Modified Biogeography Based Optimization (MBBO)

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Abstract**—**Biogeography based optimization is most familiar meta-heuristic optimization technique based on biogeography concept. In BBO, a solution of any problem is the habitat and the features of that habitat are suitability index variable (SIV). The SIV values are used by transition operators (migration and mutation).In this paper, we proposed modified BBO (MBBO) which improves the transition operators by introducing exponential average of best solutions. We applied MBBO and some other optimization algorithms (such as BBO, Blended BBO, GA and PSO) on 19 benchmark functions to demonstrate the performance. The proposed MBBO shows outperform on most of the functions.

Keywords**—***optimization; BBO; migration; mutation;*

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I. Introduction

Optimization problems are the problem of finding the best solution from all feasible solutions. Various disciplines like science, engineering, academia and industry have full of optimization problems. Vehicle routing, crew scheduling, delivery route planning are just few examples of combinatorial optimization problems.

In most combinatorial optimization problems there is more than one local solution. However, evaluating each solution in order to find a globally optimal solution is not feasible due to exponential growth of most solution spaces. In case of a large search space and high complexity of optimization problem, use of conventional mathematics is not a good choice. Therefore there is a need of a good technique that will not have a greedy approach to select the best optimal solution which means balancing between local and global search is required.

To avoid this limit of local search technique, in the recent years many nature inspired algorithms have been developed. Two important classes of nature inspired algorithms are evolutionary algorithm and swarm intelligence based algorithm. Genetic Algorithm (GA), Differential Evolution Algorithm (DE) and Biogeography-based Optimization are the most popular and widely used evolutionary algorithm lies in this category [1].

In this paper, we focused on evolutionary based biogeography based optimization (BBO) algorithms. The solution generated in BBO based algorithm is known as habitat. Each habitat has assigned some fitness value that is Habitat Suitability Index (HSI). The goal is to achieve the most promising solution having high HSI that can be done by using migration and mutation transaction operators. When the immigration and emigration rate are equal, the equilibrium state is achieved. It improves the most familiar challenges faced by clustering (such as coverage, routing, localization, lifespan etc.)[2].

BBO uses elitism operator which means the best solution retains the part of next generation and not migrated at the time of migration process. The criterion of updating the position of habitat is done by swapping the SIV parameter of required habitat to efficient habitat. In other way we can say, to enhance the performance of one habitat we degrade the other one. There are some variant of migration (immigration refusal, blended migration and enhanced BBO) which increases the optimization technique of BBO algorithm.

According to standard migration technique, the high HSI value migrate their feature to increase the low value HSI of habitat but the immigration refusal firstly ensure that its own HSI value must not degrade after receiving the poor feature of habitat. If it is so, then the good quality habitat refused from migration. It shows the conditional migration of BBO.

In blended migration, the replacement is not done with existing one. The migration is done with the mixture of its immigration and emigration of its SIV value.

In enhanced BBO (EBBO) one operator is integrated that is clear duplicate operator. This operator improves the efficiency by deleting the duplicate solution and maintains the diversity of the search space [3].

All these variants focus on the migration process to achieve optimization but not maintain the multiplicity among them. They are not exploring in multidimensional way i.e. not assessed by several view point. To overcome this problem, we try to propose a new variant that concerns with migration as well as mutation to achieve better convergence speed and the diversity with-in habitats.

The rest of paper is structured as follow: section 2 describes basic BBO, section 3 expressed the novel approach proposed in this paper. Our proposed algorithm is introduced in section 4, section 5 shows experimental results and overall conclusion is in section 6.

II. Biogepgraphic Based Optimization (BBO)

Biogeography based optimization is evolution algorithm developed for global optimization that helps in dynamic deployment problem of WSNs [8] and increases the coverage region of network. This algorithm is inspired by immigration and emigration of species between habitats. Here, each solution is habitat and the fitness value of each habitat is habitat suitability index (HSI). More the HSI value, more will be optimal the habitat.

