iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 7 **Issue:** XI **Month of publication:** November 2019

DOI: http://doi.org/10.22214/ijraset.2019.11085

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International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.177
Volume 7 Issue XI, Nov 2019- Available at www.ijraset.com

A Novel Adaptive Grey Wolf Optimizer for Global Numerical Optimization

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Abstract: A novel bio-inspired optimization algorithm based on the hunting process of wolves in nature called the Grey wolf optimizer (GWO) Algorithm in contrast to meta-heuristics; 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 GWO and exercised on unconstraint test benchmark function. GWO algorithm has quality feature that it uses simple mathematical equation to update position of grey wolf towards targeted prey or towards optimal solution over the end of maximum iteration limit. Integration of new randomization adaptive technique provides potential that AGWO algorithm to attain global optimal solution and faster convergence with less parameter dependency. Adaptive GWO (AGWO) solutions are evaluated and results shows its competitively better performance over standard GWO optimization algorithms.
Keywords: Meta-heuristic; Grey wolf optimizer; Adaptive technique; Global optimal; Hunting.

I. INTRODUCTION

A novel nature –inspired, Grey wolf optimizer algorithm [1] based on the hunting mechanism. Wolves are member of a troop in which number of grey wolf is the population size or wolves that takes part in hunting. Wolves in a troop are separated according to their leadership quality.

Troop consists of four types of wolfs alpha, beta delta and omega. Alpha wolfs have higher dominance and decision maker in the troop and rest of wolfs have their dominance decreasing sequentially as name above written.

In the meta-heuristic algorithms, randomization play a very important role in both exploration and exploitation where more strengthen randomization techniques are Markov chains, Levy flights and Gaussian or normal distribution and new 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.

In past, many optimization algorithms based on gradient search for solving linear and non-linear equation but in gradient search method value of objective function and constraint unstable and multiple peaks if problem having more than one local optimum.

Population based GWO 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 unconstraint optimization problems. GWO integrated with adaptive technique reduces the computational times for highly complex problems.

Paper under literature review are: Adaptive Cuckoo Search Algorithm (ACSA) [2] [3], QGA [4], Acoustic Partial discharge (PD) [5] [6], HGAPSO [7], PSACO [8], HSABA [9], PBILKH [10], KH-QPSO [11], IFA-HS [12], HS/FA [13], CKH [14], HS/BA [15], HPSACO [16], CSKH [17], HS-CSS [18], PSOHS [19], DEKH [20], HS/CS [21], HSBBO [22], CSS-PSO [23] etc.

Recently trend of optimization is to improve performance of meta-heuristic algorithms [24] by integrating with chaos theory, Levy flights strategy, Adaptive randomization technique, Evolutionary boundary handling scheme, and genetic operators like as crossover and mutation.

Popular genetic operators used in KH [25] that can accelerate its global convergence speed. Evolutionary constraint handling scheme is used in Interior Search Algorithm (ISA) [26] that avoid upper and lower limits of variables.

The remainder of this paper is organized as follows: The next Section describes the Grey wolf optimizer and its algebraic equations are given in Section 2. Section 3 includes description of Adaptive technique. Section 4 consists of simulation results of unconstrained benchmark test function, convergence curve and tables of results compared with source algorithm. in section 5 conclusion is drawn. Finally, acknowledgment gives regards detail and at the end, references are written.

II. GREY WOLF OPTIMIZER

Grey wolf optimizer (GWO) [1] based on natural hunting process of grey wolves. Hunting process and dominance of wolves in troops shown top to bottom in figure.

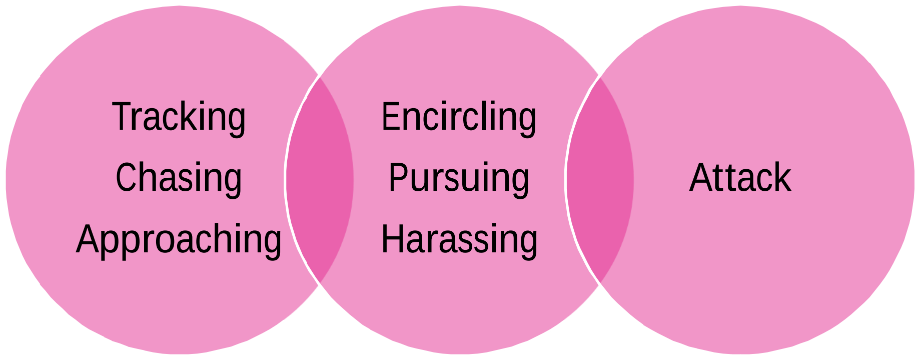


Fig. 1 Hunting process of wolves / principle of GWO

Fig. 2 Wolves in a troop (top (highest dominant) to bottom (lowest dominant))

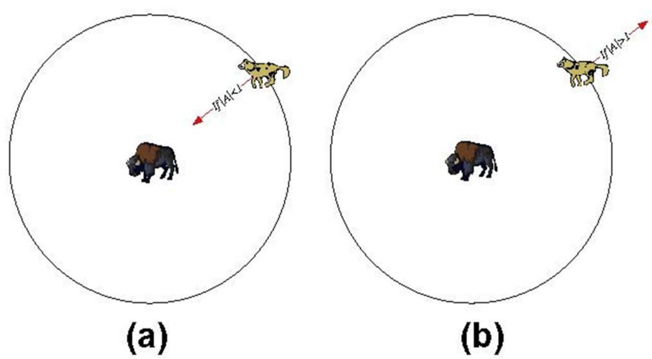


Fig. 3 Boundary condition of attack and diverge

1) When $|A| \geq 1$ diverge away from the prey and
2) When $|\bar{A}| \leq 1$ suitable position ready to attack on the prey for target archive.

