(9) APOA-rayleigh



(7) APOA-geometric



(10) APOA-weber

Fig. 6 In-line stacked plots of improved POA to solve CEC-2022 functions.

TABLE II. MATHEMATICAL DISTRIBUTIONS BASED POAS TO OPTIMIZE THE CEC-2017 FUNCTIONS

Function		POA	APOA	APOAbeta	APOAexp	APOAgam	APOAgau	APOAgeo	APOApoi	APOAray	APOAwbl
f_1	Ave	1.82E+10	1.63E+10	1.55E+10	1.03E+10	**9.67E+09**	1.48E+10	1.36E+10	1.25E+10	1.41E+10	1.03E+10
	Std	6.26E+09	5.15E+09	4.69E+09	4.06E+09	3.83E+09	6.45E+09	3.60E+09	3.89E+09	3.50E+09	**3.40E+09**
f_2	Ave	4.26E+34	4.32E+33	4.97E+32	5.26E+26	**3.16E+30**	9.73E+31	4.31E+33	1.97E+33	6.72E+32	3.08E+31
	Std	9.35E+34	1.33E+34	1.53E+33	**1.12E+27**	5.32E+30	1.82E+32	1.08E+34	5.61E+33	2.12E+33	7.33E+31
f_3	Ave	7.85E+04	5.39E+04	3.19E+04	3.04E+04	3.53E+04	3.08E+04	3.20E+04	2.94E+04	**2.91E+04**	4.10E+04
	Std	8.62E+03	1.18E+04	9.55E+03	7.44E+03	6.13E+03	6.74E+03	**6.00E+03**	8.62E+03	9.54E+03	9.26E+03
f_4	Ave	2885.98	2456.93	1926.32	1760.99	**1095.25**	1749.68	1925.07	1652.05	1477.26	1122.96
	Std	1405.86	2172.04	1048.58	1009.73	**359.84**	853.78	1077.64	942.41	1198.80	502.83
f_5	Ave	804.28	787.78	750.86	740.89	743.41	**740.35**	770.03	762.20	768.64	769.37
	Std	35.91	38.75	32.99	31.38	22.44	34.65	34.84	31.47	**21.07**	28.51

