Evolutionary Algorithms Performance Comparison For Optimizing Unimodal And Multimodal Test Functions

Dr. Hanan A.R. Akkar, Firas R. Mahdi

Abstract: Many evolutionary algorithms have been presented in the last few decades, some of these algorithms were sufficiently tested and used in many researches and papers, such as: Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Differential Evolution Algorithm (DEA). Other recently proposed algorithms were unknown and rarely used such as Stochastic Fractal Search (SFS), Symbiotic Organisms Search (SOS), and Grey Wolf Optimizer (GWO). This paper trying to made a fair comprehensive comparison for the performance of these well-known algorithms and other less prevalent and recently proposed algorithms, by using a variety of famous test functions that have multiple different characteristics, through applying two experiments for each algorithm according to the used test function, the first experiments carried out with the standard search space limits of the proposed test functions, while the second experiment multiple ten times the maximum and minimum limits of the test functions search space, recording the Average Mean Absolute Error (AMAE), Overall Algorithm Efficiency (OAE), Algorithms Stability (AS), Overall Algorithm Stability (OAS), each algorithm required Average Processing Time (APT), and Overall successful optimized test function Processing Time (OPT) for both of the experiments, and with ten epochs each with 100 iterations for each algorithm.

Index Terms: Benchmark test functions, Evolutionary population based algorithms, Meta-heuristic techniques, Optimization.

1 Introduction

Optimization is defined as a process that finds an optimal or near optimal solution for a defined problem, while An optimization problem is how to find variables and parameters that minimize or maximize an objective function, in a way that's satisfy the objective function constraints. Many optimization problems have more than one local solution, therefore, it is important to choose a good and feasible optimization method that globally looks to the search space to find the best solution without being trapped into a local minima solution. However, if the optimization problem is difficult or it has a huge search space, it becomes hard to solve using usual or exact mathematical methods [1]. Therefore, many new optimization methods have been proposed to solve such difficult optimization problems. This paper aims to test some of familiar meta-heuristic optimization algorithms such as Genetic Algorithm (GA) [2], Particle Swarm Optimization (PSO) [3], and Bee Colony Algorithm (BCA) [4] comparing them with other less prevalent population based meta-heuristic optimization algorithms such as Stochastic Fractal Search algorithm (SFS) [5], Symbiotic Organisms Search algorithm (SOS) [6], Grey Wolf Optimizer algorithm (GWO) [7], and Novel Bat Algorithm (NBA) [8], for optimizing twenty two benchmark test functions using two individual experiments, the first experiments have been carried out according to the original limits of the search space, while the second experiment multiple the upper and lower bounds of the search space limits by ten, recording the Average Mean Absolute Error (AMAE) of the algorithms due to the ten epochs for each test function, Overall Algorithms Efficiency (OAE) which is the number of successfully optimized test function to the total test function number, algorithms stability which represents the ability of an algorithm to maintain reaching optimum solutions, Overall Algorithms Stability (OAS), Algorithms average Processing Time (APT) for each algorithm to find the optimum solution, Efficiency droopiness (ED) due to these limits extending between the two experiments, and Overall algorithms Processing Time (OPT) for only the successfully optimized test function. We have carried out ten epochs, each epoch with 100 iterations for each algorithm in both experiments according to the twenty two test functions.

- *Hanan A. Akkar is a prof. Within the Electrical Engineering department, University of Technology (UOT), Baghdad, Iraq. E-mail: dr_hananuot@yahoo.com*
- *Firas R. Mahdi is a PhD student within the Electrical Engineering department, University of Technology (UOT), Baghdad, Iraq. E-mail: firasrasool1980@gmail.com*

2 Meta-heuristic Evolutionary population based algorithms

Heuristics are defined as approaches to find optimal or near optimal solutions in a rational computational cost without a guarantee to find an optimal value, while meta-heuristics are a set of intelligent schemes to improve the efficiency of the heuristic procedures. Meta-heuristics can be classified according to the number of optimal solutions used at the same time. Trajectory methods are algorithms based on a single solution at any time and cover a local search based meta-heuristics. While, population based algorithms perform search with many initial points in a parallel style. One of the most important population based algorithms are the swarm intelligence algorithms. These algorithms composed of simple agents cooperating locally with each other depending on their environment. Each single agent or particle follows one or multiple simple rules without any centralized structure for controlling its performance. Consequently, local and random interactions among the particles are directed to an intelligent global behavior. Many of these algorithms apply two approaches: global exploration for effectively find the global best solution in the selected search space, and local exploitation to modify the best global solution towards the optimum solution. A tradeoff between these two algorithm tools are applied to each algorithm in which each agent improves its performance by cooperate with other agents, sharing information with other agents and finally, compete to survive. These concepts direct an algorithm towards finding the best solution obtained so far by iteration [9]. Most of our tested algorithms have the behavior of the swarm intelligence algorithms.

3 POPULATION BASED TESTED ALGORITHMS

In this paper we have to examine twenty meta-heuristic population based evolutionary algorithms using twenty two well-known test functions with variety of characteristics, all algorithms where tested through ten different epochs for each experiment with 30 particles population size and 100 maximum iterations for each epoch, these algorithms are : Bee Colony Optimization algorithm (BCO), Bird Swarm Algorithm (BSA) [10], Cuckoo Search Algorithm (CSA) [11], Chicken Swarm Optimization (CSO) [12], Differential Evolution Algorithm (DEA), Dragonfly Algorithm (DFA) [13], Flower Pollination Algorithm (FPA) [14], Genetic Algorithm (GA), Gravitational Search Algorithm (GSA) [15], Grey Wolf Optimizer (GWO), Modified Harmony Search (MHS) [16], Moth-Flame Optimization algorithm (MFO) [17], Multi Verse Optimizer (MVO) [18], Novel Bat Algorithm (NBA), Quantum Particle Swarm Optimization (QPSO) [19], Stochastic Fractal Search (SFS), States of Matter Search (SOM) [20], Symbiotic Organisms Search (SOS), and Wind Driven Optimization (WDO) [21]. The AMAE have been recorded for each algorithm, which indicates if an algorithm succeeded to get the optimum solution or not, we have considered that if an algorithm gets less than 0.09 AMAE then its successfully optimized.

4 TEST FUNCTIONS CHARACTERISTICS

Any new proposed optimization algorithm, must have a test for its performance, and relate it with other familiar optimization algorithm in the same field over a good set of test functions. A common procedure in this field is to compare different algorithms on a large set of test functions. However, it must be noted that the efficiency of one algorithm against others cannot be simply measured by means of the problems that it solves if the set of problems are too particular and without diverse properties. Therefore, in order to assess an algorithm, one must classify the kind of problems where it performs better than other compared algorithms. This helps in characterizing the type of problems for which an algorithm is appropriate. This is only possible if the test functions set is large enough to include an extensive variability of problems, such as multimodal, separable, scalable, and differentiability. The test functions used in this paper include multimodal functions, which are functions with more than one local optimal, unimodal functions that have only a single optimum value. Unimodal property of a test function that let us examines the ability of an algorithm to escape local minima to a global one. Multimodal functions with many local minima are among the most difficult types of problems for many algorithms. Another important test function property is if the function surfaces flatness, which is difficult to optimize since it does not give the algorithm any information to direct the search towards the local minima . The dimensionality of the search space and if the function is separable or not is another important issues with the test functions. In some functions, the area that covers the global minima are too small, when it compared to a large search space, such as Easom function, in other functions the global minimum is located very close to the local minima such as Powell and Schaffer functions which make it difficult to distinguish the local from the global minima. Some test functions having narrow curved valley like Beale and Colville test functions make it difficult to keep up the direction changes, while function like Table holder that have multiple global minima makes an algorithm fail to explore the search space effectively. Another problem that algorithms may suffer is the scaling problem such as Goldstein price test function [22]. Table 1 will list the formula of the used test functions and their dimensionality (D), while table 2 shows the characteristics of the used test functions.

