STUDYING THE EFFECT OF PULSE RATE LOUDNESS AND ECHO-LOCATION IN BAT ALGORITHM

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ABSTRACT

Swarm intelligence metaheuristic search algorithms are quite popular methods to solve many complex optimization problems in the real life. Bat algorithm is a recent addition to the family of metaheuristics. Bat uses echo-location behaviour of the bats to search optima convergence point in the search trajectory. Although, it has proven its mettle in finding optimal solutions, there are certain parameters that have not been investigated to improve convergence in Bat. Therefore, this paper explores the variations in parameters such as pulse rate, loudness and echo-location in Bat algorithm. The parameter enhancement is simulated on a set of benchmark functions and compared with other state of the art algorithms such as; particle swarm optimization, wolf search, and artificial bee colony. The simulation results show that Bat algorithm performance high correlates with the parameter adjustment.

Keywords: meta-heuristics, Bat algorithm, particle swarm optimization, wolf search algorithm, artificial bee colony.

INTRODUCTION

Swarm Intelligence comprise of agents that coordinate with each other using self-organized and decentralized mechanism inspired by the biological systemsin nature (Fong, Deb, Yang;, & Li, 2014). The main characteristic of swarm intelligence is that multiple self-interested agents somehow work together without any central control. These agents as a population can exchange information, by chemical messengers (pheromone by ants), by dance (waggle dance by bees), or by broadcasting ability (Olmo, Romero, and Ventura, 2014). For example, particle swarm optimization was developed based on the swarm behaviour of birds and fish (Kennedy and Eberhart, 1995). There area lot of swarm intelligencemethods popular nowadays including Particle Swarm Optimization(PSO), Wolf Search Algorithm(WSA), Artificial Bee Colony(ABC) and Bat Algorithm. Each of these algorithms have their own advantages and disadvantages.

Particle swarm optimization which have been successfully applied in problems of antenna design (Jin and Rahmat-Samii, 2007) and electro-magnetics (Robinson and Rahmat-Samii, 2004). Ant colony algorithms is also used in many areas of optimization (Blum, 2005; Karaboga and Basturk, 2007a). Artificial bee colony (ABC) showed good performance in numerical optimization (Kang, Li, and Li, 2013), in large-scale global optimization(Fister, Jr, and Zumer, 2012), for graph-3 coloring (Fister Jr, Fister, and Brest, 2012), and also in combinatorial optimization (Blum, 2005).

Developed by Yang (X. S. Yang, 2010), Bat algorithm uses echolocation with varying pulse rates of emission and loudness to find and converge to the optimal solution. Earlier studies on Bat have shown that it has superior performance on genetic and particle swarm algorithms(X.-S. Yang, 2013); therefore, it can be applied to solve real world problems like efficient energy storage in micro-grid operations (Bahmani-Firouzi and Azizipanah-Abarghooee, 2014), for feature selection(Rodrigues *et al.*, 2014), and discrete sized optimization of weight in steel columns (Hasançebi and Carbas, 2014) etc. Bat has been used to update weights in BPNN (N. M. Nawi, Rehman, Ghazali, Yahya, and Khan, 2013) and Functional Link Artificial Neural Networks (FLANN) (Mishra, Shaw, and Mishra, 2012) and it has shown superior performance than other hybrid variants (i.e. ABC-BPNN, ABC-Levenberg-Marquardt, and BPNN) on classification problems(Nazri Mohd. Nawi, Rehman, and Khan, 2014). In this paper, the study of the effect of pulse rate, loudness and echo-location on Bat algorithm is performed. The basic aim of varying the bat parameter is to see any enhancement in its performance on selected Benchmark functions.

The structure of the paper is organized as follows;in the next sections, meta-heuristic search algorithms are discussed. Section 3 shed some light on the simulation results. Sections 4 discuss the result comparison of all methodsand finally the paper is concluded in the Section 5.

META-HEURISTIC SEARCH ALGORITHMS

Over the years several meta-heuristic search algorithms are proposed and they vary in performance according to their searching mechanisms. Some of the most popular ones are discusses in this section.