There are some parameters that affect the HSI value. Some of these are vegetation, rainfall, temperature, security, snowfall etc. These all features are Suitability Index Variable (SIV). Hence HSI is dependent variable and SIV is self-regulating variable. Initially a random set is assigned to each habitat which includes initial ecosystem of habitat (Ị), transition function (ψ) and the termination criterion (T) is given as shown in Eq.1.

$$Solution\ for\ habbitat = (Ị, \psi, T) \qquad (1)$$

If the species doesn't show optimal value then that species must be modified. There are some parameters that modify the ecosystem from one generation to other. These parameters are transition functions. It includes migration rate, mutation rate, immigration rate, emigration rate and maximum species with in habitat [2].

A. *Migration*

In migration strategy of BBO, the single offspring can be produced by many parents. This probabilistic operator helps to modify the poor solution by replacing the poor quality parameter to high quality parameter. This improves the HSI value of the species. It deals with immigration rate (λ) and emigration rate (μ) which is described below.The equilibrium state is achieved when they both lies on same plane as shown in figure 1. Higher the HSI value of species, the emigration rate increases and immigration rate decreases [2].

1) Immigration Rate (λ): It helps to decide that which parameter of SIV is modified. Initially the immigration rate has its maximum value because the species can easily place in habitat. As the number of habitat increases, the immigration rate goes decreases because of lack in resources.

$$\lambda = I\left(1 - \frac{k}{n}\right) \qquad (2)$$

Here, I is maximum possible immigration rate, 'k' is number of species of individual and ''n' is total number of species.

2) Emigration Rate (μ): After that the emigration rate (μ) of the other habitat decides which habitat share that selected SIV. When there is no space left with in habitat then the non-elite habitat moves in random manner which creates the diversity. It is done by replacing the low quality parameter with higher quality so that the optimum solution is achieved. Initially the emigration rate is low as there is no need of diversification but as the species increases, the rate also increases. It reaches its maximum value when there is maximum habitat in the search space.

$$\mu = \frac{E * K}{S_{max}} \qquad (3)$$

Here, E is maximum possible emigration rate, K is no. of species present in habitat and S_{max} is the maximum no. of species can presentwith in habitat.

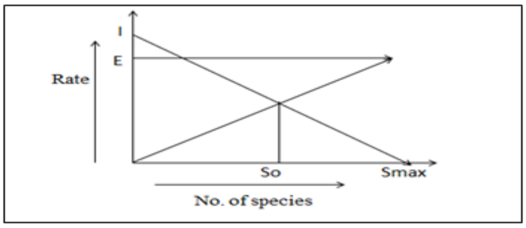

Fig 1: Relation between immigration and emigration rate

B. *Probability of Species Count*

In this function, each species has assigned some probability which is named as probability of species count. It is because of the number of species varies in each iteration [2].

$$Ps(t + \Delta t) = P_s(t)(1 - \lambda_s \Delta t - \mu_s \Delta t) + P_{s-1}\lambda_{s-1}\Delta t + P_{s+1}\mu_{s+1}\Delta t \qquad (4)$$

Here the probability is summation of three cases. Initially there are 'S' species at time "$t + \Delta t$". The first part shows the probability when there is no modification done, second part shows the species gets immigrated and in last one the emigration of one species has done.

C. *Mutation*

At last on the basis of this probability, lower one gets muted and higher remains in habitat. When the probability is less than threshold then the species has mutated by some mutation factor (m). The mutation results drastic change in HSI value of the species.

$$m = m_{max}\left(\frac{1 - p_s}{p_{max}}\right) \qquad (5)$$

Here, m_{max} is maximum mutation parameter, p_s and p_{max} are migration rate for s species and maximum species. After the habitat goes through migration and mutation phase, HSI is again calculated and the best results become the part of population till the termination criterion is reached. This brief description clearly shows the relation between HSI, immigration rate and emigration rate. Higher the HSI value higher the μ and lower the λ [2].

There are so many variants of BBO but not completely optimize the mutation process. So we try to optimize the mutation as well as migration which are further described in next section.

III. Modified BBO

In proposed algorithm, there are two main phases of updating the position of habitat i.e. migration and mutation phase. We modified the updating position exponentially using Eq.7 and 8. Here, we update the position by evaluate the average of current position of habitat and electing parameters using roulette wheel selection. This increases the convergence speed and improves the migration and mutation process.

