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# Orangutan Optimization Algorithm: An Innovative Bio-Inspired Metaheuristic Approach for Solving Engineering Optimization Problems

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**Abstract:** In this paper, a new metaheuristic algorithm called Orangutan Optimization Algorithm (OOA) is designed, which imitates the behaviors of Orangutans in nature. The fundamental inspiration of OOA is the foraging strategy of Orangutans and the skills of these animals in nesting. The theory of OOA is explained and then the implementation steps of OOA in two phases of exploration and exploitation are mathematically modeled. The performance of OOA in dealing with real-world applications is evaluated on twenty-two constrained optimization problems from the CEC 2011 test suite. The optimization results show that the proposed OOA approach, by balancing exploration and exploitation during the search process, is able to provide suitable solutions for the benchmark functions. Also, in order to measure the quality of OOA, the results obtained from the proposed approach are compared with twelve well-known metaheuristic algorithms. Analysis of the simulation results shows that OOA has provided superior performance by providing better results in 100% of the benchmark functions compared to competitor algorithms.

**Keywords:** Orangutan, Nature-inspired, Optimization, Metaheuristic, Optimization algorithm, Exploration, Exploitation.

## 1. Introduction

Many problems in both science and real-world applications present multiple feasible solutions, which makes them complex to solve. These problems are referred to as optimization problems, and the process of identifying the most suitable solution from the set of available options is known as optimization [1]. From a mathematical perspective, optimization problems consist of three main components: decision variables, constraints, and objective functions. The goal of optimization, therefore, is to determine the optimal values for the decision variables while adhering to the constraints so that the objective function achieves its most favorable outcome, either maximum or minimum [2]. Optimization problem-solving methods are broadly classified into two completely different categories: deterministic and stochastic approaches [3]. Deterministic methods, which are further divided into gradient-based and non-gradient-based techniques, are particularly effective in solving linear, convex, continuous, differentiable, and low-dimensional optimization problems [4, 5]. However, as the complexity and dimensionality of these problems increase, deterministic methods often fail by getting trapped in suboptimal local solutions [6, 7]. This is especially true for problems that are non-linear, non-convex, discontinuous, non-differentiable, and high-dimensional, which are common in scientific and practical applications [8, 9]. Due to these limitations, researchers have developed stochastic approaches to tackle more challenging optimization problems [10].

Metaheuristic algorithms, which are one of the most widely employed stochastic methods, are highly effective in addressing complex optimization challenges. These algorithms have effective applications in various sciences such as architecture [11, 12], energy [13], protection [14], electrical engineering [15], and energy carriers [16]. Metaheuristic algorithms work by utilizing a random search mechanism within the problem space, employing random operators and a trial-and-error process to find suitable solutions. The advantages of metaheuristic algorithms include the simplicity of their concepts, ease of implementation, independence from the specific problem type, and the ability to solve non-linear, non-convex, discontinuous, non-derivative, and high-dimensional optimization problems. Furthermore, they are efficient in exploring unknown, non-linear search spaces, which explains their popularity among researchers [17].

The optimization process in metaheuristic algorithms begins by randomly generating a set of initial candidate solutions that respect the constraints of the problem. In an iterative process, these solutions are progressively refined based on the updating steps defined by the algorithm. The best solution found at each iteration is saved, and ultimately, the best overall solution is presented as the final result [18]. While the random search nature of these algorithms means that they cannot guarantee a global optimum, the solutions they produce are often near-optimal, which are referred to as quasi-optimal solutions. Consequently, when comparing the performance of multiple metaheuristic algorithms, the one that provides a better quasi-optimal solution is considered the most effective one for that particular problem [19].

The search process in metaheuristic algorithms must balance two key concepts: global exploration and local exploitation. Global exploration enables the algorithm to thoroughly scan the problem space, preventing it from getting stuck in local optima and helping to identify the most promising areas in the search space. Local exploitation, on the other hand, allows the algorithm to converge towards a global optimum by intensively searching around promising regions and refining solutions. Striking a balance between exploration and exploitation is crucial for the success of any metaheuristic algorithm in providing effective solutions [20].

A key question in metaheuristics research is whether, given the vast number of algorithms already developed, there is still a need to design completely different metaheuristic algorithms. The No Free Lunch (NFL) theorem provides an answer to this. It states that the success of a metaheuristic algorithm in solving one set of optimization problems does not guarantee its success in solving others [21]. Therefore, no single algorithm is universally optimal for all optimization tasks. This insight encourages ongoing innovation in the field of metaheuristic algorithm design, as the NFL theorem suggests that newer algorithms can offer more effective solutions for specific problem sets.

The novelty of this paper lies in the development of a new metaheuristic algorithm called the Orangutan Optimization Algorithm (OOA), designed to solve a variety of optimization problems in different scientific fields and real-world applications. The key contributions of the paper are as follows:

- OOA is inspired by the natural behavior of orangutans in the wild.
- The algorithm’s core inspiration comes from the foraging strategies and nesting skills of orangutans.
- The steps of OOA are described and mathematically modeled in two phases: exploration and exploitation.
- To assess its effectiveness in real-world applications, OOA is applied to twenty-two optimization problems from the CEC 2011 test suite.
- A comparative performance analysis is conducted, comparing OOA with twelve other well-known metaheuristic algorithms.

The structure of the paper is as follows: Section 2 introduces and models the Orangutan Optimization Algorithm. Section 3 investigates the effectiveness of OOA in solving real-world applications. Finally, conclusions and suggestions for future research are discussed in Section 4.

## 2. Orangutan optimization algorithm

In this section, the source of inspiration behind the Orangutan Optimization Algorithm (OOA) is thoroughly explained, followed by a comprehensive description of the theory underlying the approach. Afterwards, the step-by-step implementation of the OOA is carefully modeled using mathematical formulations, ensuring it can be effectively applied to solve completely different types of optimization problems.

### 2.1 Algorithm initialization

The newly introduced Orangutan Optimization Algorithm (OOA) is a bio-inspired metaheuristic algorithm that draws its inspiration from the natural behaviors of orangutans. In this approach, orangutans serve as the population members, and each orangutan represents a potential solution to the given optimization problem. These solutions are completely different from one another, as each orangutan occupies a unique position within the problem's search space. The variables corresponding to each solution are determined by the orangutan's specific position, which can be mathematically modeled as a vector. As a group, these orangutans form the OOA population, which can be represented using a matrix structure using Eq. (1). This matrix is not static; it evolves as the algorithm progresses. Initially, the position of each orangutan in the search space is randomly determined. This randomness is essential in ensuring that the initial population covers diverse areas of the search space, enhancing the exploration capabilities of the algorithm. The initialization process for the population is mathematically modeled using Eq. (2), where each dimension of the orangutan's position is calculated based on random values within a predefined range. This allows for a completely different starting point for each orangutan, creating diversity in candidate solutions.

