Optimization of Some Standard Functions using Artificial Algae Algorithm

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Abstract— **In this paper three benchmark function namely Sphere, Rastrigin and Ackly taken from the CEC'05 function set are optimized using artificial algae algorithm (AAA) which is a novel bio inspired metaheuristic optimizer. The Sphere function is Unimodal function while Rastrigin and Ackly are multimodal functions. To analyze the performance of the optimizer mean, best, average and standard deviation values were calculated. Furthermore convergence curve and one sample T-test were also employed to check the consistency of the algorithm over different runs and different dimensions. The coding and simulation of the algorithm was done using FORTRAN 90 and graphs were plotted using excel software. The IBM SPSS software was employed to perform one sample T-test. AAA produced successful and balanced results over different dimensions of the benchmark functions.**

Keywords— Metaheuristic, Unimodal, Multimodal, T-test, Optimizer

I. INTRODUCTION

The Optimization is the operation of finding the optimal solution(or solutions) to a given problem. The aim is to maximize profits by keeping resources minimum. Choosing the optimal method is important for this purpose. The complexity of real-world problems makes search of all possible solutions or combinations impossible. As resources are limited in real-world applications, mathematical modeling approaches seek solutions by simplifying problems or limiting them by making assumptions. As a result, an acceptable real solution for the original problem may considerably vary from solutions obtained from the modified model [1]. Optimization problems can be formulated in many ways. So far, the most widely used formulations is to write a nonlinear optimization problem as:

Maximize or Minimize $f_i(x), (i = 1,2 \ldots \ldots, M)$

subject to following equality and inequality constraints

$h_j(x) = 0, (j = 1,2 \ldots \ldots J)$ $g_i(x) <= 0, (k = 1,2 \ldots \ldots K)$

Researchers have developed a number of high performance heuristic optimization methods by taking inspiration from biology, physics, neurology and other disciplines since the mid-20th century [5]. Recently, there has been a growing interest to solve complex optimization problems inspiring from biology. Algorithms having these approaches are called bio-inspired metaheuristic algorithms, which were modeled by finding useful simulations, and by under-standing and mimicking the behaviors in biological systems [4, 5].Generally, many studies in this area have focused on simulation of natural phenomena rather than the construction of mathematical and engineering tools. Successful bio-inspired metaheuristic methods are inspired by either Darwin's evolution rules or intelligent behaviors of swarms [6]. Evolutionary computation approaches include genetic algorithm, differential evolution, and harmony search algorithms. The main principle of these approaches is keeping the good individuals alive and being transferred them to the next generations. The first study in evolutionary computation approaches is genetic algorithm developed by the Holand et al. [7]. Basically, genetic algorithm is based on the principle that only the fittest survive during the transition of a population from one generation to the next. It offers multiple solutions to problems instead of a single solution. Each candidate solution is an individual of the population. According to the fitness value obtained from objective function in the optimization problem, new individuals, which are transferred to the next generations, are modified (recombined and mutated) and then reproduced. The number of individuals producing good solution sin new generations increases, whereas the number of individuals producing bad solutions decreases. The individuals in the new generations are mutated at a particular level in order to provide diversity and to avoid local optimums. It is observed that the best solution can be found by iterating this evolutionary process. Differential evolution algorithm developed by Storn and Pricein 1997 is another population based evolution algorithm which uses real-valued parameters [8]. Another example is harmony search algorithm developed by Geem et al. [9]. In this algorithm, the harmony of musicians in an orchestra is inspired. Although harmony search algorithm resembles genetic algorithm, they differ in forming new individuals, i.e., in crossover operation, all individuals are used in the former. The first study on swarm intelligence was The Ant Colony Algorithm presented by Dorigo in [10]. In this algorithm, the swarm intelligence of ants communicating with each other using pheromones is inspired. Ants leave pheromone to help

