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# Xerus Optimization Algorithm (XOA): a novel nature-inspired metaheuristic algorithm for solving global optimization problems

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## ABSTRACT

Over the recent years, many research has been carried out on applying the optimization approach to science and engineering problems. Thereby, numerous metaheuristic algorithms have been developed for solving such type of challenge. Despite an increase in the number of these algorithms, there is currently no specific algorithm which can be employed to optimize all varieties of problems. In the current research, a novel metaheuristic algorithm for global and continuous nonlinear optimization, named as Xerus Optimization Algorithm (XOA) has been introduced. XOA has been inspired by group living and lifestyle of cape ground squirrels (*Xerus inauris*), by taking into account their co-operation in living together, hunting, and communication, etc. In order to evaluate the efficiency of XOA, algorithms for 30 different benchmarks have been analyzed and compared to some novel and renowned metaheuristic algorithms. The simulation response illustrates a significant improvement in

*Keyword:* Xerus Optimization Algorithm; Global Optimization; Evolutionary Algorithms; Metaheuristic Algorithms.

AMS subject Classification: 05C78.

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## ARTICLE INFO

*Article history:*

Received 5, July 2018

Received in revised form 19, October 2019

Accepted 11 November 2019

Available online 31, December 2019

## 1 Abstract continued

the performance of the novel XOA, in comparison to the algorithms presented in the literature. The proposed algorithm can be employed for many applications that require a solution to different optimization problems.

## 2 Introduction

The world is facing many science and engineering related problems, with lots of them not having a particular solution. In such situations, optimization methods are employed to find the best solution. Calculus has widespread application in all parts of Science and Engineering and since optimization is one of the major subjects within calculus, it can be employed to mathematically formulate a problem, and derivatives can be determined to provide an optimal solution [10]. In doing so, metaheuristic technique and in particular, Evolutionary Algorithms (EAs) can be proposed to provide a specific solution.

Classical methods often face great difficulties in solving optimization problems. In order to overcome the shortcomings of traditional mathematical techniques, nature-inspired soft computing algorithms have been introduced [19]. Taking inspiration from natural evolution processes, EAs which are a class of metaheuristic methods, have been employed for solving complex optimization problems. Such methods typically have non-convex and highly nonlinear solution spaces, and are capable of solving optimization challenges that are otherwise computationally difficult to solve by conventional mathematical programming methods [8].

There has been a growing attempt in developing algorithms inspired by nature; for instance, Genetic Algorithms (GAs), Particle Swarm Optimization (PSO), Differential Evolution (DE) and Ant Colony Optimization (ACO). GA aims to generate high-quality solutions to optimization challenges by relying on bio-inspired operators such as mutation, crossover and selection, which was proposed by Holland [4]. PSO simulates the social behavior of a group of migrating animals (like birds) that tries to reach an unknown destination [5]. DE proposed by Storn and Price optimizes a problem by iteratively trying to improve a candidate solution with regards to a given measure of quality [14]. Ant Colony Optimization is inspired by behavior of ants which is a probabilistic technique for solving computational problems that can be reduced to finding good paths through graphs [2].

Out of the existing nature-inspired algorithms, Evolutionary Algorithm has been selected for the current research due to its quality of reaching the best solution on global functions. Evolutionary algorithms generally involve a collection of candidate solutions to an optimization problem. These candidate solutions are often called individuals, or simply solutions, and the collection of them is referred to as the population. The merging of these solutions is called recombination, and results in new candidate solutions. Candidate solutions can combine with each other and are also subject to random changes, which are referred to as mutations. Recombination and mutation creates new solutions, and the EA thus progress from one generation to the next, in an attempt to find ever-improving solutions to a given problem [13]. Despite the variation in EAs, there is no particular algorithm with the ability to obtain the most appropriate solution for all

types of optimization problems. Undoubtedly some algorithms provide better solution to some particular problems in comparison to other algorithms. Therefore, pursuing new optimization technique is an everlasting open problem [17].

Therefore, the current study aims to propose a new algorithm to achieve the best answer/solution for variety of problems and as close as it possibly can. This research focuses on cape ground squirrels (*Xerus inauris*) which are a kind of mammals that have a particular behavior on their social and group living. Their way of living on searching for the safest place to live, is an inspiration for introducing a novel evolutionary algorithm in this paper.

Section 2 initially provides a brief introduction to Xerus lifestyle and then a description on how these behaviors can be applied to establish a new Evolutionary Algorithm is added. Section 3 illustrates a discussion on the experimental setup which has been taken over 30 benchmark functions, where the obtained results confirms the competency of the XOA algorithm. Finally, section 4 provides the conclusion to the current study.

## **2. Xerus Optimization Algorithm (XOA)**

As mentioned above, many of the evolutionary algorithms are typically inspired from natural processes. In this section, the inspiration of XOA will initially be introduced and then the XOA algorithm will be proposed.

### *2.1 Inspiration*

Cape ground squirrels (*xerus inauris*) have a particular living behavior that is formed from 2 parts: initially their considerable effort on searching for the safest living place and also avoiding any danger or other types of enemies, at which point they then start to reproduce. Such living behaviors are the focus of the current paper includes

Typically, when squirrels aim to reach a safe place, they have to avoid an incoming hazard from other animals, and once a danger is encountered it is communicated to the rest of the squirrels. In doing so, particular voice signals with 2 types of variations are used to alarm others [20]. The shrill, short “bi-jo” sound indicates highest priority alarm and provokes the strongest reaction from others, while the medium-pitched, “bi-joo” sound indicated a less imminent threat [16]. Therefore, for a seriously dangerous situation, a high frequency sound and for a less dangerous one, a lower frequency will be employed. Once presence of a danger is communicated to the rest of the squirrels, they begin to search for the safest place. This is achieved by each moving towards the space dimensions with a particular length, and if that particular spot is found to be a better place to live, they continue to search for a place that is safer than other areas. Finally, once squirrels reach the safest area, they begin to reproduce there in some individual groups which consists of one female and several male squirrels in a competition to have cohabit [15].

### *2.2 The Proposed Xerus Optimization Algorithm*

In the current paper, the Xerus optimization algorithm is introduced which has been inspired by the nature of cape ground squirrels (*xerus inauris*).

Initially, there will be a number of squirrels, which is counted as the first group of solutions (initial solutions in an  $N$  number). After evaluating all the possible solutions, the best solution in this group can be found, which is represents the first Xerus.