Particle swarm optimization

Particle Swarm Optimization (PSO) is one of the algorithm that been compared in this research. Particle Swarm Optimization (PSO) was developed by Kennedy and Ebermart in 1995(Kennedy & Eberhart, 1995)]. PSO is based on the swarm behaviour such as bird schooling in nature. Due to some of the parameter of algorithm had been adjusted, PSO is one of the popular algorithm that is used in a variety of fields such as medical and physic field.The particle swarm optimization concept consists of at each time step, it changing the velocity of (accelerating) each particle toward its p^{best} and l^{best} locations (local version of PSO). Acceleration is weighted by a random term, with separate random numbers being generated for acceleration toward p^{best} and l^{best} locations.

Wolf search algorithm

The Wolf Search Algorithm (WSA) (Tang, Fong, Yang, & Deb, 2012)works in a similar way as wolves search for food and survive by avoiding their enemies. WSA is different from the bio-inspired meta-heuristics because it simultaneously possesses both individual local searching ability and autonomous flocking movement. Each wolf in WSA hunts independently by remembering its own trait and only merges with its peer when the peer is in a better position. Wolves are social predators that hunt in packs.

Artificial bee colony

The Artificial Bee Colony (ABC) algorithm is one of swarm based meta-heuristic algorithm. It was introduced by Karaboga in 2005 for optimizing numerical problems (Karaboga & Basturk, 2007). It was inspired by the intelligent foraging behaviour of honey bees. The algorithm is specifically based on the foraging behaviour of honey bee colonies. The model consists of three essential components which are employed and unemployed foraging bees, and food sources. The first two components, employed and unemployed foraging bees, search for rich food sources, while the third component, is for their hive. There are two leading modes of behaviour that are necessary for self-organizing and collective intelligence which is recruitment of foragers to rich food sources resulting in positive feedback and abandonment of poor sources by foragers that causing negative feedback.

Bat algorithm

Bat algorithm is a meta-heuristic optimization algorithm developed by Xin-She Yang in 2010 (X. S. Yang, 2010). This bat algorithm is based on the echolocation behaviour of microbats with varying pulse rates of emission and loudness. The capability of echo-location of microbats is fascinating as these bats can find their prey. Moreover, even in complete darkness, bat can discriminate the different types of insects. Besides that, most microbats are insectivores. Microbats use a type of sonar which is called echolocation. The function is to detect prey, avoid obstacles, and locate their roosting crevices in the dark. These bats emit a very loud sound pulse. They listen for the echo that bounces back from the surrounding objects. Their pulses vary in properties and can be related with their hunting strategies. This situation depends on the species. The pseudo Code of Bat Algorithm is given as;

Objective function f(x), x = $(x_1, \dots, x_d)^T$
Initialize the bat population x_i $(i = 1,2,\dots,n)$ *and* v_i
Define pulse frequency f_i *at* x_i
Initialize pulse rates r_i *and the loudness* A_i
While *(t < Max number of iterations)*
Generate new solutions by adjusting frequency, and updating velocities and locations
if*(rand >*r_i*)*
Select a solution among the best solutions
Generate a local solution around the selected best solution
end if
Generate a new solution by flying randomly
if*(rand <*A_i*&*$f(x_i)$*<*$f(x_*)$ *)*
Accept the new solutions
Increase r_i *and reduce* A_i
end if
Rank the bats and find the current best x_*
end while
Postprocess results and visualization

RESULTS AND DISCUSSIONS

To test the effect of pulse rate, loudness and echo-location of Bat Algorithm, some benchmark functions such as Ackley function, Griewank function, Rastrigin function, Rosenbrock function and Schwefel function were used. The simulations were performed on Intel Core i5 with 2.5GHz Acer laptop with 4GB of RAM. Matlab R2012b was used to perform the simulations. The Bat algorithm is compared with Particle Swarm Optimization algorithm (PSO), Wolf Search Algorithm (WSA), and artificial bee colony algorithm (ABC) based on three parameter which is frequency, f =[2,4], loudness, l=[0.1,0.7] and pulse rate, p=[0.1,0.7].For all the datasets, it is limited to 50 trials. The maximum iteration is 1000.The performance are evaluated based on the standard deviation (SD), standard error of mean (SEM), and mean. Where, mean is equal to the sum over every possible value weighted by the probability of that value while SD is a measure that is used to quantify the amount of variation or dispersion of a set of data values. The simulation results are stored using a bar chart graph for each function.

