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Participative Biogeography-Based Optimization

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Abstract

Biogeography-Based Optimization (BBO) has recently gained interest of researchers due to its simplicity in implementation, efficiency and existence of very few parameters. The BBO algorithm is a new type of optimization technique based on biogeography concept. This population-based algorithm uses the idea of the migration strategy of animals or other species for solving optimization problems. the original BBO sometimes has not resulted in desirable outcomes. Migration, mutation and elitism are three Principal operators in BBO. The migration operator plays an important role in sharing information among candidate habitats. This paper proposes a novel migration operator in Original BBO. The proposed BBO is named as PBBO and new migration operator is examined over 12 test problems. Also, results are compared with original BBO and others Meta-heuristic algorithms. Results show that PBBO outperforms over basic BBO and other considered variants of BBO.

***Keywords*:** Biogeography Based Optimization , Meta-heuristics, Migration operator, Evolutionary Algorithms

1. Introduction

Biogeography-Based Optimization is a Population-Based meta-heuristic algorithm that proposed for optimization problems introduced by (Simon, 2008). The BBO algorithm is based on the natural migration of species between habitats which the migration allows the information exchange between them. In each iteration, candidate solutions in the search space are moving toward better solutions, like Particle Swarm Optimization (PSO), i.e. The original population size does not change during the execution of the algorithm. Unlike GA, the poor solution with low fitness are not removed.

Therefore, in author’s view, BBO should not be regarded as an evolutionary algorithm. Also, it should be noted that in BBO, all the candidate solutions do not tend to cluster at a single point as in PSO. In this way, BBO process is significantly different from PSO also (Bansal, 2016).

There are many developments in BBO algorithm by implementing and improving migration and mutation operators in original BBO algorithm. In (Bansal, 2016). proposed a modified blended migration named as BBBO, Simultaneous application of proposed non-linear decreasing value of parameter α in blended migration operator and polynomial mutation create better balance in exploration and exploitation in BBO. In (Farswan et al., 2016) Proposed modified BBO named as MBBO, to improve migration operator. 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). In (Al-Roomi and El-Hawary, 2016) proposed a new hybridization between BBO and simulated annealing (SA) to enhance BBO performance. In the proposed algorithm, the inferior migrated islands will not be selected unless they pass the Metropolis criterion of SA and so the new algorithm is called MpBBO. In (Chen et al., 2016) proposed a covariance matrix based migration (CMM) to relieve BBO’s dependence upon the coordinate system so that BBO’s rotational invariance is enhanced. The proposed algorithm by embedding the CMM into BBO achieved a new BBO approach that called biogeography-based optimization with covariance matrix based migration(CMM-BBO). In (Guo et al, 2016) proposed three novel migration operators to enhance the exploration ability of BBO. In first, the uniform blended migration operator (UBMO) is proposed. In UBMO, the blended parameter $\tilde{\alpha} \in [0,1]$ is set as a random value. In the next, heuristic migration operator (HMO) and its uniform version named UHMO is proposed. In UHMO, only the solutions that are better than the emigrants can be considered as immigrants. And finally, Extended Migration Operator (EMO) is proposed. In (Feng, 2014) proposed improved migration operator named as IBBO, the proposed algorithm integrates the improved migration operator, a Gaussian operator, and the self-adaptive clear duplicate operator into BBO to improve population diversity and enhance exploration ability. In (Zheng et al.,2014) equipped BBO with local topologies, which limit that the migration can only occur within the neighborhood zone of each habitat. The proposed algorithm developed three versions of localized BBO algorithms, which use three different local topologies namely the ring topology, the square topology, and the random topology respectively. In this paper, we introduced a novel migration operator. This migration operator is able to use more than one good solution rather than one solution in original BBO to generate a new solution. In modified migration operator, candidate

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solutions can participate together to generate a new solution; in other hand, poor solution receive information from several candidate solutions which they have good features. In this way, poor solution filled with the shared information. The goal of proposed algorithm is to increase efficiency of basic BBO by modifying migration operator in BBO algorithm. The rest of the paper is organized as follows: in section 2,original Biogeography-Based Optimization is explained. In section 3, we show parameters studies of BBO algorithm for better performance. In section 4,a new BBO with modified Participative migration is proposed and analyzed. In section 5,PBBO is examined over 12 test problems. In section 6, the Performance evaluation of PBBO on the TSP described. and finally, in section 7,paper is concluded.

2. Biogeography - Based Optimization

biogeography- based optimization is a population based global optimization algorithm which is inspired by the natural migration of species within habitats. Excellent features of biological habitat cause species to migrate from one habitat to others. Here a habitat represents a candidate solution and habitat excellent features called Habitat Suitability Index (HSI). It is important to note that HSI is similar to fitness of an individual like in any meta-heuristic algorithm. Excellent properties of biological habitats depend on many parameters such as rainfall, area, temperature, humidity and so on. In BBO algorithm these properties are called Suitability Index Variables (SIV). In simple case, n-dimensional habitat formed from n SIVs and its fitness is denoted by HSI. In BBO, any solution improves based on the immigration and emigration of solution features within habitats. A high HSI habitat shares its good features with low HIS habitat and low HSI habitat accepts the new features of high HSI habitat.
According to the mechanism of BBO, good solutions have high probabilities to share their SIVs with other solutions and have a low probability to accept SIVs from other solutions. Meanwhile, poor solutions have low probabilities to share their SIVs with other solutions and have high probabilities to accept SIVs from other solutions. Emigration rate is decreases from high HSI to low HSI habitat so that highest HSI habitat has maximum emigration rate and immigration rate is increases from high HSI to low HSI habitat so that highest HSI habitat has minimum immigration rate. the immigration rate λ and emigration μ are calculated by two formulas (Farswan et al., 2016)
].

$$\lambda_i = I(1 - \frac{k_i}{n}) \quad (1)$$

$$\mu_i = E(\frac{k_i}{n}) \quad (2)$$

where λ_i and μ_i are the immigration rate and emigration rate for ith habitat, respectively, I and E are the maximum migration rate and maximum emigration rate, respectively, and N is the population size. $k_i$stands for fitness rank of i^{th} habitat after sorting fitness of i^{th} habitat,so that for worst solution $k_i$is taken as 1 and for best solution $k_i$is taken as n.