During the hunting, the grey wolves encircle prey. The mathematical model of the encircling behavior is presented in the following equations.

$$\vec{D} = \left| \vec{C}.\vec{X}p(t) - \vec{X}(t) \right| \quad (1)$$

$$\vec{X}(t+1) = \vec{X}p(t) - \vec{A}.\vec{D} \quad (2)$$

Where t is the current iteration, A and C are coefficient vectors, X_p is the position vector of the prey, and X indicates the position vector of a grey wolf. The vectors A and C are calculated as follows:

$$\vec{A} = 2\vec{a}.\vec{r}_1 - \vec{a} \quad (3)$$

$$\vec{C} = 2.\vec{r}_2 \quad (4)$$

Where components of a are linearly decreased from 2 to 0 over the course of iterations and r_1, r_2 are random vectors in [0, 1].

3) Grey wolf hunting process is calculated as following equations

$$\vec{D}_\alpha = \left|\vec{C}_1.\vec{X}_\alpha - \vec{X}\right| \quad (5)$$

$$\vec{D}_\beta = \left|\vec{C}_2.\vec{X}_\beta - \vec{X}\right| \quad (6)$$

$$\vec{D}_\delta = \left|\vec{C}_3.\vec{X}_\delta - \vec{X}\right| \quad (7)$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1.(\vec{D}_\alpha) \quad (8)$$

$$\vec{X}_2 = \vec{X}_\beta - \vec{A}_2.(\vec{D}_\beta) \quad (9)$$

$$\vec{X}_3 = \vec{X}_\delta - \vec{A}_1.(\vec{D}_\delta) \quad (10)$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \quad (11)$$

Pseudo code of Grey wolf optimize

1: Set the initial values of the population size n, parameter a, coefficient vectors A, C and the maximum number of iterations Max_{itr}.

2: Set t:=0. {Counter initialization}.

3: for (i=1 : i<=n) do

4: Generate an initial population $X_i(t)$ randomly.

5: Evaluate the fitness function of each search agent (solution) $F(X_i)$.

6: end for

7: Assign the value of the first, second and the third best solution X_α, X_β, and X_δ respectively.

8: repeat

9: for (i =1 : i<=n) do

10: Update each search agent in the population (5) to (11).

11: Decrease the parameter a from 2 to 0.

12: Update the coefficients A and C as shown in equation (3) and (4).

13: Evaluate the fitness function of each search agent (vector) $F(X_i)$.

14: end for

15: Update the vectors X_α, X_β, and X_δ.

16: Set t:=t+1. (Iteration counter increasing).

17: Until (t< Max_{itr}). (Termination criteria satisfied).

Fig. 4 Pseudo code of GWO

III. ADAPTIVE GWO ALGORITHM

In the meta-heuristic algorithms, randomization play a very important role in both exploration and exploitation where more randomization techniques are Markov chains, Levy flights and Gaussian or normal distribution and new technique is adaptive technique. Adaptive technique used by Pauline Ong in Cuckoo Search Algorithm (CSA) [2] and shows improvement in results of CSA algorithms. The Adaptive technique [3] 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 o15ver the course of iteration. So mete-heuristic algorithms on integrated with adaptive technique results in less computational time to reach optimum solution, local minima avoidance and faster convergence.

$$X_i^{t+1} = \left(\frac{1}{t}\right)^{\left|((bestf(t) - fi(t))/(bestf(t) - worstf(t)))\right|} \quad (12)$$

Where

X_i^{t+1} Step size of *i*-th dimension in *t*-th iteration $f(t)$ is the fitness value

IV. SIMULATION RESULTS FOR UNCONSTRAINT TEST BENCHMARK FUNCTION

Table 1: Benchmark Test functions

No.	Name	Function	Dim	Range	Fmin
F1	Sphere	$f(x) = \sum_{i=1}^{n} x_i^2 * R(x)$	10	[-100, 100]	0
F2	Schwefel 2.22	$f(x) = \sum_{i=1}^{n} \lvert x_i \rvert + \prod_{i=1}^{n} \lvert x_i \rvert * R(x)$	10	[-10, 10]	0
F3	Schwefel 1.2	$f(x) = \sum_{i=1}^{n} \left(\sum_{j-1}^{i} x_j \right)^2 * R(x)$	10	[-100, 100]	0
F4	Schwefel 2.21	$f(x) = \max_i \{ \lvert x_i \rvert, 1 \le i \le n \}$	10	[-100, 100]	0
F5	Rosenbrock's Function	$f(x) = \sum_{i=1}^{n-1} \left[100 \left(x_{i+1} - x_i^2 \right)^2 + \left(x_i - 1 \right)^2 \right] * R(x)$	10	[-30, 30]	0
F6	Step Function	$f(x) = \sum_{i=1}^{n} \left([x_i + 0.5] \right)^2 * R(x)$	10	[-100, 100]	0
F7	Quartic Function	$f(x) = \sum_{i=1}^{n} i x_i^4 + random[0,1) * R(x)$	10	[-1.28, 1.28]	0
F8	Schwefel 2.26	$F(x) = \sum_{i=1}^{n} - x_i sin\left(\sqrt{\lvert x_i \rvert} \right) * R(x)$	10	[-500, 500]	(-418.9829 *5)
F9	Rastrigin	$F(x) = \sum_{i=1}^{n} \left[x_i^2 - 10 cos(2\pi x_i) + 10 \right] * R(x)$	10	[-5.12, 5.12]	0
F10	Ackley's Function	$F(x) = -20 exp\left(-0.2 \sqrt{\frac{1}{n} \sum_{i=1}^{n} x_i^2} \right) - exp\left(\frac{1}{n} \sum_{i=1}^{n} cos(2\pi x_i) \right) + 20 + e * R(x)$	10	[-32, 32]	0