f_6	Ave	679.18	676.83	665.99	661.60	662.93	664.11	**659.35**	661.79	663.53	663.50
	Std	8.99	7.32	4.82	**1.84**	5.40	5.17	6.40	7.30	3.64	4.99
f_7	Ave	1288.46	1252.13	1256.90	1234.53	**1216.81**	1286.79	1319.16	1243.14	1239.33	1277.77
	Std	**38.05**	89.05	48.53	81.21	61.12	58.87	53.80	70.40	59.36	55.68
f_8	Ave	1001.45	994.06	976.66	**972.91**	976.61	998.85	1047.47	1005.45	979.28	976.48
	Std	**12.37**	26.52	21.74	13.85	20.55	20.14	56.79	37.87	21.92	22.44
f_9	Ave	5756.35	5332.13	5230.19	5419.06	5512.63	**5196.13**	8702.71	5970.17	5430.59	5516.96
	Std	**241.04**	621.29	909.84	360.87	682.57	917.55	3494.28	441.26	659.44	314.61
f_{10}	Ave	5593.49	5530.18	**4923.42**	5181.37	5223.61	4979.60	5031.85	5128.71	5260.97	5204.12
	Std	389.22	703.02	398.87	467.71	398.71	398.54	602.50	420.83	**271.74**	305.06
f_{11}	Ave	2605.24	2365.43	1579.72	1560.90	1597.10	1929.16	1886.58	1622.45	1711.99	**1523.72**
	Std	755.22	817.75	267.29	145.40	253.90	699.57	544.95	251.60	379.22	**106.32**
f_{12}	Ave	1.49E+09	1.01E+09	7.98E+08	3.67E+08	1.61E+08	9.39E+08	1.00E+09	3.69E+08	6.37E+08	**1.60E+08**
	Std	1.42E+09	1.24E+09	9.57E+08	4.31E+08	2.41E+08	9.74E+08	1.21E+09	3.29E+08	8.52E+08	**2.36E+08**
f_{13}	Ave	3.55E+07	1.29E+07	1.15E+07	1.61E+05	**9.27E+04**	6.32E+06	1.58E+06	2.11E+06	9.59E+05	1.75E+05
	Std	6.20E+07	5.40E+07	4.05E+07	2.09E+05	**8.38E+04**	1.80E+07	2.59E+06	8.53E+06	4.01E+06	3.67E+05
f_{14}	Ave	3.97E+04	1.94E+04	6.49E+03	1.86E+03	**1.69E+03**	4.53E+03	1.72E+04	5.29E+03	1.92E+03	1.78E+03
	Std	4.91E+04	2.28E+04	9.41E+03	4.03E+02	**1.02E+02**	8.24E+03	2.91E+04	5.86E+03	4.22E+02	1.99E+02
f_{15}	Ave	9.93E+04	7.26E+04	3.49E+04	2.02E+04	**1.65E+04**	2.46E+04	5.40E+04	3.84E+04	2.53E+04	1.66E+04
	Std	6.28E+04	5.25E+04	2.22E+04	8.00E+03	7.84E+03	1.04E+04	6.06E+04	2.15E+04	2.05E+04	**6.91E+03**
f_{16}	Ave	3156.74	3109.74	3088.19	2970.23	3076.34	**2929.38**	3392.29	3352.35	2947.79	3062.10
	Std	359.82	**184.14**	586.49	255.83	300.63	322.22	336.96	468.13	254.69	187.26
f_{17}	Ave	2462.46	2401.77	2242.10	**2144.57**	2200.31	2232.31	2272.03	2263.72	2242.63	2200.07
	Std	256.42	238.25	194.33	204.09	153.20	162.82	227.85	198.36	164.72	**127.26**
f_{18}	Ave	3.18E+05	2.77E+05	1.76E+05	6.46E+04	**4.03E+04**	1.41E+05	2.59E+05	1.87E+05	7.57E+04	7.17E+04
	Std	1.84E+05	6.74E+05	1.91E+05	4.78E+04	**2.14E+04**	1.60E+05	2.70E+05	1.77E+05	6.18E+04	3.94E+04
f_{19}	Ave	1.25E+06	8.74E+05	4.19E+05	1.95E+05	**1.88E+05**	3.17E+05	4.93E+05	2.33E+05	5.10E+05	1.91E+05
	Std	1.22E+06	1.16E+06	4.33E+05	2.77E+05	2.52E+05	2.62E+05	5.51E+05	1.98E+05	6.45E+05	**1.92E+05**
f_{20}	Ave	2694.39	2652.40	2487.61	2500.18	2524.65	2463.92	2538.40	**2451.67**	2463.49	2567.84
	Std	126.64	172.23	117.99	125.41	134.72	123.40	124.85	117.59	119.42	**110.52**
f_{21}	Ave	2563.81	2538.34	2543.52	2532.99	2528.26	2530.05	2659.66	2613.48	2517.48	**2510.35**
	Std	**37.50**	80.96	45.70	101.68	106.56	88.52	53.13	55.02	104.26	135.47
f_{22}	Ave	7019.05	6813.44	5713.59	**3733.79**	3867.80	5243.37	5212.72	5567.02	4350.29	4660.27
	Std	**812.64**	1096.08	1695.48	966.09	1575.72	1590.02	1932.59	1573.52	1243.99	2010.93
f_{23}	Ave	3270.93	3232.39	3120.37	3089.09	3149.19	3014.41	3038.13	3078.63	**3010.46**	3146.05
	Std	114.18	114.49	110.74	135.08	135.78	**74.20**	103.44	101.79	82.68	119.09
f_{24}	Ave	3367.88	3344.15	3251.19	3226.39	3245.49	**3168.29**	3180.05	3210.17	3182.43	3268.32
	Std	151.97	163.41	133.50	87.04	72.58	65.07	72.33	79.70	**58.95**	66.83
f_{25}	Ave	3366.64	3366.28	3267.26	3168.89	**3059.50**	3267.25	3240.79	3223.10	3225.95	3169.00
	Std	211.12	198.42	194.30	164.96	**53.38**	221.63	103.71	132.52	216.65	130.42
f_{26}	Ave	7947.87	7704.64	7817.09	6217.89	**6027.76**	7464.22	7201.60	7060.75	6185.91	6558.00
	Std	**842.64**	1446.20	1623.40	1699.06	1901.17	1410.39	1860.00	1487.29	1362.47	1817.79
f_{27}	Ave	3443.72	3417.97	3392.54	3328.88	3339.10	3354.44	3411.33	3373.70	3350.79	**3316.39**
	Std	67.37	104.75	69.21	80.26	60.95	**56.15**	88.41	66.69	85.11	56.45
f_{28}	Ave	3986.56	3933.14	3920.68	**3654.20**	3665.97	3909.95	3794.77	3825.49	3817.61	3676.21
	Std	314.92	339.07	375.16	**215.24**	274.16	399.98	215.59	367.13	229.08	262.00
f_{29}	Ave	4807.22	4736.22	4605.34	4452.24	4567.06	**4404.93**	4619.72	4542.16	4503.84	4762.38
	Std	430.89	442.56	338.53	334.97	393.43	323.77	321.98	419.35	401.39	**293.39**
f_{30}	Ave	8.64E+06	6.63E+06	5.48E+06	2.80E+06	**1.21E+06**	5.75E+06	4.86E+06	4.27E+06	2.72E+06	2.08E+06
	Std	5.95E+06	6.91E+06	4.65E+06	2.71E+06	**1.01E+06**	4.94E+06	4.65E+06	3.43E+06	2.29E+06	2.53E+06
Friedman		9.70	8.37	6.03	3.03	**2.97**	4.73	6.67	5.37	4.17	3.97
Rank		10	9	7	2	1	5	8	6	4	3