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other ants to find their ways. Another algorithm inspired by the social behaviors of a bird flock and fish school is particles warm optimization developed by American social psychologist Kennedy and engineer Eberhart [11]. In this algorithm, each individual qualified as agent mimics the behaviors of the best individual in the swarm or its own best former behavior. One of the most effective studies in this field is the Artificial Bee Colony Algorithm developed by Karaboga [12]. Another study on bees is Honey Bee Algorithm presented by Pham et al. [13]. Basically, honey bee algorithm also mimics food collecting behavior of honey bees. Another swarm intelligence-based approach is the firefly algorithm developed by Yang in 2007and is inspired by the communication between fireflies through the signaling system called "bioluminescence" [14]. As a result of increasing interest in this field, further population-based algorithms have been presented recently. For example, in 2009, Yang and Deb introduced a productive cuckoo search algorithm which was based on laying eggs, nest choosing behaviors and Levy flights of cuckoos [15]. Studies in this field in the last 20 years have drawn considerable attention and many of the bio-inspired algorithms have gained popularity mainly because of the flexible and multi-directional structure of these algorithms. Despite the progress provided during the last 20 years, optimization is still a large research area as it is required in all fields of life, especially money, time and energy optimization in engineering and industrial applications.

Hence in the continuation of these studies another bio inspired algorithm was developed by Sait Ali Uymaz, Gulay Tezel, Esra Yel in 2015 known as artificial algae algorithm (AAA). This paper basically implements the AAA algorithm.

II. ARTIFICIAL ALGAE ALGORITHM

The AAA is based on algal reproduction, adaptation, and their swimming which emerges with the motion of being close to light as a photosynthetic organism. An alga grows in the liquid where it exists as long as there is light for photosynthesis and sufficient nutrient, and it reproduces by mitotic division. In case of insufficient light and nutrient conditions species either die or adapt to the changing conditions in the environment. Algae are good swimmers because they continuously swim and try to stay close to water surface to get adequate light. In AAA the global optimum of the objective function was defined as the point on which algae can receive optimum light for photosynthesis.

Artificial algae correspond to each solution in the problem space by idealizing the characteristics of algae. Similar to the real algae, artificial algae can move toward the source of light to photosynthesize with helical swimming, and they can adapt to the environment, are able to change the dominant species can reproduce by mitotic division. Thus, the algorithm was composed of 3 basic parts called "Evolutionary Process", "Adaptation" and "Helical Movement".

A. Evolutionary Process

The evolutionary process defines the growth characteristics of the algae which is mathematically modeled by using Monod equation

$$G_j^{t+1} = \left(\frac{f_j(x)}{k+f_j(x)}\right) * G_j^t, (j = 1,2, \dots N) \quad (1)$$

where G is the size of jth algal colony in time t, N is the number of algal colonies in the system.

Algal colony providing good solutions (cost-efficient and the most appropriate solution) grow more as the amount of nutrient that they obtain is high. For each algal cell of the smallest algal colony dying in the evolutionary process, algal cell of the biggest algal colony is replicated.

$$biggest^t = \max(G_j^t), (j = 1,2, \dots N) \quad (2)$$
$$smallest^t = \min(G_j^t), (j = 1,2, \dots N) \quad (3)$$
$$smallest_m^t = biggest_m^t, (m = 1,2, \dots D) \quad (4)$$

D is the problem dimension.

B. Adaptation Process

Adaptation is the process in which an insufficiently grown algal colony tries to resemble itself to the biggest algal colony in the environment. This process is ended up with the change in starvation level in the algorithm. The initial starvation value is zero for each artificial alga. Starvation value increases with time t, when algal cell receive insufficient light.

$$starving^t = \max A_j^t, (j = 1,2, \dots N) \quad (5)$$
$$starving^{t+1} = starving^t + (biggest^t - starving^t) * rand \quad (6)$$

Where A_j^t is the starvation value of jth algal colony in time t, $starving^t$ is the algal colony with the highest starvation value in time t. The adaptation parameter (Ap) determines whether adaptation process would be applied in time t or not. Ap is constant on the interval [0,1].

