A Comparative Study of Recent Swarm Intelligence Approaches on Global Optimization

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***Abstract*—This paper presents a comparative study of three Swarm Intelligence approaches which are: Bat Algorithm (BA), Firefly Algorithm (FA) and Artificial Bee Colony (ABC) Algorithm applied to a set of standard benchmark functions. The results of this study were analyzed and compared on the basis of mean value of obtained objective values. All of these approaches were investigated taking into consideration several dimensionalities *D* which are 10, 20,30, 50 and 100. Statistical results indicated that ABC significantly surpassed BA and FA on the majority of the experimental instances and FA was able to significantly archive better objective values than BA in most of the test cases. The paper finally concludes with some future work directions.**

***Index Terms*—ABC, BA, FA, optimization, swarm intelligence.**

I. Introduction

One of the key methods of optimization is Swarm Intelligence (SI) which is mainly inspired by the social behavior of animals and insects such as birds, ants and bees [1]. SI was first introduced by Beni in 1988 where it was proposed for cellular robotic system [2]. SI algorithms have recently been extensively adopted due to several reasons. Most importantly, self-learning ability and adaptability to external variations beside their flexibility and versatility. The mainstream of SI approaches is particle swarm optimization (PSO), ant colony optimization (ACO) where as the most recent ones are bat algorithm, firefly algorithm, bacterial foraging optimization (BFO) and artificial bees colony (ABC) are widely used. Most of these approaches were adopted for different types of optimization including industrial and scientific world problems.

This paper presents a comparative study of three of the most recent SI approaches namely Bat algorithm, Firefly algorithm and Artificial bees colony (ABC). Particularly, these approaches were compared on solving global optimization problems where a set of benchmark functions were adopted with variant of dimensions ranging from 10 to 100. The results of this study would help researchers and practitioners to decide which SI approach would be suitable to adopt. The rest of the paper reviews and describe the three approaches (Section II). The experimental setup and benchmark functions are discussed in III. Experimental results are then discussed in Section IV. The paper finally concluded and directions for future work are highlighted in Section V.

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Define the objective function f(X), X = (x1, x2, ···, xd)^T
Initialize the bat population Xi and Vi (i = 1, 2, ···, N)
Define pulse frequencies fi at Xi
Initialize loudness Ai and pulse emission rate ri
while (t ≤ Maximum number of iterations)
    Adjust frequency
    Update velocities
    Update locations/solutions
    if (rand > ri)
        Select a solution among the best solutions
        Generate a local solution around the selected best solution
    end if
    if (rand < Ai & f(Xi) < f(X*))
        Accept the new solutions
        Reduce Ai
        Increase ri
    end if
    Rank the bats and find the current best X*
    t = t + 1
end while
Post-process results and visualization
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Fig. 1. Bat algorithm [3].

II. Recent Swarm Intelligent Approaches

A. Bat Algorithm

Bat Algorithm is one of the recent swarm intelligent approaches that was introduced on 2010 by Yang [3]. It was developed to imitate micro bats social behavior and their ability to determine distance based on echolocation features. Naturally, micro bats are insectivores which can use a sonar like system in order to detect their pries, discover roosting crevices and avoid any obstacles. They produce loud sound called pulse and wait for the bounced back echo. The properties of the pulse and echo are used to determine their hunting strategies. Accordingly, bat algorithm was developed by taking into consideration the following idealized rules:

- Bats can determine distance using echolocation and differentiate between prey and background barriers.
- Searching for prey bats fly arbitrarily with velocity v_i at location x_i with a static frequency f_{min} and variable wavelength γ and loudness A_0.
- Based on the closeness of their targets, they spontaneously change the wavelength of the pulses they send and the rate of pulse emission r $\in$ [0, 1].
- The loudness varies from large positive value A_0 to a lowest constant value A_0 .

