Chaotic Biogeography-based Optimization Algorithm

Jie-Sheng Wang, and Jiang-Di Song

Abstract—**Biogeography-based optimization algorithm (BBO) realizes the information circulation and sharing by using the species migration among habitats and achieves the global optimization by improving habitat adaptability. Based on the population adaptive migration mechanism, a chaotic biogeography-based optimization (CBBO) algorithm is proposed by combining the chaotic mapping strategy and the BBO optimal migration model. Simulation experiments are carried out to compare the optimization performances of the typical chaotic mapping methods on the function optimization problems. The simulation results and analysis show that CBBO algorithm has good optimization performance. The combination of migration model and chaotic map close to the natural law has higher optimization precision and faster convergence velocity.**

Index Terms—**biogeography-based optimization algorithm, chaotic map, function optimization**

I. Introduction

The nature of function optimization problem is to find the optimal solution of an objective function through iterative [1]. The function features are usually described as continuous, discrete, linear, non-linear, convex function, etc. In that the constraint function optimization problem can be converted into unconstrained problem by using the designed special operators and penalty functions to make solution always feasible, the unconstrained function optimization problem is the main research focus. The swarm intelligent optimization algorithms [2] are a kind of random search algorithm to simulate the biological population evolution and evolution, which solves the complex global optimization problems through individual cooperation and competition between species, and is applied in many fields, such as multi-objective optimization, data mining, network routing, signal processing, pattern recognition, etc. The typical swarm intelligence optimization algorithms include Ant Colony Optimization (ACO) algorithm [3], Genetic Algorithm (GA) [4], Bat Algorithm (BA) [5], Artificial Bee Colony (ABC) algorithm [6], etc.

BBO Algorithm is a new type of swarm intelligent optimization algorithms and formally put forward by an American scholar Simon in 2008[7-8], whose basic idea is based on the species migration to complete the information flow between habitats. It achieves information sharing, the suitability improvement of habitats and obtains the optimal solution through adjusting immigration rate and emigration rate, migration topology, migration interval and migration strategies in the process of migration [9]. Compared with other swarm intelligent optimization algorithms, the main advantages of BBO algorithm are little adjusted parameters, simple implement, fast convergence velocity and high searching precision, which has been successfully applied in economic load assignment [10], combinatorial optimization [11], power distribution of wireless sensor network [12] and function optimization [13] and other global optimization problems. In this paper, the basic migration balance model of biogeography theory was elaborated. Seven migrating operators including the newly proposed migration ratio models have been used to realize the information sharing of BBO algorithm. Simulation results show that the different migration strategies have different influence on the optimization performance of BBO algorithm.

Based on the standard migration models of BBO algorithm, a chaotic BBO (CBBO) algorithm is proposed by combining three kinds of chaotic map methods and three kinds of migration rate models. Simulation experiments show that the proposed algorithm has efficient searching performance. The paper is organized as follows. In section 2, the biogeography-based optimization algorithm is introduced. The chaotic biogeography-based optimization algorithm is described in section 3. The simulation experiments and results analysis are introduced in details in section 4. Finally, the conclusion illustrates the last part.

II. Biogeography-based Optimization Algorithm

A. Overview of BBO Algorithm

The biogeography-based optimization (BBO) algorithm is derived from the biogeography discipline, which is primarily based on the distribution of species in nature. Species have certain rules according to which migration is conducted among disconnected islands through various barriers. Species can realize migrations among these islands by drifting, using the wind, and many other ways. A diagram illustrating

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multiple habitats in biological geography is shown in Fig. 1. In addition to the relationship among the islands, each island has its own given factors and survival indicators, which is defined as the Habitat suitability index (HSI). The dependent index variables affecting the HSI are named the independent habitat variables. The higher the island's HSI index, the lower the immigration rate of the population. The biogeography-based optimization (BBO) algorithm adopts the integer coding rule. A probability-based migration operator (Habitat migration operator) is set up to enable information sharing among the individuals in the population. The individuals also have their antagonistic emigration rate μ and the immigration rate λ so as to control the movement probability of individuals.