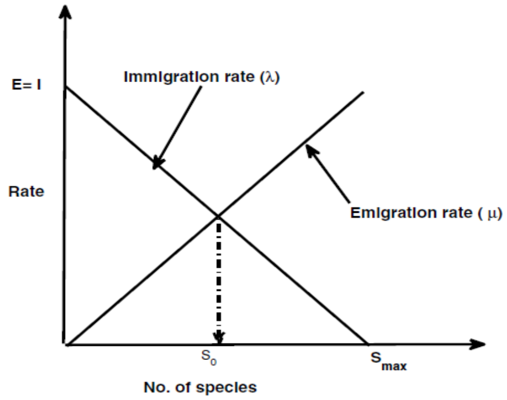

Fig.1. Relationship between number of species and migration rate Fig. from (Bansal, 2016)

Fig.1shows the relationships between the number of species ,$\boldsymbol{\lambda}$ and $\boldsymbol{\mu}$. Here S_0 is the equilibrium state of a habitat which is attained when the immigration rate and emigration rate are same. If number of species of a habitat is less than S_0 then the habitat is referred as low HSI habitat because they have high immigration and low emigration rate and if the number of species in a habitat is greater than S_0 then it is referred as high HIS habitat. More about immigration and emigration can be seen in (Bansal, 2016).
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 habitat due to random event and is responsible for maintaining the diversity of habitat in BBO process (Farswan et al., 2016).
$P_s$is the probability when there are s species in the habitat is changes from t to (t+Δt) as follows:

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

Where λ_s is immigration rate when there are s species in the habitat.$\mu_s$is emigration rate when there are s species in the habitat (Farswan et al., 2016).

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 Δt → 0

$$\dot{P}_S = \begin{cases} -(\lambda_S + \mu_S)P_S + \mu_{S+1}P_{S+1}, & S=0 \\ -(\lambda_S + \mu_S)P_S + \lambda_{S-1}P_{S-1} + \mu_{S+1}P_{S+1}, & 1 \le s \le S_{max} - 1 \\ -(\lambda_S + \mu_S)P_S + \lambda_{S-1}P_{S-1}, & S_{max} \end{cases} \quad (4)$$

Very high HSI solutions and very low HSI solutions are equally improbable. Medium HSI solutions are relatively probable [1]. The mutation rate m_i is expressed as:

$$m_i = m_{max}(1 - \frac{P_i}{P_{max}}) \quad (5)$$

wherem_{max} is a user defined maximum mutation probability,P_{max}= *Arg max Pi* ; *i* = 1,2, ...,population size.

The pseudo-code of migration operator is shown in algorithm 1, where $H_i$and $H_j$denote the *i*th habitat and the *j*th habitat, respectively, N is the maximum account of species and D is the dimension of a solution.

Algorithm. 1. Pseudo – Code of Migration Operator

Population size =n;
for i=1 to Population **do**
Select Habitat H_i According to λ_i;
if$H_i$is Selected,**if** rand (0,1) <λ_i **then**
for j=1 to D **do**
Select Habitat H_jAccording μ_i;
ifH_j is selected,**if** rand (0,1) <μ_i **then**
replace SIV H_i with Selected SIV from H_j;
end if
end for
end if
end for

Mutation is analogous to the sudden changes in the habitat. This operator is responsible to maintain the diversity in population during BBO process. Mutation randomly modifies habitat SIVs based on the habitat's a priori probability (Farswan et al., 2016). The pseudo-code of migration operator is shown in algorithm 2. Algorithm 3describes the pseudo-code of basic BBO.

Algorithm 2. Pseudo-Code of Mutation Operator

Population size =n;
for i=1 to Population **do**
Select Habitat H_i According to probabilityP_i;
if$H_i$is Selected,**if** rand (0,1) <m_i**then**
$H_i(SIV)$ ←randomly generated SIV;
end if
end for

Algorithm 3. Pseudo-Code of BBO Algorithm

Randomly initialize a Population of n Habitats H_i, i=1,…..,n;
Initialize Max Iteration;

while(termination criteria)**do**
Calculate Fitness(HSI) for each Habitat and sort Habitats according their HSI;
for i=1 to n**do**
Calculate λ and μ for each Habitat Based on HSI;
end for

/***Migration**
Select H_i with Probability based on λ_i ;
ifH_i is selected **then**
selectH_j with Probability based on μ_i ;
ifH_j is selected **then**
Randomly Select SIV from H_j;
Replace SIV in H_i with one from H_j ;
end if
end if

/* **Mutation**
Select H_i with Probability based on the Mutation rate;
if$H_i(SIV)$ is selected **then**
Perform Mutation;
end if
Evaluate the Fitness values of the Habitats;
Perform Elitism and Update the Best Solution;
end while
returnBest Solution;

3. Optimization Parameter Studies

It is important to examine the characteristics of the optimization method chosen for any particular problem, since one algorithm or one set of optimization algorithm parameters may be better suited for a given problem than others. This is a consequence of the no Free Lunch theorem, which states that all algorithms perform equally well on average when tested on the most general class of problems (Thomas et al. 2015). This motivates us to study the BBO parameters which are used for our modified migration of BBO algorithm.

3.1 BBO parameter studies

BBO algorithm for excellent performance should set its parameters. Different parameters have different answers, so better results can be achieved via the parameters studies. In this case, we consider population size impact and mutation probability impact, respectively.