TABLE III. MATHEMATICAL DISTRIBUTIONS BASED ADAPTIVE POA TO OPTIMIZE THE CEC-2022 FUNCTIONS

Function		POA	APOA	APOAbeta	APOAexp	APOAgam	APOAgau	APOAgeo	APOApoi	APOAray	APOAwbl
	Best	365.05	323.85	300.27	**300.25**	300.41	302.11	316.88	309.62	304.51	302.93
f_1	Ave	1348.22	710.46	376.31	347.14	**345.04**	432.25	455.01	518.90	377.23	356.01
	Std	1201.80	507.49	61.47	55.51	**46.44**	268.01	283.77	609.51	53.45	59.75
	Best	406.54	400.82	400.30	400.02	**400.00**	400.05	400.07	400.07	400.05	400.01
f_2	Ave	499.01	430.88	426.12	**401.45**	407.04	407.82	429.75	413.57	403.03	400.58
	Std	69.32	31.46	40.82	2.93	16.03	22.31	39.95	26.08	4.60	**1.43**
	Best	621.13	610.94	609.21	603.12	615.14	600.72	605.32	605.82	**600.19**	611.68
f_3	Ave	639.26	636.51	624.67	624.18	630.25	620.67	**618.35**	622.87	620.47	629.52
	Std	11.09	13.35	11.26	13.14	7.12	12.51	9.19	**7.29**	14.44	8.72
	Best	810.49	825.01	810.94	**806.26**	807.96	806.97	809.08	811.94	807.07	811.45
f_4	Ave	837.08	836.37	820.54	815.76	816.37	816.07	819.41	820.15	**815.57**	818.54
	Std	11.35	9.70	5.57	5.31	4.59	4.27	6.48	5.76	5.99	**4.11**
	Best	1024.70	1118.47	924.04	928.01	987.04	976.39	907.74	900.33	**900.19**	1094.67
f_5	Ave	1535.71	1323.32	1101.35	1147.79	1120.69	1213.96	1155.78	1090.02	**1101.11**	1214.43
	Std	238.87	143.97	124.10	86.70	**85.87**	125.95	123.23	115.40	143.65	92.10
	Best	1902.13	2000.15	1852.03	1823.59	1817.18	1829.35	1833.26	1840.00	**1816.67**	1818.47
f_6	Ave	3844.87	3642.66	2334.99	1936.56	**1850.06**	2117.70	2680.70	1949.93	1874.33	1903.18
	Std	2295.05	1919.28	1222.42	279.15	**28.21**	952.99	1839.35	74.92	41.72	133.94
	Best	2027.18	2016.47	2012.64	**2005.33**	2025.07	2008.13	2018.71	2020.37	2005.59	2022.54
f_7	Ave	2075.58	2071.72	2038.61	2034.19	2047.42	2031.60	2036.97	2036.60	**2030.69**	2050.56
	Std	22.97	33.25	13.27	15.45	16.28	**12.91**	11.51	17.21	16.09	16.22
	Best	2102.85	2101.89	2060.90	2074.57	2094.02	2077.99	2058.38	2085.59	2071.69	**2058.18**
f_8	Ave	2181.07	2147.46	2114.15	**2107.34**	2114.30	2109.46	2111.65	2109.37	2125.78	2116.27
	Std	52.98	26.48	38.34	25.58	19.16	23.30	31.32	**17.75**	41.59	25.51
	Best	2552.83	2368.83	2529.29	2529.28	2529.28	2529.28	2529.29	2529.29	2529.29	**2331.02**
f_9	Ave	2602.26	2552.43	2529.93	2529.30	2529.36	2535.31	2550.66	2533.07	2529.67	**2509.67**
	Std	33.09	67.39	0.67	**0.02**	0.19	13.63	27.71	7.39	0.78	62.77
	Best	2500.46	2500.35	**2500.16**	2500.40	2500.37	2500.45	2500.23	2500.47	2500.29	2500.43
f_{10}	Ave	2594.92	2589.55	**2529.44**	2552.27	2530.82	2533.86	2554.77	2534.80	2541.76	2540.02
	Std	218.48	188.72	55.08	58.55	**53.74**	58.42	61.45	60.44	57.15	55.07
	Best	2615.63	2615.72	2421.53	2486.83	2509.52	2435.29	2504.77	2420.56	**2410.48**	2523.35
f_{11}	Ave	2694.39	2652.40	2487.61	2500.18	2524.65	2463.92	2538.40	**2451.67**	2463.49	2567.84
	Std	126.64	172.23	117.99	125.41	134.72	123.40	124.85	117.59	119.42	**110.52**
	Best	2862.31	2862.21	2860.14	2859.55	2860.51	2861.29	2862.97	2859.56	**2859.46**	2859.68
f_{12}	Ave	2873.96	2867.27	2867.51	2864.60	2864.53	2865.50	2866.08	2866.37	**2863.79**	2863.90
	Std	15.36	6.41	6.14	2.77	2.62	3.26	2.37	5.56	**1.28**	1.96
Friedman		10.00	8.92	5.42	3.50	4.08	4.42	6.17	4.58	**3.08**	4.83
Rank		10	9	7	2	3	4	8	5	1	6