Fig 1 shows the pseudocode of the Bat algorithm. It can become with different variants such as Fuzzy Logic Bat Algorithm, K-Means Bat Algorithm, Chaotic Bat Algorithm and Differential Operator and Levy flights Bat Algorithm [4, 5]. In fact, it was initially developed to optimize numerical and continues problems where various studies demonstrated it robustness in solving such problems [6]. Furthermore, several hybridized versions of Bat algorithm were proposed for solving this type of problems such as [7]-[9]. On the other

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hand, it has been modified by various researchers in order to adopt it for solving combinatorial problems such as Capacitated Vehicle Routing Problem [10] and optimization in industry such as [11].

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Objective function f(x),   x = (x_1, ..., x_d)^T
Initialize a population of fireflies x_i (i = 1, 2, ..., n)
Define light absorption coefficient γ
while (t <MaxGeneration)
for i = 1 : n all n fireflies
  for j = 1 : i all n fireflies
    Light intensity I_i at x_i is determined by f(x_i)
    if (I_j > I_i)
    Move firefly i towards j in all d dimensions
    end if
    Attractiveness varies with distance r via exp[−γr]
    Evaluate new solutions and update light intensity
  end for j
end for i
Rank the fireflies and find the current best
end while
Postprocess results and visualization
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Fig. 2. FA algorithm [12].

B. Firefly Algorithm

Firefly Algorithm was also introduced first by Yang [12]. It was inspired by the flashing lights of fireflies in the summer sky in the tropical and moderate areas. Fireflies mainly use their flashes to attract mating partners or to attract potential pry. Flashing lights can have different characteristics such as rhythm, rate of flashing and amount of time which can be utilized to form a particular message to a partner [13]. Hence, the algorithm is based on the following idealized concepts:

- Fireflies are attracted to each other regardless of their gender as thy are unisex.
- Attractiveness is relative to their brightness so the less bright firefly moves towards the brighter one as well as the brightness is reduced with the increasing distance between fireflies.
- A firefly moves randomly in the space If there are no brighter fireflies around.
- The brightness of fireflies is adjusted by the landscape of the objective function to be optimized.

Fig. 2 shows the pseudocode of the Firefly algorithm. It has attracted researchers' attentions in several applications such as engineering design problems, image compression and scheduling [14]. For instance, Firefly was extended by [15] to solve multi-objective continuous optimization problems as well as was modified with Levy Flights by [16] to solve global optimization. Moreover, various modified version of Firefly was introduced for the optimization of data mining problems such as clustering [17], [18] combinatorial problems such as the traveling salesman problem [19].

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Initialization Phase
REPEAT
      Employed Bees Phase
      Onlooker Bees Phase
      Scout Bees Phase
      Memorize the best solution achieved
UNTIL  Cycle = Maximum Cycle Number
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Fig. 3. ABC Algorithm [20]

C. Artificial Bees Colony

Artificial Bees Colony (ABC) was proposed by Karaboga in 2005 [20]. The underlying idea about ABC is simulating the foraging behavior of honeybees. Naturally, two types of honeybees can be found which are unemployed bees which are two types scout, that search the surroundings of the nest for new sources of foods, and onlookers, that wait in the nest to create new food sources. Employed bees, on other hand, are associated with food sources [20]. the colony of ABC: employed, onlooker, and scout bees [30]. Hence, solutions in ABC are representations of food sources, and the amount of nectar in these sources. In fact, food source is the solution fitness value. As each employed bee in the colony is associated with a food source, number of food sources (solutions) is equal to number of employed bees. Fig 3 shows the pseudocode of the ABC algorithm. It was studied since its invention from different perspectives such as investigating its performance like [21], [22]. Furthermore, it was successfully adopted it to solve real problems such as numerical optimization [23], [24], multi-objective problems [25], [26] and combinatorial optimization [27].

III. Experiment

A. Benchmark Functions

In order to compare the performance of the three approaches, five benchmark functions were selected from the well-known test suit of benchmark functions. These functions are broadly adopted in the field of optimization especially with evolutionary computation such as [28], [29]. All selected functions are a minimization problem where the lowest the obtained objective value is the better. They are as follows:

1) Ackley

$f(x)$=-a exp

$$f(x) = -a\exp(-b\sqrt{\frac{1}{d}\sum_{i=1}^{d}\chi 2_i^2} - \exp(\frac{1}{d}\sum_{i=1}^{d}\cos(cxi)) + a + \exp(1) \quad (1)$$

Where the global minimum is $f(x) = 0$ for $x \in [-32,32]$.