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

$$x_{i,d} = lb_d + r \cdot (ub_d - lb_d) \tag{2}$$

Here $X$ is the OOA population matrix, $X_i$ is the $i$th orangutan (candidate solution), $x_{i,d}$ is its $d$th dimension in search space (decision variable), $N$ is the number of orangutans, $m$ is the number of decision variables, $r$ is a random number in the interval $[0,1]$, $lb_d$, and $ub_d$ are a lower bound and an upper bound of the $d$ th. decision variable, respectively.

After initialization, each orangutan's position corresponds to a set of variables, which are evaluated using the objective function of the optimization problem. The objective function assigns a value to each candidate solution, and this set of values can be represented mathematically using a vector, as shown in Eq. (3).

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

Here $F$ is the vector of calculated objective function and $F_i$ is the calculated objective function based on the $i$th orangutan.

The calculated values of the objective function serve as a measure of the quality of each solution. Based on these evaluations, the algorithm identifies the best-performing orangutan (i.e., the candidate solution with the most optimal value) as well as the worst-performing one. In each iteration of the algorithm, the positions of the orangutans are updated, which means that their corresponding objective function values also change. As the search progresses, the best solution must be continuously updated to reflect the most optimal orangutan found so far.

This iterative process of updating orangutan positions ensures that the algorithm effectively searches the problem space, gradually moving towards an optimal or near-optimal solution.

### 2.2 Phase 1: foraging strategy (exploration)

Orangutans, in their natural habitat, spend a significant amount of time searching for food such as fruits, tree leaves, and other diet items. This foraging behavior leads to large-scale movements and extensive exploration in their environment, allowing them to discover completely different areas in the search of resources. The simulation of this foraging strategy within OOA enhances the algorithm's exploration capability, making it more adept at scanning and searching the global space of the problem.

In the first phase of OOA, the position of each orangutan is updated to simulate this foraging behavior. Orangutans with better objective function values are considered to represent better food sources, and each orangutan seeks out these superior positions. Eq. (4) mathematically defines the set of available food resources for each orangutan by considering all orangutans with better objective function values. The diversity of food sources allows the orangutans to explore a variety of potential solutions in completely different regions of the search space.

$$FS_i = \{X_k : F_k < F_i \; and \; k \neq i\} \tag{4}$$

Here $FS_i$ is the set of candidate food sources' locations for the $i$th orangutan, $X_k$ is the is the orangutan with a better objective function value than $i$th orangutan, and $F_k$ is the its objective function value.

To model this movement mathematically, a new position is first calculated for each orangutan using Eq. (5). This movement allows the orangutan to adjust its location in a way that explores completely different regions, potentially leading to a significant improvement in the objective function value. If the objective function improves, the new position is confirmed and updated according to Eq. (6):

$$x_{i,d}^{P1} = x_{i,d} + r \cdot \left(SFS_{i,d} - I \cdot x_{i,d}\right), \tag{5}$$

$$X_i = \begin{cases} X_i^{P1}, \; F_i^{P1} \leq F_i, \\ X_i, \; else\,, \end{cases} \tag{6}$$

Here $X_i^{P1}$ is the new suggested position of the $i$th orangutan based on the first phase of OOA, $x_{i,d}^{P1}$ is its $d$th dimension, $F_i^{P1}$ is its objective function value, $r$ is a random number with a normal distribution in the range of $[0,1]$, $SFS_{i,d}$ is the $d$th dimension of the selected food source for the $i$th orangutan, $I$ is a random number from the set $\{1,2\}$, $N$ is the number of orangutans, and $m$ is the number of decision variables.

### 2.3 Phase 2: nesting skill (exploitation phase)

In addition to foraging, orangutans also demonstrate remarkable intelligence through their nesting behavior. Every day, they build nests in trees, selecting branches and leaves near their current location. This activity focuses on a more localized search, optimizing their living space. Simulating the nesting skills of orangutans in OOA enhances the algorithm's exploitation capabilities, improving the fine-tuning of solutions and allowing for more precise exploration of local regions.

During this second phase of OOA, the orangutan moves towards a nearby tree to nest. In the context of the algorithm, this nesting process is modeled by generating a new position for the orangutan based on its current location. Eq. (7) is used to simulate the movement towards the tree, and if the objective function value improves, the new position replaces the previous one, as outlined in Eq. (8):

$$x_{i,j}^{P2} = x_{i,j} + \left(1 - 2\, r_{i,j}\right) \cdot \frac{ub_j - lb_j}{t} \tag{7}$$

$$X_i = \begin{cases} X_i^{P2}, \; F_i^{P2} \leq F_i \\ X_i, \; else \end{cases} \tag{8}$$

Here $X_i^{P2}$ is the new suggested position of the $i$th orangutan based on the second phase of OOA, $x_{i,d}^{P2}$ is its $d$th dimension, $F_i^{P2}$ is its objective function value, $t$ is the iteration counter of the algorithm, and $T$ is the maximum number of algorithm iterations.

## 3. Simulation studies

In this section, the effectiveness of the proposed OOA approach in addressing optimization challenges in real-world applications is thoroughly examined. To achieve this, the CEC 2011 test suite, which comprises twenty-two constrained optimization problems derived from practical applications, has been employed. A comprehensive description and full details of the CEC 2011 test suite are available in [22]. The optimization results obtained by the proposed OOA approach are compared with the performance of twelve well-established metaheuristic algorithms, including: GA [23], PSO [24], GSA [25], TLBO [26], MVO [27], GWO [28], WOA [29], MPA [30], TSA [31], RSA [32], AVOA [33], and WSO [34].

The results of the OOA implementation, along with competitor algorithms, when applied to the CEC 2011 test suite, are summarized in Table 1 and Table 2. Additionally, the comparative performance of OOA and the other algorithms is illustrated through boxplots in Figure 1. From a detailed comparison of the simulation results, it becomes clear that the OOA approach consistently outperforms the competitors, emerging as the top optimizer across all the problems ranging from C11-F1 to C11-F22. This clearly highlights OOA's robustness and effectiveness in dealing with real-world optimization problems. Notably, the simulation results indicate that OOA ranks as the best optimizer in the majority of the optimization problems from the CEC 2011 test suite, showcasing its superior performance when compared to the other algorithms.