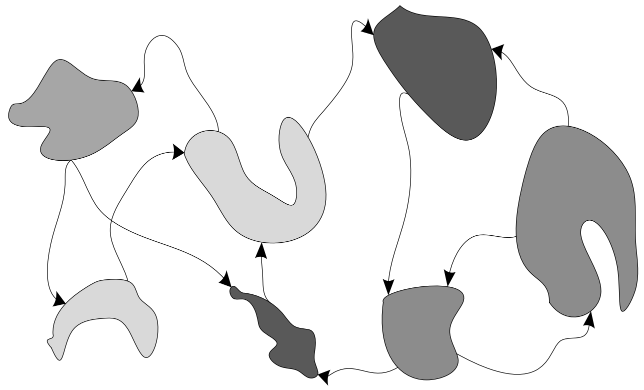


Fig. 1 Diagram of multi-habitats in biological geography.

B. Basic Migration Balance Model of Biogeography

A model representing the migration of a single species from an island is shown in Fig. 2 [15]. Assuming the ratio of emigration and immigration of the specie migration model of a single HS is μ and λ, respectively, then the number function of species in the island is established.

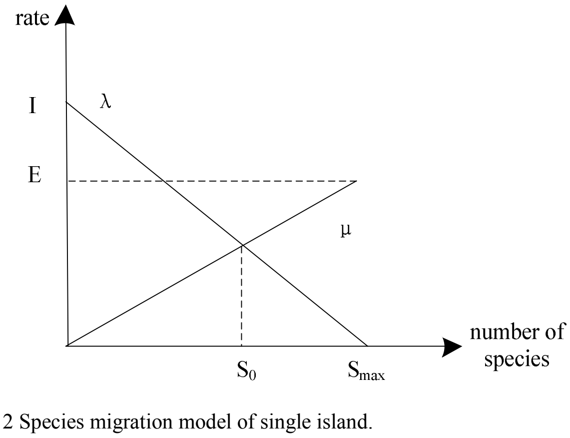


Fig. 2 Species migration model of single island.

It can be seen from Fig. 2 that when the number of species is zero, the emigration rate is zero, and when the number of species reaches the maximum capacity of species $S_{\max}$, the emigration rate reaches the maximum value E. Similarly, when the number of species is zero, the immigration rate assumes the maximum possible value I. When the number of species reaches the maximum $S_{\max}$, the corresponding emigration rate is zero. Equilibrium is reached at point S_0 when the emigration rate μ is equal to the immigration rate λ. Using the BBO algorithm and assuming the number of species on an island is S with probability P_s, its change over time $[t, t+\Delta t]$ can be described as follows.

$$\begin{aligned} P_s(t+\Delta t) &= P_s(t)(1-\lambda_s \Delta t - \mu_s \Delta t) \\ &+ P_{s-1}\lambda_{s-1}\Delta t + P_s \mu_{s+1}\Delta t \end{aligned} \tag{1}$$

When the number of species on the island is S at time $t+\Delta t$, the island's emigration rate is μ_s and the immigration rate is λ_s, and at least one of the following conditions is satisfied. (1) At time t, the number of species is S; at time $[t, t+\Delta t]$, there is no emigration and immigration of the species. (2) At time t, the number of species is $S+1$. At time $[t, t+\Delta t]$, there is at least one of the species available to immigrate. (3) At time t, the number of species is $S-1$. At time $[t, t+\Delta t]$, there is at least one of the species available to emigrate.

If Δt is sufficiently small for this specie, the probability of emigration and immigration can be ignored regardless of other factors. Define $n = S_{\max}$ and $P = [P_0, P_1, \cdots, P_n]^T$, $P_s(S = 0, 1, \cdots, n)$ can be arranged into a single matrix：

$$P = AP \tag{2}$$

$$p = \begin{cases} -(\mu_s+\lambda_s)P_s + \mu_{s+1}P_{s+1}, S = 0 \\ -(\mu_s+\lambda_s)P_s + \mu_{s\text{-}1}P_{s\text{-}1} + \mu_{s+1}P_{s+1}, 1 \le S < S_{\max} - 1 \\ -(\mu_s+\lambda_s)P_s + \mu_{s\text{-}1}P_{s\text{-}1}, S = S_{\max} \end{cases} \tag{3}$$

$$A = E\begin{bmatrix} -(\mu_0+\lambda_0) & \mu & 0 & \cdots & 0 \\ \lambda_0 & -(\mu_1+\lambda_1) & \mu_2 & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \lambda_{n-2} & -(\mu_{n-1}+\lambda_{n-1}) & \mu_n \\ 0 & \cdots & 0 & \lambda_{n-1} & -(\mu_n+\lambda_n) \end{bmatrix} \tag{4}$$

Assuming $E = I$, the situation depicted in Fig. 2 can be simplified by reducing it to that shown in Fig. 3 and Eq. (5)–(6).

