

A Novel Adaptive Whale Optimization Algorithm for Global Optimization

Indrajit N. Trivedi¹, Jangir Pradeep², Jangir Narottam², Kumar Arvind³, Ladumor Dilip²

¹Department of Electrical Engineering, G.E. College, Gandhinagar Near GEB Cross Road, Sector 28, Gandhinagar - 382028, Gujarat, India; forumtrivedi@gmail.com

²Department of Electrical Engineering, L. E. College, Sama Kathe Near Natraj Fatak, Morbi - 363641, Gujarat, India; pkjmtech@gmail.com, nkjmtech@gmail.com, ladumordilip56@gmail.com

³Department of Electrical Engineering, S.S. College, New Sidsar Campus, Post: Vartej, Sidsar, Bhavnagar - 364060, Gujarat, India; akbharia8@gmail.com

Abstract

Background/Objectives: In the meta-heuristic algorithms, randomization plays a very crucial role in both exploration and exploitation. So meta-heuristic algorithms are proposed to avoid these problems. **Methods/Statistical Analysis:** A novel bio-inspired optimization algorithm based on the special bubble-net hunting strategy used by humpback whales called the Whale Optimization Algorithm (WOA). In contrast to meta-heuristic, main feature is randomization having a relevant role in both exploration and exploitation in optimization problem. A novel randomization technique termed adaptive technique is integrated with WOA and exercised on ten unconstraint test benchmark function. **Findings:** WOA algorithm has quality feature that it uses logarithmic spiral function so it covers a broader area in exploration phase then addition with powerful randomization adaptive technique potent the adaptive whale optimization Algorithm (AWOA) to attain global optimal solution and faster convergence with less parameter dependency. **Application/Improvements:** Adaptive WOA (AWOA) solutions are evaluated and results shows its competitively better performance over standard WOA optimization algorithm.

Keywords: Adaptive Technique, Exploitation, Exploration, Hunting, Optimization, Whale Optimization Algorithm

1. Introduction

In the meta-heuristic algorithms, randomization plays a very crucial role in both exploration and exploitation. More strengthen randomization techniques are Markov chains, Levy flights and Gaussian or normal distribution and **newest technique** is adaptive technique. So meta-heuristic algorithms on integrated with adaptive technique results in less computational time to reach optimum solution, local minima avoidance and faster convergence.

Population based WOA¹ is a meta-heuristic optimization algorithm has an ability to avoid local optima and get global optimal solution that make it appropriate for practical applications without structural modifications in algorithm for solving different constrained or uncon-

strained optimization problems. WOA integrated with adaptive technique reduces the computational times for highly complex problems.

Contemporary works with adaptive technique are: Adaptive Cuckoo Search Algorithm (ACSA)^{2,3}, QGA⁴, Acoustic Partial discharge (PD)^{5,6}, HGAPSO⁷, PSACO⁸, HSABA⁹ PBILKH¹⁰, KH-QPSO¹¹, IFA-HS¹², HS/FA¹³, CKH¹⁴ HS/BA¹⁵ HPSACO¹⁶ CSKH¹⁷, HS-CSS¹⁸, PSOHS¹⁹, DEKH²⁰, HS/CS²¹, HSBBO²², CSS-PSO²³ etc.

The structure of the paper can be given as follows: - Section I consists of Introduction; Section II includes description of main algorithms; section III consists of competitive results analysis of unconstraint test benchmark problem; finally, acknowledgement and conclusion based on results is drawn.