Table 1 Optimization results of CEC 2011 test suite

| | | OOA | WSO | AVOA | RSA | MPA | TSA | WOA |
|---|---|---|---|---|---|---|---|---|
| C11-F1 | mean | 5.920103 | 17.39022 | 13.33731 | 21.05706 | 8.715436 | 18.01704 | 13.58734 |
| | best | 2E-10 | 14.61193 | 9.495939 | 18.71472 | 1.804603 | 17.30358 | 8.520687 |
| | worst | 12.30606 | 19.66117 | 16.68954 | 23.05217 | 13.19969 | 19.09799 | 16.93418 |
| | std | 7.196379 | 2.400987 | 4.013324 | 1.99914 | 5.368972 | 0.818959 | 4.018352 |
| | median | 5.687176 | 17.6439 | 13.58188 | 21.23068 | 9.928723 | 17.8333 | 14.44725 |
| | rank | 1 | 7 | 4 | 12 | 2 | 9 | 5 |
| C11-F2 | mean | -26.3179 | -14.2624 | -19.9064 | -11.8736 | -23.3368 | -11.6356 | -17.8532 |
| | best | -27.0676 | -15.7508 | -20.5241 | -12.1168 | -23.9079 | -15.1534 | -21.0988 |
| | worst | -25.4328 | -13.1382 | -19.3344 | -11.5246 | -22.093 | -9.58355 | -14.2074 |
| | std | 0.738935 | 1.333128 | 0.544996 | 0.26244 | 0.884624 | 2.715589 | 3.570128 |
| | median | -26.3856 | -14.0804 | -19.8835 | -11.9266 | -23.6732 | -10.9027 | -18.0533 |
| | rank | 1 | 8 | 5 | 10 | 2 | 11 | 6 |
| C11-F4 | mean | 1.15E-05 | 1.15E-05 | 1.15E-05 | 1.15E-05 | 1.15E-05 | 1.15E-05 | 1.15E-05 |
| | best | 1.15E-05 | 1.15E-05 | 1.15E-05 | 1.15E-05 | 1.15E-05 | 1.15E-05 | 1.15E-05 |
| | worst | 1.15E-05 | 1.15E-05 | 1.15E-05 | 1.15E-05 | 1.15E-05 | 1.15E-05 | 1.15E-05 |
| | std | 2E-19 | 1.86E-11 | 2.13E-09 | 4.18E-11 | 6.64E-14 | 5.81E-14 | 6.62E-14 |
| | median | 1.15E-05 | 1.15E-05 | 1.15E-05 | 1.15E-05 | 1.15E-05 | 1.15E-05 | 1.15E-05 |
| | rank | 1 | 11 | 13 | 12 | 6 | 8 | 4 |
| C11-F4 | mean | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | best | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | worst | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | std | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | median | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | rank | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| C11-F5 | mean | -34.1274 | -25.2175 | -27.9963 | -21.1342 | -32.3358 | -27.1746 | -27.5944 |
| | best | -34.7494 | -26.0919 | -28.9217 | -22.8513 | -32.8473 | -30.8993 | -27.7615 |
| | worst | -33.3862 | -24.4915 | -27.632 | -19.2053 | -31.2781 | -22.7089 | -27.2665 |
| | std | 0.589989 | 0.736666 | 0.651398 | 2.066682 | 0.751817 | 3.543313 | 0.235926 |
| | median | -34.1871 | -25.1432 | -27.7158 | -21.2401 | -32.609 | -27.5451 | -27.6749 |
| | rank | 1 | 9 | 4 | 10 | 2 | 7 | 5 |
| C11-F6 | mean | -24.1119 | -14.0897 | -18.2974 | -13.2521 | -21.3104 | -8.63171 | -19.0738 |
| | best | -27.4298 | -14.764 | -19.1411 | -14.6227 | -23.6053 | -16.0875 | -22.4303 |
| | worst | -23.0059 | -13.5426 | -17.602 | -12.2858 | -19.8721 | -5.52345 | -13.0723 |
| | std | 2.324951 | 0.65053 | 0.809346 | 1.065169 | 1.807309 | 5.248737 | 4.379777 |
| | median | -23.0059 | -14.026 | -18.2232 | -13.0499 | -20.8821 | -6.45794 | -20.3964 |
| | rank | 1 | 7 | 6 | 8 | 2 | 10 | 4 |
| C11-F7 | mean | 0.860699 | 1.558108 | 1.288623 | 1.820738 | 0.99202 | 1.303556 | 1.673227 |
| | best | 0.582266 | 1.521316 | 1.182697 | 1.605716 | 0.862127 | 1.172989 | 1.588548 |
| | worst | 1.025027 | 1.635861 | 1.394596 | 1.96165 | 1.059349 | 1.59616 | 1.803919 |
| | std | 0.211503 | 0.055246 | 0.118873 | 0.159565 | 0.095148 | 0.206503 | 0.098956 |
| | median | 0.91775 | 1.537629 | 1.2886 | 1.857793 | 1.023301 | 1.222537 | 1.650222 |
| | rank | 1 | 9 | 7 | 13 | 3 | 8 | 12 |
| C11-F8 | mean | 220 | 278.3988 | 241.0229 | 312.3393 | 225.8807 | 255.1568 | 262.5186 |
| | best | 220 | 255.5256 | 226.2458 | 277.3029 | 222.2252 | 222.2252 | 243.9974 |
| | worst | 220 | 310.8709 | 258.4594 | 348.7748 | 231.2187 | 340.1051 | 304.4945 |
| | std | 0 | 25.63005 | 14.43071 | 31.00166 | 4.442577 | 59.87582 | 29.60888 |
| | median | 220 | 273.5994 | 239.6932 | 311.6397 | 225.0395 | 229.1484 | 250.7913 |
| | rank | 1 | 11 | 7 | 12 | 2 | 9 | 10 |
| C11-F9 | mean | 8789.286 | 504826.7 | 354448.5 | 929153.6 | 53342.71 | 92037.41 | 351366.3 |
| | best | 5457.674 | 345338.8 | 322389.6 | 615208 | 32194.85 | 74383.89 | 197262.9 |
| | worst | 14042.29 | 584496.9 | 381767.1 | 1088516 | 65230.14 | 119930.5 | 582900.7 |
| | std | 3889.181 | 117306.7 | 26662.14 | 223901 | 15947.1 | 21113.5 | 183601 |
| | median | 7828.591 | 544735.5 | 356818.6 | 1006445 | 57972.91 | 86917.64 | 312650.8 |
| | rank | 1 | 9 | 7 | 11 | 2 | 4 | 6 |
| C11-F10 | mean | -21.4889 | -13.6607 | -16.1383 | -12.2399 | -17.9061 | -14.0129 | -12.7392 |
| | best | -21.8299 | -14.3725 | -16.7205 | -12.4723 | -18.5767 | -17.4621 | -13.2762 |
| | worst | -20.7878 | -13.1969 | -15.7944 | -11.9599 | -17.3594 | -11.938 | -12.3829 |
| | std | 0.498616 | 0.527305 | 0.445566 | 0.266005 | 0.585583 | 2.52099 | 0.409228 |
| | median | -21.669 | -13.5366 | -16.0191 | -12.2637 | -17.8442 | -13.3258 | -12.6488 |
| | rank | 1 | 7 | 3 | 10 | 2 | 5 | 9 |
| C11-F11 | mean | 571712.3 | 5272454 | 1232488 | 7839331 | 1793336 | 5392008 | 1420866 |
| | best | 260837.9 | 5107868 | 1058371 | 7600047 | 1728921 | 4633051 | 1360288 |
| | worst | 828560.9 | 5525958 | 1352575 | 7967240 | 1875084 | 6379519 | 1525324 |
| | std | 260922.1 | 207728.9 | 130596.6 | 180776.5 | 64144.21 | 762344.6 | 75885.36 |
| | median | 598725.2 | 5227994 | 1259503 | 7895018 | 1784669 | 5277731 | 1398926 |
| | rank | 1 | 10 | 2 | 13 | 6 | 11 | 3 |
| C11-F12 | mean | 1199805 | 7567324 | 3356778 | 11634817 | 1593020 | 4745383 | 5404660 |