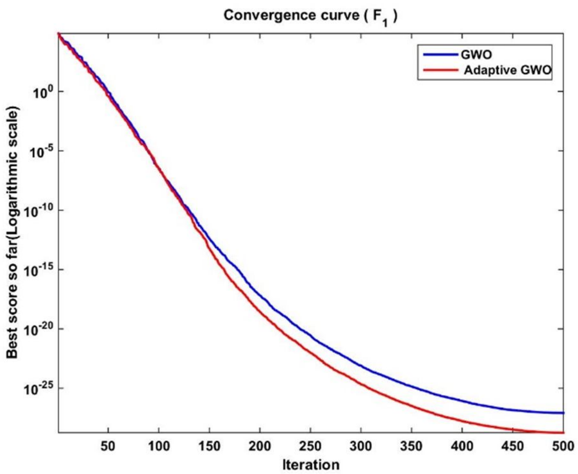
F11	Griewank Function	$F(x)=\frac{1}{4000}\sum_{i=1}^{n}x_i^2-\prod_{i=1}^{n}\cos\left(\frac{x_i}{\sqrt{i}}\right)+1*R(x)$	10	[-600, 600]	0
F12	Penalty 1	$F(x)=\frac{\pi}{n}\left\{\begin{array}{l}10\sin(\pi y_1)+\sum_{i=1}^{n-1}(y_i-1)^2\\ \left[1+10\sin^2(\pi y_{i+1})\right]+(y_n-1)^2\end{array}\right\}$ $y_i=1+\frac{x_i+1}{4},$ $u(x_i,a,k,m)=\begin{cases}k(x_i-a)^m & x_i>a\\ 0 & -a<x_i<a\\ k(-x_i-a)^m & x_i<-a\end{cases}$	10	[-50, 50]	0
F13	Penalty 2	$F(x)=0.1\left\{\begin{array}{l}\sin^2(3\pi x_1)+\sum_{i=1}^{n}(x_i-1)^2\\ \left[1+\sin^2(3\pi x_i+1)\right]\\ +(x_n-1)^2\left[1+\sin^2(2\pi x_n)\right]\end{array}\right\}$ $+\sum_{i=1}^{n}u(x_i,5,100,4)*R(x)$	10	[-50, 50]	0
F14	De Joung (Shekel's Foxholes)	$F(x)=\left(\frac{1}{500}+\sum_{j=1}^{25}\frac{1}{j+\sum_{i=1}^{2}\left(x_i-a_{ij}\right)^6}\right)^{-1}$	2	[-65.536, 65.536]	1
F15	Kowalik's Function	$f(x)=\sum_{i=1}^{11}a_i-\left[\frac{x_i\left(b_i^2+b_ix_2\right)}{b_i^2+b_ix_3+x_4}\right]^2$	4	[-5,5]	0.00030
F16	Shekel	$f(x)=-\sum_{i=1}^{10}\left[\left(X-a_i\right)\left(X-a_i\right)^T+c_i\right]^{-1}$	4	[0,10]	-10.5363
F17	Cube function	$f(x)=100(x_2-x_1^3)^2+(1-x_1)^2$	30	[-100, 100	0
F18	Matyas function	$f(x)=0.26(x_1^2+x_2^2)-0.48x_1x_2$	30	[-30, 30]	0
F19	Powell function	$f(x)=\sum_{i=1}^{D-2}\left\{\begin{array}{l}(x_{i-1}+10x_i)^2+5(x_{i+1}-x_{i+2})^2+\\ (x_i-2x_{i+1})^4+10(x_{i-1}-x_{i+2})^4\end{array}\right\}$	4	[-30, 30]	0
F20	Beale Function	$f(x)=\left\{\begin{array}{l}\left(1.5-x_1+x_1x_2\right)^2+\left(2.25-x_1+x_1x_2^2\right)^2\\ +\left(2.625-x_1+x_1x_2^3\right)^2\end{array}\right\}$	30	[-100, 100]	0
F21	levy13 function	$f(x)=\left\{\begin{array}{l}\sin^2(3\pi x_1)+(x_1-1)^2\left(1+\sin^2(3\pi x_2)\right)\\ +(x_2-1)^2\left(1+\sin^2(2\pi x_2)\right)\end{array}\right\}$	30	[-10, 10]	0

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.177
Volume 7 Issue XI, Nov 2019- Available at www.ijraset.com

Table 2: Internal Parameters

Parameter Name	Search Agents no.	Max. Iteration no.	No. of Evolution
F1-F21	30	500	20-30
Note:- Scale specified on axis, Not specified means axis are linear scale			