*Author for correspondence

2. Whale Optimization Algorithm

In the meta-heuristic algorithm, a newly purposed optimization algorithm called Whale optimization algorithm (WOA), which inspired from the bubble-net hunting strategy. Algorithm describes the special hunting behavior of humpback whales, the whales follows the typical bubbles causes the creation of circular or '9-shaped path' while

encircling prey during hunting. Simply bubble-net feeding/hunting behavior could understand such that humpback whale went down in water approximate 10-15 meter and then after the start to produce bubbles in a spiral shape

encircles prey and then follows the bubbles and moves upward the surface. Mathematic model for Whale Optimization algorithm (WOA) is given as follows:

a. Encircling Prey Equation

Humpback whale encircles the prey (small fishes) then updates its position towards the optimum solution over the course of increasing number of iteration from start to a maximum number of iteration.

$$\bar{D} = |C \cdot \bar{X}^*(t) - X(t)| \quad (1)$$

$$\bar{X}(t+1) = \bar{X}^*(t) - \bar{A} \cdot \bar{D} \quad (2)$$

Where: \bar{A} , \bar{D} are coefficient vectors, t is a current iteration, $\bar{X}^*(t)$ is position vector of the optimum solution so far and $X(t)$ is position vector.

Coefficient vectors \bar{A} , \bar{D} are calculated as follows:

$$\bar{A} = 2\bar{a} * r - \bar{a} \quad (3)$$

$$\bar{C} = 2 * r \quad (4)$$

Where: \bar{a} is a variable linearly decrease from 2 to 0 over the course of iteration and r is a random number [0, 1].

b. Bubble-net Attacking Method

In order to mathematical equation for bubble-net behavior of humpback whales, two methods are modeled as:

(a) Shrinking Encircling Mechanism

This technique is employed by decreasing linearly the value of \bar{a} from 2 to 0. Random value for a vector \bar{A} in range between [-1, 1].

(b) Spiral Updating Position

Mathematical spiral equation for position update between humpback whale and prey that was helix-shaped movement given as follows:

$$\bar{X}(t+1) = \bar{D}' * e^{bl} * \cos(2\pi l) * \bar{X}^*(t) \quad (5)$$

Where: l is a random number [-1, 1], b is constant defines the logarithmic shape, $\bar{D}' = |\bar{X}^*(t) - X(t)|$ expresses the distance between i^{th} whale to the prey mean the best solution so far.

Note: We assume that there is 50-50% probability that whale either follow the shrinking encircling or logarithmic path during optimization. Mathematically we modeled as follows:

$$\bar{X}(t+1) = \begin{cases} \bar{X}^*(t) - \bar{A} \cdot \bar{D} & \text{if } p < 0.5 \\ \bar{D}' \cdot e^{bl} \cdot \cos(2\pi l) + \bar{X}^*(t) & \text{if } p \geq 0.5 \end{cases} \quad (6)$$

Where: p expresses random number between [0, 1].

(c) Search for Prey

The vector \bar{A} can be used for exploration to search for prey; vector \bar{A} also takes the values greater than one or less than -1. Exploration follows two conditions

$$\bar{D} = |\bar{C} \cdot X_{rand} - \bar{X}| \quad (7)$$

$$\bar{X}(t+1) = X_{rand} - \bar{A} \cdot \bar{D} \quad (8)$$

Finally follows these conditions:

- $|\bar{A}| > 1$ enforces exploration to WOA algorithm to find out global optimum avoids local optima
- $|\bar{A}| < 1$ For updating the position of current search agent/best solution is selected.

3. Adaptive Whale Optimization Algorithm (AWOA)

The Adaptive technique includes best features like it consists of less parameter dependency, not required to

define initial parameter and step size or position towards optimum solution is adaptively changes according to its

functional fitness value over the course of iteration.

So meta-heuristic algorithms on integrated with adaptive technique results in less computational time to reach optimum solution, local minima avoidance and faster convergence.