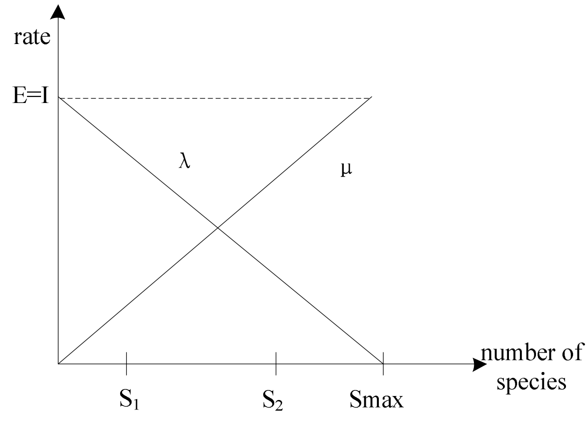


Fig. 3 Simplified species migration model on single island

$$\mu_k = \frac{E_k}{n} \tag{5}$$

$$\lambda_k = I\left(1-\frac{k}{n}\right) \tag{6}$$

where $n = S_{\max}$ and k is the number of species. Thus, Eq. (4) can be reduced to:

$$A = E\begin{bmatrix} -1 & \frac{1}{n} & 0 & \cdots & 0 \\ \frac{n}{n} & -n & \frac{2}{n} & \ddots & \cdots \\ \cdots & \ddots & \ddots & \ddots & \cdots \\ \cdots & \cdots & \frac{2}{n} & -1 & \frac{n}{n} \\ 0 & \cdots & 0 & \frac{1}{n} & -1 \end{bmatrix} = EA' \tag{7}$$

If the species migration curves in each island (solution) are the same, it can be seen from Fig. 3, S_2 would represent a high HSI solution and S_1 would indicate a low HSI solution. The emigration rate of S_1 is lower than the corresponding emigration rate S_2. Likewise, the immigration rate of S_1 is higher than the immigration rate of S_2. The migration rate of each solution enables the shared information among islands.

C. *Migration Ratio Models*

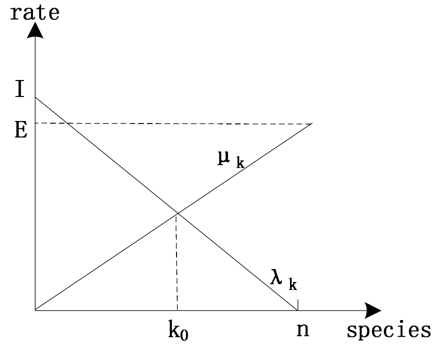
Three migration ratio models commonly used in BBO algorithm are shown in Fig. 4. As shown in Fig. 4, the immigration rate λ_k and the emigration rate μ_k are the function of species diversity k in the habitat; I indicates the maximum immigration rate; E indicates the maximum emigration rate; k_0 is the number of species at the point of habitat equilibrium, that is to say the immigration rate is equal to the emigration rate at that point.

Linear Migration Model

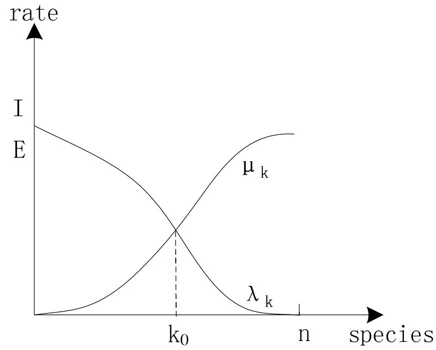
As shown in Fig. 4(a), the immigration rate λ_k and the emigration rate μ_k calculated by Eq. (8) are the linear function of species diversity k in the habitat at the linear migration ratio model (expressed as LBBO).

$$\begin{cases} \lambda_k = I(1-\dfrac{k}{n}) \\ \mu_k = E\dfrac{k}{n} \end{cases} \tag{8}$$

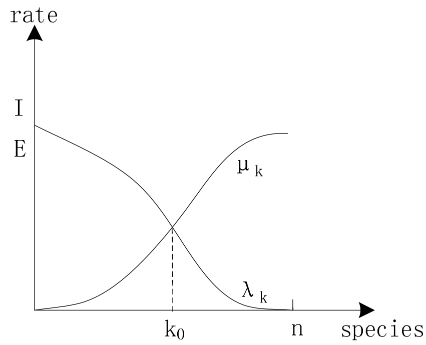
Seen from Fig. 4(a), when there is no species in the inhabit, it has the largest immigration rate I and the emigration rate is zero. With the increase of species diversity, the habitat becomes crowded, so the possibility of immigration become smaller and smaller and more and more species move to the adjacent habitat, that is to say the emigration rate increases bigger. Finally, when species reached saturation n, the immigration rate is zero and the emigration rate reaches the maximum value E.