On the basis of these modifications, we propose the algorithm given below:

A. Migration

At the time of migration, the position of habitat is updated by the summation of SIV value of selected index and exponential increment of average value as represented in Eq.6.

$$Updated\ pos = exp(avg) + SIV(Selectindex, chromosome) \quad (6)$$

The average is evaluated by SIV parameters of current and the selected index habitat.

B. Mutation

The main role of mutation is to increase the diversification with in habitat. To achieve the desired output we increased the position exponentially as in Eq. 7.

$$m = \exp(rand) * m_{max} + rand * \left(\frac{1 - p_s}{p_{max}}\right) \quad (7)$$

This result, no local stuck as well as enhance the diversity.

Algorithm : MBBO algorithm

Input: Initialize BBO parameters: Maximum species count (S_{max}), Maximum immigration rate (I), Maximum emigration rate (E), Mutation factor (m), Elitism parameters and the no. of genes in each population.
Output: Optimal solution must have maximum HSI value.

Initialize random set of habitat having potential solution for given solution as in BBO.

Evaluate the HSI, immigration rate (λ) and emigration rate (μ) for all the species.

While termination criterion is not satisfied **do**

Evaluate the average of SIV parameters of current position and selected indexed parameter.

Modify the non-elite habitats with the help of migration criterion as in Eq.6.

Re-compute their HSI values.

Update the probability of species count(Ps).

Again fetch non-elite habitat (low P_S value) and compare their SIV parameters with mutation factor using Eq.7.

Re-compute their HSI value

End

IV. Experimental Results

The performance of proposed algorithm has been computed on 19 benchmark function. This algorithm is compared with some most common algorithms (GA, PSO) and the BBO with its variant (Blended BBO). The benchmark functions and the parameters we used are outlined in section V-A. The comparison of their performance has done in terms of mean value, best solution and standard deviation which are illustrated in section V-B. Section V-C depicts the comparative study of convergence rate.

A. Benchmark Functions

Table 1 outlined the 19 bench mark functions along with the description such as range of each function, best fitness value. All of them belong to uni-model or multi model class. The functions belong to uni-model class tests their convergence rate of global optimum value and multi-model functions tests the stuck in local optimum problem. In our paper, we compared PSO, GA, BBO, Blended BBO and proposed MBBO. For all these algorithms some parameters are set as standard which is represented in Table2.

Table 1: Benchmark functions

Function	Benchmark function	Range
F1(X)	Ackley Function	[-35,35]
F2(X)	Alpine Function	[-10,10]
F3(X)	Bartels Conn Function	[-500,500]
F4(X)	Beale Function	[-4.5,4.5]
F5(X)	Bohachevsky Function	[-100,100]
F6(X)	Camel3 Function	[-5,5]
F7(X)	Camel6 Function	[-5,5]
F8(X)	DeckkersAarts Function	[-20,20]
F9(X)	Griewank Function	[-600,600]
F10(X)	Penalty1 Function	[-50,50]
F11(X)	Penalty2 Function	[-50,50]
F12(X)	Quardic Function	[-10,10]
F13(X)	Rastrigin Function	[-5.12,5.12]
F14(X)	Rosenbrock Function	[-30,30]
F15(X)	Schwewefel2 Function	[-65.53,65.53]
F16(X)	Schwewefel3Function	[-10,10]
F17(X)	Schwewefel4 Function	[-100,100]
F18(X)	Sphere Function	[0,10]
F19(X)	Step Function	[-100,100]

Table 2: Parameters set in existing and proposed algorithms

	PSO	GA	BBO	Blended BBO	MBBO
Population size	50	50	50	50	50
No. of iteration	1000	1000	1000	1000	1000
Elitism Parameter	2	2	2	2	2
Mutation probability (%)	----	10	10	10	10
Crossover probability (%)	----	10	----	----	----
Number of variables	10	10	10	10	10
Immigration rate	-----	-----	1	1	1
Emigration rate	-----	------	1	1	1

B. Experimental Comparison

The results are depicted over 30 runs. The average value, best solution and the standard deviation of the considered algorithm are shown in Table3. It is clearly analyzed that the proposed algorithm outperforms from PSO and also from GA, BBO and Blended BBO on functions (F1, F2, F3, F5, F7, F9, F11, F13, F14, F15, F17 and F19) and functions (F4, F6, F12and F16) shows the similar results on considered algorithms in terms of achieving the best value and the mean value. There are some functions (F8, F10, and F18) which