C. Helical Movement

Algal cells and colonies generally swim and try to stay close to the water surface because of adequate light for survival is available there. The movement of an algal cell is helical as it is in the real life. In AAA, the gravity restricting the movement is displayed as 0 and viscous drag is displayed as shear force, which is proportional to the size of algal cell. It is in spherical shape and the size of it is its volume in the model. Therefore, friction surface becomes the surface area of the hemisphere.

$$T(x_j) = 2\pi \left(\sqrt[\frac{2}{3}]{\frac{3G_j}{4\pi}}\right) \quad (7)$$

Three dimensions for the helical movement of the algal cell are determined randomly. Friction surface and distance to the source of light determine the step size of the movement.

$$x_{jm}^{t+1} = x_{jm}^t + (x_{im}^t - x_{jm}^t) * (\Delta - T(x_j)) * p \quad (8)$$
$$x_{jk}^{t+1} = x_{jk}^t + (x_{ik}^t - x_{jk}^t) * (\Delta - T(x_j)) * \cos\alpha \quad (9)$$
$$x_{jl}^{t+1} = x_{jl}^t + (x_{il}^t - x_{jl}^t) * (\Delta - T(x_j)) * \sin\beta \quad (10)$$

III. TEST FUNCTIONS

A. Unimodal Function

Table-1: Definition of unimodal function used

Function name	Function Formulation	D	Search range	Global Optimum	Min value
Sphere	$f_{01}=\sum_{i=1}^{D} x_i^2$	30	$[-100,100]^D$	$(0,\dots,0)$	0

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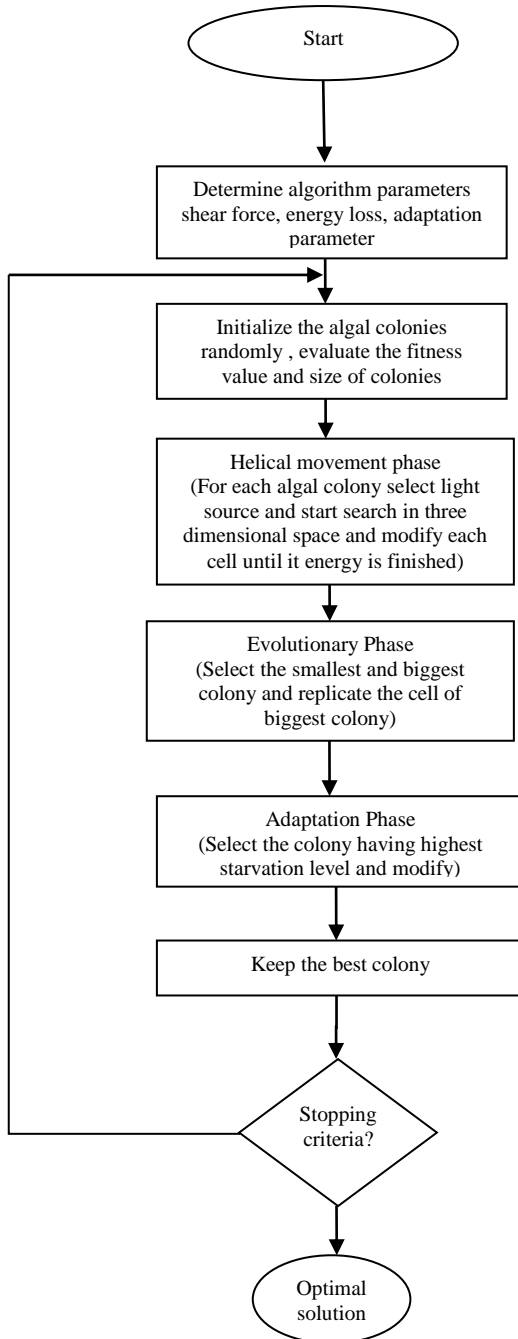**ISSN: 2278-0181**
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Fig.1: Flow chart of AAA

B. Multimodal Functions

Table-2: Definition of multimodal functions considered

Function name	Rastrigin	Ackly
Function Formulation	$f_{02}=\sum_{i=1}^{D}[x_i^2 - 10\cos(2\pi x_i) + 10]$	$f_{03}=$ -20 exp(-0.2$\sqrt{D^{-1}\sum_{i=1}^{D}x_i^2}$) - exp($D^{-1}\sum_{i=1}^{D}\cos(2\pi x_i)$)+20+e
D	30	30
Search range	$[-5.12,5.12]^D$	$[-32,32]^D$
Global Optimum	(0,…,0)	(0,…,0)
Min value	0	0

IV. SIMULATION RESULTS AND DISCUSSION

A. Sphere Function Results

The simulation results of the sphere function having 50 populations and 30 dimensions taken over 30 runs are stated in Table-3, Table-4 and Table-5.