Ackley function

The Ackley function is a multimodal and continuous function. The global minimum value is located at the origin which is at$f(x^*) = 0$. The domain of this function lies in the range of [-32.768, 32.768]. It has dimensions of 10 for this function.

From Table-1 above, it can be concluded that the best performance for Bat Algorithm in Ackley function is at the parameter f=2, l=0.7 and p=0.7. The mean for this parameter is 3.30, the SD is 0.80 and the SEM is 0.11. The second best that perform in Ackley function for Bat Algorithm is at the parameter of f=2, l=0.5 and p=0.5 which the mean is 3.53, the SD is 0.86 and the SEM is 0.12. The worst performance for Bat Algorithm on Ackley function is at the parameter of f=3, l=0.1 and p=0.1. The mean for this parameter is 5. 17, the SD is 0.91 while the SEM is 0.13.

Table-1. Performance of bat algorithm for Ackley.

PARAMETER	MEAN	SD	SEM
f=2/l=0.1/p=0.1	4.79	0.93	0.13

f=2/l=0.2/p=0.2	4.45	0.93	0.13
f=2/l=0.3/p=0.3	4.07	1.13	0.16
f=2/l=0.4/p=0.4	3.98	0.99	0.14
f=2/l=0.5/p=0.5	3.53	0.86	0.12
f=2/l=0.6/p=0.6	3.71	0.83	0.12
f=2/l=0.7/p=0.7	3.30	0.80	0.11
f=3/l=0.1/p=0.1	5.17	0.91	0.13
f=3/l=0.2/p=0.2	4.73	0.92	0.13
f=3/l=0.3/p=0.3	4.31	0.82	0.12
f=3/l=0.4/p=0.4	4.22	0.97	0.14
f=3/l=0.5/p=0.5	4.17	1.19	0.17
f=3/l=0.6/p=0.6	4.06	0.98	0.14
f=3/l=0.7/p=0.7	3.58	0.81	0.12
f=4/l=0.1/p=0.1	5.14	0.84	0.12
f=4/l=0.2/p=0.2	4.92	0.94	0.13
f=4/l=0.3/p=0.3	4.69	1.15	0.16
f=4/l=0.4/p=0.4	4.49	1.06	0.15
f=4/l=0.5/p=0.5	4.45	1.03	0.15
f=4/l=0.6/p=0.6	4.21	1.09	0.15
f=4/l=0.7/p=0.7	4.26	0.86	0.12

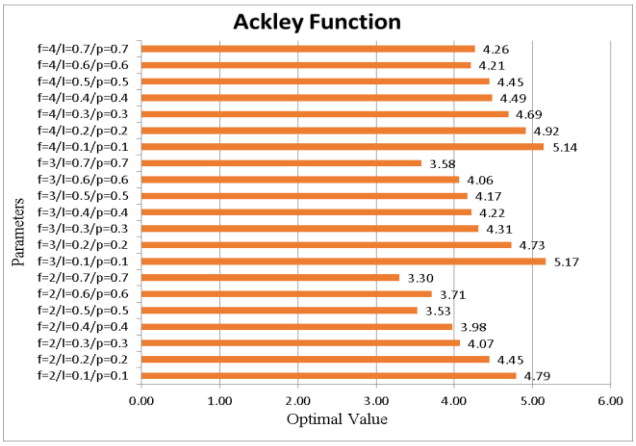

Figure-1. Performance of bat algorithm on Ackley function.

Based on Figure-1, the best performance of Bat algorithm lies on the parameter of f=2, l=0.7 and p=0.7 which is 3.30. The second best of optimal value of Ackley function is at f=2, l=0.5 and p =0.5 which is 3.53. The worst performance of Ackley on Bat Algorithm is at f=0.3, l=0.1 and p =0.1 which is 5.17.

