Performance Analysis of Earthworm Optimization Algorithm for Bound Constrained Optimization Problems

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Abstract: Numerous real life problems represents hard optimization problems that cannot be solved by deterministic algorithm. In the past decades various different methods were proposed for these kind of problems and one of the methods are nature inspired algorithms especially swarm intelligence algorithms. Earthworm optimization algorithm (EWA) is one of the recent swarm intelligence algorithm that has not been thoroughly researched. In this paper we tested EWA algorithm on 28 standard benchmark functions and compared results with particle swarm optimization algorithm. Comparison show that EWA has good characteristics and it outperformed other approach from literature.

Key–Words: hard optimization problems, optimization algorithms, swarm intelligence, earthworm optimization, EWA

1 Introduction

Optimization and solving different optimization problems represent an active research fields for decades. Numerous real life optimization problems are hard optimization problems that cannot be solved in reasonable time by deterministic algorithm and they belong to NP difficult problems. One of the well known NP difficult problem is traveling salesman where salesman needs to visit N cities once in such order that cost the least. This can be represented by graph where nodes are cities and edges of the graph have weight that represent cost of traveling cites that are connected with it. Deterministic approach has complexity of N! thus in case of more than 20 cities, calculation time will be unreasonably long.

For solving hard optimization problems different stochastic algorithms that use random factors and set of the search rules were proposed in the past. Stochastic algorithms does not guarantee optimal solution or the same solution each time, but if good algorithm runs long enough, obtained solution will be *good enough* which means that it will be in tolerance margin from optimal solution. Since different solution can be obtained for the same problem solved by the same algorithm, as final solution average result of numerous runs is usually used as final solution.

The most stochastic algorithms are natural based, i.e. they imitate some natural phenomena. It has been shown that those kind of algorithms provides good solutions even though it is not completely understood why or how exactly. All nature based stochastic algorithms can be divided into three groups: evolutionary, artificial immune systems and swarm intelligence algorithms.

As the name says, evolution algorithms use the idea of survival evolutionary. After initial population of solutions that can be randomly created the next generation combines the best solutions from previous generation. Concept of mutation is usually used as random factor. In evolution algorithms population goes trough numerous iterations of breeding and in each iteration we are closer to the solution. Evolution algorithms searched for good solution and combine them while artificial immune systems use negative selection where bad solutions are searched so they can be eliminated from the population.

Swarm intelligence algorithms are recent stochastic algorithms. Idea is to mimic collective behavior of spices from nature. Each individual represents one possible solution and by collective intelligence best solution is searched. Movement of each individual is based on its own memory, global data from swarm and random factor. Swarm intelligence algorithms represent active research area and in the past decades numerous of them were proposed. Some of the well known swarm intelligence algorithms are particle swarm optimization (PSO), ant colony optimization (ACO), artificial bee colony (ABC), bat algorithm (BA), fireworks algorithm (FWA) and others.

In this paper performance of the recent swarm intelligence algorithm, earthworm optimization algorithm (EWA) was tested. We tested (EWA) on standard CEC 2013 benchmark functions. Obtained results were compared with PSO.

2 Swarm intelligence algorithms

Various applications need to solve some kind of unconstrained or constrained optimization problem. For solving it numerous techniques and methods were proposed. Two major groups of metaheuristics are commonly used, inspired by nature and not inspired by nature. In this paper nature inspired metaheuristic called swarm intelligence was tested.

Swarm intelligence algorithms are based on the collective behavior of the social groups from nature and it is an important research topic. The main idea of this algorithms is to use simple set of rules that control individuals which exhibit collective intelligence. Swarms of worms, ants, bees, birds and fish were the main source inspiration for these methods. Brief analysis of swarm intelligence algorithm is given in [29].

Particle swarm optimization (PSO) is one of the earliest swarm intelligence algorithms [11] inspired by social behavior of fish or birds. Original form but also upgraded versions of PSO were widely used for solving various global optimization problems [15].

Ant colony optimization (ACO) imitates social behavior of ants. ACO models ants property of disposing pheromone on their way from nest to the food source. This metaheuristic have numerous variants that can be found in the literature. ACO was successfully used on minimum weight vertex cover problem [8], [26], minimum connected dominating set problem [9], and many others.

Artificial bee colony (ABC) was inspired by social behavior of honey bee swarm [10]. In ABC algorithm three types of bees are included: employed, onlookers and scouts. This algorithm was widely used and it was shown that is effective and efficient for different problems and numerous upgraded and enhanced versions of ABC were proposed [4], [6], [13]. ABC showed robustnesses when tackling engineering optimization [25].

Seeker optimization algorithm (SOA) performs search process by modeling human reasoning, memory, interactions, and past experience. Global optimization problems were successfully solved with this technique [7]. In [23] hybridization of SOA was proposed.

