A Modified Biogeography Based Optimization

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Abstract Biogeography based optimization (BBO) has recently gain interest of researchers due to its efficiency and existence of very few parameters. The BBO is inspired by geographical distribution of species within islands. However, BBO has shown its wide applicability to various engineering optimization problems, the original version of BBO sometimes does not perform up to the mark. Poor balance of exploration and exploitation is the reason behind it. Migration, mutation and elitism are three operators in BBO. Migration operator is responsible for the information sharing among candidate solutions (islands). In this way, the migration operator plays an important role for the design of an efficient BBO. This paper proposes a new migration operator in BBO. The so obtained BBO shows better diversified search process and hence finds solutions more accurately with high convergence rate. The BBO with new migration operator is tested over 20 test problems. Results are compared with that of original BBO and Blended BBO. The comparison which is based on efficiency, reliability and accuracy shows that proposed migration operator is competitive to the present one.

Keywords Biogeography based optimization · Blended BBO · Migration operator

1 Introduction

The process of inspiring from nature many evolutionary algorithms (EAs) [1] and swarm intelligence (SI) algorithms [7] have been developed. Genetic algorithm (GA) [4], Genetic programming [3], Evolutionary programming [21], Differential evolution(DE) [20] and Neuroevolution algorithms [10] are in the category of EAs. SI algorithms such as Particle swarm optimization (PSO) [14], Ant colony optimiza-

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tion (ACO) [5] , Artificial bee colony (ABC) [13] and Spider monkey optimization (SMO) [2] etc. have been developed. Biogeography based optimization (BBO) algorithm falls down in the category of evolutionary algorithms because of some similar properties as evolutionary algorithm such as mutation and sharing the information within candidate solutions, admittedly. The origin of BBO algorithm started in the 19^{th} century when the science of biogeography came in picture by Alfred Wallace and Charles Darwin. Then Robert Mac Arthur and Edward Wilson initiated work on biogeography theory and developed mathematical model of biogeography which stands for the mechanism, how species originate, how species dead and how species migrate among islands. Working process of BBO is motivated by this theory and improves the quality of solution by probabilistically sharing the information between population of candidate solutions. BBO has distinctive and effective capability to improve candidate solution using immigration rate (λ) and emigration rate (μ) of each island in all generations. These migration rates decide the immigrating habitat and emigrating habitat and responsible for updating solution by accepting information from promising solutions.

There are many developments in BBO algorithm by implementing and improving migration and mutation operators in original BBO algorithm. In [6] Du et al. proposed BBO with evolutionary strategy (ES) and immigration refusal (RE). In proposed BBO/ES/RE migration is based on immigration refusal and mutation is based on evolutionary strategy. In BBO/ES/RE immigrating island rejects the features from another islands which has low fitness than immigrating island and some threshold. In BBO/ES/RE, select only best n individuals among parent and child islands for next generation. In [17] Ma et al. proposed blended BBO. In blended BBO, migration operator combined the features of both immigrating and emigrating islands. In [19] Simon et al. proposed LBBO (linearized BBO) for improving solution of non seperable problems. LBBO combined with periodic re-initialization and local search operator and obtain algorithm for global optimization in a continuous search space. In [15] Lohakare et al. proposed a memetic BBO named as aBBOmDE, for improving convergence speed by modifying mutation operator and maintained exploitation by keeping original migration. In [12] Gong et al. proposed RCBBO (real coded BBO) in which each habitat was represented by real parameter. In RCBBO, to improving exploration ability and the diversity of population, some special mutation operators as gaussian mutation, cauchy mutation and levy mutation are incorporated into the habitat mutation. In [11] Gong et al. proposed a hybrid differential evolution with biogeography based optimization named as DE/BBO. In proposed algorithm exploration of DE combined with exploitation of BBO, generated the effective solution. In [16] Ma et al. presented BBMO for handling multiple objective with the help of BBO. In proposed algorithm, problem decomposed into sub problems and applied parallel BBO algorithm for optimizing each sub problems.