(a) Linear migration



(b) Cosine migration



(c) Sine migration

Fig. 4 Different migration ratio models

Cosine Migration Model

As shown in Fig. 4(b), the immigration rate λ_k and the emigration rate μ_k calculated by Eq. (9) are the cosine function of species diversity k in the habitat at the cosine migration ratio model (expressed as cBBO).

$$\begin{cases} \lambda_k = \dfrac{I}{2}(1+\cos(\dfrac{k\pi}{n})) \\ \mu_k = \dfrac{E}{2}(1-\cos(\dfrac{k\pi}{n})) \end{cases} \tag{9}$$

Seen from the Fig. 4(b), when there are fewer or more species in the habitat, the change ratio of immigration rate and emigration rate are relatively stable. While the habitat has a number of species, the change of immigration rate and emigration rate are relatively faster.

Sine Migration Model

As shown in Fig. 4(c), the immigration rate λ_k and the emigration rate μ_k calculated by Eq. (10) are the sine function of species diversity k in the habitat at the sine migration ratio model (expressed as sBBO).

$$\begin{cases} \lambda_k = \frac{I}{2}(1+\sin(\frac{k\pi}{n})) \\ \mu_k = \frac{E}{2}(1-\sin(\frac{k\pi}{n})) \end{cases} \tag{10}$$

Seen from Fig. 4(c), the characteristics of this migration ratio model is contrary to the cosine migration ratio model. When there are fewer or more species in the habitat, the change of immigration and emigration rate are relatively fast, while the habitat has a number of species, the change of immigration rate and emigration rate are relatively stable.

D. Algorithm Procedure

The BBO algorithm is a method composed by using n habitats with a D -dimension SIV fitness vector. H_i represents the fitness value of the habitat i . By comparing the habitat values of H_i with $S_{\max}$, the number of all species is denoted as n . Then, the remaining population of the habitat S_i is realized by the successive reduction i according to H_i from good to bad, that is to say $S_i = S_{\max} - i$ ($i = 1, 2, \cdots, n$). By the above calculation, the emigration rate μ and immigration rate λ of H_i can be obtained for the simplified migration model and the probability $P(K_i)$ of species contained in H_i can be calculated

$$M_S = M_{\max} \cdot (1 - \frac{P_S}{P_{\max}}) \tag{11}$$

Thus, the mutation rate M_i of each H_i is obtained. The global variables are composed of the highest emigration rate E , the immigration rate I , the mutation rate $M_{\max}$, the number of the elite individual Z and the global migration rate P_{mod} . The algorithm procedure is shown in Fig. 5.The flowchart is described as follows.

Step 1: Initialize all parameters variables and SIV of H_i vector for any chosen habitats.

Step 2: For different suitability degree H_i , sort the habitats from good to worse. Generally, the update rate of habitat is set as $i = 1$.

Step 3: By comparison, if the desired optimum is reached, output the optimum and the algorithm procedure ends. Otherwise, continue to Step 4.

Step 4: Suppose one specie in a habitat has the maximum number $S_{\max} = n$. Then by means of $S_i = S_{\max} - i$ ($i = 1, 2, \cdots, n$) obtain the population value S_i of habitat i , further derive λ_i and μ_i from the migration model.