Griewank function

The Griewank function is also a multimodal and continuous function. The global minimum is at origin, $(x^*) = 0$.The domain range lies on [-600,600]. The dimension for this function is 100.Based on Table-2 the parameter mostly gives almost the same for the result. Griewank function on Bat Algorithm performed the best at the parameter of f=4, l=0.2 and p=0.2 which the mean is 0.0088, the SD is 0.02 and the SEM is 0. The parameter of f=4, l=0.1 and p=0.1 shows the second best that performed in Griewank function which gives the result of mean=0.0101, SD=0.01 and SEM=0. The worst parameter that performed in Griewank function on Bat Algorithm is at f=4, l=0.7 and p=0.7. The mean of this parameter is 0.2097, the SD is 0.15 and the SEM is 0.02.

Table-2. Performance of bat algorithm for Griewank.

PARAMETER	MEAN	SD	SEM
f=2/l=0.1/p=0.1	0.02	0.02	0.00
f=2/l=0.2/p=0.2	0.02	0.03	0.00
f=2/l=0.3/p=0.3	0.02	0.02	0.00
f=2/l=0.4/p=0.4	0.02	0.04	0.01
f=2/l=0.5/p=0.5	0.05	0.06	0.01
f=2/l=0.6/p=0.6	0.07	0.10	0.01
f=2/l=0.7/p=0.7	0.11	0.12	0.01
f=3/l=0.1/p=0.1	0.01	0.03	0.00
f=3/l=0.2/p=0.2	0.01	0.02	0.00
f=3/l=0.3/p=0.3	0.02	0.04	0.01
f=3/l=0.4/p=0.4	0.03	0.04	0.01
f=3/l=0.5/p=0.5	0.05	0.08	0.01
f=3/l=0.6/p=0.6	0.08	0.12	0.02
f=3/l=0.7/p=0.7	0.19	0.17	0.02
f=4/l=0.1/p=0.1	0.01	0.01	0.00
f=4/l=0.2/p=0.2	0.01	0.02	0.00
f=4/l=0.3/p=0.3	0.01	0.02	0.00
f=4/l=0.4/p=0.4	0.03	0.05	0.01
f=4/l=0.5/p=0.5	0.06	0.08	0.01
f=4/l=0.6/p=0.6	0.08	0.09	0.01
f=4/l=0.7/p=0.7	0.21	0.15	0.02

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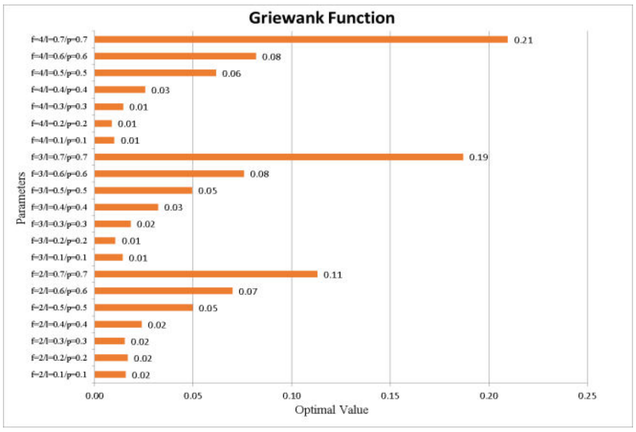

Figure-2. Performance of bat algorithm on Griewank function.

Based on Figure-2, Griewank function can be concluded such the best performance of the function on Bat Algorithm lies on the parameter of f=4, l=0.2 and p=0.2 which is 0.0088. The next best performance of Griewank function on Bat Algorithm is at the f=4, l=0.1 and p=0.1 which is 0.0101. The worst performance of Griewank function on Bat Algorithm is at the f=4, l=0.7 and p=0.7 which is 0.2097.

Rastrigin function

Rastrigin function is multimodal and continuous function. The search domain of the function is in range [−5.12, 5.12]. Global minimum of the Rastrigin function is$f\ (x^*) = 0$. The dimension of this function is 20.

Table-3. Performance of bat algorithm for Rastrigin.