In this paper we introduced a modified migration operator. This operator is able to use the four individuals' information intelligently in essential step. This operator is modified for diversified search in promising area of search space. It can not be rejected that poor solution has good feature in some dimension as well as good solutions has possibility for bad feature in some dimension. In this way, poor solution may responsible for promising result. In basic migration operator of BBO and modified migration operator developed earlier can not make the best use of the search experiences. Therefore, acceptance of information for immigrating island from other candidate solutions is the important task. In this paper, modified migration operator is given for utilizing the best information of candidate solutions. The target of this paper is to enhance the performance of BBO by modifying migration operator in BBO algorithm. This paper is organized as follows: In section 2, description of BBO algorithm and its performance. In section 3, detail description to modified migration operator in BBO algorithm. In section 4, modified BBO is tested over 20 test problems. In section 5, paper is concluded.

2 Biogeography Based Optimization

An evolutionary algorithm, Biogeography based optimization(BBO) is recently developed by Dan Simon in 2008. BBO is inspired by geographical distribution of species within islands over period of time. The mathematical model of biogeography is based on speciation of species, extinction of species and migration of species within islands, but BBO is based on only the concept of migration of species within islands. So that speciation and extinction are not considered in BBO algorithm. In BBO, island represents the solution. The island which have large number of species corresponds to good solution and the island which have few number of species corresponds to bad solution. Good islands shares their features with bad islands. The features that characterize habitability are called SIVs (suitability index variables). SIVs are considered as independent variable. Island suitability index (ISI) represents the fitness. The island which is very friendly to life is said to have high island suitability index (ISI) and the island which is relatively less friendly to life is said to have low island suitability index (ISI) and the ISI can be considered as dependent variable. Low ISI island has high probability to accepts the new feature (good feature) from high ISI island. Emigration rate is decreases from high ISI to low ISI island so that highest ISI island has maximum emigration rate and immigration rate is increases from high ISI to low ISI island so that highest ISI island has minimum immigration rate. The immigration rate λ and emigration μ are calculated by two formulas.

$$\lambda_i = I\left(1 - \frac{k_i}{n}\right) \tag{1}$$

$$\mu_i = E\left(\frac{k_i}{n}\right) \tag{2}$$

λ_i stands for immigration rate of i^{th} individual (island).
μ_i stands for emigration rate of i^{th} individual (island).
I stands for maximum possible immigration rate.
E stands for maximum possible emigration rate.
n stands for maximum possible number of species that island can support.

K_i stands for fitness rank of i^{th} island after sorting fitness of i^{th} island, so that for worst solution K_i is taken as 1 and for best solution K_i is taken as n.
It suffices to assume a linear relationship between number of species and migration rate for many application point of view. The relation between migration rate (λ and μ) and number of species is illustrated in Fig. 1. If there is zero species in the island then immigration rate is maximum, denoted by I. If there are maximum number of species (S_{max}) in the island then emigration rate is maximum, denoted by E. There is an equilibrium state where immigration rate and emigration rate are equal. The equilibrium number of species in this state is denoted by S_0. The island referred as high ISI island if the number of species is above than S_0 and the island referred as low ISI island if the number of species is less than S_0. Migration and mutation are two crucial operators in BBO. The migration operator is same as the crossover operator of evolutionary algorithm. Migration operator is responsible for sharing the feature among candidate solutions for modifying fitness. Mutation occur by sudden changes in island due to random event and is responsible for maintaining the diversity of island in BBO process. Algorithm [1, 2, 3] describes the Pseudo code of migration operator, mutation operator and BBO respectively.

Algorithm 1. Migration operator

```
Population size ← n;
for i ← 1, n do
  Select the habitat H_i according to λ_i;
  if rand(0,1) < λ_i then
    for e ← 1, n do
      Select the habitat H_e according to μ_e;
      H_i(SIV) ← H_e(SIV)
    end for
  end if
end for
```

Algorithm 2. Mutation operator

```
Population size ← n;
for i ← 1, n do
  Select the habitat H_i according to probability P_i;
  if rand(0,1) < m_i then
    H_i(SIV) ← randomly generated SIV
  end if
end for
```

Algorithm 3. Biogeography-based optimization

Population size $\leftarrow n$;
Define migration probabllity, mutation probability and elitism size ;
Evaluate ISI (fitness) value of each individual (island) ;
while Stoping condition not satisfied **do**
  Sorting the population according best fitness to least fitness;
  Apply migration :
  Update the ISI value of each island ;
  Apply mutation ;
  Keep elitism in population ;
end while