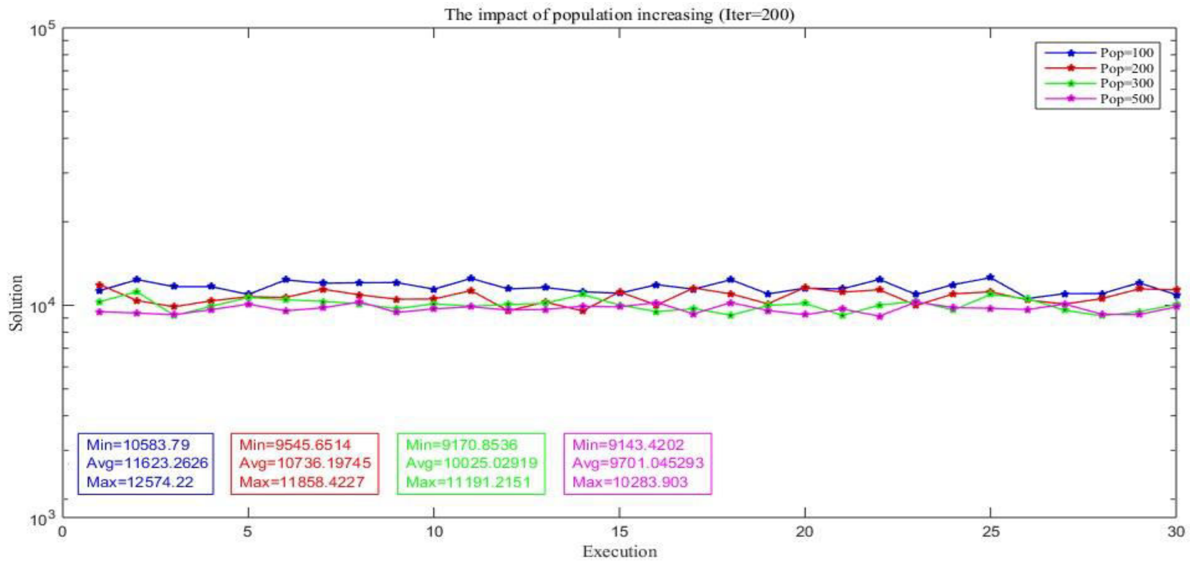

Fig. 2. Increasing the size of Population impact

3.1.1 Population size experiment

First, we examined population size by running algorithm over 50 times on an Arbitrary problem with different population size. Results show that a size of the population increases, algorithm performance improves and desirable results are achieved. This efficiency is due to the increasing population problem space becomes larger and increases its diversity. This population increase also has negative consequences such as increased time complexity of algorithm. Fig (2,3). Show the population size impact.

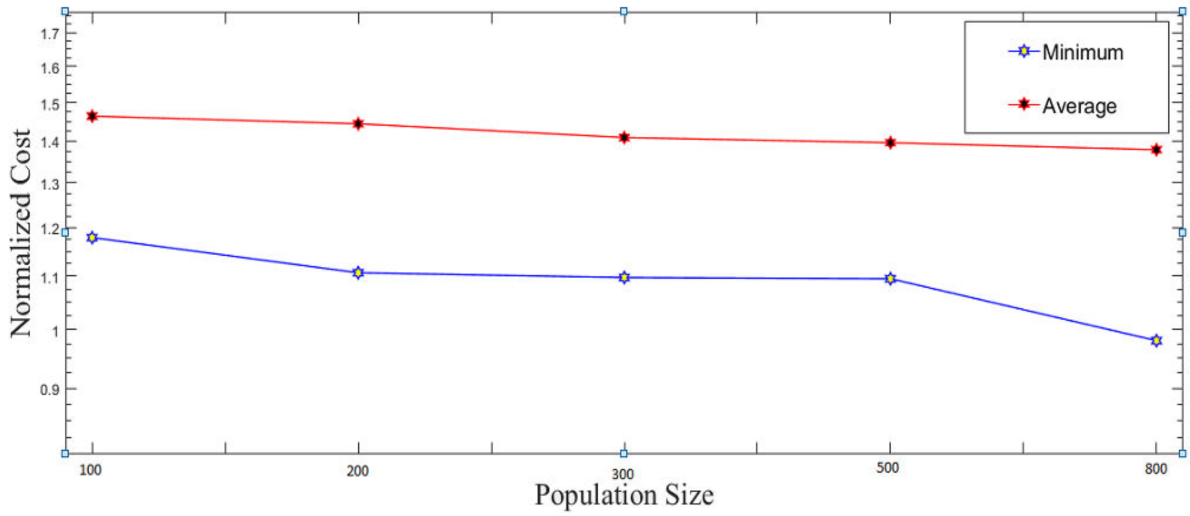

Fig. 3. Increasing the size of Population impact

3.1.2 Mutation probability experiment

In next step, we examined mutation probability impact. In this case, we also examine MP by running algorithm over 50 times on an Arbitrary problem with different values. Results show that a mutation probability value decreases, algorithm performance improves and desirable results are achieved. Experiments indicate that mutations are more involved with increasing MP variables. But on the other hand, excessive increase MP obtained responses to totally change. Thus, average value of MP obtained the best results. Mutation probability impact shown in Fig. (4,5).