TABLE 1. *TEST FUNCTIONS AND THEIR PARAMETERS*

Fn	Function	Formula	D
F1	Ackley [22]	$f(x) = -20exp(-0.2\sqrt{D^{-1}\sum_{i=1}^{D} x^2} - exp(D^{-1}\sum_{i=1}^{D} cos(2\pi c)) + 20 + \exp(1)$	30
F2	Griewank [22]	$f(x) = \sum_{i=1}^{D} \frac{x_i}{4000} - \prod_{i=1} \cos(\frac{x_i}{\sqrt{i}}) + 1, \;\; w_i = 1 + \frac{x_i}{4}$	30
F3	Rastrigin [23]	$f(x) = 10D + \sum_{i=1}^{D} [x_i^2 - 10\cos(2\pi x_i)]$	30
F4	Schwefel [22]	$f(x) = 418.9829D - \sum_{i=1}^{D} x_i \sin(\sqrt{\lvert x_i \rvert})$	30
F5	Sphere [22]	$f(x) = \sum_{i=1}^{D} x_i^2$	30
F6	Sum of squares [22]	$f(x) = \sum_{i=1}^{D} ix_i^2$	30
F7	Zakharov [22]	$f(x) = \sum_{i=1}^{D} x_i^2 + (\sum_{i=1}^{D} 0.5ix_i)^2 + (\sum_{i=1}^{D} 0.5ix_i)^4$	30
F8	Rosenbrock [22]	$f(x) = \sum_{i=1}^{D} [100(x_{i+1} - x_i^2) + (x_i - 1)^2]$	30
F9	Dixon price [22]	$f(x) = (x_1 - 1)^2 + \sum_{i=1}^{D} i(2x_i^2 - x_{i-1})^2$	30
F10	Powell [22]	$f(x) = \sum_{i=1}^{\frac{D}{4}} [(x_{4i-3} + 10x_{4i-2})^2 + 5(x_{4i-1} - x_{4i})^2 + (x_{4i-2} - 2x_{4i-1})^4 + 10(x_{4i-3} - x_{4i})^4$	30
F11	Styblinski-Tang [22]	$f(x) = \frac{1}{2}\sum_{i=1}^{D} (x_i^4 - 16_i^2 + 5x_i)$	30
F12	Cross-in-tray [22]	$f(x) = -0.0001(\left\lvert \sin(x_1)\sin(x_2)\exp\left(\left\lvert 100 - \frac{\sqrt{x_1^2 + x_2^2}}{\pi} \right\rvert\right) \right\rvert + 1)^{0.1}$	2
F13	Drop wave [23]	$f(x) = -\frac{1 + \cos(12\sqrt{x_1^2 + x_2^2})}{0.5(x_1^2 + x_2^2) + 2}$	2
F14	Shubert [22]	$f(x) = (\sum_{i=1}^{5} icos((i+1)x_1 + i)(\sum_{i=1}^{5} icos((i+1)x_2 + i)$	2
F15	Branin [24]	$f(x) = (x_2 - \frac{5.1}{4\pi^2}x_1^2 + \frac{5}{\pi}x_1 - r)^2 + 10\left(1 - \frac{1}{8\pi}\right)\cos(x_1) + 10$	2
F16	Eggholder [22]	$f(x) = -(x_2 + 47)\sin(\sqrt{\left\lvert x_2 + \frac{x_1}{2} + 47 \right\rvert}) - x_1\sin(\sqrt{\lvert x_1 - (x_2 + 47) \rvert})$	2
F17	Holder table [22]	$f(x) = -\left\lvert \sin(x_1)\cos(x_2)\exp(\left\lvert 1 - \frac{\sqrt{x_1^2 + x_2^2}}{\pi} \right\rvert) \right\rvert$	2
F18	Mccormick [22]	$f(x) = \sin(x_1 + x_2) + (x_1 - x_2)^2 - 1.5x_1 + 2.5x_2 + 1$	2
F19	Easom [22]	$f(x) = -\cos(x_1)\cos(x_2)\exp(-(x_1 - \pi)^2 - (x_2 - \pi)^2)$	2
F20	Beale [22]	$f(x) = (1.5 - x_1 + x_1x_2)^2 + (2.25 - x_1 + x_1x_2^2)^2 + (2.625 - x_1 + x_1x_2^3)^2$	2
F21	Colville [22]	$f(x) = 100(x_1^2 - x_2)^2 + (x_1 - 1)^2 + (x_3 - 1)^2 + 90(x_3^2 - x_4)^2 + 10.1((x_2 - 1)^2 \ldots.$ $\ldots + (x_4 - 1)^2) + 19.8(x_2 - 1)(x_4 - 1)$	4
F22	Goldstein-price [22]	$f(x) = [1 + (x_1 + x_2 + 1)^2(19 - 14x_1 + 3x_1^2 - 14x_2 + 6x_1x_2 + 3x_2^2)] \ldots$ $\ldots [30 + (2x_1 - 3x_2)^2(18 - 32x_1 + 12x_1^2 + 48x_2 - 36x_1x_2 + 27x_2^2)]$	4

