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Study of Effect on Performance of DE/BBO on Changing Parametric Values

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Abstract

DE\BBO is the hybridization of Differential Evolution optimization and Biogeography Based Optimization. DE is considered to have good exploration ability and BBO is considered to have good exploitation ability, to achieve goodness of both techniques, these techniques have been combined. Hybridization of Differential evaluation and biogeography based optimization dominates the performance of biogeography based optimization. The influencing factors of performance of DE are scaling factor and cross-over rate which are used to track proper optimization. In this paper, it has been shown how DE/BBO outperforms BBO. The change in the performance of DE/BBO due to variation in some pre-considered variables has also been highlighted. It has been observed that DE/BBO performs best when scaling factor is 0.11 and cross over rate is 0.2.

Keywords: *Differential evaluation, Biogeography based optimization, mutation, migration*

1. Introduction

Differential Evolution [1] was proposed to index the global optimization. Before the introduction of Differential Evolution, various other optimization methods were used which did not include any objective function. DE made use of objective function to address the global optimization. In this, mutation, crossover and selection procedures are used where mutation is used to generate the new vector, crossover is used to pick the member of population that needs modification and selection is used to decide whether to include the modified member into population or not. Mutation refers to selection of three random members from population and generation of new vector as below:

New vector = First member + Scaling factor*(Second member – Third member*)*

Biogeography based optimization [5] was proposed by Dan Simon whose inspiration came from biological distribution of species in different geographical areas. Mathematical model of biogeography has been taken from the theory of island biogeography. These models show the behavior of organisms under various conditions. If the environment is suitable for living, then organisms will migrate to that particular environment otherwise they will emigrate to other environment or we can say other habitat or island. HSI (Habitat suitability index) determines the suitability of the habitat for being on that habitat. SIV (Suitability Index variables) characterize the habitability of particular habitat. The same concept can be applied to real life problems in any area like engineering, economics, medicine etc. If there is a problem then its solutions are considered as habitats. Solutions with high value of HSI are considered as good solutions whereas solutions with low value of HSI are considered as bad solutions. Solutions with high HSI do not accept features of other solutions so as to maintain its own goodness but solutions with low HSI accept the features of good solutions and are improved generation to generation. Immigration rate and emigration rate decides which solution will take features

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of other solution and which will give features to other solutions respectively. If number of species is low, then immigration rate is higher otherwise emigration rate is higher. Migration is done to share information between the various solutions. Note that HSI decides the goodness of a solution but SIV are integers of a vector which determines the population of each candidate solution. In migration, firstly SIV (that is to be modified) of a particular solution is selected on basis of immigration rate. Then, emigration rate of other solutions decide that which solution will give randomly selected SIV value to the selected solution which is to be modified. Hence bad solutions are modified. Mutation is done to maintain the solution's goodness to a particular level. According to probability, each solution is modified so that none of solution becomes the worse solution.

DE/BBO [8] concentrates on improving the searching capability of differential algorithm by using effectiveness of BBO. It is the combination of goodness of both algorithms that is mutation, crossover, selection operator of differential algorithm and migration operator of Biogeography based optimization which in turn generates very promising solutions. DE is famous for yielding faster and better solutions but problem occurs when the complexity of the problem, that is to be solved, increases. It is due to presence of crossover rate which tend to decrease the quality of solution at the end. There is no such problem in BBO. The proposed algorithm gives the better quality solutions while providing better robustness and convergence characteristics as compared to original BBO. Steps illustrating the hybridization of Differential Evolution and Biogeography Based Optimization are as given below:

Step 1: Initialization of population, other parameters of BBO such as immigration rate, emigration rate, Mutation probability etc. and calculation of cost of each member of population.

Step 2: Modify the population using hybrid migration operator.

Step 3: Calculate the cost of modified population with previous generation population. Keep the better.

Step 4: Repeat Step 2 and Step 3 till the last generation.

Remaining paper has been organized in various sections. Literature survey has been given in Section 2. Section 3 illustrates the concept of hybridization of DE and BBO. The results taken by running DE/BBO in MATLAB environment has been shown in section 4 and 5. Then the paper has been concluded with reflection of future work in section 6.