Table-3: Descriptive Statistics showing mean, minimum, maximum and standard deviation of sphere function having 30 dimensions taken over 30 runs

Function	N	Minimum	Maximum	Mean	Std. Deviation
Sphere	30	6.908E-7	9.988E-7	9.25180E-7	6.95699E-8
Valid N (listwise)	30				

Table-4: One-Sample Statistics

Function	N	Mean	Std. Deviation	Std. Error Mean
sphere	30	9.25180E-7	6.95699E-8	1.27017E-8

Table-5: One-Sample Test for sphere function having 30 dimensions over 30 runs

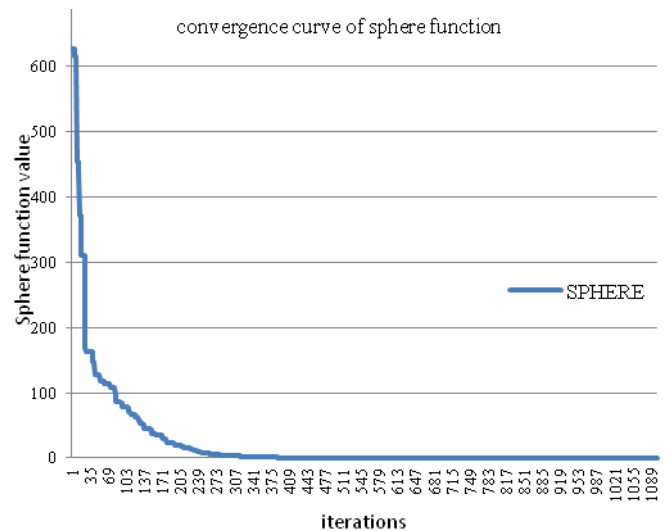| Function	Test Value = 0					
	t	df	Sig. (2-tailed)	Mean Difference	95% Confidence Interval of the Difference	
					Lower	Upper
sphere	72.839	29	.000	9.251802E-7	8.99202E-7	9.51158E-7

Fig.2: The convergence curve of the sphere function value versus number of iterations.

B. Rastrigin Function Results

The simulation results of the Rastrigin function having 50 populations and 30 dimensions taken over 30 runs are stated in table 6, 7 and 8.

C. Ackley Function Results

The simulation results of the sphere function having 50 populations and 30 dimensions taken over 30 runs are stated in Table-9, Table-10 and Table-11.

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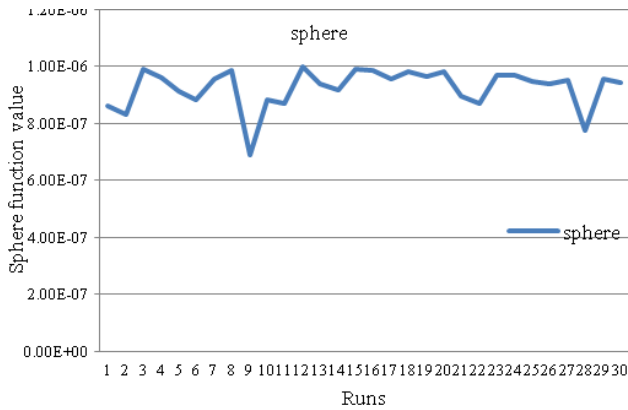**ISSN: 2278-0181**
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Fig.3: The consistency curve of sphere function values taken over 30 runs at 30 dimensions

Table-6: Descriptive Statistics showing mean, minimum, maximum and standard deviation of Rastrigin function having 30 dimensions taken over 30 runs

	N	Minimum	Maximum	Mean	Std. Deviation
Rastrigin	30	7.67132E-008	9.97662E-008	9.2051850E-008	6.83794204E-009
Valid N (list wise)	30				

Table-7: One-Sample Statistics

	N	Mean	Std. Deviation	Std. Error Mean
Rastrigin	30	9.2051850E-008	6.83794204E-009	1.24843170E-009

Table-8: One-Sample Test for Rastrigin function having 30 dimensions over 30 runs