TABLE 2 *TEST FUNCTIONS CHARACTERISTICS AND THEIR SEARCH SPACE LIMITS.*

Fn	Test functions limits 1st experiment	Test functions limits 2nd experiment	Test functions characteristics
F1	$X \in [-32.8:32.8]$	$X \in [-328:328]$	Continuous, Differentiable, Non-separable, Scalable, Multimodal [22].
F2	$X \in [-600600]$	$X \in [-6000:6000]$	Continuous, Differentiable, Non-Separable, Scalable, Multimodal [22].
F3	$X \in [-5.12:5.12]$	$X \in [-51.2:51.2]$	Continuous, Differentiable, Separable, Multimodal [23].
F4	$X \in [-500:500]$	$X \in [-5000:5000]$	Continuous, Differentiable, Partially-Separable, Scalable, Unimodal [22].
F5	$X \in [-5.12:5.12]$	$X \in [-51.2:51.2]$	Continuous, Differentiable, Separable, Scalable, Multimodal [22].
F6	$X \in [-10:10]$	$X \in [-100:100]$	Continuous, Differentiable, Separable, Scalable, Unimodal [22].
F7	$X \in [-5:10]$	$X \in [-50:100]$	Continuous, Differentiable, Non-Separable, Scalable, Multimodal [22].
F8	$X \in [-5:10]$	$X \in [-50:100]$	Continuous, Differentiable, Non-Separable, Scalable, Unimodal [22].
F9	$X \in [-10:10]$	$X \in [-100:100]$	Continuous, Differentiable, Non-Separable, Scalable, Unimodal [22].
F10	$X \in [-4:5]$	$X \in [-40:50]$	Continuous, Differentiable, Non-Separable Scalable, Unimodal [22].
F11	$X \in [-5:5]$	$X \in [-50:50]$	Continuous, Differentiable, Non-Separable, Non-Scalable, Multimodal [22].
F12	$X \in [-10:10]$	$X \in [-100:100]$	Continuous, Non-Separable, Non-Scalable, Multimodal [22].
F13	$X \in [-5.12:5.12]$	$X \in [-51.2:51.2]$	Continuous, Differentiable, Non-Separable, Multimodal [23].
F14	$X \in [-10:10]$	$X \in [-100:100]$	Continuous, Differentiable, Separable, Non-Scalable, Multimodal [22].
F15	$X_1 \in [-5:10]$, $X_2 \in [0:15]$	$X_1 \in [-50:100]$, $X_2 \in [0:150]$	Continuous, Differentiable, Non-Separable, Non-Scalable, Multimodal [24].
F16	$X \in [-512:512]$	$X \in [-5120:5120]$	Continuous, Differentiable, Non-Separable, Scalable, Multimodal [22].
F17	$X \in [-10:10]$	$X \in [-100:100]$	Continuous, Differentiable, Separable, Non-Scalable, Multimodal [22].
F18	$X_1 \in [-1.5:4]$, $X_2 \in [-3:4]$	$X_1 \in [-15:40]$, $X_2 \in [-30:40]$	Continuous, Differentiable, Non-Separable, Non-Scalable, Multimodal [22].
F19	$X \in [-100:100]$	$X \in [-1000:1000]$	Continuous, Differentiable, Separable, Non-Scalable, Multimodal [22].
F20	$X \in [-4.5:4.5]$	$X \in [-45:45]$	Continuous, Differentiable, Non-Separable, Non-Scalable, Unimodal [22].
F21	$X \in [-10:10]$	$X \in [-100:100]$	Continuous, Differentiable, Non-Separable, Non-Scalable, Multimodal [22].
F22	$X \in [-2:2]$	$X \in [-20:20]$	Continuous, Differentiable, Non-separable, Non-Scalable, Multimodal [22].

5 EXPERIMENTS AND RESULTS

It is necessary to notice that the obtained results are related to the given constants and parameters of each algorithm, but the variety of test functions and their characteristics applied to the given algorithms under these parameters can give us a good imagination on the abilities of these algorithms under these conditions. For the purpose of testing algorithms using mentioned test functions, we have used MATLAB 2013 for the AMAE and efficiency calculations, and Microsoft office excel 2010 on a 2.4GHZ core i3 CPU computer with 4GB of ram. Running these algorithms 20 times each running time represents an epoch with 100 iterations, these epochs divided into two experiments, first experiment was under the original search space scales supposed by the test functions themselves, while the second experiment repeats the first experiment but with different extended search space scope, in which the minimum and maximum limits of the proposed search space scaled by 10, so that we can examine algorithms performance. Every time we execute these algorithms the AMAE obtained for each algorithm through a complete 10 epochs were evaluated, beside the efficiency of each algorithm in terms of successful epochs, the OAE which represents the number of successfully optimized test functions to the total test function number, the average required processing time APT for each algorithm, the OPT which is the average time of the successful optimized test function, and the OAS that represents the number of times an algorithm get 100% successfully iteration epochs to the total test function number. If we define an algorithm stability as the ability of an algorithm to maintain reaching the optimum solution over all the iteration epochs, which means getting 100% efficiency for each training epoch, then the Algorithm stability indicates how good an algorithm to avoid trapping into local minima solution.

Table 3, 4, and 5 show AMAE for each algorithm with a bold text for the minimum obtained AMAE, algorithms stability, and the APT respectively for the 1st experiment. Table 4 shows that no algorithm have succeeded to optimize F4, F8, F9, and F11 with the selected search space domain. SFS, SOS, and BSA algorithms have gotten the minimum AMAE for most of the test functions. In table 4 we have taken in consideration only the 100% stability marked with bold text, while in table 5 we have marked with bold text only the APT of the succeeded optimized test functions. Table 6, 7, and 8 represent the second experiment AMAE, algorithm stability, and APT respectively. In table 6 we notice that F4 has been successfully optimized within BSA, MFO, and DFO algorithms with 100% stability, while F8, F9, and F11 still un optimized. SFS, MFO, and BSA have gotten the minimum AMAE for most of the test functions, while SOS performance have been dropped down. Table 9 shows the first and second experiment OAE, OAS, and OPT. in table 9 we have seen that SOS has gotten the highest OAE and AOS with 82% in the first experiment and dropped down to 59% for the second experiment, SFS has 73% for both OAE and OAS makes her the most efficient and stable algorithm for the second experiment, but with relatively high OPT 1.48 sec. BSA has maintain the same OAE, and OAS for both experiments with 64% and with an acceptable processing time. All algorithms OAE and OAS have been dropped down by the second experiment except for MFO, NBA which make their more suitable for large dimension problems. Table 9 shows that some algorithms have 0 OPT and this is due to the fact that these algorithms fail to get 100% stability, which means that they fails to maintain the same performance over the training epochs.