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|---|---|---|---|---|---|---|---|---|
| | best | 1155937 | 7280380 | 3293066 | 10848229 | 1533606 | 4529257 | 5016677 |
| | worst | 1249353 | 7835976 | 3423927 | 12340363 | 1669648 | 4877249 | 5583985 |
| | std | 47157.58 | 247077.4 | 56234.99 | 642185.6 | 59426.91 | 173011 | 280042.1 |
| | median | 1196965 | 7576470 | 3355059 | 11675339 | 1584414 | 4787514 | 5508990 |
| | rank | 1 | 10 | 6 | 11 | 2 | 7 | 9 |
| C11-F13 | mean | 15444.2 | 15805.61 | 15461.49 | 16185.9 | 15474.24 | 15496.94 | 15534.98 |
| | best | 15444.19 | 15647.1 | 15457.78 | 15842.51 | 15469.61 | 15485.91 | 15494.82 |
| | worst | 15444.21 | 16179.68 | 15467.86 | 17050.98 | 15479.23 | 15508.27 | 15590.66 |
| | std | 0.009091 | 264.6824 | 4.630429 | 611.0784 | 4.134745 | 13.28135 | 46.60689 |
| | median | 15444.2 | 15697.84 | 15460.17 | 15925.06 | 15474.06 | 15496.79 | 15527.22 |
| | rank | 1 | 9 | 2 | 11 | 3 | 4 | 8 |
| C11-F14 | mean | 18295.35 | 97633.27 | 18682.8 | 195620.9 | 18757.09 | 19533.06 | 19276.3 |
| | best | 18241.58 | 75011.44 | 18613.02 | 144878.1 | 18661.23 | 19307.69 | 19122.12 |
| | worst | 18388.08 | 135292.4 | 18772.36 | 280518.7 | 18827.98 | 20021.3 | 19404.44 |
| | std | 71.59938 | 28333.14 | 85.39038 | 63854.81 | 80.72001 | 345.4167 | 134.2456 |
| | median | 18275.87 | 90114.63 | 18672.9 | 178543.3 | 18769.57 | 19401.62 | 19289.31 |
| | rank | 1 | 11 | 2 | 12 | 3 | 10 | 7 |
| C11-F15 | mean | 32883.58 | 781176.2 | 108312 | 1627642 | 45341.41 | 63506.54 | 201447.2 |
| | best | 32782.17 | 319976.9 | 43595.67 | 678569 | 32904.1 | 33271.47 | 33021.41 |
| | worst | 32956.46 | 1941570 | 171262.9 | 4224324 | 51625.56 | 123795.5 | 287013.3 |
| | std | 76.94696 | 816676.8 | 70280.06 | 1822751 | 8897.118 | 42920.58 | 120525.5 |
| | median | 32897.86 | 431579.1 | 109194.6 | 803837.2 | 48417.99 | 48479.6 | 242877.1 |
| | rank | 1 | 10 | 7 | 11 | 2 | 6 | 8 |
| C11-F16 | mean | 133550 | 817900.7 | 136863 | 1662172 | 138948.3 | 145227.4 | 142736.4 |
| | best | 131374.2 | 264960.8 | 136069.7 | 420357.3 | 137599.1 | 143439.6 | 136665.8 |
| | worst | 136310.8 | 1901072 | 137623.9 | 4096895 | 142513 | 147081.2 | 147681.1 |
| | std | 2392.2 | 773155 | 895.5159 | 1737676 | 2504.36 | 1601.356 | 4827.072 |
| | median | 133257.5 | 552785 | 136879.1 | 1065717 | 137840.5 | 145194.4 | 143299.4 |
| | rank | 1 | 8 | 2 | 9 | 3 | 6 | 5 |
| C11-F17 | mean | 1926615 | 8.18E+09 | 2.59E+09 | 1.37E+10 | 6.48E+08 | 1.72E+09 | 8.8E+09 |
| | best | 1916953 | 7.28E+09 | 2.23E+09 | 1.02E+10 | 4.63E+08 | 1.35E+09 | 6.28E+09 |
| | worst | 1942685 | 8.82E+09 | 2.73E+09 | 1.64E+10 | 8.61E+08 | 2.09E+09 | 1.17E+10 |
| | std | 12003.53 | 7.26E+08 | 2.55E+08 | 2.79E+09 | 1.76E+08 | 3.26E+08 | 2.4E+09 |
| | median | 1923412 | 8.32E+09 | 2.71E+09 | 1.41E+10 | 6.35E+08 | 1.73E+09 | 8.61E+09 |
| | rank | 1 | 7 | 6 | 10 | 2 | 5 | 8 |
| C11-F18 | mean | 942057.5 | 46968550 | 6246568 | 1E+08 | 1551619 | 2458384 | 8789489 |
| | best | 938416.2 | 32165899 | 3860025 | 69122918 | 1166395 | 2105030 | 3833110 |
| | worst | 944706.9 | 53337276 | 10680388 | 1.14E+08 | 2092481 | 2764259 | 15367297 |
| | std | 2774.139 | 10456522 | 3372738 | 22297257 | 413798.4 | 297588.8 | 5119786 |
| | median | 942553.5 | 51185512 | 5222930 | 1.09E+08 | 1473799 | 2482124 | 7978775 |
| | rank | 1 | 10 | 6 | 12 | 2 | 5 | 7 |
| C11-F19 | mean | 1025341 | 46337780 | 6425512 | 98329374 | 1785097 | 2899712 | 9420437 |
| | best | 967927.7 | 39329617 | 5431525 | 84714139 | 1177061 | 2367354 | 1993479 |
| | worst | 1167142 | 59275780 | 8194119 | 1.24E+08 | 2340168 | 3422486 | 16978182 |
| | std | 99675.04 | 9379552 | 1288187 | 19079537 | 614570.1 | 483548.6 | 7410517 |
| | median | 983146.6 | 43372862 | 6038202 | 92318587 | 1811579 | 2904504 | 9355044 |
| | rank | 1 | 10 | 7 | 12 | 2 | 5 | 8 |
| C11-F20 | mean | 941250.4 | 48967515 | 5532949 | 1.06E+08 | 1385714 | 2114060 | 6700575 |
| | best | 936143.2 | 43137685 | 4951268 | 92693847 | 1359767 | 1937660 | 6319847 |
| | worst | 946866.6 | 57917146 | 6133039 | 1.26E+08 | 1422491 | 2356836 | 7209610 |
| | std | 5013.552 | 6621981 | 512099.1 | 14830816 | 29465.74 | 198216.7 | 400304.6 |
| | median | 940995.9 | 47407614 | 5523745 | 1.02E+08 | 1380299 | 2080873 | 6636421 |
| | rank | 1 | 10 | 6 | 12 | 2 | 5 | 7 |
| C11-F21 | mean | 12.71443 | 47.65386 | 23.5954 | 69.70586 | 18.79433 | 30.4773 | 38.01922 |
| | best | 9.974206 | 40.21741 | 22.58455 | 53.28962 | 17.08664 | 27.83265 | 35.2891 |
| | worst | 14.97499 | 55.7929 | 25.17928 | 86.27352 | 20.76606 | 31.91199 | 41.59334 |
| | std | 2.412667 | 7.133006 | 1.166637 | 15.39462 | 1.711693 | 1.90116 | 3.027254 |
| | median | 12.95425 | 47.30257 | 23.30889 | 69.63015 | 18.66231 | 31.08228 | 37.59723 |
| | rank | 1 | 9 | 3 | 10 | 2 | 6 | 7 |
| C11-F22 | mean | 16.12513 | 45.62653 | 29.33206 | 59.65088 | 22.29539 | 33.27953 | 45.2224 |
| | best | 11.50133 | 40.43442 | 24.92922 | 44.92083 | 19.89289 | 29.90147 | 39.94322 |
| | worst | 19.55286 | 50.76417 | 34.23744 | 68.2016 | 24.26827 | 35.40932 | 49.68618 |
| | std | 4.197797 | 4.567446 | 4.678654 | 10.69338 | 2.342326 | 2.483074 | 4.622637 |
| | median | 16.72317 | 45.65375 | 29.08079 | 62.74054 | 22.51019 | 33.90365 | 45.63009 |
| | rank | 1 | 9 | 4 | 10 | 2 | 5 | 7 |
| Sum rank | | 22 | 192 | 110 | 232 | 55 | 147 | 146 |
| Mean rank | | 1 | 8.727273 | 5 | 10.54545 | 2.5 | 6.681818 | 6.636364 |
| Total rank | | 1 | 9 | 4 | 13 | 2 | 7 | 6 |
| Wilcoxon: *p*-value | | | 2.00E-14 | 3.54E-17 | 7.12E-18 | 7.97E-06 | 2.23E-17 | 2.40E-17 |