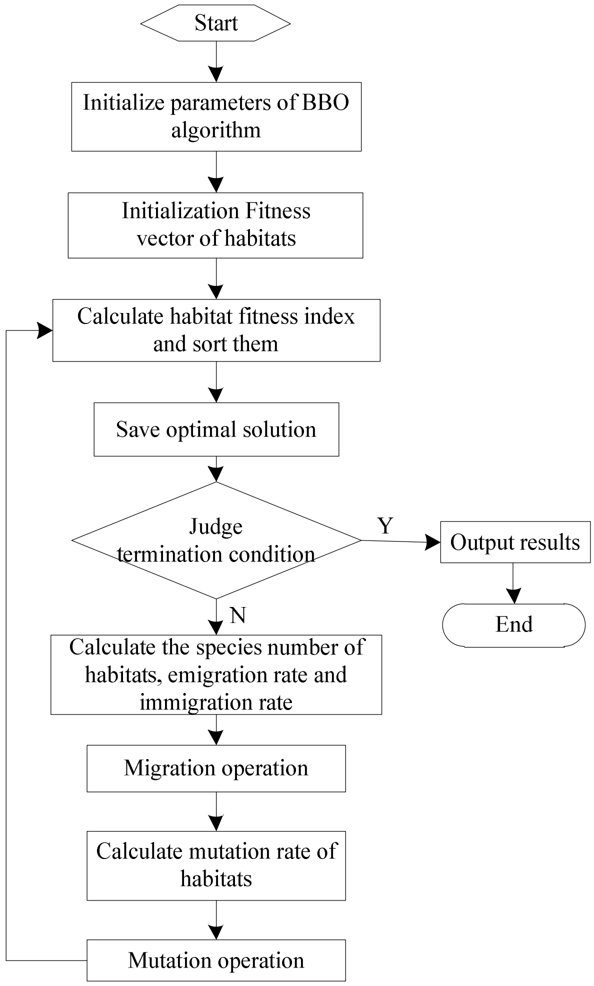


Fig. 5 Flowchart of Biogeography-Based Optimization algorithm.

Step 5: The cycle iteration number of P_{mod} is the number of habitats n . P_{mod} is used to judge whether i meets the immigration condition. If it satisfies the corresponding condition, then enter the λ_i cycle. If SIV_{ij} satisfies the immigration condition, the emigration rate of other habitats μ_m ($m = 1, 2, \cdots, n, \ m \neq i$) is used to perform a random selection to select the m characteristics component SIV_{mj} to replace the precedent i characteristics component SIV_{ij} .

Step 6: By calculating the corresponding habitat M_i , the judgment is carried out on the related variables of habitat i to see whether the mutation occurs or not, then return to step 2 for next cycle.

III. Chaotic Biogeography-based Optimization Algorithm

A. Chaotic theory

Chaotic motion was found by American meteorologist Lorenz in 1963 when he simulated atmospheric turbulence experiment between two infinite planes and achieved the conclusion of Laplace certainty theory contrary to the experiments results, that is to say the results of random can be generated by deterministic equations. Subsequently, May created a new research direction of chaos on the characteristics of the random motion. The basic concepts of chaos are described as follows: chaos is a kind of random motion state, which is obtained by the deterministic equation directly and not caused by the randomness of external factors [14]. The ergodicity of chaos movement makes the variable traverse all states in a certain range according to its rules and not to repeat. The system amplification effect makes the ultimate impact of a tiny movement far exceed the movement itself, such as a fan at the wings of a butterfly although in Britain and a typhoon may appear in China.

Due to the ergodicity characteristics of chaotic mapping, the chaos optimization algorithm falling into the local optimum is avoided and the ability to fine searching is enhanced. On the other hand, although the searching optimization ability of BBO algorithm is in some extent superior to other swarm intelligence algorithms, the problem of premature convergence exists. Therefore, the hybrid and complementary of two algorithms become a research hotspot. Saremi S. adopts three kinds of chaotic mapping methods (Circle, Sine and Sinusoidal) to be combined into BBO algorithm and uses four benchmark functions to carry out simulation experiments in order to obtain the optimal solution and verify the performance of the proposed hybrid algorithm for the first time [15-16]. The simulation results show that the chaotic mapping Sine especially can better improve the BBO algorithm not easy to fall into local optimal and slow convergence speed, and realize the better balance between the exploration and development. In this paper, chaotic biogeography-based optimization algorithm (CBBO) is proposed by using the previously mentioned three optimal migration rate model and three best chaotic mapping strategies (Gauss/mouse, sine and Chebyshev) according to. That is to say the CBBO algorithms based on three mobility models are generated, namely CBBO-L, CBBO-s and CBBO-c. Then four test functions are selected to carry out simulation experiments to show the effectiveness of the proposed CBBO algorithms. The search accuracy of variables is enhanced by narrowing the search space in the optimization process and the efficiency of searching is improved.

B. *Selection of Chaotic Mappings*

Three typical chaotic mappings adopted in this paper are shown in Table 1, whose solution set is in the range of (0, 1). Due to the greater influence of the initial value on the fluctuating pattern of chaotic mapping, the initialized points are set as 0.7.