2) Griewank

$$f(x) = -\sum_{i=1}^{d}\frac{x_i^2}{4000} - \prod_{i=1}^{d}\cos(\frac{x_i}{\sqrt{i}}) + 1 \quad (2)$$

Where the global minimum is $f(x) = 0$ for $x \in [-600,600]$.

3) Sphere

$$f(x) = -\sum_{i=1}^{d} x_i^2 \quad (3)$$

where the global minimum is $f(x) = 0$ for $x \in [-100,100]$.

4) Rastrigin

$$f(x) = 10d + \sum_{i=1}^{d}\left(\left[x_i^2 - 10\cos(2\pi x_i\right]\right) \quad (4)$$

where the global minimum is $f(x) = 0$ for $x \in [-5.12,5.12]$.

5) Rosenbrock

$$f(x) = \sum_{i=1}^{d-1} \left[\left(100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2\right] \quad (5)$$

where the global minimum is $f(x) = 0$ for $x \in [-2.048, 2.048]$.

B. Experimental Setting

TABLE I: PARAMETERS SETTINGS

Approach	Parameter	Value
BA	Loudness	$A = 0.5$
	Pulse emissions rate	$r = 0.5$
	Loudness updating factor	$\alpha = 0.9$
	Pulse updating factor	$\gamma = 0.9$
	Maximum frequency	$f_{max} = 2$
	Minimum frequency	$f_{min} = 0$
FA	Light Absorption Coefficient	$\gamma = 1$
	Attraction Coefficient	$\beta = 2$
	Mutation Coefficient	$\alpha = 0.2$
ABC	Employed bees	$n_e = 0.5 \times cs$
	Onlookers	$n_o = 0.5 \times cs$
	Scout	1
	Limit	$l = (n \times cs)/2$

TABLE II: MINIMUM, STANDARD DEVIATION AND MEAN OF OBTAINED OBJECTIVE VALUES FOR D=10

F		BA	FA	ABC
1	Best	2.17E+00	**2.22E-15**	1.8318
	σ	0.492201	7.88E-11	0.526683
	μ	3.38E+00	1.44E-11	3.12391
2	Best	1.36E-06	9.86E-03	**0**
	μ	0.022888	0.066031	2.21E-08
	σ	4.07E-02	9.63E-02	4.04E-09
3	Best	5.68E-07	**3.50E-229**	4.63E-17
	μ	3.96E-07	1.36E-20	7.23E-17
	σ	1.33E-06	2.48E-21	1.56E-16
4	Best	2.99E+00	4.97E+00	**0**
	μ	4.314663	6.539482	3.59E-10
	σ	1.25E+01	1.33E+01	6.65E-11
5	Best	2.66E+00	1.56E-02	**0.000709**
	μ	5.50333	1.706463	1.616003
	σ	7.92E+00	2.09E+00	0.729594

Here, we discuss the parameters setting of each approach as well as we describe the adopted experimental design. All three approaches were tested on the same PC which have Intel Core i7-4790s CPU at 3.2GHz and 12 GB RAM running a 64-bit Windows operating system. Using this PC, the three approaches were implemented on MATLAB R2014a. Each approach was run for 30 independent times to solve each benchmark function. The minimum objective values obtained, mean and standard deviation of these runs were recorded. Furthermore, all approaches were investigated taking into consideration various dimensionalities D which are 10, 20, 30, 50 and 100. Population and maximum number of iterations were unified amongst the three approaches which are 20, 1000 respectively. Table I shows the specific parameters' setting for each approach.