Bat algorithm is based on the echolocation behaviour of bats with varying pulse rates of emission and loudness [28]. It was successfully applied to numerous problems such as handwritten digit recognition [19], parameter tuning for support vector machine [18], multilevel image thresholding [1], etc. Beside original BA numerous hybridizations and improvements were proposed [22], [2], [20].

Fireworks algorithm was proposed in 2010 and as inspiration explosion of the fireworks was used [14]. During the last years it was intensively used for many different problems [16], [17].

Firefly algorithm was inspired by the social and flashing behavior of fireflies [27]. This algorithm was implemented for many different applications such as image processing [5], [21], for cardinality constrained mean-variance portfolio optimization problem [3], etc. In [24] firefly algorithm was used to improve seeker optimization algorithm.

3 Experimental Results

To test our proposed method we used Matlab R2016a and experiments were done on the platform with Intel ® Core$^{\text{TM}}$ i7-3770K CPU at 4GHz, 8GB RAM, Windows 10 Professional OS.

We tested earthworm optimization algorithm on 28 standard benchmark functions proposed for CEC 2013 competition [12].

EWA was compared with other approach from literature. We compared it with [30] where PSO was implemented and tested on the same benchmark functions. The obtained results were presented in Table 1.

As it can be seen, both algorithms found the optimal function value for f_1 (sphere). Standard deviation is 0 for both functions which means that EWA as well as PSO successfully determined optimal function value every time. EWA algorithm found exact optimal value for f_5 (different powers function) with standard deviation 0 while PSO found the optimal values but with some deviation. EWA as well as PSO were not able to find nearly good solutions for functions f_2, f_3 and f_4. For this function obviously some specific parameter settings are needed and probably more itera-