TABLE 1
EXPRESSION OF THREE CHAOTIC MAPS

Map name	Chaotic map expression	Range
Gauss/mouse	$j = \begin{cases} 1 & x_i = 0 \\ \dfrac{1}{\mathrm{mod}(x_i, 1)} & otherwise \end{cases}$	（0,1）
Sine	$x_{i+1} = \frac{a}{4}\sin(\pi x_i),\ a = 4$	（0,1）
Chebyshev	$x_{i+1} = \cos(i \cos^{-1}(x_i))$	(-1,1)

C. *Integration of Chaotic Mapping Strategies and BBO Operators*

The chaotic mapping operation is adopted to realize the selection, migration and mutation operators in BBO algorithm. The combination of chaos and selection operator and migration operator can improve the detection capability. The exploring capacity on the solution set is enhanced by the combination of mutation operator and chaos strategy. The chaotic mapping based two operators are described as follows.

Chaos mapping and selection operator

If the selection probability λ_i of a certain habitat in the species migration is defined by using chaotic mapping, it should be in the interval [0, 1]. Therefore, it can be standardized as [- 1,1]. The values of chaotic mapping replace the random values. The chaotic migration operator is described as follows.

$if\ C(t) < \lambda_i\ then$

$\quad Emigrate\ habi\tan ts\ from\ H_i\ to$

$\quad H_j\ chosen\ with\ the\ probability\ proportional\ to\ \mu_i$

$end\ if$

In the chaotic selection operator, the t th iteration value of chaotic mapping is represented by $C(t)$ and the i th habitat is H_i. It can be seen from the above description that the chaotic mapping plays an important role in the choice of initial immigration rate.

Chaos mapping and migration operator

After selecting the habitat, the probability of species moved out of the execution is proportional to μ. The chaotic map is used to calculate this probability, which is described as follows.

$if\ C(t) < \mu_i\ then$

$\quad select\ a\ random\ habi\tan t\ in\ x_i\ and\ replace\ it\ with\ x_j$

$end\ if$

In the chaotic migration operator, $C(t)$ is the value of t th iteration of the chaotic mapping and x_i is the i th habitat. Seen from the above description, the chaotic mapping can define the emigration rate, whose range is [-1, 1].

In summary, the chaotic selection operator is helpful to BBO algorithm to select habitats in chaos states so as to improve the exploration ability. On the other hand, the chaotic migration operator allows the CBBO algorithm to carry out the migration operation in chaos pattern so as to enhance the exploration ability again. In addition, different chaotic maps are combined with the selection operator and the migration operator to form the different exploration and exploitation patterns in CBBO algorithm, so the global searching ability is enhanced.

IV. SIMULATION EXPERIMENTS AND RESULTS ANALYSIS

The hybrid operator is realized by combining the three kinds of chaotic maps (Gauss/mouse, sine and Chebyshev) and the selection operator and migration operator in BBO algorithm. Three typical migration rate modes with better optimization performance in BBO algorithm are adopted to produce three kinds of CBBO algorithm based on the different mobility models, namely CBBO-L, CBBO-s and CBBO-c. Their parameter settings are listed in Table 2. In order to verify the algorithm's effectiveness, four high dimensional benchmark functions (Griewank, Quartic, Ackley and Rastrigin) shown in Table 3 are selected to carry out the simulation experiments. Among these function optimization problems, the previous two functions are unimodal and the remaining two functions are multimodal. Under three kinds of chaotic mapping, the simulation experiments results for three CBBO migration rate models on four optimized functions are shown in Table 4 and Figure 6-8. Each optimization simulation experiment is run independently 50 times.

It can be seen from Table 4 that the Gauss/mouse chaotic mapping are the best at both the optimal values and average values. The optimization effect of the chaotic mapping Sine is slightly inferior to that of Chebyshev chaotic mapping. For unimodal function optimization problems, CBBO-s and CBBO-c under Gauss/mouse chaotic mapping are better than CBBO-L, while in the other two kinds of chaotic mapping CBBO-L is best. For Ackley function under Gauss/mouse chaotic mapping and Sine chaotic mapping, the optimum of CBBO-L is better than other CBBO models and the optimum of CBBO-s is less than but close to CBBO-c. For Rastrigin function under Gauss/mouse chaotic mapping and Sine chaotic mapping, CBBO-s and CBBO-c also obtain the optimal value 0, and the optimal value and the average value was superior to CBBO-L. It can be seen from convergence charts that the convergence velocity of the multi-peak functions are slower than unimodal functions under three kinds of chaotic mapping, so the number of iterations to find the optimum is relatively high. In addition, under Gauss/mouse chaotic mapping, Quartic in iterative 100 times by using three CBBO models reaches minimum, but Ackley is slowest and it tends to the minimum until the end of the iteration. CBBO-s in optimization of Griewank and Ackley obtains the optimal value and for other functions three CBBO algorithms has same convergence velocity. Under Sine chaotic mapping, three CBBO algorithms for previous three functions firstly converge to the optimal value. Under Chebyshev chaotic mapping, Quartic and Rastrigin have the fastest convergence rate and three CBBO algorithms also reach the minimum at the same time.