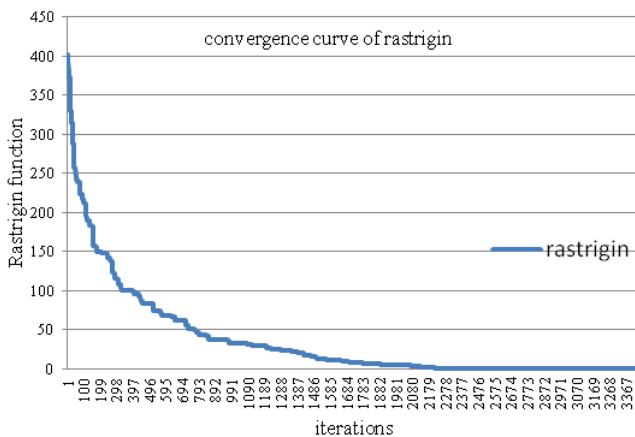| Test Value = 0					
	t	df	Sig.(2-tailed)	Mean Difference	95% Confidence Interval of the Difference
					Lower	Upper
Rastrigin	73.734	29	.000	9.20518497E-008	8.9498520E-008	9.4605179E-008

Fig.4: The convergence curve of the Rastrigin function value versus number of iterations.
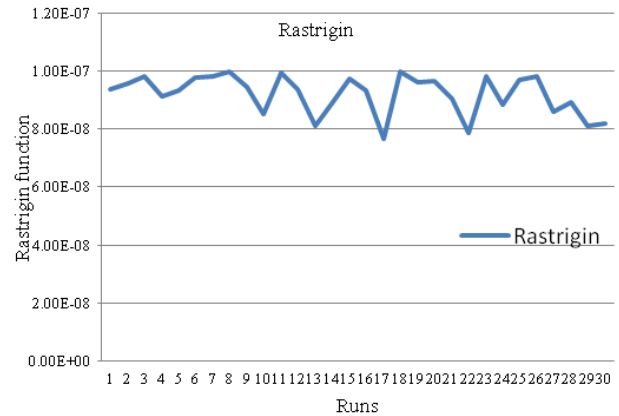

Fig.5: The consistency curve of Rastrigin function values taken over 30 runs at 30 dimensions.

Table-9: Descriptive Statistics showing mean, minimum, maximum and standard deviation of Ackley function having 30 dimensions taken over 30 runs

	N	Minimum	Maximum	Mean	Std. Deviation
Ackley	30	6.82523E-007	9.99400E-007	9.5004945E-007	6.65636936E-008
Valid N (listwise)	30				

Table3.1:One-Sample Statistics				
	N	Mean	Std. Deviation	Std. Error Mean
Ackley	30	9.5004945E-007	6.65636936E-008	1.21528122E-008

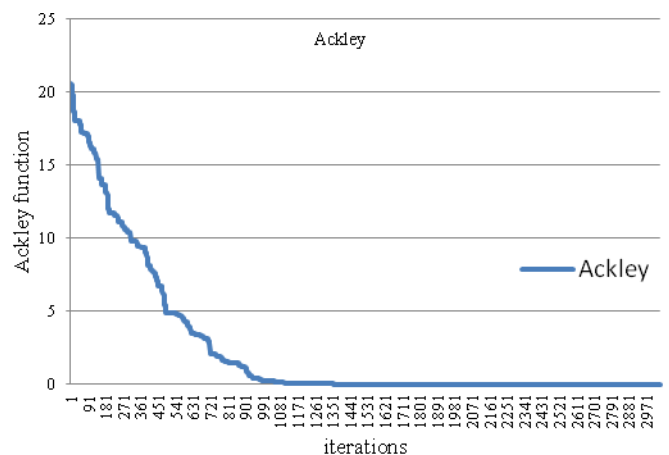| Table3.2:One-Sample Test for Rastrigin function having 30 dimensions over 30 runs					
Test Value = 0					
t	df	Sig. (2-tailed)	Mean Difference	95% Confidence Interval of the Difference	
				Lower	Upper
Ackley	78.175	29	.000	9.50049447E-007	9.2519416E-007	9.7490474E-007

Fig.6: The convergence curve of the Ackley function value versus number of iterations

V.   CONCLUSION

This paper introduced the basic structure of the developed artificial algae algorithm (AAA) which is a novel and a highly effective population-based evolutionary, metaheuristic optimization algorithm. AAA is inspired by the living behaviors of microalgae in nature. AAA has three control