***TABLE 3,** 1ST EXPERIMENT ALGORITHMS AVERAGE MEAN ABSOLUTE ERROR (AMAE) (CONTINUED)*

Fn	MFO	MHS	MVO	NBA	PSO	QPSO	SFS	SOM	SOS	WDO
F1	2.16E+00	3.91E+00	3.01E+00	2.40E-05	3.91E+00	2.23E+00	**8.88E-16**	3.10E+00	2.36E-13	4.55E-01
F2	9.60E-02	5.08E-01	4.51E-01	1.30E-10	5.08E-01	7.19E-02	**0.00E+00**	2.35E-01	**0.00E+00**	4.67E-08
F3	8.37E+01	3.03E+02	2.36E+02	3.28E+01	3.03E+02	5.01E+01	**0.00E+00**	1.69E+02	**0.00E+00**	2.93E+01
F4	4.81E+03	8.93E+03	5.64E+03	6.60E+03	8.14E+03	5.97E+03	4.68E+03	1.01E+04	5.52E+03	1.03E+04
F5	2.06E+00	1.12E+01	1.72E+00	6.18E-09	1.12E+01	2.04E+00	**3.96E-86**	2.27E-01	3.99E-27	6.56E-07
F6	2.50E+01	1.58E+02	1.39E+01	2.48E-08	1.58E+02	1.48E+01	**2.88E-85**	7.13E+00	1.31E-25	8.10E-06
F7	2.99E+01	2.59E+01	2.60E+01	3.25E-01	1.70E+01	4.34E+00	**3.04E-70**	3.20E+00	1.76E-04	6.19E-04
F8	1.66E+02	6.23E+02	1.53E+02	2.78E+01	5.67E+02	1.40E+02	2.74E+01	7.90E+01	2.55E+01	2.87E+01
F9	2.48E+01	2.22E+02	1.72E+01	6.69E-01	2.22E+02	1.84E+01	6.67E-01	4.03E+00	6.67E-01	8.99E-01
F10	1.63E+01	2.56E+02	5.50E+00	1.30E-04	2.56E+02	8.32E+00	**4.08E-77**	1.44E+00	1.67E-08	3.88E-05
F11	2.37E+02	5.47E+02	3.36E+02	3.23E+02	4.29E+02	2.53E+02	6.65E+01	6.19E+02	8.50E+01	7.27E+02
F12	1.57E-14	3.12E-03	6.06E-07	1.96E-10	8.39E-06	3.68E-09	9.66E-10	4.84E-04	1.02E-09	2.43E-02
F13	4.46E-02	6.68E-02	1.28E-02	4.46E-02	2.67E-05	6.38E-03	**0.00E+00**	2.10E-05	3.15E-15	6.38E-02
F14	1.80E-11	7.24E+00	1.07E+01	3.60E+01	1.34E-01	8.37E-03	7.10E-09	6.17E+01	1.32E-07	6.32E+01
F15	3.58E-07	6.12E-02	6.56E-06	2.07E-06	9.93E-05	1.09E-06	3.88E-07	5.97E-01	**3.58E-07**	3.14E+00
F16	3.10E+01	6.35E+01	1.74E+02	1.23E+02	6.53E+00	3.79E+01	8.34E-01	3.87E+02	**3.73E-05**	4.21E+02
F17	1.09E-11	4.01E-01	7.01E-05	4.82E-07	4.75E-06	3.23E-06	1.30E-06	6.10E+00	1.23E-06	6.69E+00
F18	2.79E-03	2.28E-02	2.79E-03	2.79E-03	**8.40E-05**	1.03E-02	2.79E-03	2.02E-03	2.79E-03	2.94E-01
F19	**0.00E+00**	9.32E-01	1.18E-03	9.59E-09	4.42E-03	1.12E-03	**0.00E+00**	8.75E-01	1.58E-07	1.00E+00
F20	2.07E-05	6.99E-02	3.84E-01	3.81E-01	1.92E-04	6.56E-09	1.67E-16	7.56E-04	**7.09E-19**	2.33E+00
F21	3.75E-01	5.24E+01	1.41E+00	5.75E-02	5.73E+00	8.48E-01	8.43E-02	1.00E-01	**3.40E-03**	1.95E+00
F22	1.78E-16	1.86E+00	2.70E+00	2.70E+00	8.66E-04	**0.00E+00**	**0.00E+00**	4.42E-03	**0.00E+00**	8.10E+00

TABLE 3, *1ST EXPERIMENT ALGORITHMS AVERAGE MEAN ABSOLUTE ERROR (AMAE)*

Fn	BCO	BSA	CSA	CSO	DEA	DFA	FPA	GA	GSA	GWO
F1	2.33E+00	**8.88E-16**	3.84E+00	2.73E-02	3.54E+00	3.05E+00	3.91E+00	3.45E+00	3.91E+00	4.52E-03
F2	3.39E-01	**0.00E+00**	4.91E-01	4.22E-03	4.46E-01	1.88E-01	5.08E-01	4.92E-01	5.08E-01	2.10E-05
F3	7.66E+01	**0.00E+00**	2.84E+02	2.64E+00	1.69E+02	1.37E+02	3.02E+02	2.26E+02	3.08E+02	2.85E+01
F4	4.14E+03	7.94E+03	8.01E+03	7.78E+03	6.89E+03	6.77E+03	8.28E+03	2.00E+03	8.71E+03	7.01E+03
F5	7.78E-02	2.32E-42	8.60E+00	5.34E-03	9.95E+00	2.84E+00	1.11E+01	2.29E+00	1.12E+01	1.41E-05
F6	2.42E+00	1.01E-37	1.44E+02	2.88E-01	1.39E+02	5.47E+01	1.58E+02	4.86E+01	1.58E+02	2.63E-04
F7	1.48E+01	3.68E-39	2.41E+01	7.31E+00	2.58E+01	1.09E+01	1.27E+01	2.71E+01	6.34E+01	4.84E-01
F8	1.14E+02	2.88E+01	3.57E+02	2.36E+02	5.35E+02	2.07E+02	6.04E+02	1.68E+02	6.23E+02	2.76E+01
F9	1.71E+01	9.91E-01	1.87E+02	4.90E+01	1.73E+02	2.71E+01	2.17E+02	8.01E+01	2.22E+02	7.07E-01
F10	4.09E+00	2.09E-40	1.59E+02	4.39E+00	2.28E+02	4.10E+01	2.43E+02	2.69E+01	2.56E+02	2.12E-03
F11	1.40E+02	2.26E+02	4.40E+02	4.04E+02	4.47E+02	2.57E+02	5.23E+02	5.41E+01	7.27E+02	2.80E+02
F12	3.79E-09	**7.24E-15**	2.47E-07	3.82E-10	4.36E-02	3.86E-10	7.19E-05	3.10E-04	1.08E-01	6.90E-08
F13	1.80E-02	**0.00E+00**	2.46E-02	6.38E-03	5.91E-02	3.19E-02	4.67E-02	6.46E-02	1.14E-01	1.91E-02
F14	6.10E-06	**2.77E-12**	1.07E-01	3.14E-07	9.07E+01	5.67E-08	9.05E-01	2.55E+00	1.27E+02	1.80E-03
F15	1.93E-06	**3.58E-07**	5.21E-05	3.79E-07	1.39E+00	8.38E-02	6.65E-04	2.91E-02	1.39E+00	8.48E-04
F16	2.22E+01	7.15E+01	6.57E+00	6.51E+00	2.14E+02	5.46E+01	9.60E-01	1.36E+02	3.73E+00	7.80E+01
F17	4.19E-06	**8.44E-13**	9.84E-05	1.36E-06	2.90E+00	1.26E-01	3.70E-03	1.18E-02	6.98E-01	4.15E-02
F18	2.79E-03	2.79E-03	2.79E-03	2.79E-03	2.87E-01	1.51E-03	2.80E-03	5.08E-03	9.34E-02	2.79E-03
F19	6.12E-01	1.13E-13	7.26E-01	2.61E-04	8.77E-01	3.82E-05	7.07E-01	8.90E-01	1.00E+00	1.07E-05
F20	1.94E-03	2.29E-01	4.60E-05	9.04E-12	1.82E+00	1.06E-02	2.10E-03	3.27E-01	1.69E+00	7.62E-02
F21	1.85E+00	3.85E+00	3.25E+00	1.09E+00	3.06E+01	2.07E+00	1.58E+01	1.36E+01	6.28E+01	3.58E+00
F22	5.90E-02	5.40E+00	1.74E-04	4.00E-16	4.11E+01	1.32E-09	2.59E-02	1.77E+01	6.12E+01	8.10E+00