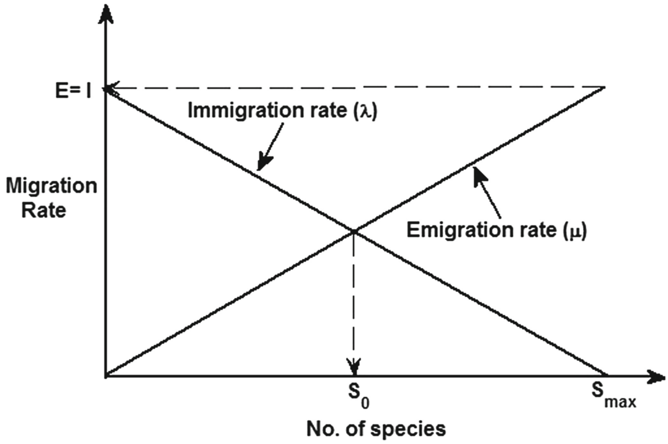

Fig. 1 Relation between number of species and migration rate Fig. from[18]

P_s is the probability when there are s species in the habitat is changes from t to (t+Δt) as follows:

$$P_s(t + \Delta t) = P_s(t)(1 - \lambda_s \Delta t - \mu_s \Delta t) + P_{s-1}\lambda_{s-1}\Delta t + P_{s+1}\mu_{s+1}\Delta t \qquad (3)$$

Where λ_s is immigration rate when there are s species in the habitat. μ_s is emigration rate when there are s species in the habitat.
At time t+Δt one of the following condition must hold for s species in the habitat.

1. If there were s species in the habitat at time t. Then no immigration and no emigration of species within time t and t+Δt.
2. If there were (s-1) species in the habitat at time t. Then one species immigrated within time t and t+Δt.
3. If there were (s+1) species in the habitat at time t. Then one species emigrated within time t and t+Δt.

For ignoring the probability of more than one immigration or emigration, we take Δt very small
Taking $\Delta t \longrightarrow 0$

$$\dot{P}_s = \begin{cases} -(\lambda_s + \mu_s)P_s + \mu_{s+1}P_{s+1}, & s = 0 \\ -(\lambda_s + \mu_s)P_s + \lambda_{s-1}P_{s-1} + \mu_{s+1}P_{s+1}, & 1 \leq s \leq s_{max} - 1 \\ -(\lambda_s + \mu_s)P_s + \lambda_{s-1}P_{s-1}, & s = s_{max} \end{cases} \tag{4}$$

3 Modified Migration in BBO

In biogeography based optimization process, migration operator plays a key role. The concept behind the migration operator is sharing the information within islands. Migration of solution feature within islands is motivated by the mathematical model of species migration in biogeography. Basic BBO algorithm suffers from lack of exploitation and stagnation at local minima. The possible way to enhance its exploitation capability is to improve the migration operator. Improved migration operator simultaneously adopts more information from other habitats and maintains population diversity as well as preserves exploitation ability and overcome stagnation at local minima. The immigrating habitat H_i and emigrating habitat H_j are selected according to the probability of immigration rate (λ_i) and probability of emigration rate (μ_i) respectively.
In basic BBO, migration process is taken as:

$$H_i(SIV) \leftarrow H_j(SIV) \tag{5}$$

In basic migration operator (5), immigrating island directly accepts the information from emigrating island only. In the modified migration operator, immigrating habitat accepts the information not only from emigrating habitat but also accepts the information from immigrating habitat, best habitat and random habitat (other than best habitat and immigration habitat). The working of new version of migration operator is given as:

$$H_i(SIV) \leftarrow \begin{cases} \frac{1}{G}(H_i(SIV)) + (1 - \frac{1}{G})(H_j(SIV)), & if\ G < G_{max} \\ \frac{1}{G}(H_r(SIV) - H_i(SIV)) + & \\ (1 - \frac{1}{G})(H_{best}(SIV) - H_j(SIV)), & if\ G = G_{max} \end{cases} \tag{6}$$

Where G is the generation index. The core idea of the proposed modified migration operator is based on three considerations. First one is that if the immigrating habitat is selected and generation index is not met maximum. Immigrating habitat accepts the information only from immigrating and emigrating habitat. It is important to use the information from other habitat in suitable ratio to improve the population diversity. Here immigrating habitat use less information from itself and more information from emigrating habitat with increasing number of generation index. Here $\frac{1}{G}$ is decreasing