2. Related Work

Biogeography based optimization method [5] has been given by Dan Simon in 2008. This method has its roots in the natural way of distribution of species in geographical area. The idea of species migration from one habitat to another on the basis of suitability of that particular habitat has been utilized to improve the quality of solutions so as to get optimum solution. Original BBO has many deficiencies. To improve original BBO, many other versions of BBO have been introduced. In 2009, Oppositional BBO [6] has been introduced which focuses on improving the convergence speed by using only migration not mutation. In 2010, real coded BBO [7] has been introduced in which modified mutation operators are used to improve the performance of original BBO. In 2010, DE/BBO [8] has been introduced which provides better robustness and increased convergence speed. In 2012, Blended BBO [9] has been introduced which includes new way of changing the features of solution. In 2012, Multi-objective BBO [10] based on predator-prey approach has been introduced which focuses on increasing the capability of finding good solutions. In 2014, Hybrid BBO [11] has been introduced which includes the combination of various evolutionary algorithms with BBO. In 2014, Linearized BBO [12] has been introduced for highly non-separable problems.

Differential Evaluation optimization method [1] has been given by Storn R and Price K in 1995. In this, trial vector is generated from three vectors randomly selected from the population. Then crossover and selection are applied. The limitation of DE is premature convergence which has been improved by changing its mutation operator and introducing modified crossover processes. Various modified mutation schemes are DE\best\1, DE\target-to-best\t, DE\best\2, DE\rand\2 etc. Recent work on modification in mutation scheme has been found in 2012 and 2014 which focus on local search mutation [13]. This results in improvement of the performance of DE in various means like efficiency, quality of solution and robustness.

3. Concept of Hybridization of DE\BBO

Differential evaluation is considered to have good exploration ability which means searching of new individuals from the current individuals but when the problem size increases, the efficiency of DE decreases. The solutions which are good at initial step may get worst after the final step. To avoid this problem, DE mutation has been combined with migration of BBO which is known as hybrid DE/BBO approach [8] for optimization process. In the algorithm, F and CR the pre-considered variables known as scaling factor and cross-over rate respectively, value of F can vary from 0 to 2 and CR can vary from 0 to 1.

Algorithm describing the process of hybrid migration of DE/BBO [8] is as given below:

a. for G = 1 to GL // GL is generation limit.
b. for n= 1 to PS // PS is population size.
c. Randomly select three members so that $a_{1} \neq a_{2} \neq a_{3} \neq n$
d. q_{rand}= randi(1,m) // randi is used to choose random integer from given numbers.
e. for q=1 to m // m is population dimension.
f. if rand< λ_n // λ is immigration rate.
g. if $rand_q$>CR or q==q_{rand} // CR is crossover rate.
h. $J_n(q)= X_{a1}(q)+F(X_{a2}(q)- X_{a3}(q))$ // F is scaling factor.
i. else
j. Randomly select X_h with probability μ_h
k. $J_n(q) = X_h(q)$
l. end
m. else
n. $J_n(q) = X_n(q)$
o. end
p. end
q. end
r. end

In the above algorithm, CR and F are the constants used in differential evaluation optimization where CR is crossover rate varying from 0 to 1 and F is scaling factor varying from 0 to 2.

This algorithm describes the migration process which has been combined using the mutation of differential evaluation and migration of biogeography based optimization.

4. Fluctuation in Results by Varying F and CR values

The performance of DE/BBO has been studied by varying the scaling factor F from 0 to 2 and crossover factor CR from 0 to 1 on MATLAB software R2012b, 32 bit window 7 and RAM 3.00 GB. Scaling factor F is considered to be 0.2, 0.5, 0.8, 0.11, 0.14, 0.17, 2 and Crossover rate is considered to be 0.2, 0.4, 0.6, 0.8, and 1. The variation in the cost, percentage of minimization of cost and convergence speed examined by taking different values of F and CR has been pin pointed in Table 1, Table 2 and Table 3 respectively.

Running time of BBO is approximately 3.131 seconds. As observed from Table 3, CPU time for DE\BBO is less than BBO for F from 0.2 to 0.14 and CR = 0.2, 0.4. But when looking at the percentage of minimization, only few combinations of F and CR outperform BBO (Minimization percentage 97.12 approx.). These combinations are F= 0.11 and CR = 0.2, F = 0.2 and CR = 0.4, F = 0.11 and CR = 0.4. If both running time and percentage of minimization is to be taken into account then suitable combination is F= 0.11 and CR = 0.2.