TABLE III: MINIMUM, STANDARD DEVIATION AND MEAN OF OBTAINED OBJECTIVE VALUES FOR D=20

F		BA	FA	ABC
1	Best	2.12E+00	**6.66E-15**	4.93E-12
	σ	0.390287	0.58551	4.77E-11
	μ	3.44E+00	3.41E-01	5.12E-11
2	Best	2.25E-02	**0.00E+00**	1.11E-16
	μ	0.044514	0.030527	1.40E-10
	σ	1.09E-01	2.12E-02	3.56E-11
3	Best	1.97E-01	**3.59E-25**	3.18E-16
	μ	2.30E+00	4.43E-03	1.39E-16
	σ	9.41E+00	1.34E-03	5.35E-16
4	Best	1.49E+01	2.49E+01	**1.28E-12**
	μ	6.488879	18.00615	5.74E-07
	σ	2.77E+01	4.42E+01	1.25E-07
5	Best	1.08E+01	**3.53E-02**	0.06598
	μ	44.63939	181.1792	4.973805
	σ	7.77E+01	4.41E+01	4.647004

TABLE IV: MINIMUM, STANDARD DEVIATION AND MEAN OF OBTAINED OBJECTIVE VALUES FOR D=30

F		BA	FA	ABC
1	Best	2.08E+00	**1.55E-14**	1.08E-07
	σ	0.399499	0.929164	5.07E-07
	μ	3.54E+00	1.23E+00	6.91E-07
2	Best	2.25E-02	**0.00E+00**	9.99E-16
	μ	0.044514	0.012425	3.32E-07
	σ	1.09E-01	1.10E-02	8.73E-08
3	Best	2.16E-05	**1.85E-63**	3.49E-15
	μ	8.57E-01	2.51E-10	3.67E-13
	σ	1.79E+00	4.58E-11	1.45E-13
4	Best	2.39E+01	5.87E+01	**1.17E-06**
	μ	9.609859	19.30315	9.02E-01
	σ	4.34E+01	8.81E+01	1.09E+00
5	Best	6.67E+01	**1.30E-02**	0.32094
	μ	95.73667	33.11176	15.08654
	σ	2.49E+02	3.56E+01	15.20524

IV. RESULTS AND DISCUSSION

TABLE V: MINIMUM, STANDARD DEVIATION AND MEAN OF OBTAINED OBJECTIVE VALUES FOR D=50

F		BA	FA	ABC
1	Best	2.08E+00	**1.80E-09**	0.000342
		0.399499	1.102805	0.000678
	μ	3.54E+00	2.75E+00	0.001344
2	Best	3.63E-03	**1.44E-15**	2.85E-09
	μ	0.075472	0.008504	9.56E-08
		2.71E-01	6.13E-03	7.26E-08
3	Best	1.97E-01	**3.59E-25**	3.41E-08
	μ	2.30E+00	4.43E-03	4.52E-07
		9.41E+00	1.34E-03	4.71E-07
4	Best	4.38E+01	1.29E+02	**5.9924**
	μ	11.72772	67.88037	2.69E+00
		7.05E+01	2.35E+02	1.14E+01
5	Best	6.37E+01	**4.20E+00**	4.8193
	μ	297.4183	188.8463	39.54329
		9.99E+02	1.10E+02	87.74938

Tables II-VI show the best value obtained by the three approaches as well as the standard deviation and the mean. The best obtained value (lowest) was bolded. It can be noticed that has not recorded better values in all functions for all dimensions. Furthermore, the results indicated that the best obtained values fluctuated between FA and ABC amongst all

TABLE VI: MINIMUM, STANDARD DEVIATION AND MEAN OF OBTAINED OBJECTIVE VALUES FOR D=100

F		BA	FA	ABC
1	Best	1.98E+00	2.96E+00	**0.13827**
	σ	0.352066	1.09663	0.211023
	μ	3.71E+00	5.05E+00	0.702774
2	Best	8.16E-02	**2.66E-15**	0.000313
	μ	0.098923	0.153435	1.56E-03
	σ	4.95E-01	6.83E-02	2.00E-03
3	Best	3.72E+00	**2.94E-16**	1.76E-04
	μ	8.25E+00	2.03E+00	1.29E-02
	σ	4.18E+01	1.02E+00	8.79E-03
4	Best	1.20E+02	5.03E+02	**64.511**
	μ	12.64609	121.0575	1.26E+01
	σ	1.45E+02	6.93E+02	9.12E+01
5	Best	4.53E+02	**1.08E+02**	178.07
	μ	1496.565	509.523	77.33772
	σ	5.99E+03	3.84E+02	370.932