Table 2 Optimization results of CEC 2011 test suite

| | | **OOA** | **MVO** | **GWO** | **TLBO** | **GSA** | **PSO** | **GA** |
|---|---|---|---|---|---|---|---|---|
| C11-F1 | mean | 5.920103 | 14.23293 | 11.54006 | 18.04442 | 20.81796 | 17.62171 | 22.26941 |
| | best | 2E-10 | 12.06721 | 2.440182 | 16.94885 | 18.26611 | 11.98458 | 21.09797 |
| | worst | 12.30606 | 16.75519 | 17.9142 | 20.10811 | 22.0111 | 23.14246 | 24.25607 |
| | std | 7.196379 | 2.542719 | 6.891004 | 1.494681 | 1.835857 | 5.329393 | 1.456657 |
| | median | 5.687176 | 14.05466 | 12.90292 | 17.56037 | 21.49731 | 17.67991 | 21.8618 |
| | rank | 1 | 6 | 3 | 10 | 11 | 8 | 13 |
| C11-F2 | mean | -26.3179 | -9.528 | -21.2568 | -11.3023 | -15.241 | -21.2983 | -13.0262 |
| | best | -27.0676 | -11.2824 | -23.3867 | -12.0527 | -19.2658 | -22.4767 | -15.3514 |
| | worst | -25.4328 | -8.10438 | -18.0907 | -10.7637 | -11.6643 | -19.023 | -11.3361 |
| | std | 0.738935 | 1.384544 | 2.41029 | 0.60266 | 3.68196 | 1.640456 | 1.953962 |
| | median | -26.3856 | -9.36262 | -21.775 | -11.1964 | -15.0169 | -21.8468 | -12.7086 |
| | rank | 1 | 13 | 4 | 12 | 7 | 3 | 9 |
| C11-F4 | mean | 1.15E-05 | 1.15E-05 | 1.15E-05 | 1.15E-05 | 1.15E-05 | 1.15E-05 | 1.15E-05 |
| | best | 1.15E-05 | 1.15E-05 | 1.15E-05 | 1.15E-05 | 1.15E-05 | 1.15E-05 | 1.15E-05 |
| | worst | 1.15E-05 | 1.15E-05 | 1.15E-05 | 1.15E-05 | 1.15E-05 | 1.15E-05 | 1.15E-05 |
| | std | 2E-19 | 9E-13 | 6.7E-14 | 1.08E-13 | 6.62E-14 | 6.62E-14 | 6.62E-14 |
| | median | 1.15E-05 | 1.15E-05 | 1.15E-05 | 1.15E-05 | 1.15E-05 | 1.15E-05 | 1.15E-05 |
| | rank | 1 | 10 | 7 | 9 | 3 | 2 | 5 |
| C11-F4 | mean | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | best | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | worst | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | std | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | median | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | rank | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| C11-F5 | mean | -34.1274 | -27.0569 | -30.9071 | -13.3897 | -27.3571 | -11.5656 | -12.2902 |
| | best | -34.7494 | -31.0961 | -33.1007 | -15.1957 | -30.9286 | -14.6193 | -13.5569 |
| | worst | -33.3862 | -25.0029 | -27.5749 | -12.0369 | -24.7099 | -10.0326 | -10.9043 |
| | std | 0.589989 | 3.016868 | 2.471951 | 1.43243 | 2.882071 | 2.246734 | 1.211154 |
| | median | -34.1871 | -26.0642 | -31.4763 | -13.1632 | -26.8949 | -10.8052 | -12.3498 |
| | rank | 1 | 8 | 3 | 11 | 6 | 13 | 12 |
| C11-F6 | mean | -24.1119 | -10.2921 | -18.8022 | -4.21747 | -20.6998 | -4.94712 | -5.71111 |
| | best | -27.4298 | -17.7564 | -20.7928 | -4.93827 | -24.3079 | -7.0585 | -9.74747 |
| | worst | -23.0059 | -3.7729 | -17.0597 | -3.7729 | -16.9161 | -3.7729 | -4.0188 |
| | std | 2.324951 | 7.752062 | 1.994112 | 0.529975 | 3.477442 | 1.570632 | 2.860723 |
| | median | -23.0059 | -9.81963 | -18.6782 | -4.07935 | -20.7876 | -4.47854 | -4.53909 |
| | rank | 1 | 9 | 5 | 13 | 3 | 12 | 11 |
| C11-F7 | mean | 0.860699 | 0.951373 | 1.107406 | 1.65236 | 1.117491 | 1.15425 | 1.670577 |
| | best | 0.582266 | 0.885728 | 0.881194 | 1.479679 | 0.968488 | 0.897931 | 1.35767 |
| | worst | 1.025027 | 1.02631 | 1.309296 | 1.756946 | 1.298184 | 1.369651 | 1.829346 |
| | std | 0.211503 | 0.075607 | 0.186797 | 0.131117 | 0.158446 | 0.258564 | 0.224931 |
| | median | 0.91775 | 0.946726 | 1.119568 | 1.686408 | 1.101647 | 1.17471 | 1.747647 |
| | rank | 1 | 2 | 4 | 10 | 5 | 6 | 11 |
| C11-F8 | mean | 220 | 227.2504 | 229.9897 | 227.2504 | 245.9581 | 433.4045 | 225.9188 |
| | best | 220 | 222.2252 | 222.2252 | 222.2252 | 222.2252 | 246.7904 | 222.2252 |
