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Comparison of Meta-heuristic Algorithms on Benchmark Functions

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Abstract

Optimization is a process to search the most suitable solution for a problem within an acceptable time interval. The algorithms that solve the optimization problems are called as optimization algorithms. In the literature, there are many optimization algorithms with different characteristics. The optimization algorithms can exhibit different behaviors depending on the size, characteristics and complexity of the optimization problem. In this study, six well-known population based optimization algorithms (artificial algae algorithm - AAA, artificial bee colony algorithm - ABC, differential evolution algorithm - DE, genetic algorithm - GA, gravitational search algorithm - GSA and particle swarm optimization - PSO) were used. These six algorithms were performed on the CEC'17 test functions. According to the experimental results, the algorithms were compared and performances of the algorithms were evaluated.

Key words: Benchmark functions, metaheuristic algorithms, optimization

1. Introduction

Optimization is the process of searching and identifying the most appropriate solution for a particular problem or a set of problems. The algorithms that solve the optimization problems are called as optimization algorithms. These algorithms are examined under two categories: deterministic and stochastic. Deterministic algorithms always follow the same path when the same starting points are given. However, stochastic algorithms are based on randomness [1, 2]. Stochastic algorithms can be examined under two categories as heuristic and meta-heuristic. Heuristic algorithms use trial and error approach to find reasonable solutions for complex problems within an acceptable period of time [3]. Metaheuristic is a superior strategy that is more general than heuristics, which can be easily applied to different optimization problems. The aim of the metaheuristics is to combine basic heuristic methods that will enable a more comprehensive investigation of the solution space [4]. The metaheuristic algorithms keep the solution set of the problem in a structure which is called as population [2].

In literature, it is seen that many studies have been done on the comparison of metaheuristic algorithms. Azimi [5] tested four main algorithms (Simulated Annealing - SA, Tabu Search - TS, GA and Ant Colony System - ACS) on exam scheduling problems and compared their performance. As a result, ACS was found to be more successful. Kannan et al. [6] applied metaheuristic techniques (GA, DE, Evolutionary Programming, Evolutionary Strategy, Ant Colony

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Optimization - ACO, PSO, TS, SA and Hybrid Approach) to the Generation Expansion Planning (GEP) problem and then compared them. According to the results, DE was found to be the most successful method. Civicioglu and Besdok [7] analyzed and compared four algorithms (Cuckoo-search - CK, PSO, DE and ABC) in 50 different benchmark functions. As a result, it was seen that CK and DE algorithms provide better results than PSO and ABC algorithms. Arora et al. [8] compared the three meta-heuristic algorithms (Firefly Algorithm - FA, Bat Algorithm - BA and CK) on benchmark functions. As a result, FA was found to be more successful than other algorithms.

In this study, six well-known population based optimization algorithms (AAA, ABC, DE, GA, GSA and PSO) were used. Each of these algorithms has its own parameters. Changing these parameters creates differences on the local and global search abilities of the algorithm. These six algorithms were performed on the CEC'17 test functions. According to the experimental results, the algorithms were compared and the performances of the algorithms were evaluated.

Organization of this paper is as follows: Firstly, the definition of base algorithms and CEC'17 test functions were done in Section 2. Then, the experimental results were presented in Section 3. In the last section, total conclusions of the paper was done.

2. Materials and Method

In this section, the algorithms used in the study and the CEC'17 test functions in which these algorithms are tested are defined.

2.1. Base algorithms

Artificial algae algorithm (AAA) is an optimization algorithm, which is modelled based on the characteristics and behavior of moving micro-algae, proposed in 2015. AAA consists of three main stages: evolutional process, helical movement process and adaptation process. Helical movement process is based on the helical movements of algae in the liquid and their attitude towards approaching the light. The evolutionary process is based on the proliferation of algae by mitosis. The adaptation process is based on the adaptation of the algae to their environment. In the algorithm, an alga is the main component and the all population consists of algae colonies. The number of algae cells in each algae colony is equal to the problem size. Thus, each solution in the solution space corresponds to an artificial algae colony [3].

The Artificial Bee Colony (ABC) algorithm is a population - based optimization algorithm which was developed in 2005. The algorithm was modelled based on the intelligent behavior of bees with swarm intelligence during the food search process. There are two types of bees in the artificial bee colony. The first type of bees is employed bee. Other type of bees is unemployed bee. Onlooker bees are unemployed bees. The ABC algorithm makes some assumptions. The first is that only one bee receives the nectar of each resource. Thus, the number of employed bees is equal to the total number of food sources. Another assumption is that the number of employed bees is equal to the number of onlooker bees [2, 9, 10].