Following that, the space dimensions for finding a safer place to live can be analyzed, where the distance that a squirrel have to travel in one dimension with respect to  $D$  can be defined as (1):

$$D(x,t) = AS \sin(kx - \omega t) \quad (1)$$

Equation (1) is the mathematical representation of a traveling wave, where:

- $A$  defines the loudness of the squirrel's sound
- $k$  can be written as  $\frac{2\pi}{\lambda}$ ,  $\lambda$  is the wavelength of squirrel's sound wave
- $\omega$  is  $2\pi f$ ,  $f$  is the frequency of the wave
- $t$  is time – in this paper it is considered as iterations

When a squirrel feels any form of danger, it makes sounds to warn others and if the hazard is of a serious form, then the loudness and frequency of the produced sound are high, and hence the distance  $D$  will increase; and therefore the rest of the squirrels located in their first dimension of search space will move further in that line. Later, the secondary locations are evaluated and if these positions are better (for minimization, less cost for the function) we go to the new point and search toward the next dimension. If the solution from the new point isn't comparatively better, we go back and search opposite direction. Alternatively, if no better solution is found, it can be said that this point is good enough to search in shorter distances and hence  $A$  is multiplied in a damp radius of  $k$ . After reaching the best point in each iteration, squirrels begin to reproduce, and therefore, number of new squirrels ( $nNew$ ) in the search space that came from normal distribution with a mean of  $0$  and  $r$  (radius) can be included.

The best selected area has been divided into some smaller spaces for the reproduction, where these areas have equal space for new squirrels.

The pseudo code for the above described Xerus optimization algorithm is shown in Fig. 1:

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Generating N initial solutions and evaluate them. The best solution
is the
for iteration 1 to n
    for n=1 to n=nvar
        Move toward the nth dimensional vector in space with
distance
        D to reach the second point.
        If cost function for second point was better
            Best point=second point
        Else
            Move toward opposite direction
        End if
    End for
    Generate nNew numbers of solutions with normal distribution
End for

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Fig. 1. Xerus Optimization Algorithm pseudo code.

### 3. Simulation Response

In this section the proposed algorithm of XOA is tested with 30 benchmark functions extracted from the IEEE Congress on Evolutionary Computation 2014 (CEC 2014 Competition) on Single Objective Real-Parameter Numerical Optimization. The series of benchmark consist of a

wide range of different types of function optimization problems. Within these 30 benchmarks, the problems can be classified into 4 types: 3 Unimodal, 13 Multimodal, 6 of Hybrid and 8 Composition benchmark functions. These functions are provided in Table 1. Full details and definitions of all the different benchmark functions with their figures can be found in [6].

### 3.1 Comparative Methods

In order to evaluate the efficiency of XOA, this proposed algorithm can be compared to 7 new and popular evolutionary algorithms: Invasive Weed Optimization (IWO) [7], Biogeography-Based Optimization (BBO) [12], Gravitational Search Algorithm (GSA) [11], Hunting Search (HuS) [9], Bat Algorithm (BA) [18], Imperialist Competitive Algorithm (ICA) [1] and Harmony Search (HS) algorithm [3].

Each of these evolutionary algorithms can reach many different solutions by changing the parameters of the algorithm. For a fair comparison and to tune each algorithm, the recommended settings need to be used, where some of these settings come from improvement of the previously suggested parameters [19]. Following presents, the settings that have been used for each algorithm.

IWO: Initial population size  $N_0 = 10$ , maximum population size  $N = 30$ , minimum and maximum number of seeds are  $S_{min} = 0$  and  $S_{max} = 3$ , variance reduction exponent  $E = 2$ , initial value of standard deviation  $\sigma_{initial} = 0.25$  and final value of standard deviation  $\sigma_{final} = 0.0005$ .

BBO: Number of habitats (population size)  $N = 50$ , keep rate  $k = 0.2$ , number of kept habitats  $n_k = \text{round}(k*N)$ , number of new habitats  $n_{New} = N - n_k$ , emigration rate  $E = \text{random number from } 0 \text{ to } 1$ , immigration rate  $I = 1 - E$  and  $\alpha = 0.9$ .

GSA: The initial gravitational constant  $G_0 = 100$  and its decreasing coefficient  $\alpha = 2$ , number of population  $N = 50$ .

HuS: Hunting group size  $HGS = 10$ , maximum movement toward leader  $MML = 0.3$ , hunting group consideration rate  $HGCR = 0.3$ , minimum radiation and maximum radiation are  $Ra_{Min} = 5e-6$  and  $Ra_{Max} = 0.01$ , maximum difference  $e = 10 \wedge -100$  and alpha and beta are 0.05.

BA: The minimum and maximum frequency rates  $Q_{min} = 0$  and  $Q_{max} = 2$ , loudness  $A = 1$ , pulse rate  $r = 1$ , population size  $N=25$  and alpha and gamma are 0.9.

ICA: Population size  $N = 50$ , number of empires/imperialists  $n_{Emp} = 10$ , selection pressure  $\alpha = 1$ , assimilation coefficient  $\beta = 2$ , revolution probability  $p_{Revolution}=0.1$ , revolution rate  $\mu=0.05$  and colonies mean cost coefficient  $\zeta = 0.1$ .

HS: Harmony memory size  $HMS = 50$ , number of new harmonies  $n_{New} = 50$ , harmony memory consideration rate  $HMCR = 0.5$  and pitch adjustment rate  $PAR = 0.1$ .

XOA: Number of population  $N = 50$ ,  $A = (\text{upper bound of decision variable} - \text{lower bound of decision variable}) / 10$ , searching radius  $r = 0.05 * (\text{upper bound of decision variable} - \text{lower bound of decision variable})$ , damp radius  $k = 1/2$ , number of new born squirrels  $n_{New}=20$ .

Table 1. Summary of the CEC 2014 benchmarks which used in experimental study.