TABLE 2
INITIAL PARAMETERS OF CBBO ALGORITHMS

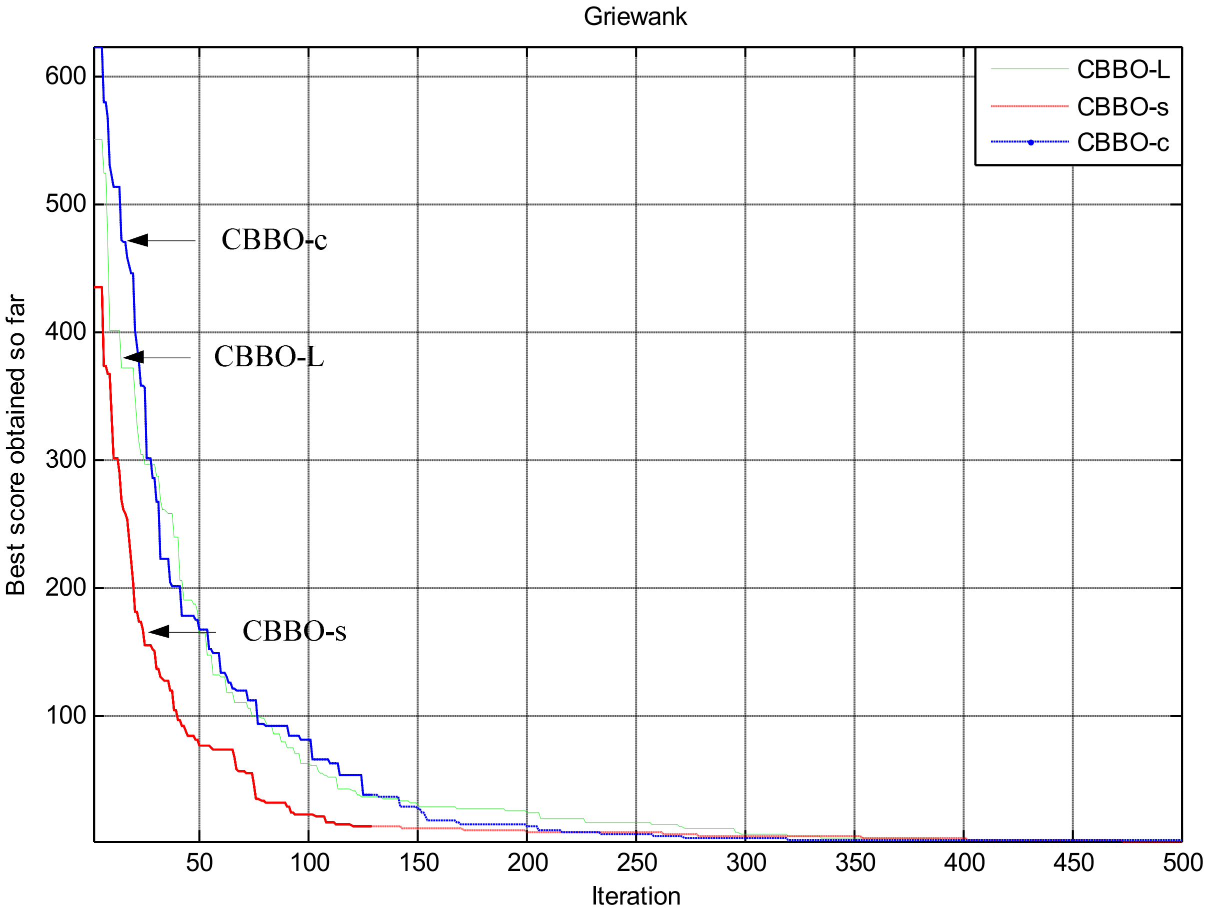
Parameters	Values
Number of population individual	30
Probability of habitat change	1
Migration probability of each species	[0,1]
Step probability of numerical integration	1
Largest immigration rate (*I*) and the minimum emigration rate (*E*)	1
Maximum Iterations	500