Differential evolution algorithm (DE) was presented by Price and Storn in 1995. Differential evolution algorithm is one of population based optimization algorithms based on genetic algorithm in general. Crossover, mutation and natural selection operators in GA are also included in DE. In DE, chromosomes are handled one by one and a new individual is formed using three randomly selected chromosomes. These operations are performed with mutation and crossover operators [9, 11-13].

Genetic algorithms (GA) are evolutionary algorithms that optimize optimization problems modeled by biological processes. Genetic algorithms are optimization methods based on natural selection principles. The algorithm was set up by John Holland. Later, many studies on genetic algorithms were published. GA parameters represent genes. The aggregate set of parameters constitutes the chromosome. Each chromosome represents a solution. In the algorithm, firstly the initial population is randomly generated and the suitability values of this population are calculated. Then, with the natural selection process, crossover and mutation, are used to produce solutions in the next generation [9, 14, 15].

The gravitational search algorithm (GSA) is an optimization algorithm presented in 2009 inspired by Newton's laws of gravity and motion. GSA tries to find the optimal solution according to Newton's laws of gravity and motion by using a series of agents called masses. Each possible solution corresponds to an agent in the GSA. The mass of each agent is represented by its fitness value. According to the fitness function, the best and worst agent of the population is detected and used in the algorithm [16].

Particle Swarm Optimization (PSO) is an optimization algorithm developed in 1995 inspired by fish and birds traveling in swarm. The algorithm is basically based on swarm intelligence. Social information sharing among individuals is important in PSO. In the algorithm, each individual is called a particle. The population formed by the combination of these particles is called swarm. When determining the position of each particle, it takes advantage of its previous experience and adjusts it to the best position in the swarm [17-20].

2.2. CEC^17 test functions

The population-based algorithms which were mentioned above have been tested on CEC’17 test functions. The CEC’17 function set consists of 30 functions presented at the IEEE Evolutionary Computing Congress in 2017 and used to evaluate the performance of algorithms under equal conditions. These functions have function groups defined in four different classes, single-mode (F1-F3), multi-mode (F4-F10), hybrid (F11-F20) and composite (F21-F30), and all functions are minimization problems. The search range is defined as [-100, 100] for all functions [21].

AAA	ABC	DE
Step 1: Determination of parameters and initiation of algae colonies **REPEAT** **Step 2**: Helical movement stage **Step 3**: Evolutionary process **Step 4**: Adaptation process **Step 5**: Keep the best algae colony **UNTIL (number of iterations = Maximum number of iterations)**	**Step 1**: Determination of initial food sources **REPEAT** **Step 2**: Sending employed bees to food sources **Step 3**: Calculation of probability values **Step 4**: Selection of food source by onlooker bees **Step 5**: Resource release and explorer bee production **UNTIL (number of iterations = Maximum number of iterations)**	**Step 1**: Creating the initial population **REPEAT** **Step 2**: Mutation and regeneration **Step 3**: Crossover **Step 4**: Selection **UNTIL (number of iterations = Maximum number of iterations)**

Figure 1. Algorithm steps of AAA [3], ABC and DE [9]

GA	GSA	PSO
Step 1: Creating the initial population **REPEAT** **Step 2**: Calculation of the fitness values **Step 3**: Natural selection **Step 4**: Crossover **Step 5**: Mutation **UNTIL (number of iterations = Maximum number of iterations)**	**Step 1**: Creating the initial population **REPEAT** **Step 2**: Calculation of the fitness values **Step 3**: Finding the best and worst agent and updating the gravity value **Step 4**: Calculation of mass and acceleration of each agent **Step 5**: Updating speeds and locations **UNTIL (number of iterations = Maximum number of iterations)**	**Step 1**: Creating the initial population **REPEAT** **Step 2**: Calculation of the fitness values **Step 3**: The local best (pbest) is found for each particle. **Step 4**: Global best (gbest) is found **Step 5**: Positions and velocities are updated **UNTIL (number of iterations = Maximum number of iterations)**

Figure 2. Algorithm steps of GA [9], GSA [16] and PSO [18]

3. Results

All algorithms were tested according to CEC'17 evaluation criteria. CEC'17 evaluation criteria is given in Table 1. The basic states of the algorithms are used. The specific parameters of each algorithm used in the algorithms are given in Table 2.