Type	ID	Function	$f^*$
<b>Unimodal</b>	$f_1$	Rotated high conditioned elliptic function	100
	$f_2$	Rotated bent cigar function	200
	$f_3$	Rotated discus function	300
<b>Multimodal</b>	$f_4$	Shifted and rotated Rosenbrock function	400
	$f_5$	Shifted and rotated Ackley's function	500
	$f_6$	Shifted and rotated Weierstrass function	600
	$f_7$	Shifted and rotated Griewank's function	700
	$f_8$	Shifted Rastrigin function	800
	$f_9$	Shifted and rotated Rastrigin's function	900
	$f_{10}$	Shifted Schwefel function	1000
	$f_{11}$	Shifted and rotated Schwefel's function	1100
	$f_{12}$	Shifted and rotated Katsuura function	1200
	$f_{13}$	Shifted and rotated HappyCat function	1300
	$f_{14}$	Shifted and rotated HGBat function	1400
	$f_{15}$	Shifted and rotated Expanded Griewank's plus Rosenbrock's function	1500
	$f_{16}$	Shifted and rotated Expanded Scaffer's F6 function	1600
<b>Hybrid</b>	$f_{17}$	Hybrid function 1 (f9,f8,f1)	1700
	$f_{18}$	Hybrid function 2 (f2,f12,f8)	1800
	$f_{19}$	Hybrid function 3 (f7,f6,f4,f14)	1900
	$f_{20}$	Hybrid function 4 (f12,f3,f13,f8)	2000
	$f_{21}$	Hybrid function 5 (f14,f12,f4,f9,f1)	2100
	$f_{22}$	Hybrid function 6 (f10,f11,f13,f9,f5)	2200
<b>Composition</b>	$f_{23}$	Composition function 1 (f4,f1,f2,f3,f1)	2300
	$f_{24}$	Composition function 2 (f10,f9,f14)	2400
	$f_{25}$	Composition function 3 (f11,f9,f1)	2500
	$f_{26}$	Composition function 4 (f11,f13,f1,f6,f7)	2600
	$f_{27}$	Composition function 5 (f14,f9,f11,f6,f1)	2700
	$f_{28}$	Composition function 6 (f15,f13,f11,f16,f1)	2800
	$f_{29}$	Composition function 7 (f17,f18,f19)	2900
	$f_{30}$	Composition function 8 (f20,f21,f22)	3000

### 3.2 Experimental Results

The experiments have been carried out using a computer with Intel Core i7-7500U and 16GB of DDR4 Ram. The dimension of search space in each benchmark function for testing is 30, also decision variables bound are from -100 to 100 and the maximum number of cost function evaluations (NFE) is set to be 150000 for running every algorithm on benchmarks. Each algorithm had run over 60 times and the results are reported in Table 2 where "Maximum", "Minimum" and "Average" represent the maximum, minimum and average of the resultant cost function values for over the 60 runs. Also, "Median" and "std" denotes the median and standard deviation

of the resultant cost function value for all 60 runs.

Table 2. Comparative results on 30 test functions extracted from from CEC 14.

	IWO	BBO	GSA	HuS	BA	ICA	HS	XOA	
f1	Maximum	1.84E+06	4.57E+06	3.09E+09	3.95E+08	5.20E+08	3.64E+06	6.03E+08	<b>1.56E+06</b>
	Minimum	2.41E+05	7.12E+05	3.69E+08	1.78E+07	3.94E+06	2.89E+05	2.48E+08	<b>8.03E+04</b>
	Average	9.73E+05	2.43E+06	1.33E+09	1.47E+08	7.77E+07	1.44E+06	4.00E+08	<b>5.19E+05</b>
	Median	8.44E+05	2.68E+06	9.07E+08	9.02E+07	7.94E+07	1.00E+06	3.91E+08	<b>4.74E+05</b>
	std	3.50E+05	8.70E+05	6.57E+08	8.16E+07	9.07E+07	8.46E+05	7.66E+07	<b>2.76E+05</b>
f2	Maximum	1.20E+06	2.59E+05	1.58E+11	6.98E+09	2.85E+09	3.45E+05	2.68E+10	<b>2.06E+05</b>
	Minimum	6.51E+05	5.95E+04	9.43E+10	3.30E+03	6.61E+06	2.09E+02	1.53E+10	<b>2.00E+02</b>
	Average	1.03E+06	1.49E+05	1.24E+11	6.37E+08	1.50E+09	1.12E+05	2.12E+10	<b>3.05E+04</b>
	Median	1.12E+06	1.08E+05	1.30E+11	8.35E+08	2.38E+09	6.19E+03	2.21E+10	<b>1.81E+03</b>
	std	1.08E+05	4.61E+04	1.44E+10	1.38E+09	7.69E+08	<b>1.20E+04</b>	2.39E+09	4.79E+04
f3	Maximum	4.60E+04	2.93E+04	6.78E+05	3.83E+05	<b>1.11E+04</b>	4.48E+04	6.09E+04	2.75E+04
	Minimum	1.43E+04	5.10E+02	2.05E+05	1.00E+05	9.13E+03	4.03E+02	2.67E+04	<b>3.81E+02</b>
	Average	2.76E+04	7.43E+03	4.23E+05	2.45E+05	1.01E+04	1.54E+04	4.06E+04	<b>4.48E+03</b>
	Median	2.90E+04	7.51E+03	4.81E+05	2.48E+05	1.06E+04	<b>2.96E+03</b>	4.33E+04	4.01E+03
	std	7.73E+03	6.38E+03	1.05E+05	6.88E+04	4.55E+02	8.31E+03	8.49E+03	<b>3.59E+02</b>
f4	Maximum	5.65E+02	5.44E+02	4.83E+04	1.01E+03	2.43E+03	5.64E+02	3.50E+03	<b>4.96E+02</b>
	Minimum	4.08E+02	4.23E+02	6.42E+03	4.87E+02	4.98E+02	4.12E+02	1.61E+03	<b>4.04E+02</b>
	Average	4.51E+02	4.70E+02	2.11E+04	6.37E+02	1.27E+03	4.81E+02	2.72E+03	<b>4.36E+02</b>
	Median	<b>4.48E+02</b>	4.72E+02	1.39E+04	6.21E+02	1.50E+03	5.50E+02	2.75E+03	4.85E+02
	std	4.38E+01	3.42E+01	1.02E+04	9.91E+01	5.47E+02	3.63E+01	4.36E+02	<b>2.59E+01</b>
f5	Maximum	5.21E+02	5.20E+02	5.21E+02	<b>5.20E+02</b>	<b>5.20E+02</b>	5.20E+02	5.21E+02	<b>5.20E+02</b>
	Minimum	5.21E+02	5.20E+02	5.21E+02	<b>5.20E+02</b>	<b>5.20E+02</b>	<b>5.20E+02</b>	5.21E+02	<b>5.20E+02</b>
	Average	5.21E+02	5.20E+02	5.21E+02	<b>5.20E+02</b>	<b>5.20E+02</b>	5.20E+02	5.21E+02	<b>5.20E+02</b>
	Median	5.21E+02	5.20E+02	5.21E+02	<b>5.20E+02</b>	<b>5.20E+02</b>	5.20E+02	5.21E+02	<b>5.20E+02</b>
	std	5.92E-02	3.04E-02	1.01E-01	2.33E-05	7.57E-05	3.34E-02	4.55E-02	<b>5.60E-06</b>
f6	Maximum	6.50E+02	6.25E+02	6.50E+02	6.43E+02	6.24E+02	6.25E+02	6.39E+02	<b>6.21E+02</b>
	Minimum	6.37E+02	6.09E+02	6.39E+02	6.26E+02	6.21E+02	6.14E+02	6.33E+02	<b>6.07E+02</b>
	Average	6.43E+02	6.16E+02	6.45E+02	6.35E+02	6.23E+02	6.21E+02	6.36E+02	<b>6.15E+02</b>
	Median	6.41E+02	6.12E+02	6.48E+02	6.37E+02	6.23E+02	6.22E+02	6.36E+02	<b>6.11E+02</b>
	std	2.85E+00	4.13E+00	2.58E+00	3.63E+00	<b>6.77E-01</b>	2.56E+00	1.42E+00	2.84E+00
					<b>01</b>				
	Maximum	7.01E+02	7.01E+02	2.05E+03	7.59E+02	8.61E+02	7.00E+02	9.43E+02	<b>7.00E+02</b>
	Minimum	7.01E+02	7.00E+02	1.42E+03	7.00E+02	7.50E+02	<b>7.00E+02</b>	8.34E+02	<b>7.00E+02</b>