F1



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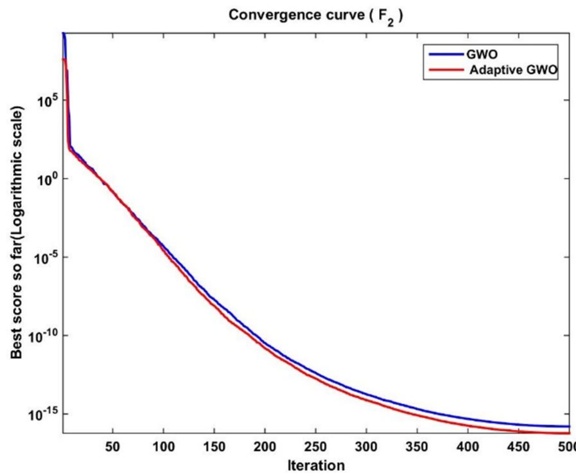
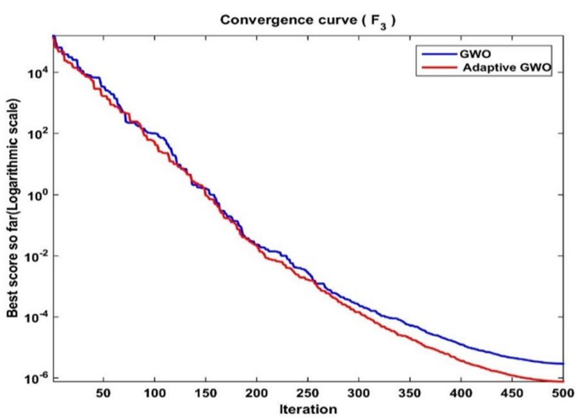
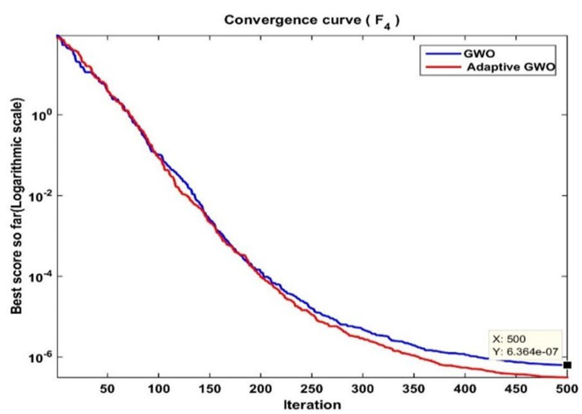


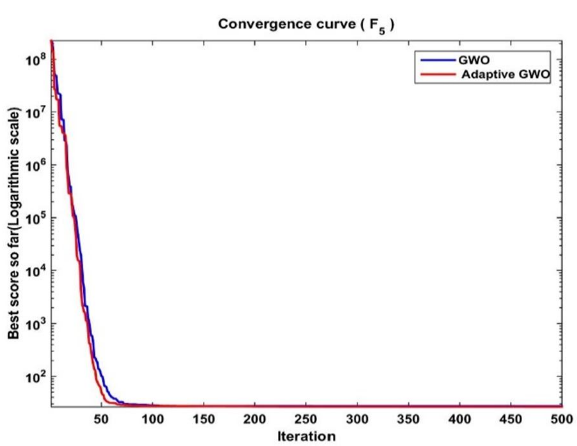
F3



F4



F5



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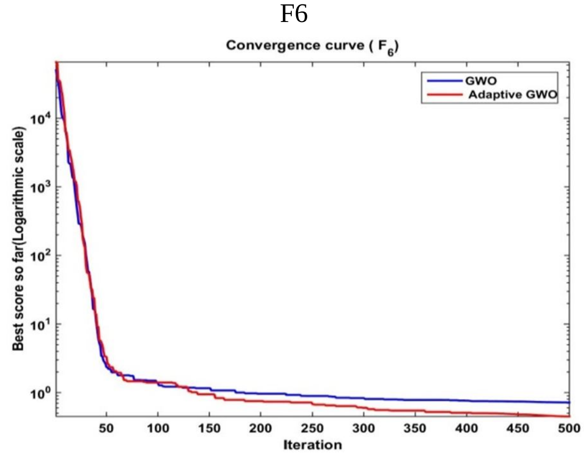