Table 1. Benchmark Test Function

No.	Name	Function	Dim	Range
F1	Sphere	$f(x) = \sum_{i=1}^n x_i^2 * R(x)$	10	[-100, 100]
F2	Schwefel 2.22	$f(x) = \sum_{i=1}^n x_i + \prod_{i=1}^n x_i * R(x)$	10	[-10, 10]
F3	Schwefel 1.2	$f(x) = \sum_{i=1}^n \left(\sum_{j=1}^i x_j \right)^2 * R(x)$	100	[-100, 100]
F4	Schwefel 2.21	$f(x) = \max_i \{ x_i , 1 \leq i \leq n\}$	10	[-100, 100]
F5	Rosenbrock's Function	$f(x) = \sum_{i=1}^{n-1} \left[100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2 \right] * R(x)$	100	[-30, 30]
F6	Step Function	$f(x) = \sum_{i=1}^n ([x_i + 0.5])^2 * R(x)$	100	[-100, 100]
F7	Quartic Function	$f(x) = \sum_{i=1}^n ix_i^4 + random[0,1] * R(x)$	100	[-1.28, 1.28]
F8	Schwefel 2.26	$F(x) = \sum_{i=1}^n -x_i \sin(\sqrt{ x_i }) * R(x)$	100	[-500, 500]
F9	Penalty 1	$F(x) = \frac{\pi}{n} \left\{ \begin{array}{l} 10 \sin(\pi y_1) + \sum_{i=1}^{n-1} (y_i - 1)^2 \\ [1 + 10 \sin^2(\pi y_{i+1})] + (y_n - 1)^2 \end{array} \right\}$ $y_i = 1 + \frac{x_i + 1}{4},$ $u(x_i, a, k, m) = \begin{cases} k(x_i - a)^m & x_i > a \\ -0 & a < x_i < a \\ k(-x_i - a)^m & x_i < -a \end{cases}$	10	[-50, 50]
F10	Penalty 2	$F(x) = 0.1 \left\{ \begin{array}{l} \sin^2(3\pi x_1) + \sum_{i=1}^n (x_i - 1)^2 \\ [1 + \sin^2(3\pi x_i + 1)] \\ + (x_n - 1)^2 [1 + \sin^2(2\pi x_n)] \end{array} \right\}$ $+ \sum_{i=1}^n u(x_i, 5, 100, 4) * R(x)$	10	[-50, 50]

Table 2. Internal Parameters

Parameter Name	Search Agents no.	Max. Iteration no.	No. of Evolution
F1-F10	30	500	5-10

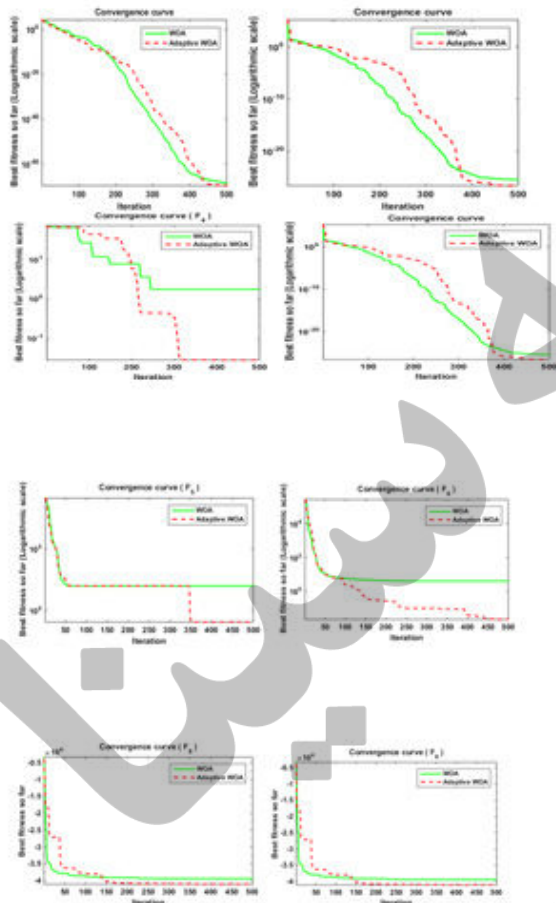


Figure 1. Convergence curve of test function.