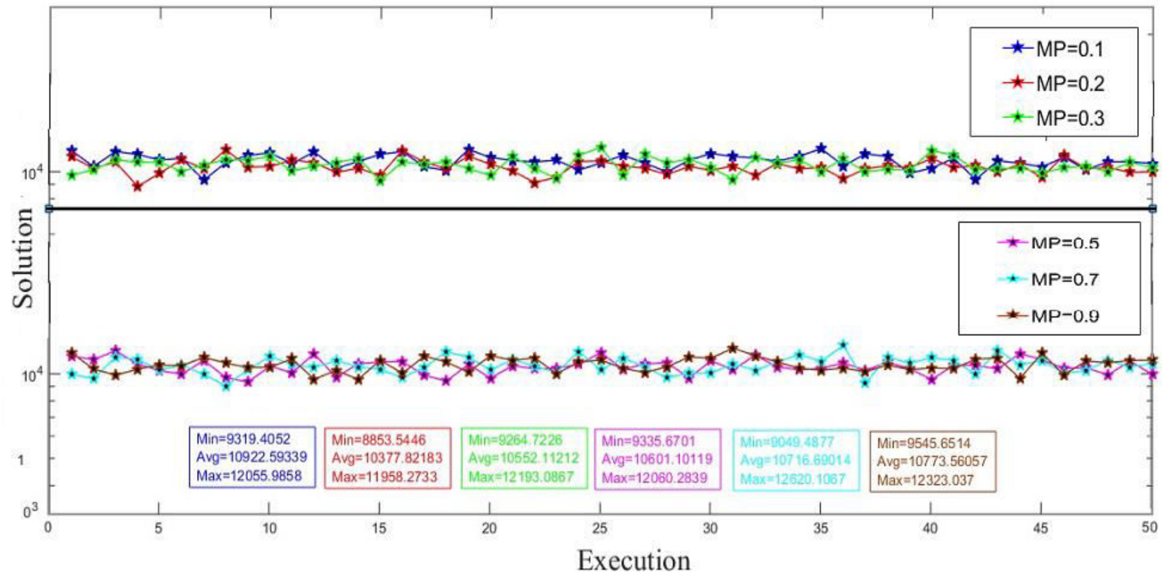

Fig. 4. Mutation probability impact

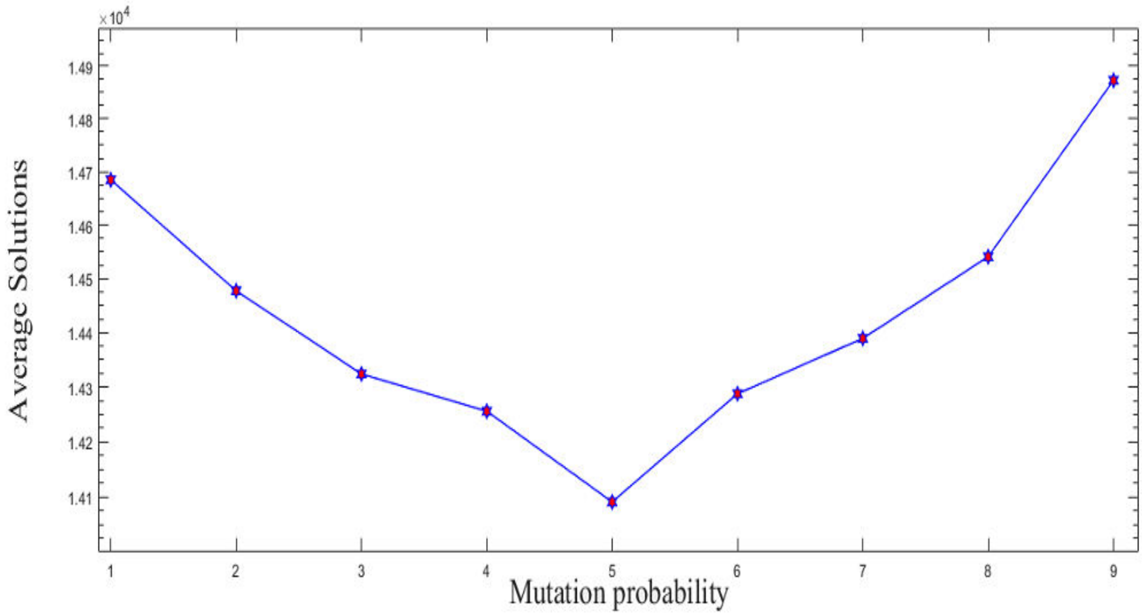

Fig. 5. Mutation probability impact

Studies show that changing the parameters significantly affect the results. According to the results it is clear that the number of initial population increases, the diversity of solutions in the search space will increase. Clearly, this ratio is not linear, meaning that favorable results are not always achieved by increasing the size of population. This increasing is partially effective and result are not influenced by it totally. we concluded that the initial population should increase to some extent.

We also did some studies on the mutation probability. Whatever reduce the mutation probability value, the number of variable thatcan be performed on the mutation are more. Thus, increasing the number of variables in Mutation causes the favorable result is achieved. As is clear from Fig.5 MP=0.5 causes the desired results is achieved.

4. Proposed the Modified Biogeography-Based Optimization

In BBO algorithm, migration operator is a very important operator that plays an important role in achieving the desired results. Actually, main task of migration operator is to share information between habitats. The original BBO algorithm, in most cases is stuck in local optimum due to the lack of cooperation and lack of habitat relationship with each other. The
solution may be to improve the algorithm and to avoid of local optimum is improving the migration operator. This improvement of migration operator helps obtain more information from the habitats and the diversity of the problem space increases. In this way, we use several habitats in collaborative for emigration instead of choosing a one habitat for emigration. The habitat $H_i$and habitat $H_j$are selected according to the probability of immigration rate (λ_i) and probability of emigration rate (μ_i), respectively. In Original BBO algorithm migration process is as follows:

$$H_i(SIV) \leftarrow H_j(SIV) \quad (6)$$

In original migration operator (6), immigrating habitat receives information directly from only one emigrating habitat. In new migration operator, immigrating habitat receives information from more than one emigrating habitat. new migration operator is shown below:

$$H_i(SIV) \leftarrow \sum_{j=1}^{k} \gamma_j H_j \quad (7)$$

where γ_i is the Percentage of participation for each habitat that achieved from (8). each habitat has its own percentage of participation in the partnership. k is the number of habitat that participate in partnership. in new migration operator $H_i(SIV)$ will be filled by several $H_j(SIV)s$ that each H_j has its own Percentage. The contribution of each habitat depends on his fitness. Each habitat has a better fitness has a greater share in the partnership.

$$\gamma_i = \frac{\mu_i}{\sum_i^k \mu_i} \quad (8)$$

for example, assume six habitats have participated in the partnership. according (2) each habitat has its own emigration rate (μ_i).

$$\mu_i = \{1 \quad 0.8 \quad 0.6 \quad 0.4 \quad 0.2 \quad 0\}$$

$$\sum_{i=1}^{6} \mu_i = 3$$

$\gamma_1 = \frac{\mu_1}{\sum \mu_i} \cong 33.33$ $\quad \gamma_2 = \frac{\mu_2}{\sum \mu_i} \cong 26.667$ $\quad \gamma_3 = \frac{\mu_3}{\sum \mu_i} \cong 20$
$\gamma_4 = \frac{\mu_4}{\sum \mu_i} \cong 13.3$ and so on

therefore

$$H_i \leftarrow (\,33\%H_{j1}(SIV) + 26\%H_{j2}(SIV) + \cdots)$$

Accordingly, the share of the first habitat is 33.33%, the share of the second habitat is 26.66%,the share of the third habitat is 20% and so on. that's mean immigrating habitat $H_i$will be filled by 33% $H_{j1}(SIV)$, 26%$H_{j2}(SIV)$ and 20%$H_{j3}(SIV)$ and so on. In this case,
habitats with high fitness have greater impact. The remarkable thing is that whatever number of participants increases percentage of participation decreases and vice versa. for simplicity we define a Partnership Probability (PP) parameter that will determine number of habitats that participate in partnership. The pseudo-code of modified migration operator is shown in algorithm 4.