TABLE 4, *1ST EXPERIMENT ALGORITHMS STABILITY*

Fn	BCO	BSA	CSA	CSO	DEA	DFA	FPA	GA	GSA	GWO	MFO	MHS	MVO	NBA	PSO	QPSO	SFS	SOM	SOS	WDO
F1	0%	**100%**	0%	90%	0%	0%	0%	0%	0%	**100%**	0%	0%	0%	**100%**	0%	0%	**100%**	0%	**100%**	80%
F2	0%	**100%**	0%	**100%**	0%	0%	0%	0%	0%	**100%**	50%	0%	0%	**100%**	0%	80%	**100%**	0%	**100%**	**100%**
F3	0%	**100%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	**100%**	0%	**100%**	0%
F4	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
F5	80%	**100%**	0%	**100%**	0%	0%	0%	0%	0%	**100%**	0%	0%	0%	**100%**	0%	0%	**100%**	10%	**100%**	**100%**
F6	0%	**100%**	0%	70%	0%	0%	0%	0%	0%	**100%**	0%	0%	0%	**100%**	0%	0%	**100%**	0%	**100%**	**100%**
F7	0%	**100%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	30%	0%	0%	**100%**	0%	**100%**	**100%**
F8	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
F9	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
F10	0%	**100%**	0%	30%	0%	0%	0%	0%	0%	**100%**	0%	0%	0%	**100%**	0%	0%	**100%**	0%	**100%**	**100%**
F11	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
F12	**100%**	**100%**	**100%**	**100%**	80%	**100%**	**100%**	**100%**	50%	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
F13	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	90%	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
F14	**100%**	**100%**	50%	**100%**	0%	**100%**	10%	30%	0%	**100%**	**100%**	0%	90%	50%	90%	**100%**	**100%**	0%	**100%**	0%
F15	**100%**	**100%**	**100%**	**100%**	10%	80%	**100%**	90%	0%	**100%**	**100%**	80%	**100%**	**100%**	**100%**	**100%**	**100%**	0%	**100%**	0%
F16	0%	40%	50%	90%	0%	40%	50%	0%	20%	0%	70%	0%	20%	30%	90%	60%	20%	0%	**100%**	0%
F17	**100%**	**100%**	**100%**	**100%**	20%	90%	**100%**	**100%**	10%	80%	**100%**	20%	**100%**	**100%**	**100%**	**100%**	**100%**	0%	**100%**	0%
F18	**100%**	**100%**	**100%**	**100%**	30%	**100%**	**100%**	**100%**	70%	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	90%	**100%**	**100%**	**100%**	20%
F19	30%	**100%**	20%	**100%**	0%	**100%**	0%	10%	0%	**100%**	**100%**	0%	**100%**	**100%**	**100%**	**100%**	**100%**	0%	**100%**	0%
F20	**100%**	70%	**100%**	**100%**	20%	90%	**100%**	60%	20%	90%	**100%**	90%	50%	50%	**100%**	**100%**	**100%**	**100%**	**100%**	20%
F21	0%	10%	0%	0%	0%	20%	0%	0%	0%	10%	50%	0%	20%	80%	0%	40%	90%	80%	**100%**	50%
F22	80%	80%	**100%**	**100%**	0%	**100%**	**100%**	10%	0%	90%	**100%**	10%	90%	90%	**100%**	**100%**	**100%**	**100%**	**100%**	70%

Table 5, *1st experiment algorithms average processing time (APT) (sec)*

Fn	BCO	BSA	CSA	CSO	DEA	DFA	FPA	GA	GSA	GWO	MFO	MHS	MVO	NBA	PSO	QPSO	SFS	SOM	SOS	WDO
F1	1.09	**0.92**	0.95	0.86	1.49	4.94	0.53	0.44	0.84	**0.46**	0.45	2.08	1.04	**0.54**	0.44	0.56	**2.26**	0.50	**1.89**	0.44
F2	0.72	**0.33**	0.80	**0.68**	1.01	4.99	0.39	0.30	0.74	**0.31**	0.30	2.12	0.92	**0.39**	0.28	0.43	**0.36**	0.34	**0.88**	**0.28**
F3	0.75	**0.38**	0.81	0.72	1.11	5.62	0.42	0.33	0.77	0.32	0.32	1.99	0.91	0.39	0.28	0.40	**0.33**	0.34	**1.14**	0.28
F4	0.75	0.66	0.74	0.65	0.97	4.72	0.39	0.30	0.72	0.32	0.31	2.11	0.97	0.41	0.31	0.42	1.61	0.38	1.43	0.31
F5	0.73	**0.70**	0.75	**0.70**	1.03	5.93	0.40	0.30	0.69	**0.31**	0.30	1.93	0.90	**0.38**	0.27	0.40	**1.47**	0.34	**1.23**	**0.28**
F6	0.72	**0.68**	0.71	0.66	1.00	5.80	0.47	0.37	0.78	**0.34**	0.32	2.04	0.92	**0.38**	0.28	0.40	**1.45**	0.34	**1.22**	**0.27**
F7	0.77	**0.69**	0.75	0.68	0.98	4.66	0.36	0.28	0.55	0.30	0.30	1.92	0.89	0.38	0.28	0.41	**1.63**	0.36	**1.29**	**0.28**
F8	0.71	0.66	0.69	0.64	0.96	4.75	0.36	0.28	0.55	0.30	0.29	1.92	0.90	0.38	0.28	0.40	1.47	0.34	1.25	0.28
F9	0.72	0.69	0.75	0.68	1.01	5.13	0.40	0.30	0.63	0.32	0.32	1.96	0.89	0.39	0.28	0.40	1.48	0.35	1.25	0.29
F10	0.77	**0.72**	0.80	0.73	1.09	5.55	0.42	0.32	0.60	**0.33**	0.32	2.01	0.93	**0.40**	0.29	0.42	**1.55**	0.36	**1.30**	**0.29**
F11	0.73	0.69	0.75	0.68	1.08	5.28	0.43	0.32	0.65	0.34	0.34	2.06	0.94	0.41	0.30	0.43	1.60	0.37	1.32	0.29
F12	**0.76**	**0.66**	**0.69**	**0.68**	1.00	**2.48**	**0.40**	**0.30**	0.59	**0.28**	**0.28**	**0.38**	**0.42**	**0.36**	**0.26**	**0.37**	**1.42**	**0.33**	**1.18**	**0.26**
F13	**0.70**	**0.39**	**0.70**	**0.56**	**1.03**	**2.48**	**0.42**	**0.30**	0.54	**0.18**	**0.27**	**0.38**	**0.41**	**0.31**	**0.17**	**0.37**	**0.31**	**0.34**	**1.06**	**0.26**
F14	**0.75**	**0.66**	0.67	**0.66**	1.06	**2.51**	0.43	0.30	0.42	**0.30**	**0.29**	0.40	0.46	0.47	0.35	**0.46**	**1.68**	0.39	**1.30**	0.28
F15	**0.70**	**0.69**	**0.69**	**0.67**	1.05	2.29	**0.47**	0.38	0.54	**0.37**	**0.36**	0.55	**0.57**	**0.50**	**0.35**	**0.47**	**1.70**	0.38	**1.32**	0.31
F16	0.74	0.70	0.74	0.69	1.03	2.32	0.42	0.31	0.44	0.31	0.31	0.41	0.50	0.44	0.30	0.43	1.53	0.34	**1.37**	0.30
F17	**0.77**	**0.64**	**0.66**	**0.66**	1.02	2.41	**0.43**	**0.33**	0.49	0.32	**0.32**	0.42	**0.44**	**0.39**	**0.28**	**0.39**	**1.48**	0.34	**1.22**	0.27
F18	**0.72**	**0.65**	**0.68**	**0.68**	1.05	**2.58**	**0.46**	**0.33**	0.46	**0.33**	**0.31**	**0.46**	**0.51**	**0.48**	**0.34**	0.48	**1.70**	**0.37**	**1.30**	0.28
F19	0.69	**0.63**	0.67	**0.65**	0.97	**2.52**	0.43	0.32	0.64	**0.30**	**0.28**	0.41	**0.46**	**0.45**	**0.33**	**0.44**	**1.40**	0.39	**1.48**	0.32
F20	**0.72**	0.68	**0.69**	**0.67**	1.06	2.56	**0.44**	0.33	0.45	0.33	**0.32**	0.42	0.47	0.41	**0.30**	**0.41**	**1.50**	**0.35**	**1.45**	0.33
F21	0.71	0.65	0.67	0.64	0.97	2.81	0.44	0.34	0.47	0.36	0.34	0.64	0.57	0.47	0.34	0.46	1.81	0.40	**1.51**	0.16
F22	0.73	0.55	**0.72**	**0.64**	1.06	**2.69**	**0.43**	0.33	0.46	0.38	**0.36**	0.51	0.59	0.51	**0.34**	**0.26**	1.32	**0.40**	**0.98**	0.34