Table 3. Statical Results

Fun.	Whale Optimization Algorithm (WOA)			Adaptive WOA (AWOA)		
	Ave	Best	S.D.	Ave	Best	S.D.
F1	8.0771e-69	1.9381e-69	8.6819e-69	6.7908e-57	1.7272e-70	9.6036e-57
F2	6.7699e-24	3.7467e-26	9.5211e-24	1.2349e-24	2.5846e-27	1.7427e-24
F3	1411753.69	1180140.733	327550.185	1251270.94	1065090.031	263299.6148
F4	8.2428	1.7214	9.2226	0.21458	0.027739	0.26423
F5	98.2835	98.2749	0.012064	0.14324	0.11416	0.041135
F6	4.659	3.9536	0.99749	0.032477	0.021538	0.015471

$$X_i^{t+1} = X_i^t + randn * \left(\frac{1}{t}\right)^{\left|\frac{(bestf(t) - fi(t))}{(bestf(t) - worstf(t))}\right|} \quad (9)$$

Where X_i^{t+1} new solution of i -th dimension in t -th iteration $f(t)$ is the fitness value.

4. Simulation Results for Unconstraint Test Benchmark Function

Unconstraint Test Benchmark Functions (Sphere, Schwefel 2.22, Schwefel 1.2, Schwefel 2.21, Rosenbrock's function, Step Function, Quartic Function, Schwefel 2.26, Penalty 1,2 etc.) are given in Table I and internal parameters are given in Table II. Results are given in Table III. Here we consider high dimension to test its effectiveness of new AWOA strategy. Internal parameter also plays vital role so these are clearly expressed in Table I. Convergence curve of test function is shown in Figure I that's proof that AWOA algorithm has very good results compare to standard recently Proposed Whale Optimization Algorithm (WOA).

5. Conclusion

Whale optimization Algorithm has an ability to find out optimum solution with constrained handling which includes both equality and inequality constraints. While obtaining optimum solution constraint limits should not be violated. Adaptive technique causes faster convergence,

F7	0.00080305	0.00067362	0.00018304	0.002901	0.00061163	0.0032378
F8	-35649.227	-39442.0078	5363.8013	-34729.685	-41077.2577	8976.8229
F9	0.013828	0.0090427	0.0067677	0.002071	0.00062873	0.0020396
F10	0.091796	0.039021	0.074636	0.030366	0.0037635	0.037622

randomness, and stochastic behavior for improving solutions. Adaptive technique also used for random walk in search space when no neighboring solution exists to converge towards optimal solution. The AWOA result of various unconstrained problems proves that it is also an effective method in solving challenging problems within unknown search space.