PARAMETER	MEAN	SD	SEM
f=2/l=0.1/p=0.1	36.77	13.65	1.93
f=2/l=0.2/p=0.2	32.58	14.25	2.02
f=2/l=0.3/p=0.3	29.58	13.78	1.95
f=2/l=0.4/p=0.4	35.88	14.03	1.98
f=2/l=0.5/p=0.5	32.13	14.59	2.06
f=2/l=0.6/p=0.6	26.12	13.07	1.85
f=2/l=0.7/p=0.7	32.23	12.31	1.74
f=3/l=0.1/p=0.1	37.85	13.30	1.88
f=3/l=0.2/p=0.2	34.77	14.32	2.03
f=3/l=0.3/p=0.3	36.21	13.73	1.94
f=3/l=0.4/p=0.4	32.62	12.02	1.70
f=3/l=0.5/p=0.5	30.67	11.90	1.68
f=3/l=0.6/p=0.6	32.07	11.69	1.65
f=3/l=0.7/p=0.7	31.35	11.68	1.65
f=4/l=0.1/p=0.1	37.65	14.20	2.01
f=4/l=0.2/p=0.2	34.96	12.80	1.81
f=4/l=0.3/p=0.3	35.58	11.98	1.69
f=4/l=0.4/p=0.4	36.91	14.24	2.01
f=4/l=0.5/p=0.5	34.12	11.89	1.68
f=4/l=0.6/p=0.6	32.15	13.96	1.97
f=4/l=0.7/p=0.7	30.98	12.84	1.82

From Table-3, we can see that Bat Algorithm did not performed onRastrigin function. This is due to local minima. The best parameter that performed in Rastrigin function is at f=2, l=0.6 and p=0.6 which the mean is 26.12, the SD is 13.07 and SEM is 1.85. The second best that performed on Rastrigin function is at the parameter of f=2, l=0.3 and p=0.3 which the mean is 29.58, the SD is 13.78 and the SEM is 1.95. The worst parameter that performed on Rastrigin function is at the parameter of f=3, l=0.1 and p=0.1. The mean for this parameter is 37.85, the SD is 13.30 and the SEM is 1.88.

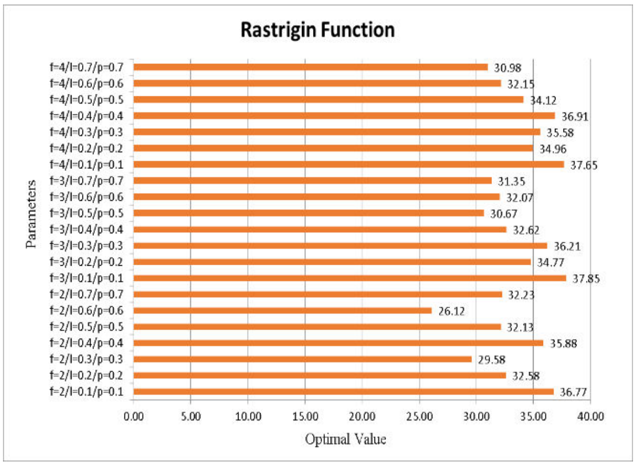

Figure-3. Performance of bat algorithm on Rastrigin function.

Based on Figure 3, mostly Rastrigin function was not convergence on Bat Algorithm. This is due to the local minima. But, based on the result, the best performance of Rastrigin is at the f=2, l= 0.6, and p=0.6 which is 26.12. The second best performance of Rastrigin function on Bat Algorithm is at parameter of f=2, l=0.3, and p=0.3 which the mean is 29.58. The worst performance of Rastrigin is at the f=3, l=0.1 and p=0.1 which is 37.85.

Rosenbrock function

Rosenbrock is aunimodal and continuous function. It is unimodal for two and three dimensions but it may have multiple minima in high dimension cases and its global minimum is inside a narrow, curved valley at$f\ (x^*) = 0$. The search domain for Rosenbrock is in the range of [−100, 100]. Rosenbrock has a dimension of 10.

Table-4. Performance of bat algorithm for Rosenbrock.