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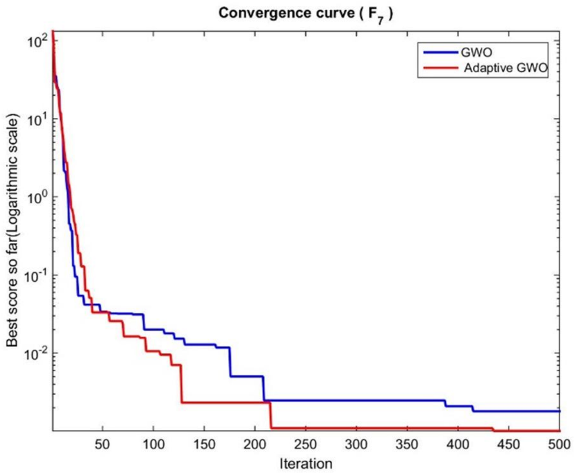
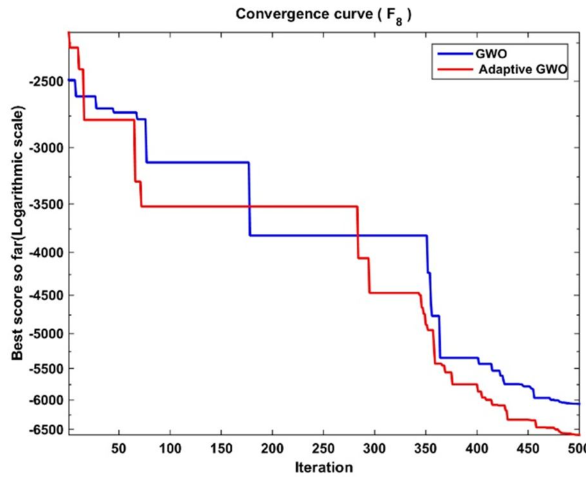
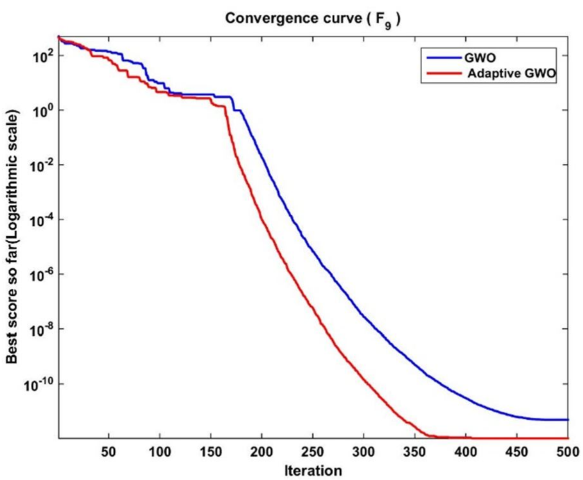


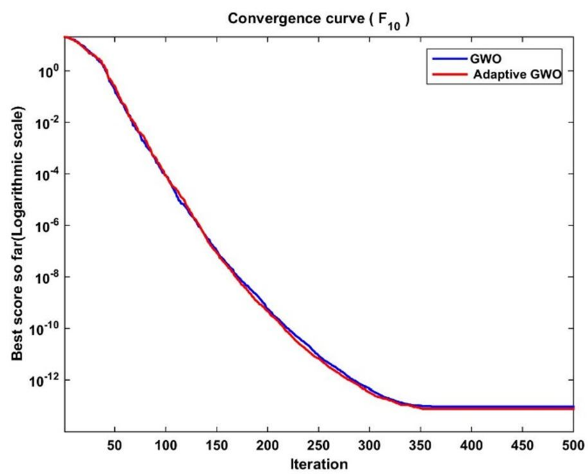
F8



F9



F10



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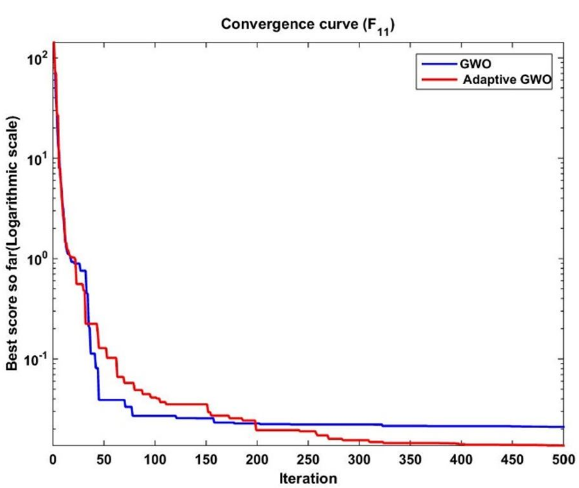

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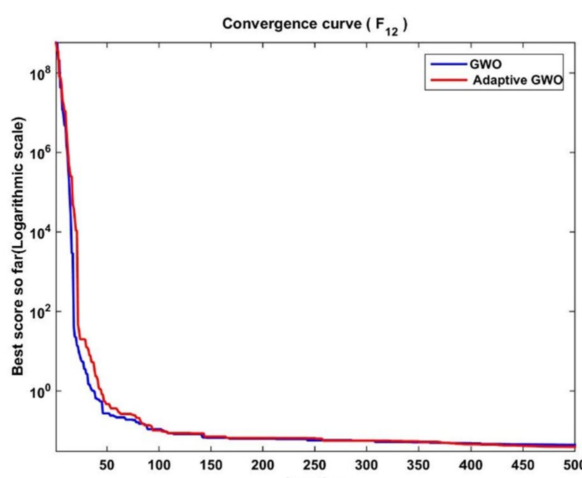

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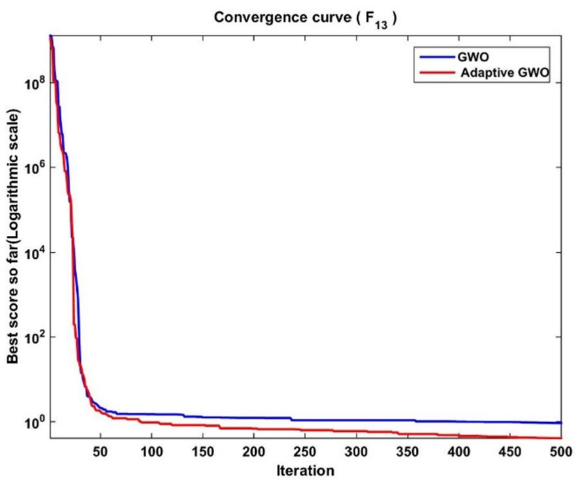