Algorithm 4. Pseudo-Code of Modified Migration Operator

Population size =n;
for i=1 to Population **do**
Select Habitat H_i According to λ_i;
if $H_i$is Selected,**if** rand (0,1) <λ_i**then**
for j=1 to D **do**
Select all habitat H_js According PP;
if $all\ H_js$ are selected,**if** $\mu_j > PP$ **then**
Calculate γ for each habitat that participate in partnership;
Calculate new SIV according (7);
replace SIV H_i with new SIV;
end if
end for
end if
end for

5. Experimental Results

In this section, we compare the Participative Biogeography Based Optimization (PBBO) algorithm with other version of BBO algorithms and with different evolutionary algorithms such as PSO, GA, ICA and etc. Experiments performed on 12 standard benchmark functions. Also experiments performed over 50 times running algorithm on any benchmark functions. Table 1 represent the list of standard benchmark functions that used in experiments.A more detailed description of these benchmark functions can be found in (Chen et al.,2016) & (Guo et al, 2016) & (Suganthan, 2005)

5.1. Performance criteria

Some performance criteria are selected to evaluate the performance of the algorithms. These criteria are described as follows:
Error: The error of a solution x is defined as f (x) − f $(x*)$, where $x*$ is the global minimum of function. The minimum error is recorded when the maximum number of functional evaluations (Max FEs) is reached in 50 independent runs (Chen et al.,2016). The Max FEs values for all functions are set the same as in Refs. [10,11].

Also,the average and standard deviation of the error values are calculated.

Success rare (SR): The successful run of an algorithm manifests the ability of the algorithm to obtain an optimization result no worse than the required accuracy level (RAL) before the search is terminated by the Max FEs condition (Chen et al.,2016) and (Gong et al. 2010).

Convergence: The convergence graphs show the mean error performance of the best solution over the total runs, in the respective experiments (Gong et al. 2010).

According parameters studies in section 3.1 the parameter settings of the four existing BBO variants are the same as in their original literature, respectively, as presented in Table 2.

Table 1
Standard Benchmark Functions used in our experimental studies

	Function	D	Range Space	Global Minimum
f_1	Sphere	d	[-5.12, +5.12]	0
f_2	Ackley	d	[-32.768, +32.768]	0
f_3	Griewank	d	[-600, +600]	0
f_4	Rastrigin	d	[-5.12, +5.12]	0
f_5	Zakharov	d	[-5, +10]	0
f_6	Rosenbrock	d	[-2.048, +2.048]	0
f_7	Michalewicz	d	$[0,\pi]$	at d=2: -1.8013 at d=5: -4.687658 at d=10: -9.66015
f_8	Langermann	2	[0, 10]	at d=2: -5.1621259 at d=5: -1.4
f_9	Levy	d	[-10, +10]	0
f_{10}	Rotated Hyper Ellipsoid	d	[-65.536, +65.536]	0
f_{11}	Schaffer N.2	2	[-100, +100]	0
f_{12}	Matyas	2	[-10, +10]	0

Table 2
Parameter settings of the 4 existingBBO algorithms.

Algorithm	Values
BBO	Iter=1000, Pop=300,MP=0.5, I=E=1
BBBO	Iter=1000, Pop=300,MP=0.5, I=E=1
MBBO	Iter=1000, Pop=300,MP=0.5, I=E=1
PBBO	Iter=1000, Pop=300,MP=0.5, I=E=1

In order to have a better understanding of the performance of the algorithm in Table 3 for various functions Success rate (SR), Mean value and standard deviation of each algorithm is presented. In this table, the proposed PBBO algorithm is compared with basic BBO and other version of BBO. The results show that the proposed algorithm has better performance from all other version of BBO algorithm. In function (f_1,$f_9$and f_{10}) only the proposed algorithm has a success rate. Also, in function f_5 only the PBBO has a SR. In all functions the proposed Algorithm has the best performance in the mean value.

Table 3
Comparison of proposed algorithm with other version of BBO algorithms

Function	Algorithm	SR	Mean	Std
f_1	BBO	0	5.29E-05	2.32E-05
	BBBO	0	7.43E-05	1.93E-05
	MBBO	0	4.30E-05	1.98E-05
	PBBO	50	8.18E-13	1.09E-12
f_2	BBO	0	5.40E-02	1.43E-02
	BBBO	0	7.86E-02	1.38E-02
	MBBO	0	4.94E-02	1.48E-02
	PBBO	0	6.89E-06	5.65E-06
f_3	BBO	0	1.11E-01	2.98E-02
	BBBO	0	2.33E-01	4.19E-02
	MBBO	0	1.10E-01	3.00E-02
	PBBO	0	1.06E-02	5.54E-03
f_4	BBO	0	3.772218	1.159120
	BBBO	0	2.242972	9.55E-01
	MBBO	0	2.94E-01	3.18E-01
	PBBO	0	9.16E-01	2.72E-01
f_5	BBO	0	1.53E-03	7.08E-04
	BBBO	0	7.78E-04	2.58E-04
	MBBO	0	1.37E-03	5.13E-04
	PBBO	15	2.68E-07	2.49E-07
f_6	BBO	0	3.30907	1.496001
	BBBO	0	5.05597	2.28E-01
	MBBO	0	4.73343	2.03E-01
	PBBO	0	6.00E-01	3.47E-01
f_7	BBO	0	-9.25997	2.74E-01
	BBBO	0	-9.39509	2.95E-01
	MBBO	0	-9.51259	1.42E-01
	PBBO	0	-9.34941	2.50E-01
f_8	BBO	0	-4.12784	2.81E-02
	BBBO	0	-4.13916	2.03E-02
	MBBO	0	-4.13262	2.08E-02
	PBBO	0	-4.14461	1.68E-02
f_9	BBO	0	9.92E-05	3.57E-05
	BBBO	0	1.31E-04	4.19E-05
	MBBO	0	8.04E-05	3.50E-05
	PBBO	50	8.78E-10	8.19E-10
f_{10}	BBO	0	4.01E-02	1.90E-02
	BBBO	0	6.09E-02	1.79E-02
	MBBO	0	2.06E-02	9.21E-03
	PBBO	50	4.36E-10	3.96E-10
f_{11}	BBO	0	4.04E-10	6.25E-10
	BBBO	0	2.05E-12	2.40E-12
	MBBO	0	0.00E+00	0.00E+00
	PBBO	0	0.00E+00	0.00E+00

Table 4 compares the Success rate(SR), Mean value and standard deviation between the Participative Biogeography Based Optimization(PBBO) algorithm with different evolutionary algorithms such as PSO, GA, ICA and etc.The results show that the proposed algorithm has better performance from GA and PSO algorithms. In some functions (like f_1, f_9, f_{10} and f_{12}) the proposed algorithm in terms of success rate with ICA and ABC algorithms is equivalent and in some functions the proposed algorithm is ranked third. Also, in function f_5 only the PBBO has a SR and There is no algorithm has success rate.