Table 1: Comparison of PSO and EWA

Fun.	Alg.	Optimal	Best	Median	Worst	St.Dev.
f_1	PSO	-1.400E+03	-1.400E+03	-1.400E+03	-1.400E+03	0.000E+00
	EWA	-1.400E+03	-1.400E+03	-1.400E+03	-1.400E+03	0.000E+00
f_2	PSO	-1.300E+03	7.597E+02	3.504E+04	4.755E+05	**7.356E+04**
	EWA	-1.300E+03	**1.853E+02**	**2.934E+04**	**4.129E+05**	8.328E+04
f_3	PSO	-1.200E+03	**-1.200E+03**	2.670E+05	**8.251E+07**	1.656E+07
	EWA	-1.200E+03	-1.158E+03	**1.284E+05**	1.795E+08	**6.834E+06**
f_4	PSO	-1.100E+03	2.454E+02	7.769E+03	1.856E+04	4.556E+03
	EWA	-1.100E+02	**1.195E+02**	**2.359E+03**	**5.270E+03**	**1.631E+03**
f_5	PSO	-1.000E+03	-1.000E+03	-1.000E+03	-1.000E+03	3.142E-05
	EWA	-1.00E+03	-1.000E+03	-1.000E+03	-1.000E+03	**0.00E+00**
f_6	PSO	-9.000E+02	-9.000E+02	-8.902E+02	-8.898E+02	4.974E+00
	EWA	-9.000E+02	-9.000E+02	-8.902E+02	-8.898E+02	**4.140E+00**
f_7	PSO	-8.000E+02	-7.974E+02	-7.789E+02	7.434E+02	1.327E+01
	EWA	-8.000E+02	**-7.974E+02**	**-7.870E+02**	**-7.793E+02**	1.013E+01
f_8	PSO	-7.000E+02	-6.789E+02	-6.797E+02	-6.796E+02	6.722E-02
	EWA	-7.000E+02	**-6.797E+02**	-6.797E+02	-6.797E+02	**4.338E-03**
f_9	PSO	-6.000E+02	-5.987E+02	-5.952E+02	-5.929E+02	1.499E+00
	EWA	-6.000E+02	**-5.991E+02**	**-5.969E+02**	-5.929E+02	**1.039E+00**
f_{10}	PSO	-5.000E+02	-4.999E+02	-4.997E+02	**-4.989E+02**	2.713E-01
	EWA	-5.000E+02	**-5.000E+02**	**-4.999E+02**	-4.984E+02	**1.449E-01**
f_{11}	PSO	-4.000E+02	-3.970E+02	-3.891E+02	-3.731E+02	5.658E+00
	EWA	-4.000E+02	**-3.972E+02**	**-3.907E+02**	**-3.781E+02**	**4.198E+00**
f_{12}	PSO	-3.000E+02	-2.970E+02	-2.861E+02	-2.682E+02	6.560E+00
	EWA	-3.000E+02	**-2.971E+02**	**-2.870E+02**	**-2.623E+02**	6.019E+00
f_{13}	PSO	-2.000E+02	-1.946E+02	-1.792E+02	-1.523E+02	9.822E+00
	EWA	-2.000E+02	**-1.992E+02**	**-1.801E+02**	**-1.617E+02**	**8.992E+00**
f_{14}	PSO	-1.000E+02	2.228E+02	7.338E+02	**1.109E+03**	2.335E+02
	EWA	-1.000E+02	**-1.419E+02**	**2.914E+02**	4.990E+02	**1.282E+02**
f_{15}	PSO	1.000E+02	4.372E+02	8.743E+02	1.705E+03	2.507E+02
	EWA	1.000E+02	**4.271E+02**	**5.695E+02**	**1.044E+03**	**2.429E+02**
f_{16}	PSO	2.000E+02	**2**.002E+02	2.005E+02	2.014E+02	2.457E-01
	EWA	2.000E+02	**2.000E+02**	**2.003E+02**	**2.007E+0**2	**1.396E-01**
f_{17}	PSO	3.000E+02	3.104E+02	3.189E+02	3.416E+02	5.873E+00
	EWA	3.000E+02	**3.098E+02**	**3.164E+02**	**3.341E+02**	3.183E+00
f_{18}	PSO	4.000E+02	**4**.125E+02	4.178E+02	4.365E+02	**4.534E+00**
	EWA	4.000E+02	**4.109E+02**	4.178E+02	**4.364E+02**	4.982E+00
f_{19}	PSO	5.000E+02	**5**.003E+02	5.009E+02	**5.019E+02**	3.886E-01
	EWA	5.000E+02	**5.001E+02**	5.009E+02	5.041E+02	**2.153E-01**
f_{20}	PSO	6.000E+02	6.020E+02	6.034E+02	6.040E+02	4.194E-01
	EWA	6.000E+02	**6.017E+02**	**6.025E+02**	6.034E+02	**4.006E-01**
f_{21}	PSO	7.000E+02	1.100E+03	1.100E+03	1.100E+03	0.00E+00
	EWA	7.000E+02	1.100E+03	1.100E+03	1.100E+03	0.00E+00
f_{22}	PSO	8.000E+02	1.206E+03	1.706E+03	2.388E+03	3.431E+02
	EWA	8.000E+02	**1.190E+03**	**1.428E+03**	**1.998E+03**	**3.083E+02**
f_{23}	PSO	9.000E+02	1.016E+03	1.810E+03	2.776E+03	**3.596E+02**
	EWA	9.000E+02	**9.991E+02**	**1.193E+03**	**1.987E+03**	5.121E+02
f_{24}	PSO	1.000E+03	1.162E+03	1.214E+03	1.222E+03	9.166E+00
	EWA	1.000E+03	**1.091E+03**	**1.179E+03**	**1.207E+03**	**6.917E+00**
f_{25}	PSO	1.100E+03	1.300E+03	1.309E+03	1.320E+03	**5.943E+00**
	EWA	1.100E+03	**1.220E+03**	**1.300E+03**	**1.312E+03**	6.152E+00
f_{26}	PSO	1.200E+03	1.307E+03	1.400E+03	1.520E+03	5.513E+01
	EWA	1.200E+03	**1.193E+03**	**1.307E+03**	**1.400E+03**	**1.131E+01**
f_{27}	PSO	1.300E+03	1.602E+03	1.636E+03	1.898E+03	7.359E+01
	EWA	1.300E+03	**1.521E+03**	**1.596E+03**	**1.705E+03**	**5.251E+01**
f_{28}	PSO	1.400E+03	**1**.500E+03	1.700E+03	2.009E+03	8.362E+01
	EWA	1.400E+03	**1.400E+03**	**1.698E+03**	**2.001E+03**	**7.672E+01**

tions.

For functions f_6, f_8 and f_{21} PSO and EWA reached the same median and the best solution. Interesting is that for f_{21} both algorithm had standard deviation 0 which means that obtained solution is probably some local optimum. For functions f_{10}, f_{16} and f_{28} EWA successfully found at least once optimal solution while PSO was not. For all other functions EWA reached better minimal, maximal and median solution and standard deviation was lower in the most cases. Smaller standard deviation around bad solution is not an advantage of the PSO algorithm. Based on the results presented in Table 1 we can conclude that EWA perform better then PSO and it was shown good characteristics.

4 Conclusion

In this paper we tested noves novel swarm optimization algorithms, earthworm algorithm. The algorithms was tested on 28 CEC 2013 benchmark functions. Based on the experimental results we concluded that EWA has good characteristics as optimization algorithm and it perform better than PSO algorithm that was used for comparison. In further work, modification or hybridization of EWA algorithm can be proposed and tested against several other swarm optimization algorithms.

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