| | worst | 220 | 236.4643 | 239.4366 | 240.8062 | 288.7436 | 521.1187 | 231.5722 |
| | std | 0 | 6.826963 | 9.25062 | 9.508314 | 32.95358 | 135.3033 | 4.579606 |
| | median | 220 | 225.156 | 229.1484 | 222.985 | 236.4317 | 482.8545 | 224.9389 |
| | rank | 1 | 5 | 6 | 4 | 8 | 13 | 3 |
| C11-F9 | mean | 8789.286 | 148488.9 | 72528.14 | 379914.4 | 728516.7 | 946357 | 1669534 |
| | best | 5457.674 | 112757.3 | 38425.67 | 333470.8 | 624500.4 | 753374.8 | 1597320 |
| | worst | 14042.29 | 201975.7 | 104307.5 | 472974.3 | 768053.7 | 1146793 | 1778056 |
| | std | 3889.181 | 41402.58 | 28515.35 | 66519.34 | 73166.54 | 216193.9 | 88492.94 |
| | median | 7828.591 | 139611.4 | 73689.68 | 356606.2 | 760756.3 | 942629.9 | 1651381 |
| | rank | 1 | 5 | 3 | 8 | 10 | 12 | 13 |
| C11-F10 | mean | -21.4889 | -14.2748 | -13.7729 | -11.4072 | -12.9746 | -11.491 | -11.2428 |
| | best | -21.8299 | -20.137 | -14.5805 | -11.9091 | -13.8309 | -11.9553 | -11.6709 |
| | worst | -20.7878 | -11.2489 | -12.4952 | -11.0793 | -12.0186 | -11.1889 | -10.9583 |
| | std | 0.498616 | 4.184379 | 0.941716 | 0.371762 | 0.818242 | 0.343631 | 0.318359 |
| | median | -21.669 | -12.8566 | -14.0078 | -11.3203 | -13.0246 | -11.4099 | -11.171 |
| | rank | 1 | 4 | 6 | 12 | 8 | 11 | 13 |
| C11-F11 | mean | 571712.3 | 1498856 | 3618899 | 4774892 | 1585228 | 4784193 | 5541427 |
| | best | 260837.9 | 859467.4 | 3495887 | 4729579 | 1539942 | 4748182 | 5463937 |
| | worst | 828560.9 | 2772377 | 3928789 | 4846534 | 1677837 | 4846534 | 5679235 |
| | std | 260922.1 | 906932.5 | 217780.3 | 52692.61 | 67680.62 | 45577.61 | 99412.38 |
| | median | 598725.2 | 1181790 | 3525459 | 4761727 | 1561566 | 4771028 | 5511268 |
| | rank | 1 | 4 | 7 | 8 | 5 | 9 | 12 |
| C11-F12 | mean | 1199805 | 1637420 | 1718522 | 12552409 | 5383533 | 2465510 | 12687503 |
| | best | 1155937 | 1473502 | 1584886 | 11856053 | 5104008 | 2332813 | 12602758 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | worst | 1249353 | 1780806 | 1844952 | 13104339 | 5562149 | 2663064 | 12761027 |
| | std | 47157.58 | 132583.4 | 112208.9 | 553507.6 | 211689.3 | 148250.5 | 68583.36 |
| | median | 1196965 | 1647685 | 1722125 | 12624622 | 5433988 | 2433081 | 12693114 |
| | rank | 1 | 3 | 4 | 12 | 8 | 5 | 13 |
| C11-F13 | mean | 15444.2 | 15511.81 | 15506.11 | 15869.08 | 110296.6 | 15497.48 | 27688.41 |
| | best | 15444.19 | 15491.36 | 15497.6 | 15609.61 | 80421.19 | 15480.31 | 15478.16 |
| | worst | 15444.21 | 15550.36 | 15512.72 | 16342.08 | 150810.9 | 15524.7 | 64042.27 |
| | std | 0.009091 | 28.12276 | 6.737851 | 348.5 | 33308.79 | 20.1553 | 25474.47 |
| | median | 15444.2 | 15502.77 | 15507.06 | 15762.32 | 104977.1 | 15492.45 | 15616.61 |
| | rank | 1 | 7 | 6 | 10 | 13 | 5 | 12 |
| C11-F14 | mean | 18295.35 | 19439.01 | 19282.13 | 264278.7 | 19164.53 | 19191.89 | 19181.17 |
| | best | 18241.58 | 19329.12 | 19134.19 | 28547.81 | 18912.02 | 19044.6 | 18932.51 |
| | worst | 18388.08 | 19534.56 | 19465.07 | 507229.8 | 19316.17 | 19321.83 | 19459.96 |
| | std | 71.59938 | 91.02157 | 152.7497 | 241544.1 | 188.2708 | 122.2792 | 227.9891 |
| | median | 18275.87 | 19446.17 | 19264.63 | 260668.5 | 19214.96 | 19200.56 | 19166.11 |
| | rank | 1 | 9 | 8 | 13 | 4 | 6 | 5 |
| C11-F15 | mean | 32883.58 | 45468.92 | 45450.31 | 12983382 | 269689.6 | 45627.01 | 6690553 |
| | best | 32782.17 | 33026.54 | 33051.55 | 2736525 | 228340.9 | 33253.65 | 3042549 |
| | worst | 32956.46 | 51781.2 | 51703.43 | 19358805 | 291640.4 | 51902.61 | 11460012 |
| | std | 76.94696 | 8899.828 | 8868.206 | 7940200 | 30947.35 | 8853.229 | 4054593 |
| | median | 32897.86 | 48533.97 | 48523.12 | 14919100 | 279388.6 | 48675.9 | 6129825 |
| | rank | 1 | 4 | 3 | 13 | 9 | 5 | 12 |