Algorithm 4. Modified migration operator

Population size $\leftarrow n$;
Generation index $\leftarrow G$;
For the selected habitat $H_i(SIV)$
if rand(0,1) $< \lambda_i$ **then**
  Initialize generation index G=1;
  if G $\leftarrow$ 1 to $G_{max} - 1$ **then**
    Select the random habitat within population other than best habitat and running index habitat;
    Update the current solution as
    $H_i(SIV) \leftarrow \frac{1}{G}(H_r(SIV) - H_i(SIV)) + (1 - \frac{1}{G})(H_{best(SIV)} - H_j(SIV))$
  else
    Update the current solution as
    $H_i(SIV) \leftarrow \frac{1}{G}(H_i(SIV)) + (1 - \frac{1}{G})(H_j(SIV))$
  end if
else
  Update the current solution as $H_i(SIV) \leftarrow H_{best}(SIV)$
end if

function of G and 1-$\frac{1}{G}$ is increasing function of G. Second consideration is that if generation index is met maximum, then immigrating habitat uses information from first elite habitat, immigrating habitat, emigrating habitat and random habitat (except immigrating habitat and first elite habitat). Here immigrating habitat uses very less information from random habitat and immigrating habitat but uses relatively maximum information from first elite habitat and emigrating habitat. Third consideration is that if rand (0,1) $< \lambda_i$ is not met then immigrating habitat adopts the information of first elite habitat.

4 Numerical Experiments

In this section we compare modified BBO with other version of BBO algorithms and experiments performed on 20 unconstrained test problems. Parameters used in the algorithms are:
Maximum immigration rate:I=1
Maximum emigration rate :E=1
Mutation probability=0.01
Elitism size=2
Population size=50
Maximum no. of iteration=1000
No. of runs=100

Table 1 Test problems; TP: Test Problem, D: Dimensions, C: Characteristic, U: Unimodal, M: Multimodal, S: Separable, NS: Non-Separable, AE: Acceptable Error