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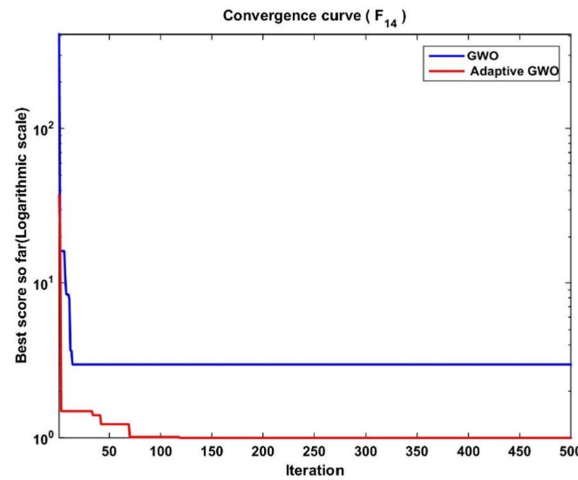

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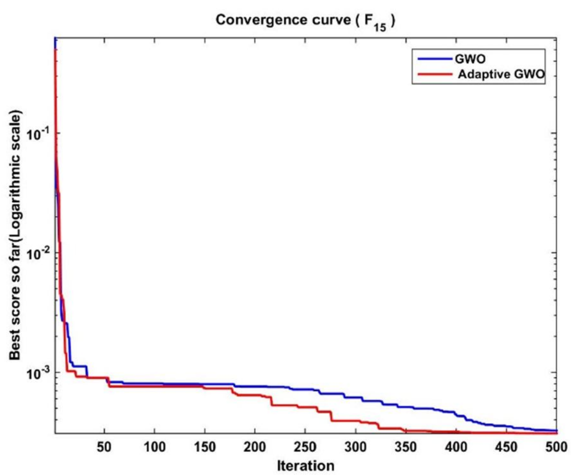

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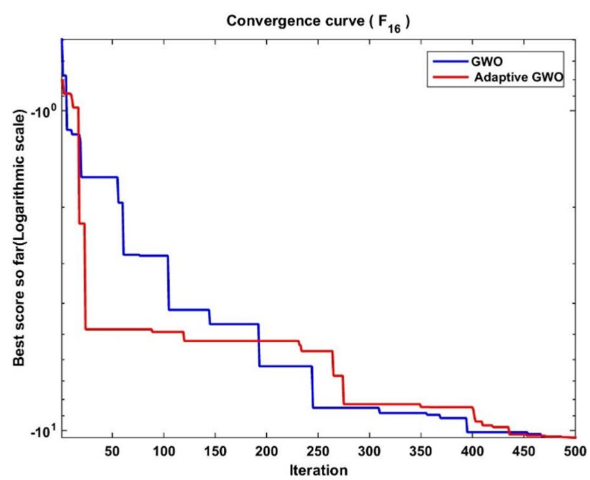

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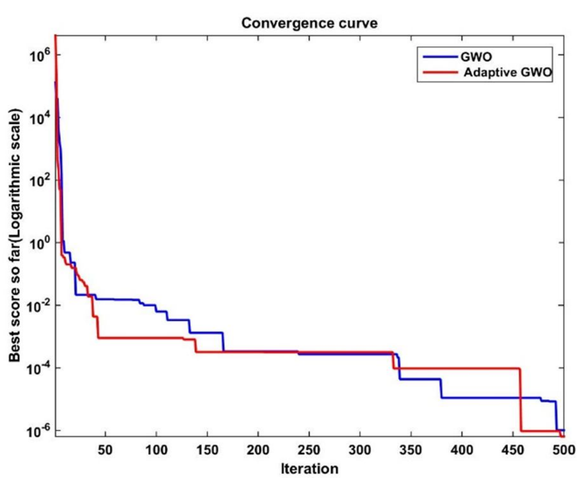

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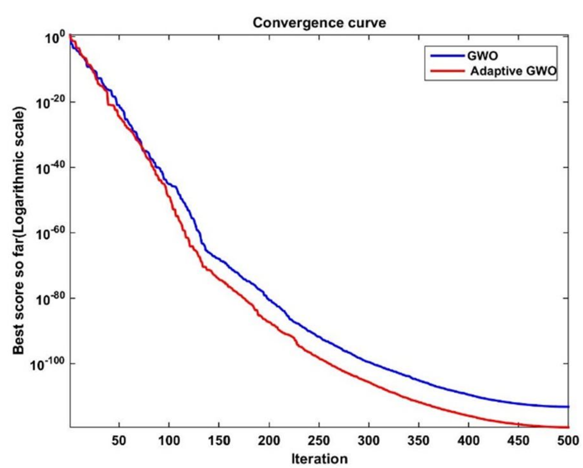