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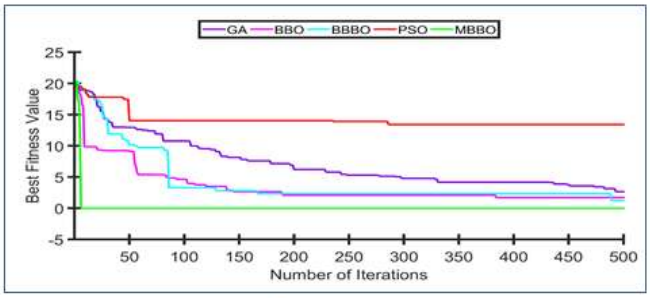
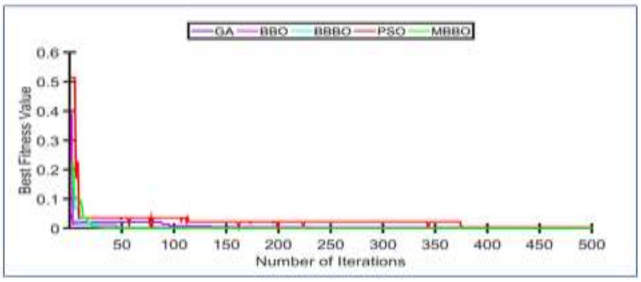
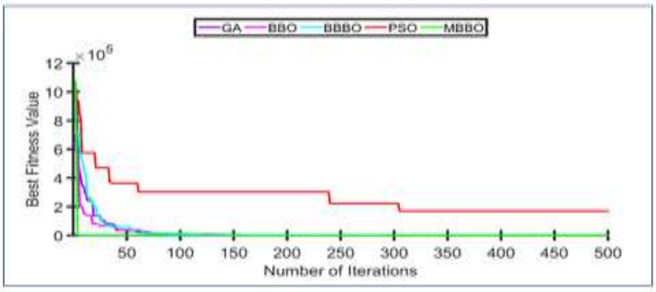
perform slightly better on other algorithms i.e. the optimal value is achieved by them and our MBBO is approximately near to best value.