f7	Average	7.01E+02	7.00E+02	1.74E+03	7.05E+02	7.97E+02	7.00E+02	8.94E+02	<b>7.00E+02</b>
	Median	7.01E+02	7.00E+02	1.71E+03	7.02E+02	7.99E+02	7.00E+02	9.12E+02	<b>7.00E+02</b>
	std	3.89E-02	9.96E-02	1.53E+02	8.82E+00	2.92E+01	2.28E-01	2.78E+01	<b>2.27E-02</b>
	Maximum	1.23E+03	8.64E+02	1.37E+03	1.11E+03	8.82E+02	<b>8.33E+02</b>	1.00E+03	8.60E+02
	Minimum	9.51E+02	8.23E+02	1.23E+03	9.17E+02	8.42E+02	8.30E+02	9.54E+02	<b>8.09E+02</b>
f8	Average	1.11E+03	8.40E+02	1.30E+03	1.02E+03	8.57E+02	8.30E+02	9.80E+02	<b>8.28E+02</b>
	Median	1.08E+03	8.46E+02	1.28E+03	9.90E+02	8.70E+02	8.30E+02	9.83E+02	<b>8.22E+02</b>
	std	5.43E+01	9.73E+00	3.03E+01	4.10E+01	7.83E+00	<b>5.70E-01</b>	1.10E+01	1.19E+01
	Maximum	1.54E+03	1.01E+03	1.62E+03	1.38E+03	<b>9.56E+02</b>	1.18E+03	1.24E+03	1.27E+03
	Minimum	1.14E+03	<b>9.35E+02</b>	1.36E+03	1.08E+03	9.36E+02	9.92E+02	1.17E+03	9.66E+02
f9	Average	1.35E+03	9.67E+02	1.50E+03	1.21E+03	<b>9.50E+02</b>	1.08E+03	1.20E+03	1.05E+03
	Median	1.35E+03	9.82E+02	1.55E+03	1.26E+03	<b>9.51E+02</b>	1.10E+03	1.21E+03	1.05E+03
	std	7.71E+01	1.75E+01	4.31E+01	7.45E+01	<b>3.08E+00</b>	3.68E+01	1.56E+01	5.89E+01
	Maximum	7.59E+03	3.97E+03	1.07E+04	8.42E+03	2.61E+03	<b>2.52E+03</b>	4.82E+03	3.01E+03
	Minimum	4.12E+03	1.36E+03	8.08E+03	3.70E+03	1.90E+03	1.26E+03	3.23E+03	<b>1.19E+03</b>
f10	Average	6.00E+03	2.44E+03	9.02E+03	5.49E+03	2.29E+03	2.20E+03	4.27E+03	<b>1.97E+03</b>
	Median	5.86E+03	2.29E+03	9.50E+03	5.65E+03	2.11E+03	<b>1.91E+03</b>	4.28E+03	2.01E+03
	std	7.84E+02	5.80E+02	5.29E+02	8.33E+02	<b>1.31E+02</b>	2.59E+02	3.09E+02	4.15E+02
	Maximum	7.14E+03	5.96E+03	1.09E+04	7.08E+03	<b>2.93E+03</b>	5.21E+03	8.76E+03	5.23E+03
	Minimum	4.55E+03	3.60E+03	8.07E+03	3.86E+03	<b>2.10E+03</b>	2.60E+03	7.31E+03	2.92E+03
f11	Average	5.81E+03	4.66E+03	9.66E+03	5.38E+03	<b>2.66E+03</b>	4.08E+03	8.26E+03	4.13E+03
	Median	6.06E+03	3.99E+03	9.82E+03	5.54E+03	<b>2.87E+03</b>	3.72E+03	8.49E+03	4.61E+03
	std	5.77E+02	4.82E+02	5.76E+02	6.89E+02	<b>2.24E+02</b>	5.51E+02	2.97E+02	5.43E+02
	Maximum	1.20E+03	1.20E+03	1.21E+03	1.20E+03	1.20E+03	<b>1.20E+03</b>	1.20E+03	1.20E+03
	Minimum	1.20E+03	1.20E+03	1.20E+03	1.20E+03	1.20E+03	1.20E+03	1.20E+03	<b>1.20E+03</b>
f12	Average	1.20E+03	1.20E+03	1.20E+03	1.20E+03	1.20E+03	1.20E+03	1.20E+03	<b>1.20E+03</b>
	Median	1.20E+03	1.20E+03	1.20E+03	1.20E+03	1.20E+03	1.20E+03	1.20E+03	<b>1.20E+03</b>
	std	1.48E-01	6.47E-02	8.18E-01	4.48E-01	7.23E-01	<b>5.60E-02</b>	3.48E-01	7.04E-02
	Maximum	1.30E+03	<b>1.30E+03</b>	1.31E+03	1.30E+03	1.30E+03	1.30E+03	1.30E+03	1.30E+03
	Minimum	1.30E+03	1.30E+03	1.31E+03	1.30E+03	1.30E+03	1.30E+03	1.30E+03	<b>1.30E+03</b>
f13	Average	1.30E+03	<b>1.30E+03</b>	1.31E+03	1.30E+03	1.30E+03	1.30E+03	1.30E+03	1.30E+03
	Median	1.30E+03	<b>1.30E+03</b>	1.31E+03	1.30E+03	1.30E+03	1.30E+03	1.30E+03	1.30E+03
	std	1.00E-01	<b>6.59E-02</b>	9.20E-01	1.19E-01	9.01E-01	1.02E-01	3.05E-01	1.74E-01
	Maximum	1.40E+03	<b>1.40E+03</b>	1.87E+03	1.42E+03	1.42E+03	1.40E+03	1.48E+03	1.40E+03
	Minimum	1.40E+03	1.40E+03	1.63E+03	1.40E+03	1.40E+03	1.40E+03	1.44E+03	<b>1.40E+03</b>