Figure 1 shows convergence of DE\BBO algorithm at F= 0.2 and CR= 0.2, 0.4. In the same way, rest of Figurers from Figure 2 to Figure 6 shows convergence characteristics of DE\BBO for various combinations of F and CR.

Table 1. Maximum Cost and Minimum Cost For Different Values of F and CR

CR / F		0.2	0.4	0.6	0.8	1
0.2	Max Cost	2210.7483	2803.4806	4236.7899	4050.3128	4304.2406
	Min Cost	144.5644	71.0857	78.9915	59.7302	128.7639
0.5	Max Cost	3363.5122	2963.5488	4070.6872	4094.676	3600.1896
	Min Cost	959.1732	798.2002	151.2922	103.8729	132.211
0.8	Max Cost	3438.8241	3743.2242	3474.1933	2706.4322	3133.6853
	Min Cost	3173.241	1448.7841	798.9554	247.2559	130.3291
0.11	Max Cost	4583.9421	3546.9031	4450.7566	3489.6403	5196.9771
	Min Cost	111.9542	80.9988	78.7398	62.3844	187.6929
0.14	Max Cost	4266.4411	4169.8674	4477.6703	4513.2741	4569.1875
	Min Cost	187.774	122.4853	138.6704	111.025	153.5529
0.17	Max Cost	3004.1959	3259.9541	3094.2452	3867.0626	3072.932
	Min Cost	151.7914	131.5858	100.0615	87.9332	143.0761
2	Max Cost	2597.2421	4097.5729	2666.0819	2799.9188	2862.6699
	Min Cost	5860.831	3385.9158	4414.2317	1963.0557	164.2672

Table 2. CPU time Utilized in Seconds for Different Values of F and CR

CR / F	0.2	0.4	0.6	0.8	1
0.2	1.648	2.744	3.522	4.266	5.32
0.5	1.67	2.722	3.55	4.466	5.304
0.8	1.79	2.54	3.536	4.427	5.203
0.11	1.661	2.63	3.368	4.254	5.309
0.14	1.714	2.614	8.469	10.701	13.033
0.17	3.989	6.481	8.358	9.957	12.747
2	3.94	6.426	8.486	10.577	12.516

Table 3. Percentage of Minimization

CR / F	0.2	0.4	0.6	0.8	1
0.2	93.4608	97.4644	98.1356	98.5253	97.0084
0.5	71.4829	73.0661	96.2833	97.4632	96.3277
0.8	7.7231	61.2958	77.0031	90.8641	95.841
0.11	97.5576	97.7164	98.2309	98.2123	96.3884
0.14	95.5988	97.0626	96.9031	97.54	96.6394
0.17	94.9473	95.9636	96.7662	97.7260	95.3439
2	Cost does not minimized	17.3678	Cost does not minimized	29.8888	94.2617