Table 1. Evaluation criteria of CEC'17 functions

Population size (*N*)	50
Dimension (*D*)	10, 30, 50, 100
Maximum function evaluation number (*MaxFES*)	10000 * D
Lower limit	-100
Upper limit	100
The number of runs (*run*)	20

Table 2. Parameters of algorithms

AAA	**ABC**	**DE**
Loss of energy (e) = 0.3 Shear force (K) = 2 Adaptation coefficient (A_p) = 0.2	Limit=100	Step size (F_{weight}) = 1 Crossover probability constant (F_{CR}) = 0.9 *strategy* is DE/Best/1
GA	**GSA**	**PSO**
Crossover probability (p_c) = 0.9 Mutation probability p_m) = 0.1 Stochastic Universal Sampling in Selection (SUS)	α parameter = 20 Gravity constant initial value (G_0) = 100	Inertia weight (w) = 1 Inertia Weight reduction ratio (*wdamp*) = 0.99 Learning Constants (c_1, c_2) = 2

The statistical results such as best, worst, average, median and standard deviation were used in all studies to evaluate the quality of the solutions. When comparing the algorithms, they were compared according to the mean value.

Considering the average values of algorithms on CEC'17 test functions given in Table 3.; AAA was superior to other algorithms in a total of four functions. ABC was superior to other algorithms in only one function. DE was superior to other algorithms in three functions. GA and GSA were not superior to other algorithms in any function. PSO was superior to a single-mode function only. In ten dimensions, first AAA, then DE are more successful than other algorithms.

Considering the average values of algorithms on CEC'17 test functions given in Table 4.; AAA was superior to other algorithms in a total of three functions. ABC was superior to other algorithms in only one function. DE was superior to other algorithms in four functions. GA, GSA and PSO were not superior to other algorithms in any function. In thirty dimensions, first DE, then AAA are more successful than other algorithms.

Considering the average values of algorithms on CEC'17 test functions given in Table 5.; AAA outperformed other algorithms in a total of five functions. ABC and DE were superior to other algorithms in only one function. GA and GSA were not superior to other algorithms in any function. PSO was superior to a single-mode function only. Thus, AAA has become the most successful algorithm in fifty dimensions.

Considering the average values of algorithms on CEC'17 test functions given in Table 6.; AAA outperformed other algorithms in a total of six functions. ABC were not superior to other algorithms in any function. DE was superior to other algorithms in only one function. GA and GSA were not superior to other algorithms in any function. PSO was superior to a single-mode function only. Thus, AAA has become the most successful algorithm in one hundred dimensions.

Table 3. Results for D = 10

F	AAA		ABC		DE		GA		GSA		PSO	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
f1	548,3094	722,1522	516,0723	331,8186	**100**	**9,78E-15**	1754,212	1920,683	3256385	982396	2225,222	3003,303
f3	300,7239	1,291553	7020,331	3095,331	**300**	**0**	3485,912	2227,834	12409,91	3401,796	**300**	3,19E-14
f5	**505,3354**	2,500759	507,4328	**2,068964**	517,5809	4,185455	523,1328	9,360668	512,6153	3,162125	515,8198	8,798471
f10	**1205,318**	104,1597	1243,456	**92,35052**	1487,389	243,3933	1835,158	300,1635	1893,53	261,5546	1589,326	220,8742
f12	9908,342	11118,9	43021,56	27370,98	**1391,737**	**146,9554**	1474852	1511178	430841,2	649086	10057,64	6214,563
f20	**2000**	**0**	2000,58	0,45474	2009,676	11,29201	2034,683	33,28553	2156,073	64,20072	2072,909	56,22434
f22	2283,375	35,48829	**2247,817**	16,04363	2294,345	23,6377	2313,31	7,682216	2309,22	**0,776729**	2346,79	175,4462
f30	**6040,085**	**1718,481**	7225,352	3527,063	395006,3	510264,1	844714,2	1075300	269233,5	174561,2	277272,8	487284,3