Table 4
Comparison of proposed algorithm with different evolutionary algorithms

Function	Algorithm	SR	Mean	Std
f_1	PBBO	50	8.18E-13	1.09E-12
	ICA	50	4.57E-25	2.02E-24
	GA	0	1.28E-06	9.06E-07
	PSO	45	5.34E-08	1.60E-07
	ABC	50	7.81E-50	3.35E-49
f_2	PBBO	0	6.89E-06	5.65E-06
	ICA	50	6.87E-14	1.23E-13
	GA	0	7.37E-03	1.96E-03
	PSO	0	1.78E-02	2.50E-02
	ABC	50	2.88E-14	7.28E-15
f_3	PBBO	0	1.06E-02	5.54E-03
	ICA	0	3.08E-02	1.64E-02
	GA	0	3.48E-02	3.00E-02
	PSO	0	2.03E-01	1.18E-01
	ABC	0	6.59E-03	7.98E-03
f_4	PBBO	0	9.16E-01	2.72E-01
	ICA	0	1.48E-04	1.04E-03
	GA	0	3.22E-04	1.72E-04
	PSO	0	11.24737	5.975528
	ABC	47	2.02E-07	4.941E-07
f_5	PBBO	15	2.52E-06	1.84E-06
	ICA	0	5.55E-05	7.70E-05
	GA	0	1.46E-01	9.02E-02
	PSO	0	2.20E-01	2.62E-01
	ABC	0	9.230691	3.953846
f_6	PBBO	0	6.00E-01	3.47E-01
	ICA	0	4.79E-01	6.33E-01
	GA	0	6.711351	1.206713
	PSO	0	5.387153	2.675939
	ABC	0	1.056651	4.39E-01
f_7	PBBO	0	-9.34941	2.50E-01
	ICA	0	-9.6602	1.07E-14
	GA	0	-9.02469	2.75E-01
	PSO	0	-6.08352	1.03100
	ABC	0	-9.66006	7.18E-04
f_8	PBBO	0	-4.14461	1.68E-02
	ICA	0	-4.14734	1.30E-02
	GA	0	-4.13968	2.46E-02
	PSO	0	-4.13526	3.16E-02
	ABC	0	-4.15567	2.53E-04
f_9	PBBO	50	8.78E-10	8.19E-10
	ICA	50	1.84E-24	6.51E-24
	GA	0	2.71E-06	1.19E-06
	PSO	2	1.18E-03	2.26E-03
	ABC	50	1.50E-32	8.29E-48
f_{10}	PBBO	50	4.36E-10	3.96E-10
	ICA	50	6.00E-22	2.03E-21
	GA	0	9.10E-04	5.18E-04
	PSO	0	6.91E-04	1.60E-03
	ABC	50	7.12E-41	1.07E-40
f_{11}	PBBO	0	0.00E+00	0.00E+00
	ICA	0	0.00E+00	0.00E+00
	GA	0	0.00E+00	0.00E+00
	PSO	0	0.00E+00	3.55E-07
	ABC	24	2.27E-07	3.55E-07

To determine the ranking algorithms and better understanding between them,the Friedman test is carried out and Bonferroni–Dunn's procedure was used as a post hoc procedure. As shown in Table 5. Also, Descriptive Statistics of Friedman test is shown in Table 6.

Fig.6 shows the convergence graphs of the four BBO algorithms and evolutionary algorithms on 6 selected functions,namelyf_1,f_3,f_5,f_6, f_9 and f_{10}.

Table 5
Average ranking of PBBO and another version of BBO and with different EAs

Algorithm	Average ranking	Final rank
BBO	6.42	5
BBBO	6.25	6
MBBO	4.83	3
PBBO	3.00	2
ICA	2.00	1
GA	4.83	3
PSO	5.67	4
ABC	3.00	2

Table 6
Descriptive Statistics of Friedman test

	N	Mean	Std	Minimum	Maximum
BBO	12	-5.0831E-001	3.36941E+000	-9.26E+000	3.77E+000
BBBO	12	-4.8849E-001	3.47975E+000	-9.40E+000	5.06E+000
MBBO	12	-7.0302E-001	3.35943E+000	-9.51E+000	4.73E+000
PBBO	12	-9.9728E-001	2.92098E+000	-9.35E+000	9.16E-001
ICA	12	-1.1081E+000	2.95443E+000	-9.66E+000	4.79E-001
GA	12	-5.2197E-001	3.57234E+000	-9.02E+000	6.71E+000
PSO	12	5.7153E-001	4.32545E+000	-6.08E+000	1.12E+001
ABC	12	-2.9348E-001	4.21981E+000	-9.66E+000	9.23E+000

Table 7
PBBOTSP results compared with other methods

Datasets	Algorithm	Result (Mean)
Djibouti38	BBO	8058.336 (8560.428)
	PBBO	**8026.286 (8419.986)**
	ABC	10846.291(12359.65)
	PSO	10731.38 (13063.77)
	GA	9554.784 (12555.42)
	ICA	9040.52 (11264.950)
Oliver30	BBO	426.1972 (485.3536)
	PBBO	**424.4643 (424.4643)**
	ABC	489.6570 (603.4631)
	PSO	424.6354 (424.6354)
	GA	491.3255 (618.6263)
	ICA	493.4308 (588.2054)
Burma14	BBO	30.8785 (31.0718)
	PBBO	**30.8785 (31.05772)**
	ABC	30.8785 (31.3108)
	PSO	32.5168 (37.87551)
	GA	30.8785 (32.6198)
	ICA	30.8785 (32.04595)

6. Evaluation of the Proposed Algorithm on the Travelling Salesman Problem

In this section, we consider the Practical application of the proposed algorithm on the One of the NP-hard problems that called traveling salesman problem (TSP). The Travelling Salesman Problem (often called TSP) is a classic algorithmic problem in the field of computer science. It is focused on optimization. In this context better solution often means a solution that is cheaper. TSP is a mathematical problem. It is most easily expressed as a graph describing the locations of a set of nodes.To investigate the algorithm's performance in the given set of datasets, A few datasets are selected from the TSP dataset Lib (TSPLIB, 2017).