TABLE VII: OVERALL MEAN VALUE AND ANOVA RESULTS

D	Mean		Results
10	BA	4.69	$F(2,87) = 80, p < 0.01$
	FA	3.10	
	ABC	**0.77**	
20	BA	21.79	$F(2,87) = 7.6, p < 0.01$
	FA	17.81	
	ABC	**0.93**	
30	BA	59.60	$F(2,87) = 164.5, p < 0.01$
	FA	24.99	
	ABC	**3.26**	
50	BA	216.47	$F(2,87) = 175, p < 0.01$
	FA	69.44	
	ABC	**19.82**	
100	BA	1236	$F(2,87) = 350, p < 0.01$
	FA	216.61	
	ABC	**92.43**	

TABLE VIII: T-TEST RESULTS

D	ABC vs FA	FA vs BA
10	$t = 4.5, df = 29\ p < 0.01$	$t = 8.5, df = 29\ p < 0.01$
20	$t = 2.5, df = 29\ p < 0.01$	$t = 0.6, df = 29\ p > 0.05$
30	$t = 14.3, df = 29\ p < 0.01$	$t = 9.2, df = 29\ p < 0.01$
50	$t = 6.2, df = 29\ p < 0.01$	$t = 11.6, df = 29\ p < 0.01$
100	$t = 6.4, df = 29\ p < 0.01$	$t = 17.28, df = 29\ p < 0.01$

Benchmark functions for all dimensions. However, it can be noticed that FA was able to achieve slightly more better values than ABC especially for larger dimensions ($D = 30\ ,50\ and\ 100$). Nevertheless, by taking a look at the mean of obtained values of the 30 runs in each function for all dimensions it can be noticed that ABC has the lowest value amongst the three approaches in most of the cases. The overall mean value of the five benchmark functions was calculated for the three approach in each dimensions in order to statistically investigate this difference. Table VII shows that ABC was the best approach in terms of mean objective values in all dimensions whereas BA was the worst where it recorded highest mean value amongst the three approaches. ANOVA was applied to investigate the significance of this difference. Statistical results indicated that the difference in the performance of the three approaches were different in all dimensions.

In addition, t-test was applied to find out whether ABC significantly outperform FA as well as to investigate whether BA can be considered the worst approach amongst the three approaches in terms of objective values obtained. Firstly, paired t-test was applied on the overall mean values obtained by ABC and FA for the five dimensions. The results indicated that ABC significantly outperforms FA (see Table VIII). Secondly, paired t-test was also applied on the overall mean values obtained by FA and BA for the five dimensions. The results indicated that FA significantly outperforms BA (see Table VII). Thus, it can be concluded that ABC is the best

Swarm intelligent approach amongst the three approaches in the optimization of continues problems.

V. CONCLUSION

This paper presented a comparative study of three of the most recent SI approaches which are BA, FA and ABC. The paper started with a review of each approach presented its pseudocode and its underlying idea. All of these approaches were investigated on a set of five standard benchmark functions taking into consideration variant dimensions as well as generic parameters such as population size and maximum cycle number were unified for all approaches to ensure fair comparisons. Statistical tests particularly ANOVA and paired t-test were applied on the mean obtained objective values to investigate the significance of the difference between approaches. The results indicated that ABC was able to obtained best objective whereas BA recorded the worst values. Further experiments will be carried out in the future to investigate and compare these approaches from different perspectives such execution time. The effect of hybridization with other approaches will be investigated, as well. Furthermore, the performance of SI approaches will be investigated for different types of optimization problems such as combinatorial and multi-objective problems.

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