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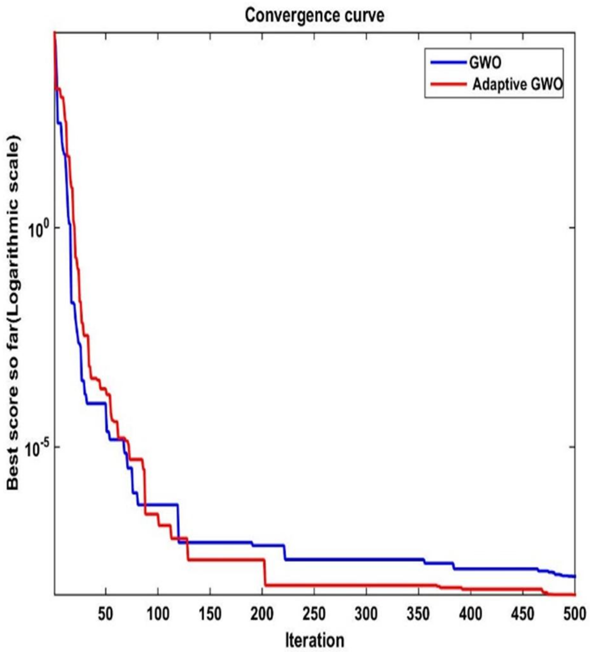

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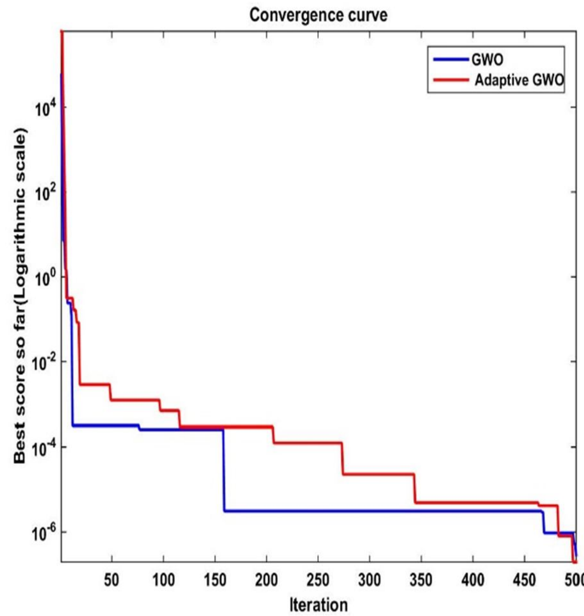

F21

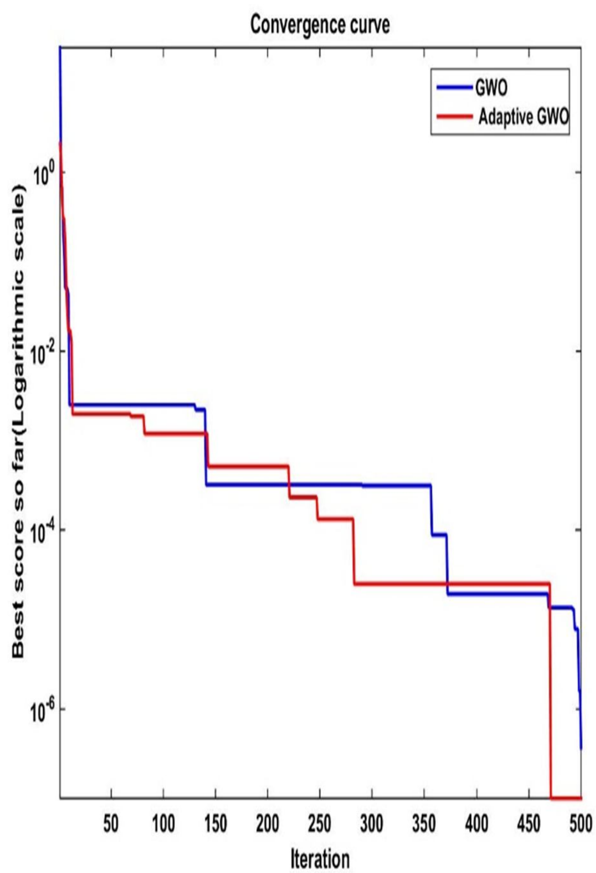

Fig. 5: Convergence Curve of Benchmark Test Function

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Volume 7 Issue XI, Nov 2019- Available at www.ijraset.com

Table 3: Result for benchmark functions

Fun.	Grey wolf optimizer (GWO)			Adaptive Grey wolf Optimizer (AGWO)		
	Ave	Best	S.D.	Ave	Best	S.D.
F1	1.181E-27	8.4259E-28	4.785E-28	1.6974E-28	1.8058E-29	2.1451E-28
F2	1.6891E-16	1.576E-16	1.5994E-17	8.0155E-17	5.8067E-17	3.1236E-17
F3	9.3408E-06	2.9251E-06	9.0731E-06	3.581E-05	7.5664E-07	4.9574E-05
F4	1.1029E-06	6.3635E-07	6.3635E-07	1.1013E-06	3.1456E-07	1.1126E-06
F5	27.1668	27.1574	0.013245	27.1064	26.2695	1.1836
F6	0.98986	0.71907	0.38295	0.73301	0.44929	0.40123
F7	0.0024822	0.0018047	0.00095814	0.0011139	0.0010094	0.00014787
F8	-6000.4501	-6063.1864	88.7226	-6112.1627	-6603.6221	695.0286
F9	1.7569	4.8885E-12	2.4847	1.0923	1.0232E-12	1.5448
F10	1.0214E-13	9.6811E-14	7.5364E-15	8.9706E-14	7.9048E-14	1.5073E-14
F11	0.0509	0.021061	0.0422	0.015748	0.013732	0.0028504
F12	0.0701	0.043894	0.037062	0.044573	0.039188	0.0076156
F13	1.0382	0.92549	0.15943	0.73517	0.40537	0.46641
F14	6.8726	2.9821	5.5021	0.998	0.998	1.4588E-10
F15	0.010344	0.00032534	0.014169	0.00038262	0.00030822	0.00010522
F16	-10.5345	-10.5351	0.00092324	-10.535	-10.5357	0.00093196
F17	1.361E-06	1.0252E-06	4.7483E-07	6.972E-07	6.4705E-07	7.0913E-08
F18	8.6499E-104	6.808E-114	1.2233E-103	2.0827E-104	3.5435E-120	2.9453E-104
F19	3.8146E-08	1.1174E-08	3.8145E-08	6.199E-09	4.2344E-09	2.7783E-09
F20	6.0394E-07	2.8958E-07	4.4458E-07	2.0745E-07	1.9532E-07	1.716E-08
F21	5.6947E-07	3.726E-07	2.7842E-07	6.5165E-07	1.0084E-07	7.7896E-07