In order to explore the benefits of PBBO, we compared its performance on some classical TSPs with original BBO and four other population-based optimization methods, including ABC, GA, PSO and ICA. The benchmarks areOliver30, Djibouti38and burma14 in TSPLIB.Also experiments performed over 50 times running algorithm on any benchmarks. for all algorithms iteration and population size are fixed to 200 and 300, respectively. In table 7, the comparison results of TSP are shown. Also Fig.7and Fig.8 show the results of the simulations for each dataset.

In Fig.9, the best path of Djibouti38 locations is shown.

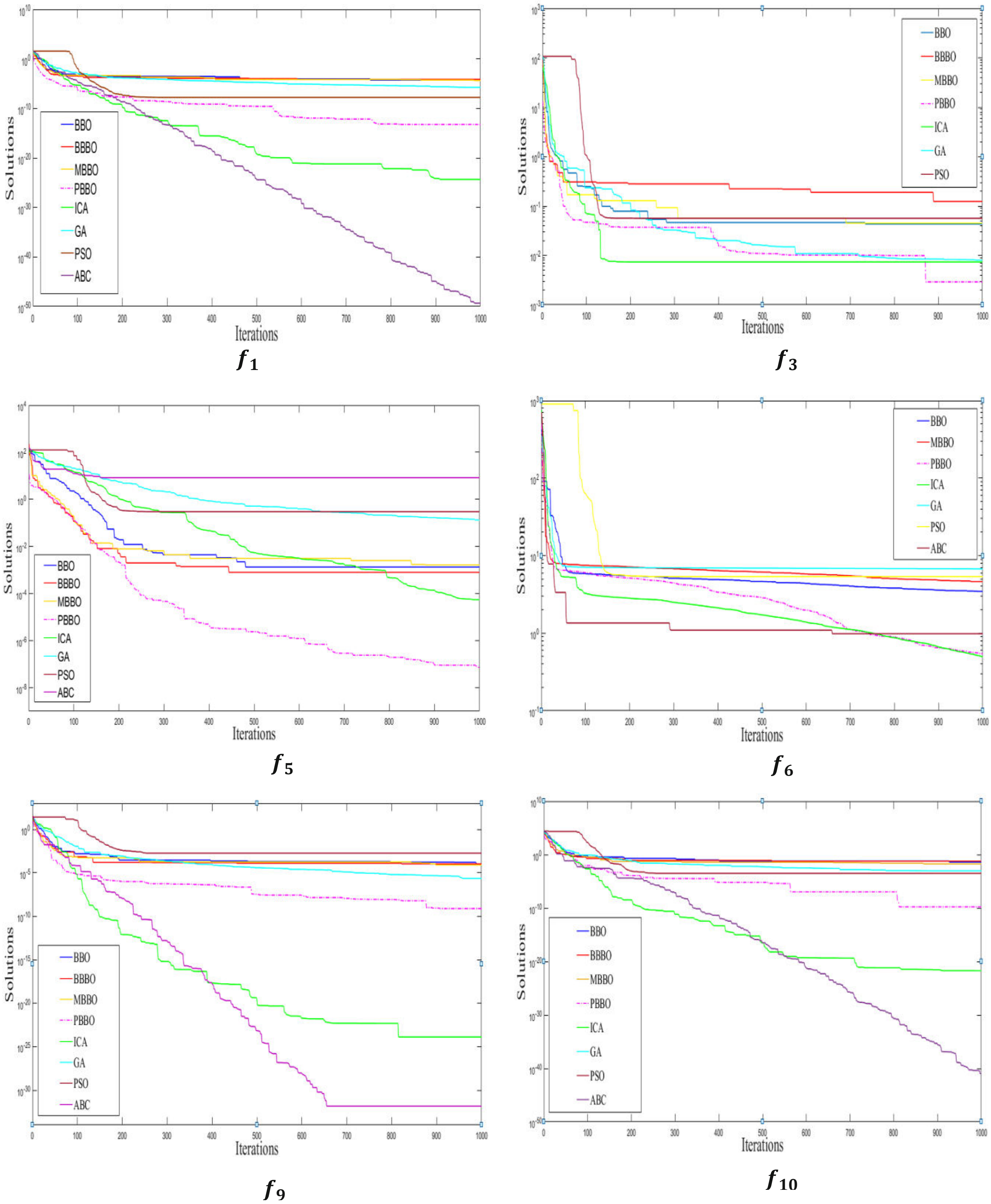

Fig. 6. Convergence graphs of proposed algorithm with other algorithmson f_1,f_3,f_5,f_6,f_9 and f_{10}

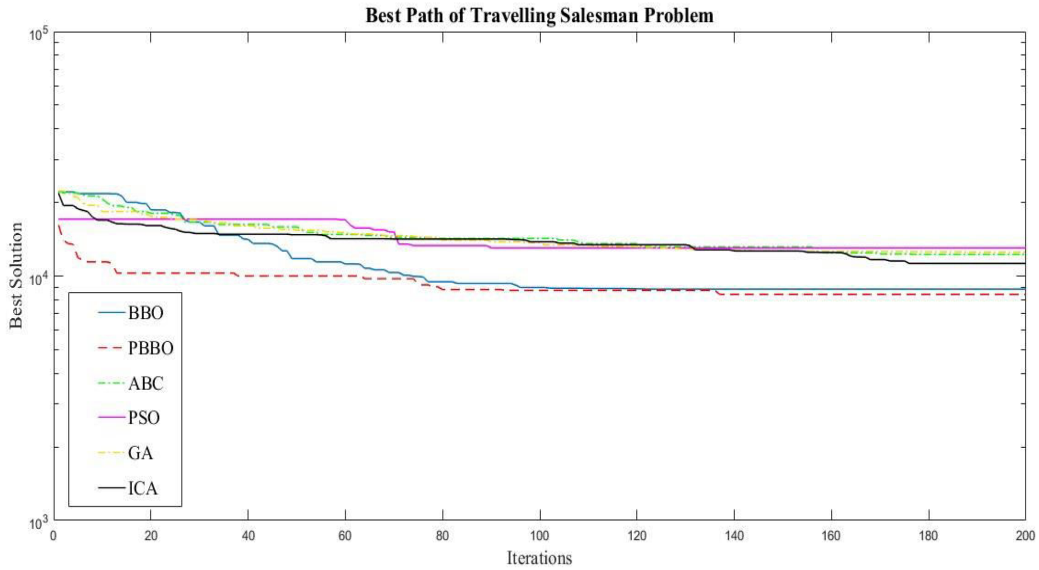

Fig.7. The comparison results of PBBOTSP with the other algorithms on Djibouti 38