Each update involves constant-time arithmetic and threshold on d-dimensional vectors plus a few fitness evaluations, for $O(d+t)$ per individual, giving $O(N(d+t)$ per iteration. Multiplying by the number of iterations yields $O(T \times N(d+t))$. If each fitness evaluation itself scans m samples over d features then the total complexity can be expressed as $O(T \times N \times m \times d)$.

V. CONCLUSION

This study proposes an enhanced Pelican Optimization Algorithm (POA) that incorporates the African vulture satiety strategy and multiple mathematical distributions to improve optimization performance. Inspired by the African Vulture Optimization Algorithm (AVOA), the satiety strategy was integrated into both the exploration and exploitation phases, enhancing the algorithm's search capability and balancing global exploration with local exploitation. This modification mitigates premature convergence and helps the algorithm avoid local optima, thereby improving solution quality.

Furthermore, to further diversify the search process and introduce adaptive randomness, eight distinct mathematical distributions were incorporated into the exploration phase. These distributions were designed to regulate the step size and movement patterns of the search agents, ensuring a more comprehensive and diverse exploration of the search space. By incorporating statistical distributions such as Gamma, Exponential, Rayleigh, and Weibull, the improved POA demonstrated a heightened ability to navigate complex, multi-modal landscapes and avoid stagnation in sub-optimal regions.

The effectiveness of the proposed enhancements was rigorously evaluated using two widely recognized benchmark test suites: 30 benchmark functions from CEC-BC-2017 and 12 benchmark functions from CEC-BC-2022. Comparative analyses based on statistical metrics, including mean values and variance, confirmed that the improved POA consistently outperformed the standard POA and its adaptive variants across a wide range of test functions. The experimental results provided strong evidence that the integration of the African vulture satiety strategy, combined with mathematical distributions, significantly enhances convergence speed, solution accuracy and overall robustness in optimization tasks.