| C11-F16 | mean | 133550 | 142437.6 | 145854.6 | 74771248 | 15765094 | 66926236 | 64261251 |
| | best | 131374.2 | 134044.7 | 142569.7 | 72863394 | 8018850 | 55365044 | 51941418 |
| | worst | 136310.8 | 150317.3 | 150973.4 | 76922213 | 28504369 | 79970878 | 82187377 |
| | std | 2392.2 | 7126.149 | 3777.487 | 1787965 | 9310709 | 11148097 | 13504451 |
| | median | 133257.5 | 142694.1 | 144937.6 | 74649692 | 13268579 | 66184512 | 61458106 |
| | rank | 1 | 4 | 7 | 13 | 10 | 12 | 11 |
| C11-F17 | mean | 1926615 | 6.49E+08 | 6.49E+08 | 1.94E+10 | 1.01E+10 | 1.82E+10 | 1.9E+10 |
| | best | 1916953 | 4.64E+08 | 4.63E+08 | 1.89E+10 | 8.88E+09 | 1.6E+10 | 1.79E+10 |
| | worst | 1942685 | 8.61E+08 | 8.62E+08 | 2E+10 | 1.07E+10 | 2.07E+10 | 2.13E+10 |
| | std | 12003.53 | 1.76E+08 | 1.76E+08 | 5.05E+08 | 8.76E+08 | 2.17E+09 | 1.7E+09 |
| | median | 1923412 | 6.35E+08 | 6.36E+08 | 1.93E+10 | 1.04E+10 | 1.8E+10 | 1.85E+10 |
| | rank | 1 | 4 | 3 | 13 | 9 | 11 | 12 |
| C11-F18 | mean | 942057.5 | 1565381 | 1601545 | 26802059 | 10091478 | 1.14E+08 | 97052378 |
| | best | 938416.2 | 1208053 | 1185497 | 21028845 | 7729212 | 95817548 | 93529199 |
| | worst | 944706.9 | 2036921 | 2235896 | 29424540 | 13030136 | 1.26E+08 | 1E+08 |
| | std | 2774.139 | 368195.2 | 475034.6 | 4090135 | 2516208 | 14506058 | 3013638 |
| | median | 942553.5 | 1508275 | 1492394 | 28377426 | 9803282 | 1.17E+08 | 97106275 |
| | rank | 1 | 3 | 4 | 9 | 8 | 13 | 11 |
| C11-F19 | mean | 1025341 | 2070008 | 1974259 | 30755816 | 6098260 | 1.46E+08 | 97467953 |
| | best | 967927.7 | 1210246 | 1380176 | 21455451 | 3147832 | 1.33E+08 | 94730931 |
| | worst | 1167142 | 3061406 | 2544052 | 38744416 | 8333924 | 1.68E+08 | 1.01E+08 |
| | std | 99675.04 | 845585.3 | 632984 | 7705989 | 2276422 | 16187798 | 2637573 |
| | median | 983146.6 | 2004190 | 1986404 | 31411698 | 6455643 | 1.41E+08 | 97257575 |
| | rank | 1 | 4 | 3 | 9 | 6 | 13 | 11 |
| C11-F20 | mean | 941250.4 | 1396197 | 1417828 | 29648330 | 12578064 | 1.35E+08 | 97487351 |
| | best | 936143.2 | 1377810 | 1385798 | 28996475 | 8553436 | 1.23E+08 | 92859483 |
| | worst | 946866.6 | 1424318 | 1451737 | 30311072 | 19190127 | 1.46E+08 | 1.01E+08 |
| | std | 5013.552 | 23341.83 | 32784.24 | 576825.8 | 4891126 | 13500555 | 3641038 |
| | median | 940995.9 | 1391330 | 1416889 | 29642886 | 11284346 | 1.35E+08 | 98019702 |
| | rank | 1 | 3 | 4 | 9 | 8 | 13 | 11 |
| C11-F21 | mean | 12.71443 | 28.5535 | 24.21289 | 90.0843 | 39.62681 | 94.3193 | 91.6871 |
| | best | 9.974206 | 25.60463 | 22.88643 | 45.69564 | 35.56843 | 81.89725 | 54.46949 |
| | worst | 14.97499 | 31.2056 | 26.23347 | 130.3305 | 41.73212 | 104.4449 | 110.8826 |
| | std | 2.412667 | 3.198601 | 1.538292 | 36.44639 | 3.002921 | 11.57281 | 27.60483 |
| | median | 12.95425 | 28.70189 | 23.86583 | 92.15553 | 40.60334 | 95.46753 | 100.6981 |
| | rank | 1 | 5 | 4 | 11 | 8 | 13 | 12 |
| C11-F22 | mean | 16.12513 | 33.41087 | 27.26913 | 92.56565 | 45.52291 | 95.95859 | 84.12789 |
| | best | 11.50133 | 26.60935 | 26.82319 | 61.62802 | 39.50369 | 81.4849 | 83.34725 |
| | worst | 19.55286 | 38.15783 | 27.77753 | 108.4826 | 52.56221 | 105.311 | 85.4577 |
| | std | 4.197797 | 5.34673 | 0.464144 | 22.23837 | 5.653775 | 11.1633 | 0.993915 |
| | median | 16.72317 | 34.43814 | 27.2379 | 100.076 | 45.01286 | 98.51922 | 83.8533 |
| | rank | 1 | 6 | 3 | 12 | 8 | 13 | 11 |
| Sum rank | | 22 | 119 | 98 | 222 | 158 | 199 | 224 |
| Mean rank | | 1 | 5.409091 | 4.454545 | 10.09091 | 7.181818 | 9.045455 | 10.18182 |
| Total rank | | 1 | 5 | 3 | 11 | 8 | 10 | 12 |
| Wilcoxon: *p*-value | | | 7.29E-14 | 8.79E-15 | 1.52E-17 | 3.67E-17 | 7.12E-18 | 1.04E-17 |