f14	Average	1.40E+03	1.40E+03	1.71E+03	1.40E+03	1.41E+03	1.40E+03	1.46E+03	<b>1.40E+03</b>
	Median	1.40E+03	<b>1.40E+03</b>	1.83E+03	1.40E+03	1.41E+03	1.40E+03	1.47E+03	1.40E+03
	std	7.57E-02	<b>4.75E-02</b>	5.14E+01	4.55E+00	5.82E+00	2.29E-01	9.01E+00	4.15E-01
	Maximum	1.55E+03	<b>1.51E+03</b>	2.51E+07	3.09E+03	5.73E+03	1.54E+03	1.01E+05	1.52E+03
	Minimum	1.53E+03	1.50E+03	9.79E+05	1.54E+03	1.62E+03	1.51E+03	1.01E+04	<b>1.50E+03</b>
f15	Average	1.53E+03	1.51E+03	8.64E+06	1.76E+03	4.40E+03	1.52E+03	4.87E+04	<b>1.51E+02</b>
	Median	1.53E+03	<b>1.51E+03</b>	1.03E+07	1.64E+03	3.85E+03	1.52E+03	4.81E+04	1.51E+03
	std	4.95E+00	<b>2.13E+00</b>	5.69E+06	3.31E+02	7.41E+02	7.30E+00	2.09E+04	6.81E+00
	Maximum	1.61E+03	1.61E+03	1.61E+03	1.61E+03	1.61E+03	<b>1.61E+03</b>	1.61E+03	1.61E+03
	Minimum	1.61E+03	1.61E+03	1.61E+03	1.61E+03	1.61E+03	1.61E+03	1.61E+03	<b>1.61E+03</b>
f16	Average	1.61E+03	1.61E+03	1.61E+03	1.61E+03	1.61E+03	1.61E+03	1.61E+03	<b>1.61E+03</b>
	Median	1.61E+03	1.61E+03	1.61E+03	1.61E+03	1.61E+03	1.61E+03	1.61E+03	<b>1.61E+03</b>
	std	4.63E-01	7.01E-01	<b>1.77E-01</b>	4.02E-01	2.27E-01	6.07E-01	1.99E-01	6.54E-01
	Maximum	1.44E+05	1.46E+06	3.22E+08	2.42E+07	<b>1.35E+05</b>	1.29E+06	1.88E+07	3.02E+06
	Minimum	<b>9.12E+03</b>	5.18E+04	7.63E+06	7.03E+05	4.52E+04	3.66E+04	2.34E+06	6.26E+04
f17	Average	<b>5.44E+04</b>	3.85E+05	7.27E+07	6.36E+06	7.05E+04	5.26E+05	1.00E+07	1.03E+06
	Median	<b>1.92E+04</b>	3.96E+05	4.40E+07	8.36E+06	5.91E+04	4.01E+05	1.26E+07	1.44E+06
	std	3.74E+04	2.65E+05	5.95E+07	5.42E+06	<b>1.55E+04</b>	3.48E+05	3.23E+06	7.24E+05
	Maximum	4.01E+04	<b>1.06E+04</b>	1.29E+10	3.52E+04	1.07E+04	2.75E+04	1.86E+07	8.30E+04
	Minimum	6.01E+03	4.85E+03	1.37E+09	2.10E+03	5.95E+03	2.92E+03	1.57E+06	<b>1.96E+03</b>
f18	Average	2.15E+04	6.09E+03	4.69E+09	6.98E+03	8.60E+03	8.19E+03	6.76E+06	<b>5.79E+03</b>
	Median	2.40E+04	6.80E+03	5.52E+09	<b>5.76E+03</b>	8.92E+03	9.57E+03	9.57E+06	1.47E+04
	std	6.97E+03	1.64E+03	2.61E+09	6.91E+03	<b>9.57E+02</b>	6.59E+03	3.36E+06	1.31E+04
	Maximum	2.04E+03	1.92E+03	3.26E+03	2.02E+03	2.07E+03	1.99E+03	2.01E+03	<b>1.91E+03</b>
	Minimum	1.91E+03	1.91E+03	2.19E+03	1.92E+03	1.91E+03	1.91E+03	1.94E+03	<b>1.90E+03</b>
f19	Average	1.93E+03	1.91E+03	2.49E+03	1.94E+03	1.97E+03	1.92E+03	1.97E+03	<b>1.91E+03</b>
	Median	1.95E+03	1.91E+03	2.61E+03	1.92E+03	1.93E+03	1.91E+03	1.99E+03	<b>1.91E+03</b>
	std	2.86E+01	3.03E+00	1.87E+02	2.60E+01	3.25E+01	2.36E+01	1.46E+01	<b>2.13E+00</b>
	Maximum	2.23E+04	2.80E+04	2.04E+07	1.33E+06	<b>1.29E+04</b>	7.71E+04	6.05E+04	5.88E+04
	Minimum	2.66E+03	2.77E+03	1.08E+05	8.74E+04	4.83E+03	3.93E+03	8.26E+03	<b>2.28E+03</b>
f20	Average	9.05E+03	1.12E+04	2.79E+06	5.69E+05	<b>8.25E+03</b>	2.61E+04	3.00E+04	1.75E+04
	Median	<b>5.27E+03</b>	8.37E+03	1.77E+05	1.99E+05	8.57E+03	1.86E+04	3.18E+04	1.62E+04
	std	5.03E+03	6.94E+03	4.38E+06	3.54E+05	<b>1.22E+03</b>	1.65E+04	1.09E+04	1.35E+04
	Maximum	<b>9.65E+04</b>	7.72E+05	1.41E+08	1.44E+07	1.03E+06	1.13E+06	5.69E+06	2.00E+06
	Minimum	9.70E+03	2.84E+04	1.28E+06	4.31E+04	<b>3.36E+03</b>	3.33E+04	4.51E+05	1.31E+04
f21	Average	<b>3.88E+04</b>	2.17E+05	3.18E+07	3.17E+06	9.48E+04	2.11E+05	2.38E+06	3.90E+05
	Median	<b>3.04E+04</b>	2.66E+05	3.55E+07	6.67E+05	5.20E+05	4.01E+05	2.04E+06	2.24E+05