V. CONCLUSION

Grey Wolf Optimizer have 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. Randomization plays an important role in both exploration and exploitation. Adaptive technique causes faster convergence, randomness, and stochastic behavior for improving solutions. Adaptive technique also used for random walk in search space when no neighboring solution exits to converse towards optimal solution. The AGWO result of various unconstrained problems proves that it is also an effective method in solving challenging problems with unknown search space.

VI. ACKNOWLEDGMENT

The authors would also like to thank Professor Seyedali Mirjalili for his valuable comments and support.
http://www.alimirjalili.com/GWO.html.

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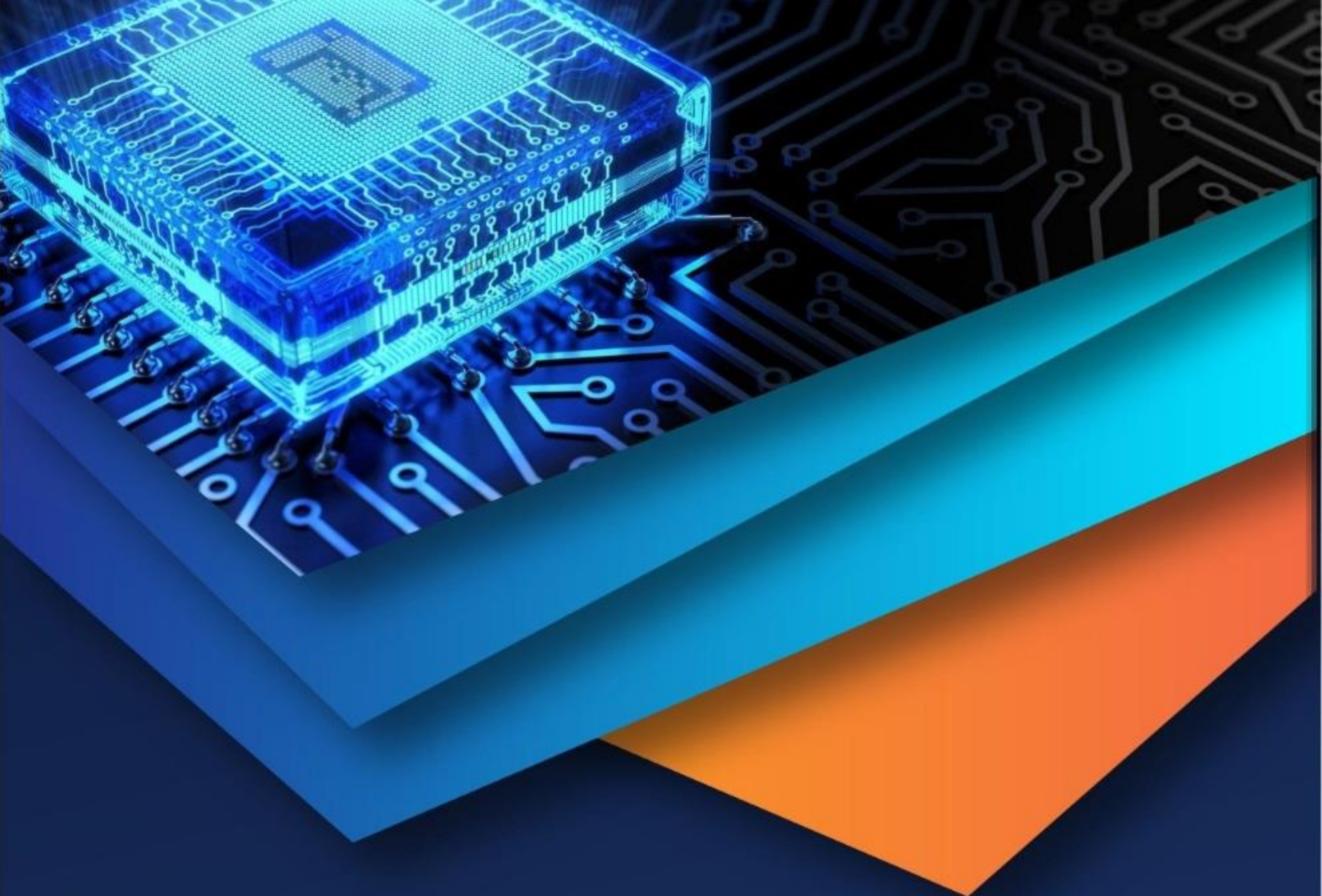

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