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parameters (energy loss, adaptation parameter and shear force). Energy loss parameter determines the number of new candidate solutions of algal colonies produced at each iteration. The results are analyzed using IBM SPSS software which indicates that for every function the standard deviation was less than one which shows that the AAA algorithm is a consistent algorithm for both Unimodal and Multimodal functions.
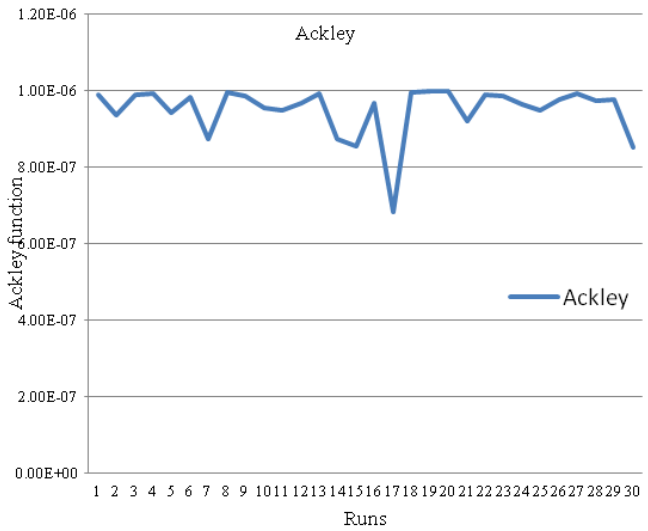

Fig.7: The consistency curve of Ackley function values taken over 30 runs at 30 dimensions

REFERENCES

[1] R.A. Sarker, C.S. Newton, "Optimization Modeling: A Practical Introduction", Taylor & Francis: CRC Press, Boca Raton, Fl, Isbn 9781420043105, 2008.

[2] X.S. Yang, Z. Cui, "Swarm Intelligence And Bio-Inspired Computation: Theory Andapplication", Elsevier Inc., Newness, London, Isbn 978-0-12-405163-8, 2013.

[3] X. Yang, "Nature-Inspired Metaheuristic Algorithms", Second Edition, Luniverpress, United Kingdom, Pp. 1–9, 2010.

[4] J. Brownlee, "Clever Algorithms: Nature-Inspired Programming Recipes", Lulu, Melbourne, Vic, 2011.

[5] S. Gao, "Bio-Inspired Computational Algorithms And Their Applications", Intech,Rijeka, Croatia, ISBN 978-953-51-0214-4, 2012.

[6] S. Binitha, S. Siva Sathya, "A Survey Of Bio Inspired Optimization Algorithms", International Journal on Soft Computing Engineering, vol. 2, no. 2, ISSN: 2231-2307, 2012.

[7] J. Holland, "Adaptation In Natural And Artificial Systems", University Of Michiganpress, Ann Anbor, Mi, 1975.

[8] R. Storn, K. Price, "Differential Evolution—A Simple And Efficient Heuristic Forglobal Optimization Over Continuous Spaces", Journal of Global Optimization, vol. 11, pp: 341–359, 1997.

[9] J. Kennedy, R. Eberhart, "Particle Swarm Optimization", in Proceedings of IEEE International Conference On Neural Networks, Piscataway, NJ, pp. 1942–1948, 1995.

[10] D. Karaboga, "An Idea Based On Honey Bee Swarm For Numerical Optimization", in Technical Report, Erciyes University, Kayseri, Turkey, 2005.

[11] D.T. Pham, A. Ghanbarzadeh, E. Koc, S. Otri, S. Rahim, M. Zaidi, "The Beesalgorithm—A Novel Tool For Complex Optimization Problems", in Proceedingsof Innovative Production Machines And Systems Virtual Conference, IPROMS, pp. 451–461, 2006.

[12] X.S. Yang, "Firefly Algorithms For Multimodal Optimization", in O. Watanabe, T. Zeugmann (Eds.), Proceedings of 5th Symposium on Stochastic Algorithms, Founda-Tions And Applications, Saga, 5792, pp. 169–178 (Lecture Notes Incomputer Science), 2009.

[13] X.S. Yang, S. Deb, "Cuckoo Search Via Lévy Flights", in World Congress on Nature & Biologically Inspired Computing (NABIC 2009), IEEE Publications, USA, pp. 210–214, 2009.