Table 4. Results for D = 30

F	AAA		ABC		DE		GA		GSA		PSO	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
f1	413,7362	494,4011	284,0746	210,1476	**105,6497**	**10,77497**	3568,909	3500,495	21106214	2741513	4968,306	4957,096
f3	12498,48	4888,482	113197,8	13338,66	**300,7691**	**1,34263**	40205,6	11889,7	86124,96	8638,118	700,0096	94,71391
f5	**548,4956**	13,11609	582,8642	**11,05938**	583,9146	20,03061	639,5926	31,77202	619,5504	13,3173	603,8734	27,83699
f10	**3009,749**	470,7161	3453,672	**387,5225**	4028,107	475,444	4480,793	625,1672	3909,513	451,0676	4372,159	661,1606
f12	404336,2	438480,8	863018,5	391913,4	**31920,08**	18698,01	1593877	905297,3	1800055	359337,5	183670,5	134789,3
f20	**2184,293**	**92,04635**	2253,328	97,83508	2363,013	191,3026	2575,301	201,6304	2860,988	176,3126	2416,524	179,0806
f22	2612,117	798,8385	**2316,863**	4,41403	4651,637	1264,299	3694,694	1965,436	2324,64	**0,953147**	3931,149	1909,109
f30	6311,008	1104,967	22251,54	6429,958	**5209,236**	**303,126**	9548,945	3834,544	422888,8	218684	7991,14	2370,043

Table 5. Results for D = 50

F	AAA		ABC		DE		GA		GSA		PSO	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
f1	**1343,859**	**1937,302**	5478,563	3629,434	110295,9	449055,2	2146,017	2460,114	41073502	3336303	2581,606	3435,918
f3	51748,49	10750,36	218918,9	16869,05	14166,21	8405,686	50980,55	16996,47	172888,7	15720,77	**2510,281**	**336,977**
f5	**620,9754**	28,66166	709,0088	**16,22331**	668,5416	33,35741	761,9688	31,47703	739,6801	18,29658	714,4855	34,99184
f10	**4692,097**	399,035	5781,634	**305,9652**	6420,338	858,6828	6718,707	689,5363	5978,402	629,192	7112,426	738,651
f12	2323544	781609,9	5912038	1743065	**262745**	**202321,9**	1571410	1027040	10223582	1727840	2503299	1443522
f20	**2542,383**	181,4159	2835,407	**150,0376**	2958,325	295,9058	3172,098	283,3195	3218,146	313,7009	2885,216	345,8901
f22	6734,62	**595,5494**	**6163,722**	2269,247	8243,951	654,2127	8604,949	849,6155	9379,629	594,1044	9037,959	802,4533
f30	**678764,4**	**67172,4**	897889,8	85000,39	788982,7	134364,5	950537,9	162756,5	11789103	1718468	949428,4	158887,6

Table 6. Results for D = 100

F	AAA		ABC		DE		GA		GSA		PSO	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
f1	**1549,013**	**1773,791**	7086,622	2725,961	9E+08	1,75E+09	5276,668	4893,978	88728813	6824717	372423,5	1037631
f3	259553,7	51891,94	544666,2	26880,16	406537,1	50258,03	22722,55	8060,169	351396	13715,56	**19386,64**	**3543,84**
f5	**922,0151**	79,88361	1190,875	36,31489	993,6954	72,0572	1173,864	47,43559	1161,991	**32,95538**	1109,008	79,89368
f10	**11467,45**	1093,672	13319,7	**557,5428**	14086,82	1392,404	13916,84	1542,727	13000,93	823,8296	14886,07	1085,898
f12	9537800	4562707	32557161	5565672	**2980774**	**1242770**	4628203	1662427	27854901	4449577	18040323	10364770
f20	**4153,722**	382,1174	4877,073	**252,0881**	4622,408	632,839	5228,502	500,267	5636,349	472,1443	5039,173	798,8544
f22	**13970,75**	1037,243	16271,03	**411,5263**	16265,81	1101,098	16905,05	1206,611	18081,55	868,3242	18058,93	1446,213
f30	**8728,311**	**2572,475**	23349,73	4499,72	21417,28	23578,7	11658,23	5535,559	2038764	481774,8	11108,28	3432,18

Conclusions

In this study, six well known population-based meta-heuristic algorithms were tested on CEC'17 test functions. And thus, their characteristics were determined and their performances were compared. If a general assessment is made considering all the results; the difference between the AAA, ABC and DE algorithms in ten dimensions is small. However, as dimension increased, AAA maintained its success. Other algorithms decreased their success as the dimension increased. GA, GSA and PSO have failed results compared to other algorithms. As a result, AAA was found to be successful among these six meta-heuristic algorithms. Future studies may investigate the underlying reasons for the success of AAA and the failure of other algorithms. And AAA can be applied to different problems.

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