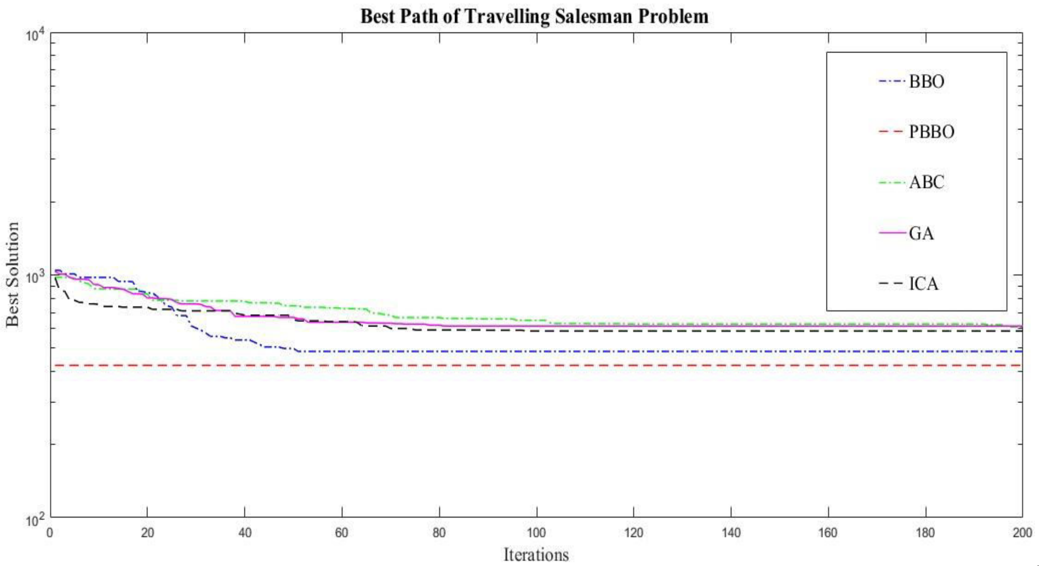

Fig. 8. The comparison results of PBBOTSP with the other algorithms on Oliver30.

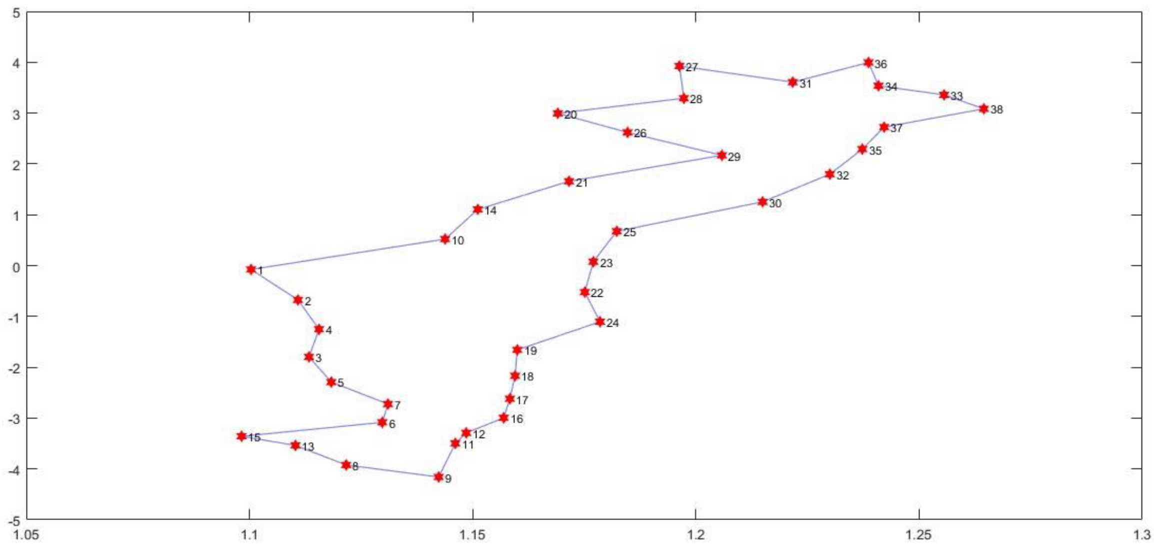

Fig. 9. The Best path found by PBBO for Djibouti38 locations.

The parameters of the PBBO have already been described in the table 2. For ABC, we used the parameters according (Zhong, 2017). For PSO, we used Inertia Factor and Inertia Factor Reduction weight 1.5 and 0.9 respectively, and Social Coefficient 0.7 for swarm interaction. For GA and ICA, we used parameters according (Mo and Xu, 2010) & (Ardalan, 2015) respectively.

6. Conclusion

This paper proposes a new modified migration operator to achieve better results and the diversity of the search space. The proposed modified BBO algorithm (PBBO) is to achieve better results,using several emigrating habitats as partnership instead of using one emigrating habitat. Each habitat has its own Percentage of participation in the partnership. The contribution of each habitat depends on his fitness. Each habitat that has a better fitness, has a greater share in the partnership. The proposed modified migration operator (PBBO) is compared with the original BBO and with

others version of BBO. Also, proposed PBBO algorithm compared with other evolutionary algorithms. The comparison results show that the proposed PBBO algorithm comparing to other algorithms have achieved more acceptable results.In all comparisons proposed algorithm with original BBO and to others version of BBO algorithms has achieved more favorable results.

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