TP	**Objective function**	**Search Range**	**Optimum Value**	**D**	C	**AE**
Alpine	$f_1(x) = \sum_{i=1}^{D} \mid (x_i sin(x_i) \mid +0.1x_i$	[-10,10]	f($\mathbf{0}$) = 0	30	M, S	1.0E-05
Axis parallel hyper ellipsoid	$f_2(x) = \sum_{i=1}^{D} ix_i^2$	[-5.12,5.12]	f($\mathbf{0}$) = 0	30	U, S	1.0E-05
Cosine mixture	$f_3(x) = \sum_{i=1}^{D} x_i^2 - 0.1 \sum_{i=1}^{D} \cos(5\pi x_i)$	[-1,1]	f($\mathbf{0}$) = -D*0.1	30	M, S	1.0E-05
De jong's f_4	$f_4(x) = \sum_{i=1}^{D} ix_i^4$	[-5.12,5.12]	f($\mathbf{0}$) = 0	30	U, S	1.0E-05
Exponential	$f_5(x) = -\exp\left(-0.5 \sum_{i=1}^{D} x_i^2\right)$	[-1,1]	f($\mathbf{0}$) = -1	30	M, NS	1.0E-05
Griewank	$f_6(x) = \sum_{i=1}^{D} \frac{x_i^2}{4000} - \prod_{i=1}^{D} \cos(\frac{x_i}{\sqrt{i}}) + 1$	[-600,600]	f($\mathbf{0}$) = 0	30	M, NS	1.0E-05
Rosenbrock	$f_7(x) = \sum_{i=1}^{D}[100(x_i^2 - x_{i+1})^2 + (x_i - 1)^2]$	[-2.048,2.048]	f($\mathbf{1}$) = 0	30	U, NS	1.0E-02
Salomon prob 3	$f_8(x) = 1 - \cos\left(2\pi\sqrt{\sum_{i=1}^{D} x_i^2}\right) + 0.1\sqrt{\sum_{i=1}^{D} x_i^2}$	[-100,100]	f($\mathbf{0}$) = 0	30	M, S	1.0E-01
Schwefel	$f_9(x) = -\sum_{i=1}^{D} x_i sin(\mid x_i \mid^{1/2})$	[-512,512]	$f(\pm[\pi(0.5+k)]^2)$ = -418.9829 * D	30	M, S	1.0E-05
Schwefel221	$f_{10}(x) = \max\mid x_i \mid, 1 \leq i \leq D$	[-100,100]	f($\mathbf{0}$) = 0	30	U, S	1.0E-05
Schwefel222	$f_{11}(x) = \sum_{i=1}^{D} \mid x_i \mid + \prod_{i=1}^{D} \mid x_i \mid$	[-10,10]	f($\mathbf{0}$) = 0	30	U, NS	1.0E-05
Sphere	$f_{12}(x) = \sum_{i=1}^{D} x_i^2$	[-5.12,5.12]	f($\mathbf{0}$) = 0	30	U, S	1.0E-05
Step function	$f_{13}(x) = \sum_{i=1}^{D} (\lfloor x_i + 0.5 \rfloor)^2$	[-100,100]	$f(-0.5 \leq x \leq 0.5) = 0$	30	U, S	1.0E-05
Michalewicz	$f_{14}(x) = -\sum_{i=1}^{D} sin(x_i)\left[\frac{sini(x_i)^2}{\pi}\right]^{20}$	[0,π]	f_{min} = 9.66015	10	M, S	1.0E-05
Zakharov's	$f_{15}(x) = \sum_{i=1}^{D} x_i^2 + \left(\sum_{i=1}^{D} \frac{i}{2} x_i\right)^2 + \left(\sum_{i=1}^{D} \frac{i}{2} x_i\right)^4$	[-5.12,5.12]	f($\mathbf{0}$) = 0	30	M, NS	1.0E-02
Cigar	$f_{16}(x) = x_0^2 + 100000 \sum_{i=1}^{D} x_i^2$	[-10,10]	f($\mathbf{0}$) = 0	30	U, S	1.0E-05
Brown 3	$f_{17}(x) = \sum_{i=1}^{D-1}\left[(x_i^2)^{(x_{i+1}^2+1)} + (x_{i+1}^2)^{(x_i^2+1)}\right]$	[-1,4]	f($\mathbf{0}$) = 0	30	U, NS	1.0E-05
Easom	$f_{18}(x) = -cosx_1 cosx_2 e^{((-(x_1-\pi)^2-(x_2-\pi)^2))}$	[-100,100]	$f(-\pi,\pi)$ = -1	2	U, N	1.0E-13
Ackley	$f_{19}(x) = -20\exp\left(-0.2\sqrt{\frac{1}{D}\sum_{i=1}^{D} x_i^2}\right) - \exp(\frac{1}{D}\sum_{i=1}^{D} \cos(2\pi x_i)) + 20 + e$	[-30,30]	f($\mathbf{0}$) = 0	30	M, NS	1.0E-05
Rastrigin	$f_{20}(x) = \sum_{i=1}^{D}[x_i^2 - 10\cos(2\pi x_i)] + 10D$	[-5.12,5.12]	f($\mathbf{0}$) = 0	30	M, S	1.0E-05

Table 1 represents the list of benchmark functions used in the experiments. In order to see the effect of proposed modified BBO process success rate (SR), mean generation index (MGenIndex), mean error (ME), standard deviation (SD) and minimum error (Min E) are reported in Table 2. Table 2 shows that proposed modified BBO (MBBO) outperforms in terms of reliability, efficiency and accuracy as compare to basic BBO, blended BBO (BBBO) and previously modified BBO (m1_BBO) given in [8]. The proposed algorithm MBBO is compared with BBO, BBBO and M1_BBO based on SR, MGenIndex, ME and SD. The comparison of algorithms are based on this sequence as SR, MGenIndex, ME than SD . Firstly all algorithms are compared according to SR, if it is difficult to distinguish than compare based on MGenIndex, if still comparison is not possible than compare according to ME. Finally, if find difficulty to compare than compare according to SD. From Table 2 it is clearly shown that according to success rate, MBBO outperforms among all considered algorithms for the functions (f_1, f_2, f_3, f_5, f_6, f_8, f_{11}, f_{12}, f_{13}, f_{15}, f_{17}, f_{18}, f_{20}). Further comparison for remaining function is not possible by success rate than comparison according to mean generation index, MBBO is good for function f_4 among all considered algorithms. Still comparison is not possible by mean generation index. Then according to mean error, MBBO outperforms for functions (f_7, f_9, f_{10}, f_{16}, f_{19}) among all considered algorithms. Then finally according to SD, MBBO performance is better for the function f_{14} among all considered algorithms. From the above comparison the proposed modified BBO algorithm (MBBO) outperforms the considered algorithms. It is clearly says that MBBO is cost effective. All function given in Table 1 are high dimensional and include unimodal, multimodal, separable, non separable with different optimum solution.