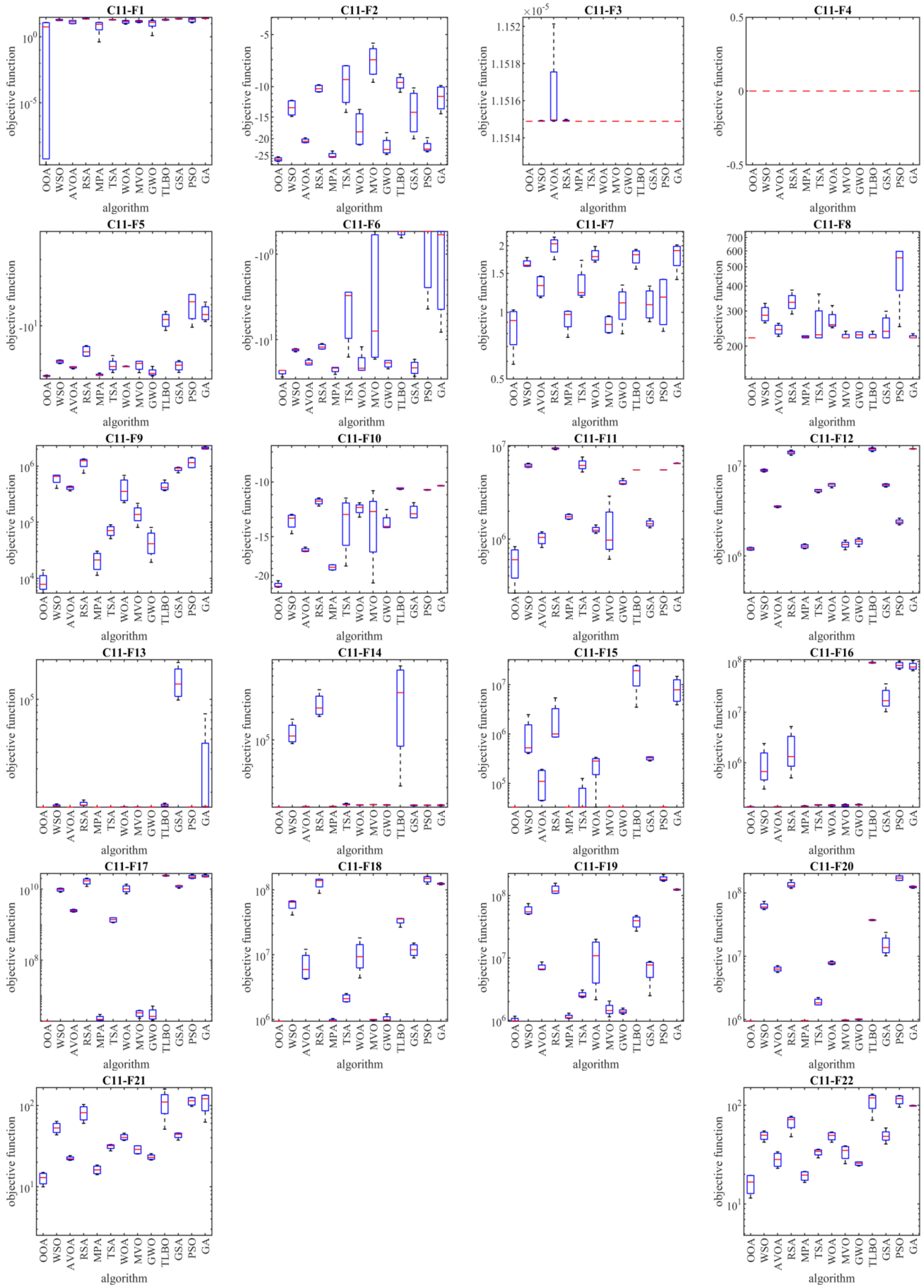


Figure 1 Boxplot diagrams of OOA and the competitor algorithms performances for the CEC 2011 test suite

Moreover, the statistical analysis conducted using the Wilcoxon rank-sum test further reinforces the advantage of the OOA approach. The results demonstrate a significant statistical superiority for OOA over the competing algorithms, confirming its enhanced ability to optimize the CEC 2011 test suite more effectively.

## 4. Conclusions and future Works

In this paper, a completely different bio-inspired metaheuristic algorithm called the Orangutan Optimization Algorithm (OOA) was introduced, showcasing its capability in solving optimization problems across a variety of scientific disciplines and real-world applications. This novel approach is inspired by two distinct natural behaviors of orangutans: their foraging strategies for obtaining food and their nesting behavior for resting. These behaviors formed the foundation for the design of OOA, which was mathematically structured into two key phases—exploration and exploitation. The performance of OOA was applied to twenty-two optimization problems from the CEC 2011 test suite, further validating its effectiveness in solving real-world optimization challenges. When compared to twelve other widely-recognized metaheuristic algorithms, OOA showed a superior performance, producing better optimization results for most benchmark functions. Moreover, the introduction of OOA opens several new avenues for future research. One of the most promising directions is the development of binary and multi-objective versions of OOA. Furthermore, expanding the application of OOA to address optimization challenges in completely different scientific fields and a broader range of real-world scenarios provides exciting opportunities for future studies.

## Conflicts of Interest

"The authors declare no conflict of interest."

## Author Contributions

Conceptualization, T.H, B.B, E.A, R.K.J, and G.M.G; methodology, TH, M.D, G.D, F.W, and K.E; software, K.E, B.B, G.D, R.K.J, and G.M.G; validation, K.E, M.D, I.K.I, and F.W; formal analysis, Z.M, M.D, and K.E; investigation, B.B, I.K.I, Z.M, E.A, and G.M.G; resources, T.H, R.K.J, Z.M, F.W, G.D, and B.B; data curation, K.E, I.K.I, and G.M.G; writing—original draft preparation, M.D, T.H, F.W, E.A, and O.P.M; writing—review and editing, G.M.G, Z.M, B.B, G.D, R.K.J, and K.E; visualization, E.A, I.K.I, and K.E; supervision, M.D; project administration, K.E, T.H, I.K.I, and F.W; funding acquisition, K.E.

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