PARAMETER	MEAN	SD	SEM
f=2/l=0.1/p=0.1	4.93	2.90	0.41
f=2/l=0.2/p=0.2	14.35	33.09	4.68
f=2/l=0.3/p=0.3	13.97	34.70	4.91

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f=2/l=0.4/p=0.4	15.43	20.99	2.97
f=2/l=0.5/p=0.5	30.05	58.74	8.31
f=2/l=0.6/p=0.6	42.48	61.46	8.69
f=2/l=0.7/p=0.7	119.21	223.41	31.59
f=3/l=0.1/p=0.1	7.81	13.05	1.84
f=3/l=0.2/p=0.2	13.66	23.50	3.32
f=3/l=0.3/p=0.3	21.02	52.56	7.43
f=3/l=0.4/p=0.4	23.52	53.86	7.62
f=3/l=0.5/p=0.5	53.73	102.97	14.56
f=3/l=0.6/p=0.6	66.89	79.39	11.23
f=3/l=0.7/p=0.7	166.19	246.33	34.84
f=4/l=0.1/p=0.1	8.25	15.52	2.20
f=4/l=0.2/p=0.2	10.85	18.13	2.56
f=4/l=0.3/p=0.3	19.06	33.82	4.78
f=4/l=0.4/p=0.4	35.79	77.97	11.03
f=4/l=0.5/p=0.5	81.24	131.50	18.60
f=4/l=0.6/p=0.6	91.56	144.10	20.38
f=4/l=0.7/p=0.7	277.92	338.37	47.85

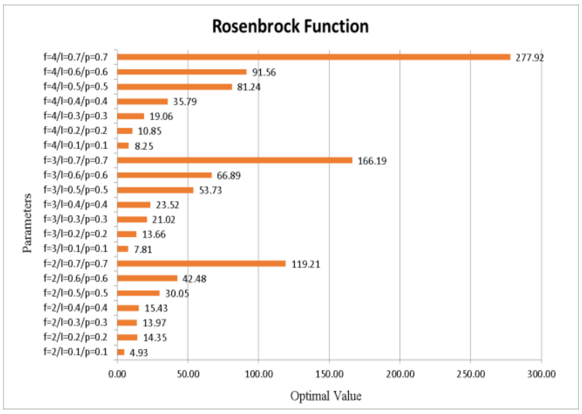

Figure-4. Performance of bat algorithm on Rosenbrock function.

Based on Table-4, Rosenbrock function on Bat Algorithm performed the best at parameter of f=2, l=0.1 and p=0.1 which the mean is 4.93 the SD is 2.90 and the SEM is 0.41. The second best that performed on Rosenbrock function is at the parameter of f=3, l=0.1 and p=0.1 which the mean is 7.81, the SD is 13.05 and the SEM is 1.84. At the parameter f=4, l=0.7 and p=0.7 Rosenbrock function performed the worst. The function was not converged on this parameter which gives the result of mean=277.92, SD=338.37 and SEM=47.85.For Rosenbrock function based on Figure-4, the best performance of the function on Bat Algorithm is at the f=2, l=0.1 and p=0.1 which is 4.93. The second best of this function on Bat Algorithm is at the f=3, l=0.1 and p=0.1 which is 7.81. The f=4, l=0.7 and p=0.7 shows the worst performance of Rosenbrock function on Bat Algorithm which is 277.92. Rosenbrock function was not convergence on this parameter due to the local minima.

Schwefel function

The Schwefel is multimodal and continuous function. The function is evaluated on the hypercube in a range of $[-100,100]$ and the global minima is at $f\ (x^{*}) = 0$. The dimension for this function is 2.

Table-5. Performance of bat algorithm for Schwefel.

PARAMETER	MEAN	SD	SEM
f=2/l=0.1/p=0.1	0.03	0.09	0.01
f=2/l=0.2/p=0.2	0.16	0.47	0.07
f=2/l=0.3/p=0.3	0.80	1.47	0.21
f=2/l=0.4/p=0.4	1.22	1.66	0.23
f=2/l=0.5/p=0.5	2.82	3.81	0.54
f=2/l=0.6/p=0.6	3.70	3.69	0.52
f=2/l=0.7/p=0.7	5.31	3.60	0.51
f=3/l=0.1/p=0.1	0.02	0.09	0.01
f=3/l=0.2/p=0.2	0.21	0.63	0.09
f=3/l=0.3/p=0.3	0.74	1.24	0.18
f=3/l=0.4/p=0.4	1.58	2.55	0.36
f=3/l=0.5/p=0.5	2.89	3.17	0.45
f=3/l=0.6/p=0.6	4.10	3.51	0.50
f=3/l=0.7/p=0.7	7.37	5.07	0.72
f=4/l=0.1/p=0.1	0.21	0.76	0.11
f=4/l=0.2/p=0.2	0.37	1.02	0.14
f=4/l=0.3/p=0.3	0.82	1.57	0.22
f=4/l=0.4/p=0.4	2.28	2.86	0.40
f=4/l=0.5/p=0.5	4.53	3.91	0.55
f=4/l=0.6/p=0.6	6.14	4.54	0.64
f=4/l=0.7/p=0.7	0.11	6.61	0.94