Table 2 Comparison of results of BBO , BBBO, M1_BBO and MBBO

Test problem	Algorithm	SR	MGenIndex	ME	SD	Min E
f_1	BBO	0	1000.00	3.4172E-02	7.4295E-03	2.3251E-02
	BBBO	0	1000.00	2.3055E-02	1.8532E-02	7.6838E-03
	M1_BBO	0	1000.00	1.7875E-02	9.3983E-03	5.5819E-03
	MBBO	64	1000.00	1.0952E-05	1.2781E-05	4.2636E-07
f_2	BBO	0	1000.00	1.5005E-01	6.2059E-02	4.1119E-02
	BBBO	0	1000.00	1.1160E-02	4.8538E-03	3.7219E-03
	M1_BBO	0	1000.00	3.2510E-03	1.3871E-03	9.6735E-04
	MBBO	100	719.97	8.9174E-06	1.3975E-06	1.3044E-06
f_3	BBO	0	1000.00	4.5212E-03	1.7002E-03	1.4823E-03
	BBBO	0	1000.00	4.4780E-04	2.3971E-04	9.0809E-05
	M1_BBO	0	1000.00	1.1105E-04	4.8881E-05	4.0523E-05
	MBBO	100	392.67	9.2256E-06	9.1214E-07	5.2037E-06
f_4	BBO	0	1000.00	3.0398E-04	2.3429E-04	1.1133E-05
	BBBO	78	901.51	1.1061E-05	7.5301E-06	2.6671E-06
	M1_BBO	100	703.40	8.9391E-06	1.1892E-06	3.9210E-06
	MBBO	100	419.86	9.2644E-06	1.0104E-06	3.9390E-06

Table 2 (*Continued*)

Test problem	Algorithm	SR	MGenIndex	ME	SD	Min E
f_5	BBO	0	1000.00	1.9318E-04	6.0680E-05	7.5146E-05
	BBBO	10	994.36	1.9646E-05	8.0968E-06	7.8973E-06
	M1_BBO	94	824.13	9.5943E-06	1.3308E-06	7.0683E-06
	MBBO	100	337.17	8.6550E-06	1.4708E-06	1.9623E-06
f_6	BBO	0	1000.00	1.0345E+00	2.0308E-02	9.5733E-01
	BBBO	0	1000.00	4.2443E-01	1.3223E-01	1.6039E-01
	M1_BBO	0	1000.00	1.6664E-01	6.1318E-02	4.6993E-02
	MBBO	77	998.34	8.7389E-05	4.3441E-04	4.5035E-08
f_7	BBO	0	1000.00	5.8374E+01	2.9611E+01	1.3392E+01
	BBBO	0	1000.00	2.7988E+01	2.1686E-01	2.7148E+01
	M1_BBO	0	1000.00	3.5730E+01	2.1227E+01	7.9407E+00
	MBBO	0	1000.00	2.6829E+01	2.7721E+00	1.2812E+01
f_8	BBO	0	1000.00	1.3140E+00	2.2226E-01	7.9994E-01
	BBBO	0	1000.00	6.2195E-01	8.3602E-02	3.9987E-01
	M1_BBO	0	1000.00	5.5688E-01	7.5555E-02	3.9987E-01
	MBBO	9	1000.00	2.7669E-01	2.3649E-01	3.0275E-02
f_9	BBO	0	1000.00	9.4633E+00	3.3807E+00	3.7806E+00
	BBBO	0	1000.00	3.2176E+02	1.1911E+02	1.0410E+02
	M1_BBO	0	1000.00	1.7118E+00	1.0323E+00	4.7631E-01
	MBBO	0	1000.00	1.5174E+00	1.6345E+00	4.1500E-03
f_{10}	BBO	0	1000.00	5.1713E+00	1.1149E+00	2.2578E+00
	BBBO	0	1000.00	1.3480E+00	2.2576E-01	7.6256E-01
	M1_BBO	0	1000.00	1.1732E+00	2.0218E-01	6.9738E-01
	MBBO	0	1000.00	9.4184E-01	1.4169E+00	2.5628E-02
f_{11}	BBO	0	1000.00	6.8226E-01	1.1697E-01	4.2116E-01
	BBBO	0	1000.00	1.6261E-01	3.7529E-02	8.1126E-02
	M1_BBO	0	1000.00	6.7395E-02	1.4251E-02	3.4737E-02
	MBBO	8	1000.00	1.0901E-04	9.7789E-05	3.6625E-06
f_{12}	BBO	0	1000.00	1.0887E-02	3.9542E-03	3.3969E-03
	BBBO	0	1000.00	1.0088E-03	4.5187E-04	3.2521E-04
	M1_BBO	0	1000.00	2.8587E-04	1.2832E-04	4.5832E-05
	MBBO	100	470.41	9.3789E-06	6.5679E-07	7.0421E-06
f_{13}	BBO	0	1000.00	4.3800E+00	1.8683E+00	1.0000E+00
	BBBO	54	910.06	5.9000E-01	7.7973E-01	0.0000E+00
	M1_BBO	92	644.76	8.0000E-02	2.7266E-01	0.0000E+00
	MBBO	99	983.56	1.0000E-02	1.0000E-01	0.0000E+00