TABLE 6, *2ND EXPERIMENT ALGORITHMS AVERAGE MEAN ABSOLUTE ERROR (AMAE)*

Fn	BCO	BSA	CSA	CSO	DEA	DFA	FPA	GOA	GSA	GWO
F1	3.66E+00	4.55E-10	3.79E+00	7.11E-01	3.59E+00	3.06E+00	3.77E+00	3.73E+00	3.79E+00	3.79E+00
F2	4.63E-01	**0.00E+00**	4.76E-01	9.80E-03	3.82E-01	2.59E-01	4.76E-01	4.76E-01	4.76E-01	5.01E-05
F3	2.11E+02	**0.00E+00**	3.30E+02	1.71E+01	2.59E+02	1.44E+02	3.26E+02	3.19E+02	3.30E+02	3.16E+01
F4	1.04E+00	7.72E-03	5.13E+00	6.06E+00	4.81E+01	3.20E-03	4.68E+00	1.93E+00	1.30E+01	5.24E+00
F5	1.71E+00	2.49E-38	1.03E+01	2.44E-01	7.40E+00	4.17E+00	1.04E+01	7.69E+00	1.04E+01	5.35E-05
F6	4.19E+01	2.54E-39	1.54E+02	8.29E-01	1.12E+02	5.92E+01	1.54E+02	1.34E+02	1.54E+02	1.48E-03
F7	1.46E+02	7.40E-37	2.28E+03	1.10E+03	1.87E+03	2.09E+03	1.42E+03	2.35E+03	7.03E+03	5.09E+02
F8	1.73E+02	2.88E+01	5.94E+02	2.35E+02	4.54E+02	2.49E+02	5.88E+02	3.55E+02	5.97E+02	2.78E+01
F9	6.14E+01	9.90E-01	2.16E+02	6.48E+01	1.55E+02	5.50E+01	2.18E+02	1.92E+02	2.18E+02	8.79E-01
F10	1.00E+02	1.71E-36	2.97E+02	1.53E+01	1.58E+02	5.46E+01	2.98E+02	1.90E+02	3.01E+02	4.04E-03
F11	1.19E+02	4.94E+02	8.03E+02	6.82E+02	1.05E+03	3.71E+02	9.57E+02	6.22E+02	1.13E+03	4.28E+02
F12	3.13E-09	**1.26E-14**	6.59E-06	3.52E-09	1.02E-02	5.23E-10	2.62E-03	1.53E-02	1.10E-01	8.10E-06
F13	2.37E-02	**0.00E+00**	4.23E-02	**0.00E+00**	1.24E-01	3.19E-02	9.35E-02	8.78E-02	4.76E-01	3.19E-02
F14	1.01E+00	1.66E-05	8.29E-01	2.24E+00	3.40E+00	1.55E+01	1.33E+00	1.80E+00	3.42E+01	4.59E+00
F15	1.51E-01	**3.58E-07**	1.54E-02	1.05E-04	5.70E+00	1.40E+00	2.26E-02	1.64E+00	3.70E+00	1.14E-04
F16	2.52E+00	1.21E-01	5.60E-01	8.85E-01	1.37E-01	3.14E-03	5.69E-01	7.24E+00	2.46E+00	8.02E-01
F17	2.76E-02	2.44E-05	7.91E-03	7.82E-03	1.79E+00	8.70E-04	1.40E-02	2.75E-01	3.19E+00	1.31E-02
F18	1.11E-01	3.85E-05	7.68E-04	8.54E-05	2.01E+00	8.29E-06	2.53E-03	8.16E-01	7.49E-01	7.62E-04
F19	1.00E+00	1.28E-01	9.18E-01	5.04E-01	5.48E-01	1.29E-05	1.00E+00	1.00E+00	1.00E+00	9.88E-01
F20	6.69E-03	1.25E-01	3.00E-03	2.98E-09	3.72E+00	1.29E-01	7.36E-02	6.50E-01	1.02E+01	5.04E-02
F21	2.23E+01	8.94E-01	1.81E+01	8.86E-01	9.42E+00	1.60E+00	4.46E+01	1.43E+01	4.46E+01	1.64E+00
F22	1.30E-01	4.10E-01	2.58E-01	7.63E-02	1.31E+00	3.93E-01	7.09E-01	5.81E-01	1.61E+00	1.51E-02