	std	<b>1.86E+04</b>	1.61E+05	3.41E+07	2.86E+06	1.79E+05	2.22E+05	1.18E+06	3.72E+05
	Maximum	4.32E+03	3.21E+03	4.10E+03	3.93E+03	<b>3.17E+03</b>	3.47E+03	3.23E+03	3.39E+03
	Minimum	2.71E+03	2.39E+03	2.95E+03	2.68E+03	<b>2.29E+03</b>	2.50E+03	2.70E+03	2.37E+03
f22	Average	3.38E+03	2.77E+03	3.61E+03	3.25E+03	<b>2.72E+03</b>	2.88E+03	2.97E+03	2.84E+03
	Median	3.39E+03	2.78E+03	3.36E+03	3.24E+03	2.84E+03	2.94E+03	2.93E+03	<b>2.48E+03</b>
	std	2.68E+02	2.01E+02	2.50E+02	2.59E+02	2.16E+02	1.82E+02	<b>1.19E+02</b>	2.38E+02
	Maximum	2.62E+03	2.61E+03	4.82E+03	2.78E+03	<b>2.50E+03</b>	2.62E+03	2.72E+03	2.63E+03
	Minimum	2.62E+03	2.61E+03	3.12E+03	2.63E+03	<b>2.50E+03</b>	2.62E+03	2.66E+03	2.61E+03
f23	Average	2.62E+03	2.61E+03	3.95E+03	2.67E+03	<b>2.50E+03</b>	2.62E+03	2.69E+03	2.61E+03
	Median	2.62E+03	2.61E+03	3.95E+03	2.71E+03	<b>2.50E+03</b>	2.62E+03	2.69E+03	2.61E+03
	std	4.57E-03	6.41E-03	3.90E+02	2.72E+01	1.48E-03	<b>4.48E-07</b>	1.28E+01	2.20E+00
	Maximum	3.07E+03	2.65E+03	3.02E+03	2.81E+03	<b>2.60E+03</b>	2.65E+03	2.73E+03	2.65E+03
f24	Minimum	2.65E+03	2.62E+03	2.85E+03	2.65E+03	<b>2.60E+03</b>	2.62E+03	2.70E+03	2.63E+03
	Average	2.77E+03	2.63E+03	2.93E+03	2.69E+03	<b>2.60E+03</b>	2.63E+03	2.71E+03	2.64E+03
	Median	2.76E+03	2.63E+03	2.91E+03	2.68E+03	<b>2.60E+03</b>	2.63E+03	2.71E+03	2.65E+03
	std	1.06E+02	7.15E+00	3.86E+01	3.53E+01	<b>3.80E-01</b>	6.85E+00	6.53E+00	7.00E+00
	Maximum	2.85E+03	2.73E+03	2.90E+03	2.78E+03	2.70E+03	2.73E+03	2.76E+03	<b>2.70E+03</b>
	Minimum	2.71E+03	2.70E+03	2.73E+03	2.72E+03	2.70E+03	2.70E+03	2.74E+03	<b>2.70E+03</b>
f25	Average	2.74E+03	2.72E+03	2.79E+03	2.74E+03	2.70E+03	2.71E+03	2.75E+03	<b>2.70E+03</b>
	Median	2.73E+03	2.73E+03	2.81E+03	2.73E+03	2.70E+03	2.71E+03	2.74E+03	<b>2.70E+03</b>
	std	2.52E+01	8.91E+00	3.64E+01	1.59E+01	<b>1.06E-05</b>	5.46E+00	6.04E+00	3.19E-01
	Maximum	3.02E+03	2.80E+03	3.02E+03	2.99E+03	2.80E+03	2.80E+03	<b>2.70E+03</b>	2.96E+03
	Minimum	2.70E+03	2.70E+03	2.70E+03	2.70E+03	2.80E+03	2.70E+03	2.70E+03	<b>2.70E+03</b>
f26	Average	2.78E+03	2.73E+03	2.79E+03	2.79E+03	2.80E+03	2.71E+03	2.70E+03	<b>2.70E+03</b>
	Median	<b>2.70E+03</b>	2.75E+03	2.80E+03	2.81E+03	2.80E+03	2.70E+03	2.70E+03	2.70E+03
	std	7.80E+01	4.62E+01	1.23E+02	5.95E+01	<b>6.74E-08</b>	2.78E+01	2.88E-01	3.32E+01
	Maximum	4.75E+03	3.59E+03	4.29E+03	4.34E+03	<b>3.10E+03</b>	3.85E+03	3.97E+03	3.69E+03
	Minimum	3.10E+03	3.10E+03	3.83E+03	3.12E+03	3.10E+03	3.10E+03	3.45E+03	<b>3.10E+03</b>
f27	Average	4.09E+03	3.30E+03	4.09E+03	3.87E+03	<b>3.10E+03</b>	3.28E+03	3.83E+03	3.38E+03
	Median	3.69E+03	3.42E+03	4.09E+03	3.95E+03	<b>3.10E+03</b>	3.43E+03	3.84E+03	3.43E+03
	std	5.61E+02	1.41E+02	8.67E+01	3.81E+02	<b>2.23E-04</b>	2.70E+02	1.08E+02	1.67E+02
	Maximum	1.07E+04	6.67E+03	6.41E+03	1.02E+04	6.10E+03	5.91E+03	5.07E+03	<b>3.36E+03</b>
	Minimum	6.36E+03	3.83E+03	3.93E+03	5.16E+03	<b>3.10E+03</b>	3.77E+03	4.33E+03	3.20E+03
f28	Average	8.63E+03	4.63E+03	4.85E+03	7.70E+03	4.50E+03	4.84E+03	4.77E+03	<b>3.24E+03</b>