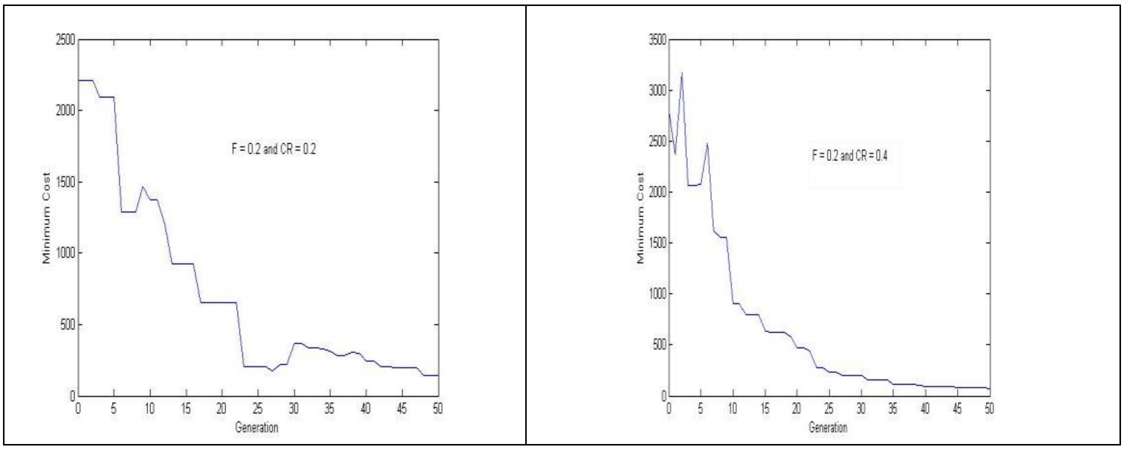

Figure 1. Graph Showing Minimum Cost For Each Generation for F = 0.2 and CR = 0.2, 0.4

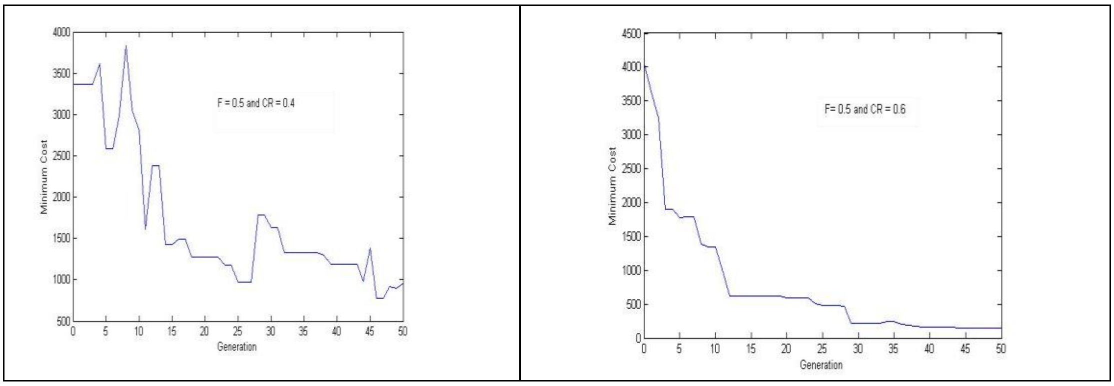

Figure 2. Graph Showing Minimum Cost For Each Generation for F = 0.5 and CR = 0.2, 0.6

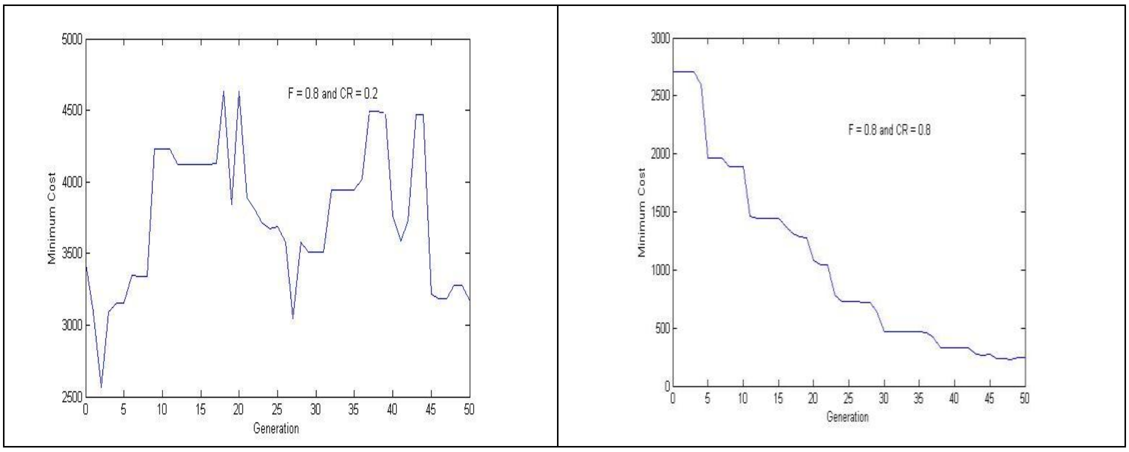

Figure 3. Graph Showing Minimum Cost For Each Generation for F = 0.8 and CR = 0.2, 0.8