TABLE 6, *2ND EXPERIMENT ALGORITHMS AVERAGE MEAN ABSOLUTE ERROR (AMAE)*

Fn	MFO	MHS	MVO	NBA	PSO	QPSO	SFS	SOM	SOS	WDO
F1	2.06E+00	3.79E+00	3.64E+00	1.13E-05	3.79E+00	3.79E+00	**8.88E-16**	2.96E+00	2.58E+00	4.44E-01
F2	1.01E-01	4.76E-01	4.76E-01	2.09E-10	4.76E-01	5.88E-02	**0.00E+00**	2.08E-01	**0.00E+00**	6.78E-08
F3	8.66E+01	3.30E+02	2.83E+02	2.03E+01	3.30E+02	5.63E+01	**0.00E+00**	1.86E+02	7.96E-14	2.99E+01
F4	**1.14E-03**	1.04E+01	2.53E+00	1.48E+00	5.31E+00	7.60E+00	1.87E+00	3.67E+01	1.30E+00	1.21E+03
F5	2.24E+00	1.04E+01	3.89E+00	3.72E-08	1.04E+01	1.42E+00	**4.27E-84**	4.90E+00	1.85E-25	8.70E-07
F6	3.00E+01	1.54E+02	7.48E+01	9.28E-08	1.54E+02	3.12E+01	**6.77E-83**	6.35E+01	1.33E-23	1.23E-05
F7	3.71E+03	2.90E+03	3.00E+03	5.44E+02	1.68E+03	9.08E+02	**8.81E-64**	1.96E+02	5.51E+01	8.52E-04
F8	1.74E+02	5.97E+02	2.12E+02	2.75E+01	5.97E+02	1.52E+02	2.74E+01	2.21E+02	2.56E+01	2.87E+01
F9	2.89E+01	2.18E+02	1.26E+02	6.67E-01	2.18E+02	2.20E+01	6.67E-01	7.42E+01	6.67E-01	8.93E-01
F10	1.84E+01	3.01E+02	5.42E+01	8.60E-04	3.01E+02	1.02E+01	**1.33E-82**	8.64E+01	2.98E-10	7.78E-05
F11	4.27E+02	1.13E+03	4.47E+02	3.94E+02	1.13E+03	3.83E+02	7.72E+01	1.05E+03	1.44E+02	9.16E+02
F12	1.77E-12	9.93E-02	6.39E-05	1.02E-10	2.03E-03	4.46E-09	1.05E-09	2.31E-07	4.89E-10	2.84E-02
F13	3.83E-02	3.19E-01	3.37E-02	3.83E-02	1.91E-02	6.38E-03	**0.00E+00**	2.39E-05	4.01E-11	6.38E-02
F14	**1.58E-09**	5.65E+00	4.27E-01	3.12E-01	2.05E+00	1.63E+00	1.15E-01	8.26E+01	1.67E-01	6.46E+01
F15	**3.58E-07**	6.17E-01	9.67E-04	3.64E-05	2.59E-01	1.85E-04	2.89E-04	2.90E+00	8.46E-06	1.38E+01
F16	**1.46E-06**	9.85E-01	1.22E+00	1.45E+00	2.59E-01	9.89E-01	2.53E-01	8.40E+01	3.11E-01	1.83E+02
F17	**4.23E-08**	5.72E-01	1.94E-02	1.77E-03	5.27E-02	4.40E-03	5.36E-03	3.18E+00	6.78E-03	1.13E+01
F18	3.08E-05	8.83E-02	1.44E-03	6.47E-05	3.37E-03	7.02E-05	2.96E-05	2.95E-03	7.03E-05	3.85E-01
F19	**3.33E-17**	1.00E+00	1.24E-01	4.78E-10	7.14E-01	9.45E-01	2.11E-05	9.06E-01	1.00E+00	1.00E+00
F20	3.24E-10	2.30E+00	2.83E-02	4.86E-02	8.93E-03	5.45E-02	**4.92E-16**	4.36E-05	7.70E-16	4.37E+00
F21	8.29E-02	4.46E+01	2.92E+00	1.21E-01	4.46E+01	7.60E-01	**7.46E-03**	1.26E-01	9.75E-03	3.94E-01
F22	3.11E-02	1.61E+00	7.23E-02	1.88E-02	7.11E-01	1.21E-01	3.07E-02	4.37E-02	**1.23E-02**	6.11E-02

TABLE 7, *2ND EXPERIMENT ALGORITHMS STABILITY*

Fn	BCO	BSA	CSA	CSO	DEA	DFA	FPA	GA	GSA	GWO	MFO	MHS	MVO	NBA	PSO	QPSO	SFS	SOM	SOS	WDO
F1	0%	**100%**	0%	50%	0%	0%	0%	0%	0%	0%	0%	0%	0%	**100%**	0%	0%	**100%**	0%	20%	80%
F2	0%	**100%**	0%	**100%**	0%	0%	0%	0%	0%	**100%**	50%	0%	0%	**100%**	0%	**100%**	**100%**	0%	**100%**	**100%**
F3	0%	**100%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	10%	0%	0%	**100%**	0%	**100%**	0%
F4	10%	**100%**	0%	0%	0%	**100%**	0%	0%	0%	0%	**100%**	0%	0%	10%	10%	0%	0%	0%	10%	0%
F5	0%	**100%**	0%	70%	0%	0%	0%	0%	0%	**100%**	0%	0%	0%	**100%**	0%	0%	**100%**	0%	**100%**	**100%**
F6	0%	**100%**	0%	50%	0%	0%	0%	0%	0%	**100%**	0%	0%	0%	**100%**	0%	0%	**100%**	0%	**100%**	**100%**
F7	0%	**100%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	**100%**	0%	0%	**100%**
F8	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
F9	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
F10	0%	**100%**	0%	20%	0%	0%	0%	0%	0%	**100%**	0%	0%	0%	**100%**	0%	0%	**100%**	0%	**100%**	**100%**
F11	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
F12	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	50%	**100%**	**100%**	70%	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
F13	**100%**	**100%**	**100%**	**100%**	60%	**100%**	70%	70%	0%	**100%**	**100%**	20%	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
F14	0%	**100%**	10%	10%	20%	60%	10%	10%	0%	0%	**100%**	0%	10%	60%	20%	40%	50%	0%	60%	0%
F15	40%	**100%**	**100%**	**100%**	0%	0%	**100%**	20%	0%	**100%**	**100%**	20%	**100%**	**100%**	80%	**100%**	**100%**	0%	**100%**	0%
F16	0%	80%	10%	20%	50%	**100%**	40%	0%	10%	10%	**100%**	20%	0%	0%	60%	20%	40%	0%	10%	0%
F17	**100%**	**100%**	**100%**	**100%**	90%	**100%**	**100%**	40%	0%	**100%**	**100%**	20%	**100%**	**100%**	**100%**	**100%**	**100%**	10%	**100%**	0%
F18	50%	**100%**	**100%**	**100%**	20%	**100%**	**100%**	70%	10%	**100%**	**100%**	50%	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	0%
F19	0%	80%	0%	10%	20%	**100%**	0%	0%	0%	0%	**100%**	0%	60%	**100%**	20%	0%	**100%**	0%	0%	0%
F20	**100%**	80%	**100%**	**100%**	0%	50%	70%	30%	0%	90%	**100%**	10%	90%	90%	**100%**	**100%**	**100%**	**100%**	**100%**	0%
F21	0%	30%	0%	40%	0%	20%	0%	0%	0%	30%	80%	0%	0%	40%	0%	40%	**100%**	70%	**100%**	90%
F22	40%	0%	0%	70%	0%	10%	0%	0%	0%	**100%**	**100%**	0%	80%	**100%**	0%	40%	**100%**	**100%**	**100%**	60%