Median	8.28E+03	4.37E+03	5.04E+03	6.42E+03	5.81E+03	4.44E+03	4.70E+03	<b>3.21E+03</b>
std	1.10E+03	5.69E+02	5.71E+02	1.11E+03	5.93E+02	5.09E+02	1.54E+02	<b>4.04E+01</b>
Maximum	1.84E+07	8.39E+03	3.75E+07	3.38E+06	1.58E+04	5.85E+03	1.46E+07	<b>3.34E+03</b>
Minimum	7.65E+03	3.11E+03	1.74E+06	7.13E+03	9.03E+03	3.46E+03	2.14E+06	<b>3.10E+03</b>
f29 Average	1.94E+06	4.34E+03	1.34E+07	3.20E+05	1.33E+04	4.46E+03	6.63E+06	<b>3.12E+03</b>
Median	5.11E+06	3.97E+03	1.74E+07	1.55E+05	1.50E+04	4.51E+03	7.02E+06	<b>3.11E+03</b>
std	5.07E+06	7.22E+02	7.22E+06	5.70E+05	1.47E+03	6.01E+02	2.47E+06	<b>3.75E+01</b>
Maximum	1.73E+04	<b>4.55E+03</b>	6.36E+05	4.95E+05	5.60E+03	8.81E+03	2.83E+05	6.39E+03
Minimum	5.53E+03	3.50E+03	6.08E+04	2.49E+04	4.42E+03	4.32E+03	4.25E+04	<b>3.36E+03</b>
f30 Average	9.53E+03	4.26E+03	2.67E+05	1.31E+05	5.04E+03	6.04E+03	1.57E+05	<b>4.07E+03</b>
Median	8.74E+03	3.94E+03	3.03E+05	6.36E+04	5.15E+03	5.90E+03	1.56E+05	<b>3.74E+03</b>
std	2.65E+03	2.86E+02	1.33E+05	1.07E+05	<b>2.44E+02</b>	1.15E+03	5.04E+04	4.43E+02

Different algorithms have been classified based on their average value for each benchmark function. As illustrated in Table 3, the rank for each algorithm has been collected within unimodal, multimodal, hybrid and composition classes. The final row shows the total rank for each algorithm, where the best algorithm is the one with a lowest value. It is clear that the proposed XOA algorithm has the best overall ranking on the whole group of benchmarks and the test functions and therefore it shows to be the most efficient method.

Table 3. Sum of the ranks for comparative algorithms on CEC benchmarks

	IWO	BBO	GSA	HuS	BA	ICA	HS	XOA
<b>Unimodal</b>	11	9	24	18	14	9	20	3
<b>Multimodal</b>	65	39	103	63	61	37	79	21
<b>Hybrid</b>	21	16	48	34	17	23	38	19
<b>Composition</b>	49	23	59	48	22	26	45	16
<b>Total</b>	146	87	234	163	114	95	182	59

Fig. 2 to Fig. 5 illustrates the progression of finding the best cost of benchmark functions after 150000 rounds of evaluations for each algorithm on one of the chosen benchmarks from every group of benchmark functions. In order to see a clear comparison, the function number 2 (f2) from Unimodal, number 10 (f10) from Multimodal, number 18 (f18) from Hybrid and number 30 (f30) from Composition benchmarks have been selected and illustrated.

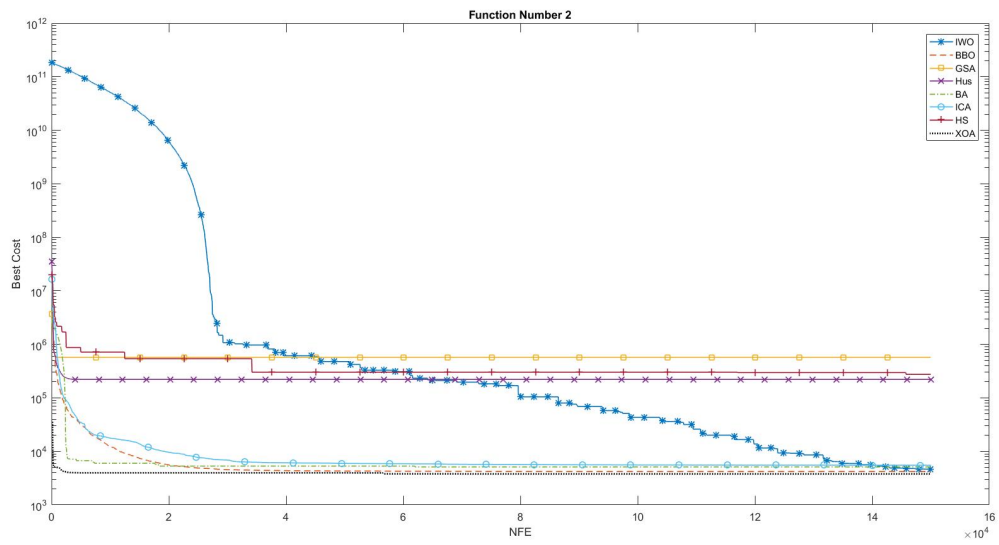


Fig. 2. Convergence of comparative algorithms for f2.