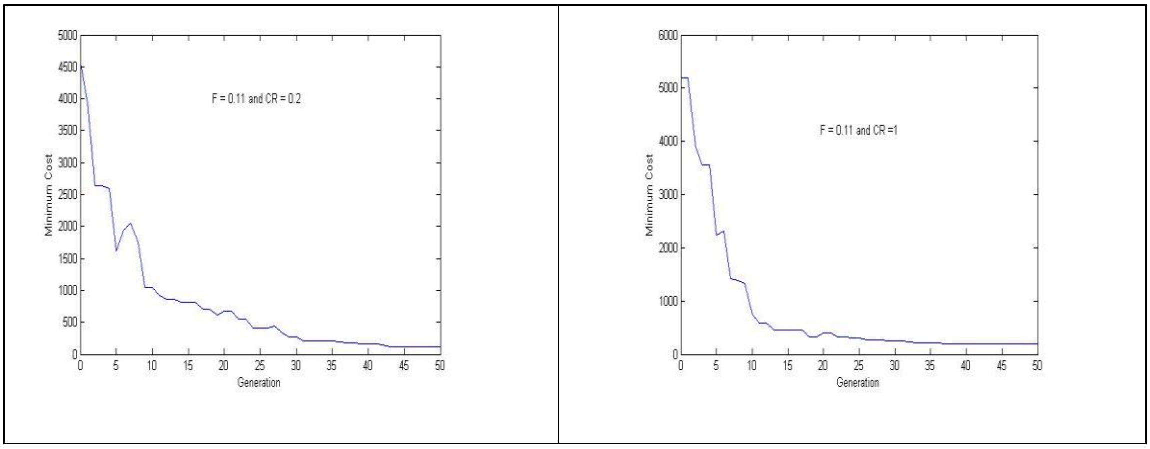

Figure 4. Graph Showing Minimum Cost For Each Generation for F = 0.11 and CR = 0.2, 1

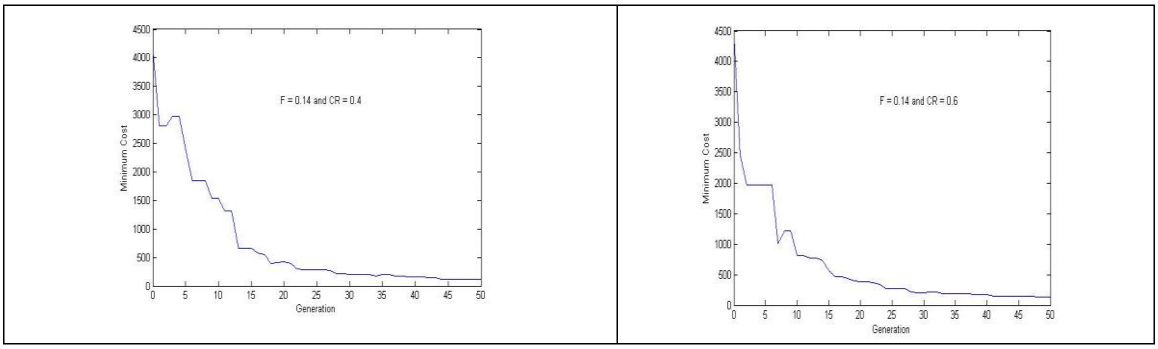

Figure 5. Graph Showing Minimum Cost For Each Generation for F = 0.14 and CR = 0.4, 0.6

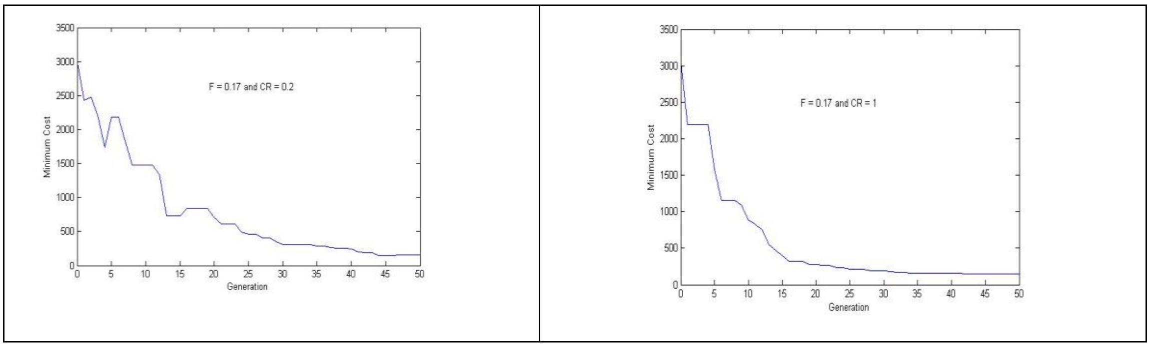

Figure 6. Graph Showing Minimum Cost For Each Generation for F = 0.17 and CR = 0.2, 1