TABLE 8, *2ND EXPERIMENT ALGORITHMS AVERAGE PROCESSING TIME (APT) (SEC)*

Fn	BCO	BSA	CSA	CSO	DEA	DFA	FPA	GA	GSA	GWO	MFO	MHS	MVO	NBA	PSO	QPSO	SFS	SOM	SOS	WDO
F1	1.12	**0.96**	1.00	0.85	1.54	4.94	0.56	0.51	0.96	0.52	0.49	2.28	1.10	**0.64**	0.50	0.61	**2.34**	0.51	1.94	0.45
F2	0.75	**0.37**	0.81	**0.67**	1.02	5.24	0.39	0.29	0.74	**0.32**	0.30	1.94	0.89	**0.38**	0.28	**0.41**	**0.36**	0.35	**1.05**	**0.30**
F3	0.70	**0.34**	0.74	0.64	0.97	5.04	0.39	0.30	0.73	0.31	0.31	1.95	0.88	0.38	0.28	0.40	**0.35**	0.34	**1.26**	0.29
F4	0.73	**0.70**	0.78	0.69	1.02	**4.53**	0.37	0.28	0.70	0.31	**0.30**	1.93	0.88	0.39	0.28	0.40	1.53	0.36	1.27	0.29
F5	0.71	**0.65**	0.69	0.62	1.04	5.39	0.38	0.29	0.69	0.30	0.29	1.92	0.88	**0.38**	0.28	0.41	**1.48**	0.34	**1.22**	**0.28**
F6	0.73	**0.69**	0.73	0.66	0.98	5.62	0.38	0.29	0.70	**0.30**	0.29	2.18	0.98	**0.40**	0.29	0.41	**1.50**	0.34	**1.23**	**0.28**
F7	0.74	**0.69**	0.76	0.66	0.97	5.00	0.38	0.29	0.64	**0.31**	0.29	1.93	0.88	0.38	0.28	0.39	**1.47**	0.34	1.23	**0.28**
F8	0.71	0.70	0.79	0.70	1.03	5.64	0.38	0.29	0.65	0.30	0.30	1.97	0.88	0.38	0.28	0.42	1.62	0.36	1.29	0.30
F9	0.70	0.67	0.73	0.66	0.98	5.23	0.38	0.29	0.70	0.30	0.29	2.14	0.93	0.39	0.29	0.41	1.51	0.35	1.25	0.29
F10	0.66	**0.63**	0.73	0.63	0.95	4.95	0.38	0.29	0.67	**0.31**	0.31	2.07	0.93	**0.40**	0.30	0.43	**1.67**	0.37	**1.40**	**0.31**
F11	0.79	0.74	0.78	0.74	1.08	5.28	0.41	0.31	0.73	0.33	0.32	2.45	1.05	0.45	0.34	0.48	1.75	0.38	1.38	0.31
F12	**0.75**	**0.66**	**0.71**	**0.67**	**1.09**	**2.56**	**0.42**	**0.31**	0.43	**0.31**	**0.30**	0.42	**0.46**	**0.39**	**0.28**	**0.39**	**1.42**	**0.34**	**1.31**	**0.28**
F13	**0.77**	**0.45**	**0.75**	**0.45**	1.06	**2.25**	0.45	0.34	0.67	**0.23**	**0.32**	0.47	**0.52**	**0.35**	**0.13**	**0.43**	**0.35**	**0.37**	**1.12**	**0.27**
F14	0.82	**0.77**	0.78	0.74	1.18	2.76	0.50	0.38	0.53	0.37	**0.38**	0.51	0.60	0.52	0.36	0.48	1.80	0.43	1.64	0.38
F15	0.88	**0.83**	**0.86**	**0.84**	1.29	2.60	**0.45**	0.36	0.46	**0.33**	**0.33**	0.44	**0.48**	**0.42**	0.31	**0.42**	**1.56**	0.39	**1.29**	0.31
F16	0.79	0.75	0.82	0.81	1.30	**3.28**	0.58	0.43	0.59	0.43	**0.44**	0.56	0.65	0.56	0.41	0.57	2.11	0.50	1.66	0.38
F17	**0.79**	**0.75**	**0.84**	**0.81**	1.29	**3.63**	**0.58**	0.44	0.60	**0.44**	**0.42**	0.58	**0.64**	**0.54**	**0.41**	**0.53**	**2.02**	0.45	**1.49**	0.38
F18	0.79	**0.75**	**0.79**	**0.73**	1.17	**2.92**	**0.47**	0.35	0.48	**0.36**	**0.35**	0.46	**0.54**	**0.46**	**0.32**	**0.45**	**1.66**	**0.41**	**1.41**	0.31
F19	0.78	0.68	0.72	0.70	1.15	**2.83**	0.45	0.35	0.79	0.37	**0.35**	0.50	0.52	**0.46**	0.32	0.46	**1.59**	0.36	1.23	0.27
F20	**0.75**	0.74	**0.78**	**0.75**	1.18	3.49	0.55	0.42	0.61	0.44	**0.44**	0.61	0.69	0.64	**0.43**	**0.60**	**2.07**	**0.47**	**1.68**	0.41
F21	0.73	0.72	0.75	0.71	1.11	3.19	0.42	0.31	0.47	0.32	0.31	0.56	0.50	0.41	0.28	0.40	**1.62**	0.37	**1.38**	0.04
F22	0.83	0.77	0.82	0.79	1.32	3.44	0.57	0.43	1.51	**0.43**	**0.43**	0.98	0.77	**0.56**	0.44	0.61	**2.15**	**0.50**	**1.62**	0.36

TABLE 9 *OVERALL EFFICIENCY, STABILITY, AND PROCESSING TIME*

	1st experiment			2nd experiment		
Alg.	OAE	OAS	OPT(sec)	OAE	OAS	OPT (sec)
BCO	41%	32%	0.73	18%	18%	0.77
BSA	64%	64%	0.62	64%	64%	0.66
CSA	32%	32%	0.69	27%	27%	0.79
CSO	55%	50%	0.65	36%	32%	0.7
DEA	9%	5%	1.03	5%	5%	1.09
DFA	36%	27%	2.54	32%	32%	3.14
FPA	32%	32%	0.43	27%	18%	0.48
GA	23%	18%	0.31	9%	5%	0.31
GSA	5%	0%	0	0%	0%	0
GWO	59%	50%	0.32	50%	45%	0.33
MFO	45%	41%	0.31	55%	50%	0.37
MHS	23%	14%	0.41	9%	0%	0
MVO	27%	27%	0.47	32%	23%	0.53
NBA	55%	50%	0.42	59%	55%	0.45
PSO	36%	36%	0.3	23%	23%	0.31
QPSO	45%	36%	0.4	32%	32%	0.46
SFS	77%	73%	1.35	**73%**	**73%**	1.48
SOM	23%	23%	0.36	23%	23%	0.42
SOS	**82%**	**82%**	1.28	59%	59%	1.17
WDO	23%	32%	0.27	36%	32%	0.29

6 CONCLUSIONS

This paper has tried to make a fair and comprehensive performance comparison between different meta-heuristic population based algorithms during two individual experiments on a twenty two benchmark test functions, some of these algorithms were classic and well-known and have been used in many researches, other algorithms are recently proposed and rarely have been used or tested, so that we have spot the light to these algorithms. The comparison take into account the stability, required processing time, and the mean absolute error for each algorithms through a variety of test function. We tried to make this paper as a reference to other people how like to introduce a new meta-heuristic optimization algorithm , so that anybody can compare the proposed algorithm performance to the algorithms introduced and tested in this paper without needing to program all these algorithms and test them.

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