Based on Table-5, the parameter of f=3, l=0.1 and p=0.1 shows the best performance on Schwefel function which the mean=0.0196, SD=0.09 and SEM=0.01. The second best that performed in Schwefel function is at the parameter of f=2, l=0.1 and p=0.1 which the mean=0.0252, SD=0.09 and SEM=0.01. The parameter of f=3, l=0.7and p=0.7 shows the worst performance of Schwefel function on Bat Algorithm which the mean=7.37, SD=5.07 and SEM=0.72.

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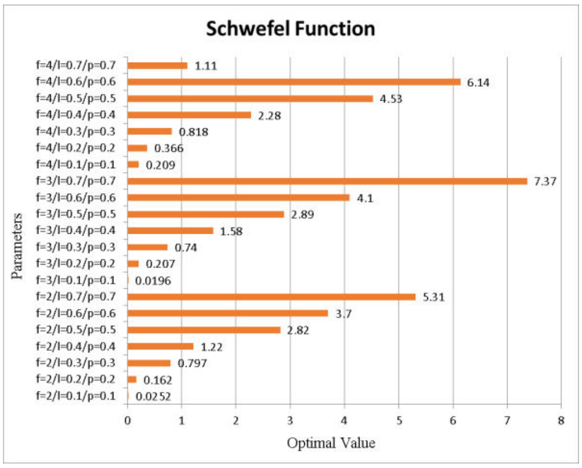

Figure-5. Performance of bat algorithm on Schwefel function.

Figure-5 shows that f=3, l=0.1 and p=0.1 is the best performance of Schwefel function on Bat Algorithm which gives the result of 0.0196. The second best performance of Schwefel function on Bat Algorithm is at the f=2, l=0.1 and p =0.1 which is 0.0252. The parameter of f=3, l=0.7 and p=0.7 gives the worst result for the Bat Algorithm in Schwefel function which is 7.37.

RESULTS COMPARISON

Bat Algorithm is compared with other algorithms such as; PSO, WSA, and ABC in terms of the optimal value. Table-6 shows the average optimization results for benchmark testing functions.

Table-6. Average optimization results for benchmark testing functions.

Function(s)		PSO	WSA	ABC	BAT
Ackley	MEAN	0.16	5.13	0.21	3.30
	SD	0.49	0.74	0.27	0.80
	SEM	0.09	0.13	0.05	0.11
Griewank	MEAN	0.02	0.12	0.33	0.01
	SD	0.02	0.01	0.23	0.02
	SEM	0.004	0	0.04	0
Rastrigin	MEAN	43.97	114.67	0.1	26.12
	SD	11.73	15.27	0.30	13.07
	SEM	2.14	2.79	0.05	1.85
Rosenbrock	MEAN	15.08	5.04	9.32	4.93
	SD	24.17	1.72	10.91	2.90
	SEM	4.41	0.31	1.99	0.41
Schwefel	MEAN	0.03	0.01	0	0.02
	SD	0.06	0	0	0.09
	SEM	0.01	0	0	0.01

CONCLUSIONS

Bat algorithm is a recent addition to the family of metaheuristics. It uses echo-location behaviour of the bats to search optima convergence point in the search trajectory. Although, it has proven its mettle in finding optimal solutions, there are certain parameters that have not been investigated to improve convergence in Bat. Therefore, this paper explored the variations in parameters such as pulse rate, loudness and echo-location in Bat algorithm. Bat Algorithm shows promising results after parameter enhancement is performed. It shows that it is better than particle swarm optimization, wolf search algorithm and artificial bee colony when trained on benchmark functions such as Ackley function, Griewank function, Rosenbrock function, and Schwefel function.

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