Table 2 (*Continued*)

Test problem	Algorithm	SR	MGenIndex	ME	SD	Min E
f_{14}	BBO	0	1000.00	9.6601E+00	1.4342E-12	9.6601E+00
	BBBO	0	1000.00	9.6601E+00	4.2958E-12	9.6601E+00
	M1_BBO	0	1000.00	9.6601E+00	2.5619E-12	9.6601E+00
	MBBO	0	1000.00	9.6601E+00	9.6772E-13	9.6601E+00
f_{15}	BBO	0	1000.00	2.5698E+01	1.1451E+01	9.0935E+00
	BBBO	0	1000.00	4.6674E-01	1.7943E-01	1.9471E-01
	M1_BBO	0	1000.00	1.1357E+00	6.9909E-01	2.8541E-01
	MBBO	50	1000.00	6.0615E+00	1.5010E+01	2.5766E-05
f_{16}	BBO	0	1000.00	3.1193E+03	1.1982E+03	9.9760E+02
	BBBO	0	1000.00	2.6013E+02	1.2657E+02	6.7269E+01
	M1_BBO	0	1000.00	7.1825E+01	2.6809E+01	2.4157E+01
	MBBO	0	1000.00	2.3801E-03	2.2788E-03	1.7076E-05
f_{17}	BBO	0	1000.00	5.0369E-03	1.8759E-03	1.5551E-03
	BBBO	0	1000.00	8.0826E-02	2.9152E-02	2.7447E-02
	M1_BBO	0	1000.00	1.9267E-04	9.8574E-05	5.1375E-05
	MBBO	100	785.24	5.9497E-06	3.1751E-06	3.6920E-09
f_{18}	BBO	0	1000.00	6.1028E-01	4.8976E-01	9.0018E-06
	BBBO	0	1000.00	5.0165E-06	7.3606E-06	2.0052E-08
	M1_BBO	23	894.04	1.2787E-12	2.6254E-12	1.2212E-15
	MBBO	85	441.13	1.4999E-01	3.5884E-01	1.1102E-16
f_{19}	BBO	0	1000.00	8.6347E-01	1.9081E-01	4.8123E-01
	BBBO	0	1000.00	3.6781E-01	3.2400E-01	1.0799E-01
	M1_BBO	0	1000.00	7.2645E-02	2.0529E-02	3.8511E-02
	MBBO	0	1000.00	1.0587E-03	1.7407E-03	3.6592E-05
f_{20}	BBO	0	1000.00	1.4866E+00	5.2716E-01	6.3522E-01
	BBBO	0	1000.00	7.5405E+00	2.4895E+00	2.3855E+00
	M1_BBO	0	1000.00	6.8402E+00	2.1345E+00	2.0802E+00
	MBBO	95	993.51	4.3060E-06	5.3902E-06	1.2352E-08

5 Conclusion

This paper proposes a novel modified migration operator for better diversified search in promising area of search space. The proposed modified BBO (MBBO) uses the information from selected candidate solutions to find global optima more accurately with high convergence rate. To verify the performance of MBBO, 20 test problems with different characteristics are employed. Basic comparison with original BBO and other variant of BBO are conducted. In terms of efficiency, reliability and accuracy, the comparison results shows that MBBO outperforms the all considered algorithms.

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