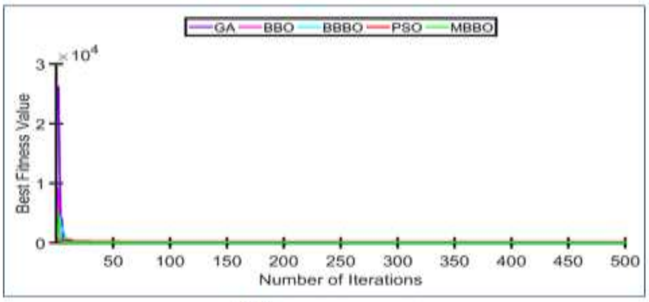
a) F_1



b) F_2



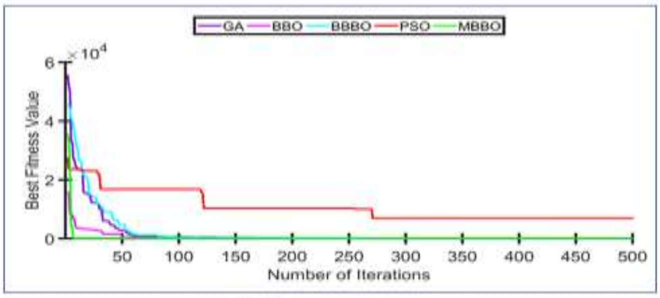
c) F_3



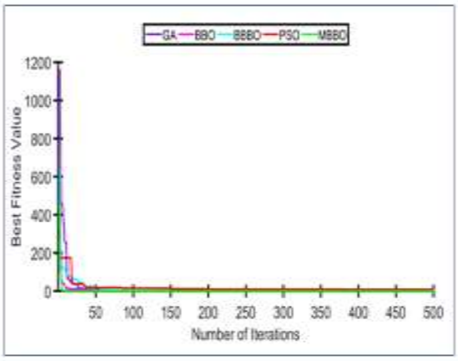
d) F_4

Table 3: Comparison of some parameters for 30 runs on benchmark functions

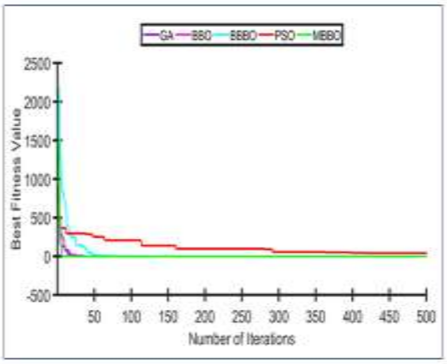
		PSO	GA	BBO	Blended BBO	MBBO
F1	Mean	12.86	1.64	0.467	0.47	**-8.9E-16**
	Best	7.319	**-8.9E-16**	**-8.9E-16**	**-8.9E-16**	**-8.9E-16**
	Std.	2.32	0.87	0.63	0.72	**0**
F2	Mean	0.016	9.23E-04	8.31E-04	1.80E-04	**7.74E-05**
	Best	**0**	4.04E-05	**0**	2.04E-06	**0**
	Std.	0.015	0.0008	0.0013	**0.0001**	0.0002
F3	Mean	2.00E+05	111.5838	134.22	93.86	**9**
	Best	58973.38	20.337	51.49	**9**	**9**
	Std.	61560.68	98.58	81.66	200.17	**0**
F4	Mean	190.72	**127.82**	**127.82**	**127.82**	**127.82**
	Best	150.38	**127.82**	**127.82**	**127.82**	**127.82**
	Std.	23.236	**0**	**0**	**0**	**0**
F5	Mean	9.17E+03	4.66	7.885	11.21	**0**
	Best	5496.91	1.05	1.05	**0**	**0**
	Std.	2964.91	3.703	4.634	19.73	**0**
F6	Mean	8.23	**0**	**0**	0.0015	**0**
	Best	2.95	**0**	**0**	**0**	**0**
	Std.	4.228	**0**	**0**	0.008	**0**
F7	Mean	41.86	-0.51	-0.75	-0.929	**-0.99**
	Best	3.41	-0.75	-0.75	-0.99	**-1**
	Std.	33.43	0.28	**0**	0.084	0.010
F8	Mean	8.73E+04	3.64E+04	3.59E+04	**3.41E+04**	4.42E+04
	Best	22711.47	5384.075	2585.514	**3007.275**	5884.588
	Std.	61843.9	36959.74	27873.05	**35597.14**	38726.9
F9	Mean	36.02	1.031	1.034	1.015	**1**
	Best	20.44	1.009	1.004	**1**	**1**
	Std.	11.84	0.013	0.030	0.026	**0**
F10	Mean	5.85E+05	**0.004**	**0.004**	0.1793	0.112
	Best	3940.07	**1.57E-32**	**1.57E-32**	0.0449	0.025
	Std.	871142.7	0.0196	**0.0192**	0.0123	0.063
F11	Mean	3.37E+06	1.19	1.256	1.514	**1**
	Best	290535.8	**1**	**1**	**1**	**1**
	Std.	3055560	0.23	0.29	1.579	**0**
F12	Mean	1.47E+03	**0**	**0**	0.008	**0**
	Best	104.197	**0**	**0**	**0**	**0**
	Std.	890.43	**0**	**0**	0.021	**0**
F13	Mean	24.6002	0.87	0.423	1.310	**0**
	Best	**0**	**0**	**0**	**0**	**0**
	Std.	13.19	0.84	0.54	0.98	**0**
F14	Mean	1.80E+06	10.08	14.41	83.049	**9**
	Best	213245.3	**9**	**9**	**9**	**9**
	Std.	1406309	5.93	12.31	226.49	**0**
F15	Mean	2.57E+04	5.55	8.669	3.095	**0**
	Best	10258.49	0	0.50	0	**0**
	Std.	8198.531	8.465	6.455	6.89	**0**
F16	Mean	7.2098	**0**	**0**	0.083	**0**
	Best	3.25	**0**	**0**	0	**0**
	Std.	2.56	**0**	**0**	0.172	**0**
F17	Mean	14.96	6.85	5.233	0.732	**0**
	Best	**0**	2.5	2	**0**	**0**
	Std.	5.82	3.34	2.85	1.022	**0**
F18	Mean	29.27	**0**	**0**	3.77E-08	3.1
	Best	14.03	**0**	**0**	1.83E-11	**0**
	Std.	10.18	**0**	**0**	4.62E-08	2.64
F19	Mean	3.74E+03	0.3	1.2	0.233	**0**
	Best	1644	**0**	**0**	**0**	**0**
	Std.	1539.64	0.65	1.39	0.817	**0**