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7. References

- Mirjalili Seyedali, Lewis Andrew. The Whale Optimization Algorithm. *Advances in Engineering Software*. 2016 May; 95:51-67.
- Ong P. Adaptive Cuckoo search algorithm for unconstrained optimization. *Hindawi Publication: The Scientific World Journal*. 2014 Sep; 2014:1-8.
- Naik Manoj Kumar, Panda Rutupaparna. A novel adaptive cuckoo search algorithm for intrinsic discriminant analysis based face recognition. *Applied Soft Computing*. 2016 Jan; 38:661-75.
- Hua-Long Liu. Acoustic partial discharge localization methodology in power transformers employing the quantum genetic algorithm. *Applied Acoustics*. 2016 Jan; 102:71-8.
- Liu HL, Liu HD. Partial discharge localization in power transformers based on the sequential quadratic programming-genetic algorithm adopting acoustic emission techniques. *The European Physical Journal Applied Physics*. 2014 Oct; 68(1):1-16.
- Alvarez Fernando, Garnacho Fernando, Ortego Javier, Sanchez-Uran Miguel Angel. Application of HFCT and UHF Sensors in On-Line Partial Discharge Measurements for Insulation Diagnosis of High Voltage Equipment. *Sensors*. 2015 Apr; 15(4):7360-87.
- Kaveh A, Malakouti Rad S. Hybrid Genetic Algorithm and Particle Swarm Optimization for the Force Method-Based Simultaneous Analysis and Design. *Iranian Journal of Science & Technology, Transaction B: Engineering*. 2010 Feb; 34:15-34.
- Kaveh A, Talatahari S. A Hybrid Particle Swarm and Ant Colony Optimization for Design of Truss Structures. *Asian Journal of Civil Engineering (Building and Housing)*. 2008 Jan; 9(4):329-48.
- Fister Iztok, Fong Simon, Brest Janez, Fister Iztok. A Novel Hybrid Self-Adaptive Bat Algorithm. *Hindawi Publishing Corporation the Scientific World Journal*. 2014 Apr; 2014:1-12.
- Gai-Ge Wang, Amir H Gandomi, Amir H Alavi, Deb Suash. A hybrid PBIL-based Krill Herd Algorithm. 2015 3rd International Symposium on Computational and Business Intelligence (ISCBI). 2015 Dec, pp.39 - 44.
- Gai-Ge Wang, Amir H Gandomi, Amir H Alavi, Deb Suash. A hybrid method based on krill herd and quantum-behaved particle swarm optimization. *Neural Computing and Applications*. 2016 May; 27(4):989-1006.
- Tahershamsi A, Kaveh A, Sheikholeslami R, Kazemzadeh Azad S. An improved reynolds algorithm with harmony search scheme for optimization of water distribution systems. *Scientia Iranica*. 2015 Jan; 2015:1-6.
- Lihong Guo, Gai-Ge Wang, Heqi Wang, Dinan Wang. An Effective Hybrid Firefly Algorithm with Harmony Search for Global Numerical Optimization. *Hindawi Publishing Corporation. The Scientific World Journal*. 2013 Sep; 2013:1-9.
- Gai-Ge Wang, Lihong Guo, Gandomi Amir Hossein, Guo-Sheng Hao, Heqi Wang. Chaotic krill herd algorithm. *Information Sciences*. 2014 Aug; 274:17-34.
- Gaige Wang, Lihong Guo. A Novel Hybrid Bat Algorithm with Harmony Search for Global Numerical Optimization. *Hindawi Publishing Corporation Journal of Applied Mathematics*. 2013; 2013:1-12.
- Kaveh A, Talatahari S. Hybrid Algorithm of Harmony Search, Particle Swarm and Ant Colony for Structural Design Optimization. *Harmony Search Algo. for Structural Design Optimization*. 2009; p. 159-98.

17. A new hybrid method based on krill herd and cuckoo search for global optimization tasks. *International Journal of Bio-Inspired Computation*. Date Accessed: 14/08/2015; Available from: https://www.researchgate.net/publication/280723176_A_New_Hybrid_Method_Based_on_Krill_Herd_and_Cuckoo_Search_for_Global_Optimization_Tasks.
18. Kaveh Ali, Hosseini Omid Khadem. A hybrid HS-CSS algorithm for simultaneous analysis, design and optimization of trusses via force method. *Civil Engineering*. 2012 Sep; 56(2):197-212.
19. Kaveh A, Nasrollahi A. Engineering Design Optimization Using a Hybrid PSO and HS Algorithm. *Asian Journal of Civil Engineering (Bhrc)*. 2013 Apr; 14(2):201-23.
20. Gai-Ge Wang, Gandomi Amir Hossein, Alavi Amir Hossein, Guo-Sheng Hao. Hybrid krill herd algorithm with differential evolution for global numerical optimization. *Neural Computing & Applications*. 2014 Aug; 25(2):297-308.
21. Gai-Ge Wang, Gandomi Amir Hossein, Xiangjun Zhao, Chu Hai Cheng Eric. Hybridizing harmony search algorithm with cuckoo search for global numerical optimization. *Soft Computing*. 2016 Jan; 20(1):273-85.
22. Gaige Wang, Lihong Guo, Hong Duan, Heqi Wang, Luo Liu, Mingzhen Shao. Hybridizing Harmony Search with Biogeography Based Optimization for Global Numerical Optimization. *Journal of Computational and Theoretical Nanoscience*. 2013 Oct; 10(10):2312-22.
23. Talatahari S, Sheikholeslami R, Farahmand Azar B, Daneshpajouh H. Optimal Parameter Estimation for Muskingum Model Using a CSS-PSO Method. *Hindawi Publishing Corporation Advances in Mechanical Engineering*. 2013; 2013:1-6.