REFERENCES

[1] M. Jain, V. Saihjpal, and N. Singh. "An Overview of Variants and Advancements of PSO Algorithm," *Applied Sciences*, vol. 12, no. 17, pp. 8392, 2022.
[2] G. Negi, A. Kumar, and S. Pant. "GWO: A Review and Applications," *International Journal of System Assurance Engineering and Management*, vol. 12, pp. 1-8, 2021.
[3] P. Trojovský and M. Dehghani. "Pelican Optimization Algorithm: A Novel Nature-Inspired Algorithm for Engineering Applications," *Sensors*, vol. 22, no. 3, pp. 855, 2022.
[4] C. Miao, G. Chen, and C. Yan. "Path Planning Optimization of Indoor Mobile Robot Based on Adaptive Ant Colony Algorithm," *Computers & Industrial Engineering*, vol. 156, pp. 107230, 2021.
[5] Y. X. Li, J. S. Wang, and X. Y. Guan. "Arithmetic Optimization Algorithm with Three-dimensional Chaotic Mapping in Spherical Coordinate System for Combined Economic Emission Dispatch Problem," *Applied Energy*, vol. 380, pp. 124953, 2025.
[6] S. W. Zhang, J. S. Wang, and Y. X. Li. "Improved Honey Badger Algorithm Based on Elementary Function Density Factors and Mathematical Spirals in Polar Coordinate System," *Artificial Intelligence Review*, vol. 57, no. 3, pp. 55, 2024.
[7] Y. Li, W. Li, and Q. Yuan. "Multi-Strategy Improved Seagull Optimization Algorithm," *International Journal of Computational Intelligence Systems*, vol. 16, no. 1, pp. 154, 2023.
[8] M. Ye, H. Zhou, and H. Yang. "Multi-Strategy Improved Dung Beetle Optimization Algorithm and Its Applications," *Biomimetics*, vol. 9, no. 5, pp. 291, 2024.
[9] L. Qian, M. Khishe, and Y. Huang. "SEB-ChOA: An Improved Chimp Optimization Algorithm Using Spiral Exploitation Behavior," *Neural Computing and Applications*, vol. 36, no. 9, pp. 4763-4786, 2024.
[10] L. Chaib, M. Tadj, and A. Choucha. "Improved Crayfish Optimization Algorithm for Parameters Estimation of Photovoltaic Models," *Energy Conversion and Management*, vol. 313, pp. 118627, 2024.
[11] D. Lzci. "A Novel Improved Atom Search Optimization Algorithm for Designing Power System Stabilizer," *Evolutionary Intelligence*, vol. 15, no. 3, pp. 2089-2103, 2022.
[12] H. Deng, L. Liu, and J. Fang. "A Novel Improved Whale Optimization Algorithm for Optimization Problems with Multi-Strategy and Hybrid Algorithm," *Mathematics and Computers in Simulation*, vol. 205, pp. 794-817, 2023.
[13] K. Li, S. Li, and Z. Huang. "Grey Wolf Optimization Algorithm Based on Cauchy-Gaussian Mutation and Improved Search Strategy," *Scientific Reports*, vol. 12, no. 1, pp. 18961, 2022.
[14] C. Ouyang, Y. Qiu, and D. Zhu. "Adaptive Spiral Flying Sparrow Search Algorithm," *Scientific Programming*, vol. 2021, no. 1, pp. 6505253, 2021.
[15] B. Abdollahzadeh, F. S. Gharehchopogh, and S. Mirjalili. "African Vultures Optimization Algorithm: A New Nature-Inspired Metaheuristic Algorithm for Global Optimization Problems," *Computers & Industrial Engineering*, vol. 158, pp. 107408, 2021.
[16] A. Faramarzi, M. Heidarinejad, and S. Mirjalili. "Marine Predators Algorithm: A Nature-Inspired Metaheuristic," *Expert Systems with Applications*, vol. 152, pp. 113377, 2020.
[17] A. Ahrari, S. Elsayed, and R. Sarker. "Problem Definition and Evaluation Criteria for the CEC'2022 Competition on Dynamic Multimodal Optimization," *Proceedings of the IEEE World Congress on Computational Intelligence (IEEE WCCI 2022)*, pp. 18-23, 2022.