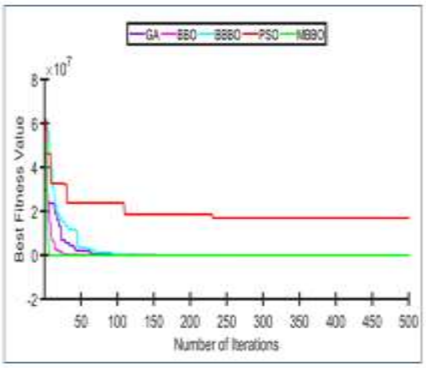
e) F_5



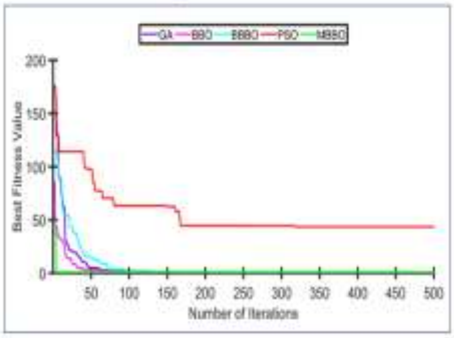
f) F_6



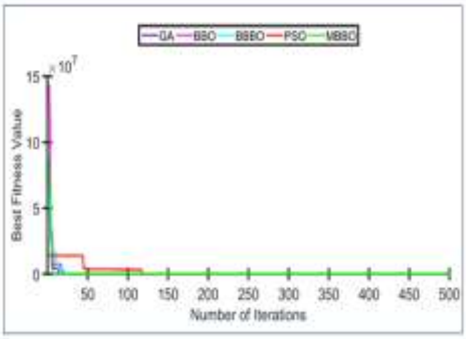
g) F_7



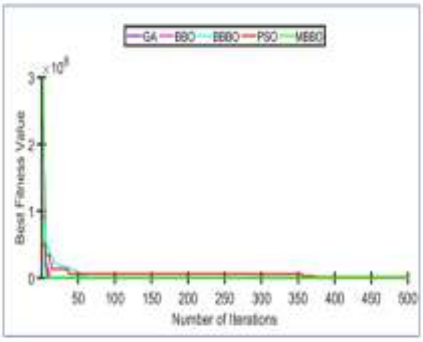
h) F_8



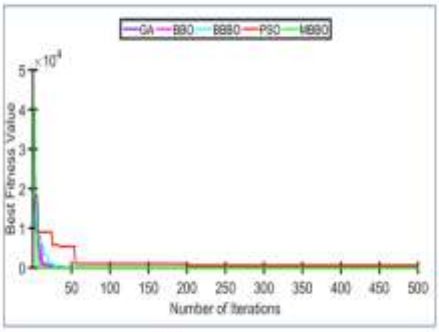
i) F_9



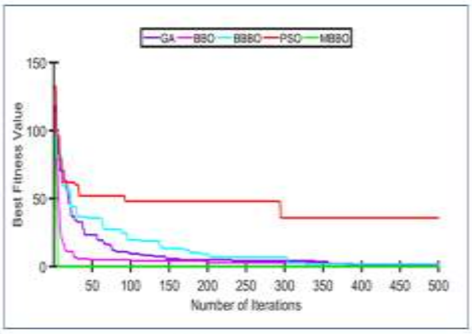
j) F10



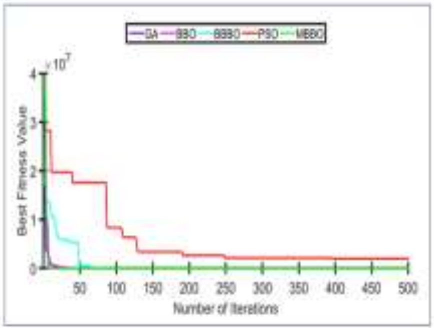
k) F_{11}



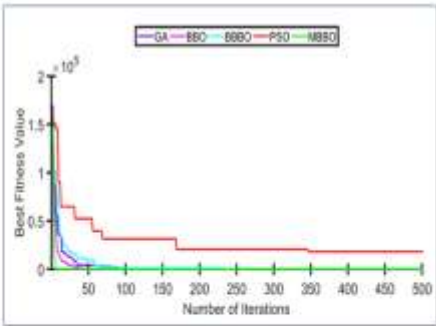
l) F_{12}



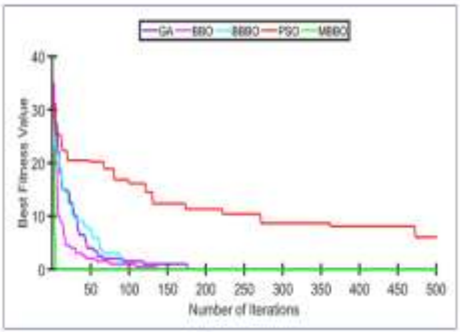
m) F_{13}



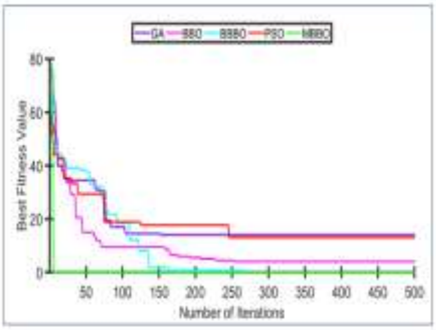
n) F_{14}



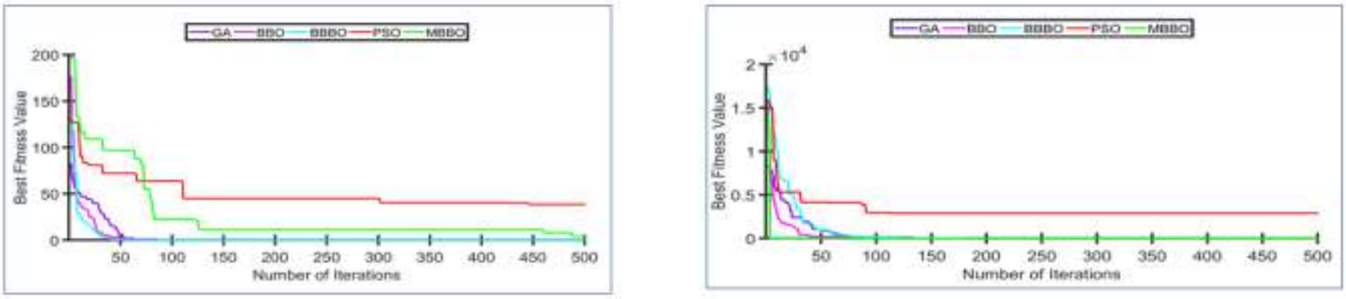
o) F_{15}



p) F_{16}



q) F_{17}



r) F_{18} s) F_{19}

Fig.2: Convergence graph of considered benchmark functions

C. Convergance Rate

The convergence graph shows the performance from the scratch to number of iterations. It concerns with the best solution till end. We evaluate the convergence rate of all the considered benchmark functions as shown in figure 2(a-s). The graph is plotted between the no. of iterations and the fitness value. The figure clearly illustrates the proposed MBBO is more efficient that other algorithms. Overlapping means the performance is similar in some functions.

V. CONCLUSION

In this paper, we proposed a novel approach "Modified BBO". We compared our optimization algorithm with some basic and advanced algorithms such as genetic algorithm (GA), particle swarm optimization (PSO), standard biogeography based optimization (BBO) and most common variant of BBO (Blended BBO) in terms of mean, standard deviation and best value. We applied all these algorithms on 19 bench mark function which shows the better results of proposed MBBO. We also evaluate the convergence rate of all the algorithms on each benchmark function to depict the impact of iterations and whose pictorial results shows the optimum results of our proposed algorithm.

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