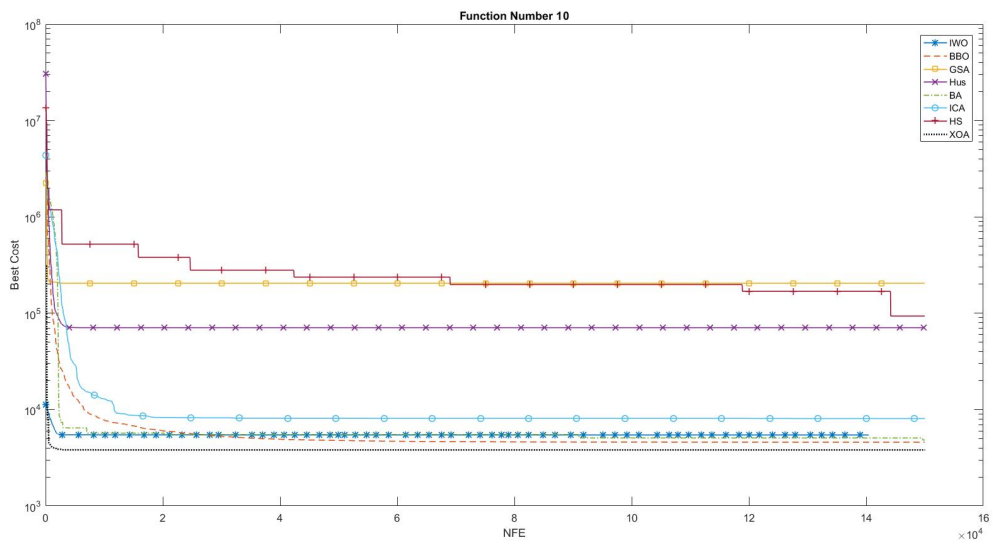


Fig. 3. Convergence of comparative algorithms for f10

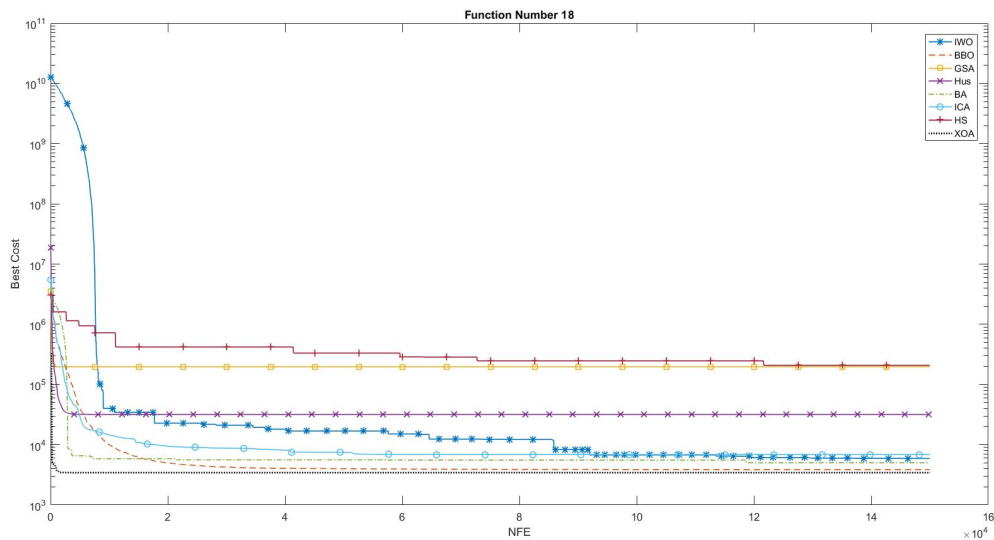


Fig. 4. Convergence of comparative algorithms for f18.

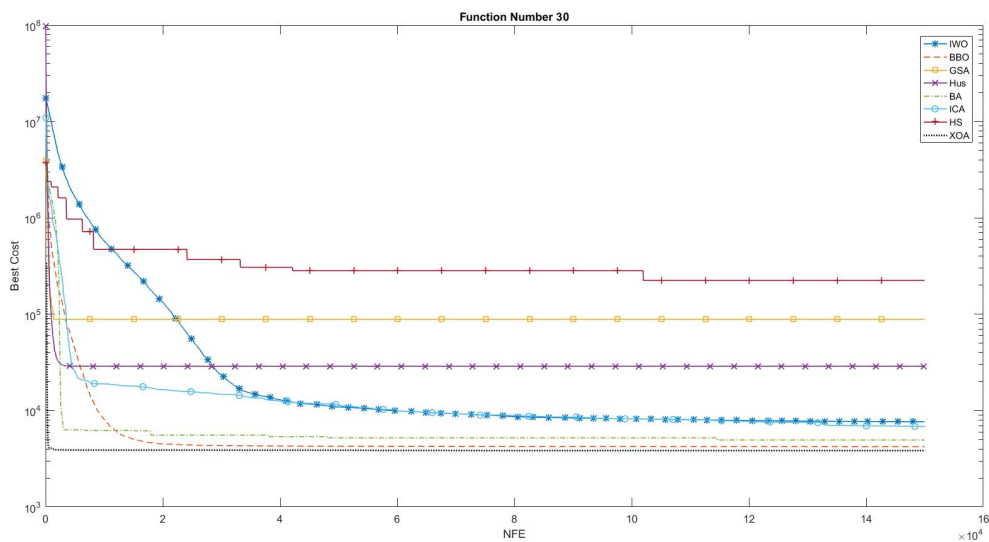


Fig. 5. Convergence of comparative algorithms for f30.

### 3.3 Discussion of Results

As illustrated in Table 3, on the first group of unimodal benchmark, XOA presents a better performance. This is also evident from Figs 2 – 5, as for functions of f1 and f2, XOA shows a better result for maximum, minimum, average and median. On f3, XOA also has better minimum, average and median values.

On the second group of multimodal, and for 13 test functions, XOA is shown to reach its best values for minimum and average in 10 benchmarks (f4, f5, f6, f7, f8, f10, f12, f14, f15, f16) and it has the best minimum value on f13. It can also be seen that, BBO reaches its best minimum

value and BA reaches its best average value on f9, while XOA has been ranked as the third for its average value on this function. IWO shows its best values for maximum, average and median on f13. HuS and BA also reach their best values for minimum and average on f5, but XOA has the best standard deviations on its 60 runs. Generally, XOA shows an efficient performance for these group of benchmarks which is counted as the best results.

On the third group of hybrid benchmarks, XOA has the best minimum and average values on f18 and f19 and also the best minimum and median values on f20 and f22, respectively. IWO has the best values for minimum and average on f17, while XOA has been ranked as the 5<sup>th</sup> for its average on this benchmark. BA also has the best minimum and average values on f22, best minimum value on f21 and best average value on f20. For function f21 benchmark, IWO reaches its best average and median values, while XOA stands on the 5<sup>th</sup> place for the average value. Therefore, for this group of benchmark, BBO, BA and XOA have shown to perform better.

Finally, on the composition benchmarks, XOA reaches its best minimum and average values on f25, f26, f29 and f30, and also has the minimum value on f27. BA reaches its best minimum and average values on f23 and f24, where XOA has been placed on the 3<sup>rd</sup> and 4<sup>th</sup> place of ranking for average values. BA also has the best minimum and average values on f28 and f27, respectively. In this group of benchmarks, once again, XOA has shown to have the best performance, followed by BA and BBO.

The results and comparison illustrated in the current paper, has shown that XOA is the best approach for solving global optimization problems, since it has the best performance on total of 30 benchmarks and also has the best minimum and average values on unimodal, multimodal and composition benchmarks, though it also produces an efficient performance on hybrid functions.

#### **4. Conclusions**

In this paper, a novel nature-inspired evolutionary algorithm called Xerus Optimization Algorithm (XOA) is proposed, where it is inspired from group living behaviors and life style of cape ground squirrels. In this study, XOA was compared with seven other known evolutionary algorithms on benchmark problems which were extracted from the Congress on Evolutionary Computations 2014 (CEC 14) competition. The presented results illustrated that XOA provides an efficient and competitive performance on this wide range of diverse benchmarks. This work can be further extended to solve more complex and real optimization problems. XOA approach can also be generalized and employed for solving problems in discrete and combinatorial optimization areas.

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