5. Comparative Analysis of BBO and DE\BBO

When performance of BBO is compared with DE\BBO, it has been observed that DE\BBO performs better than BBO giving improvement in convergence speed. Figure 7 illustrates the performance of both algorithms.

BBO v/s DE/BBO(F = 0.11 and CR = 0.2)	
BBO with Convergence speed = 3.131s	DE/BBO with convergence speed = 1.661s

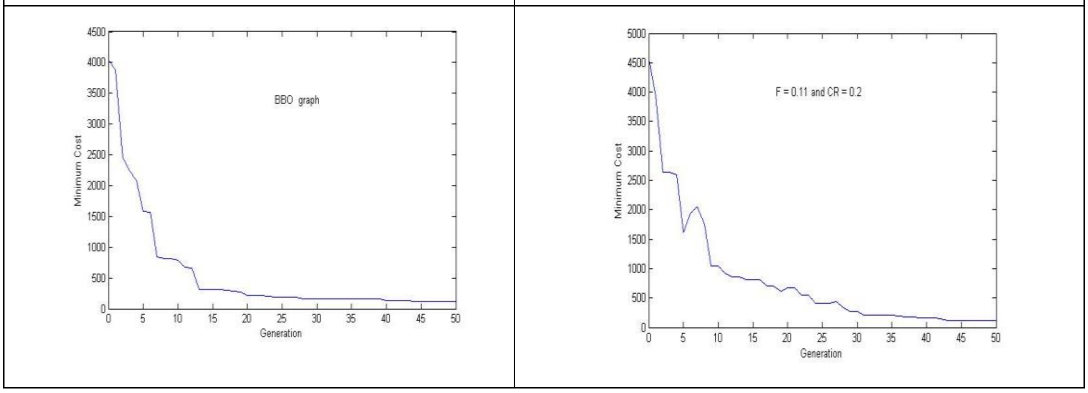

Figure 7. Graph Showing Convergence for BBO and DE\BBO

6. Conclusion and Future Scope

This paper is dedicated to evaluate the performance of DE\BBO by varying scaling factor and cross over rate. From the performance evaluation, it can be concluded that BBO takes more time to converge than DE\BBO. Performance of DE\BBO fluctuates very rapidly with increase in crossover rate. For scaling factor F = 0.2, convergence speeds are 1.648, 2.744, 3.522, 4.266, 5.32 seconds for corresponding crossover rate 0.2, 0.4, 0.6, 0.8 and 1 respectively. Figure 8 conforms to the conclusion of increase in convergence speed with increase in crossover rate.

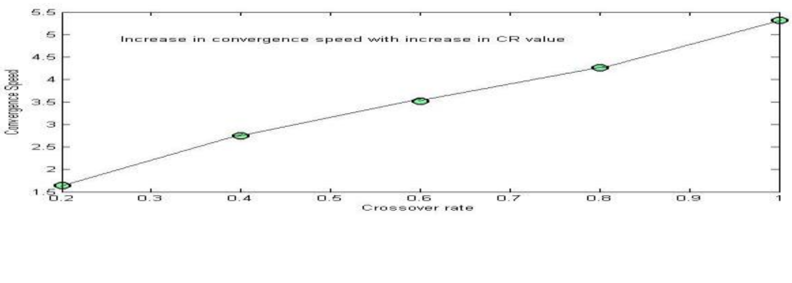

Figure 8. Illustration of Increase in Convergence Speed with Increase in Crossover Rate for F = 0.2

DE\BBO evaluated in this paper is based on simple mutation technique. But in the survey of differential evolution optimization, it has been noticed that there are many new mutation mechanism. In future, DE\BBO can be modified by using the recent mutation mechanism and corresponding performance can be evaluated.

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