TABLE 3
TESTING FUNCTIONS

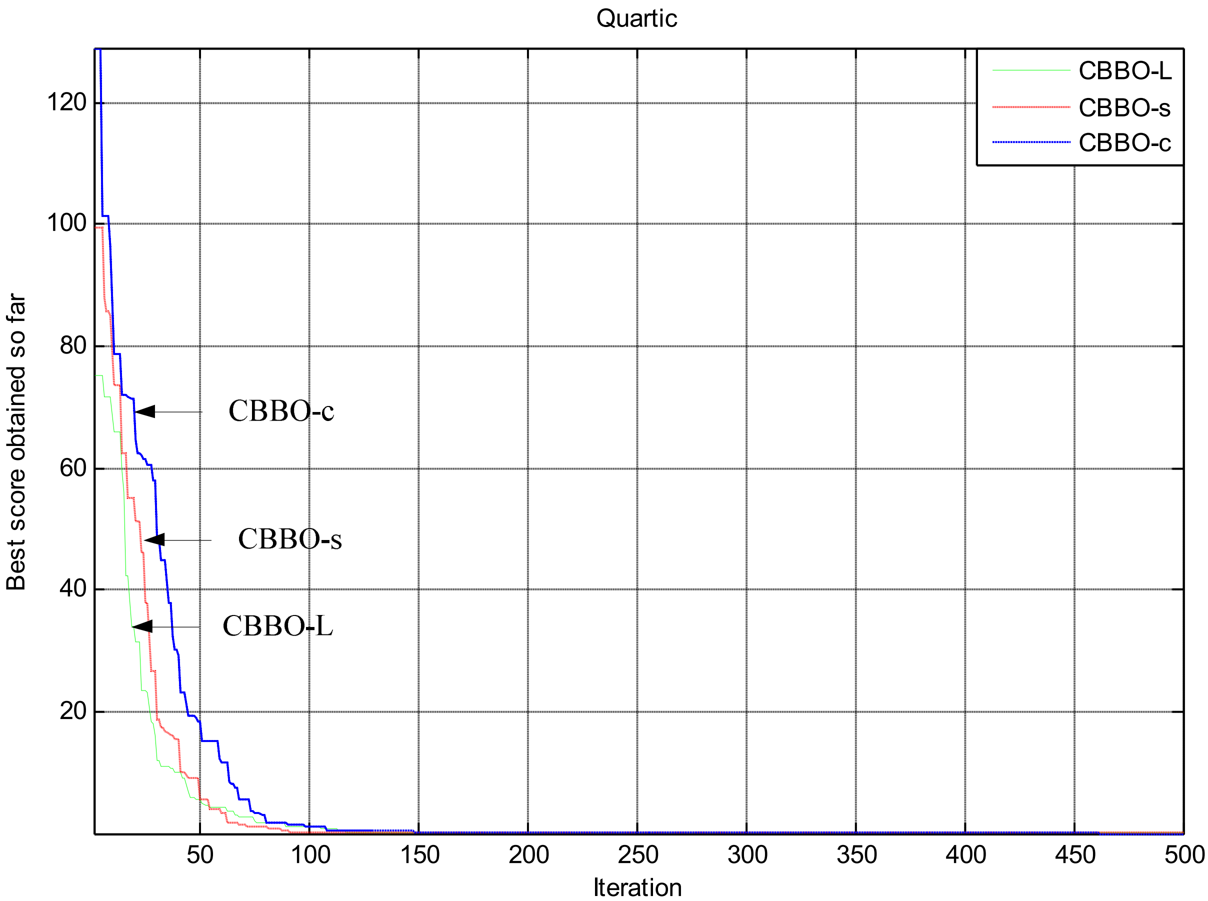
Function	Expression	Scope	Dimension
Griewank	$\sum_{i=1}^{n}\frac{x_i^2}{4000}-\prod_{i=1}^{n}\cos\left(\frac{x_i}{\sqrt{i}}\right)+1$	[-32,32]	30
Quartic	$\sum_{i=1}^{n} ix_i^4 + random[0,1)$	[-1.28,1.28]	30
Ackley	$20+e-20e^{(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n}x_i^2})}-e^{(\frac{1}{n}\sum_{i=1}^{n}\cos(cx_i))}$	[-32,32]	30
Rastrigin	$\sum_{i=1}^{n}\left[x_i^2-10\cos(2\pi x_i)+10\right]$	[-5.12,5.12]	30

TABLE 4
FUNCTION OPTIMIZATION RESULTS BASED ON CBBO ALGORITHMS

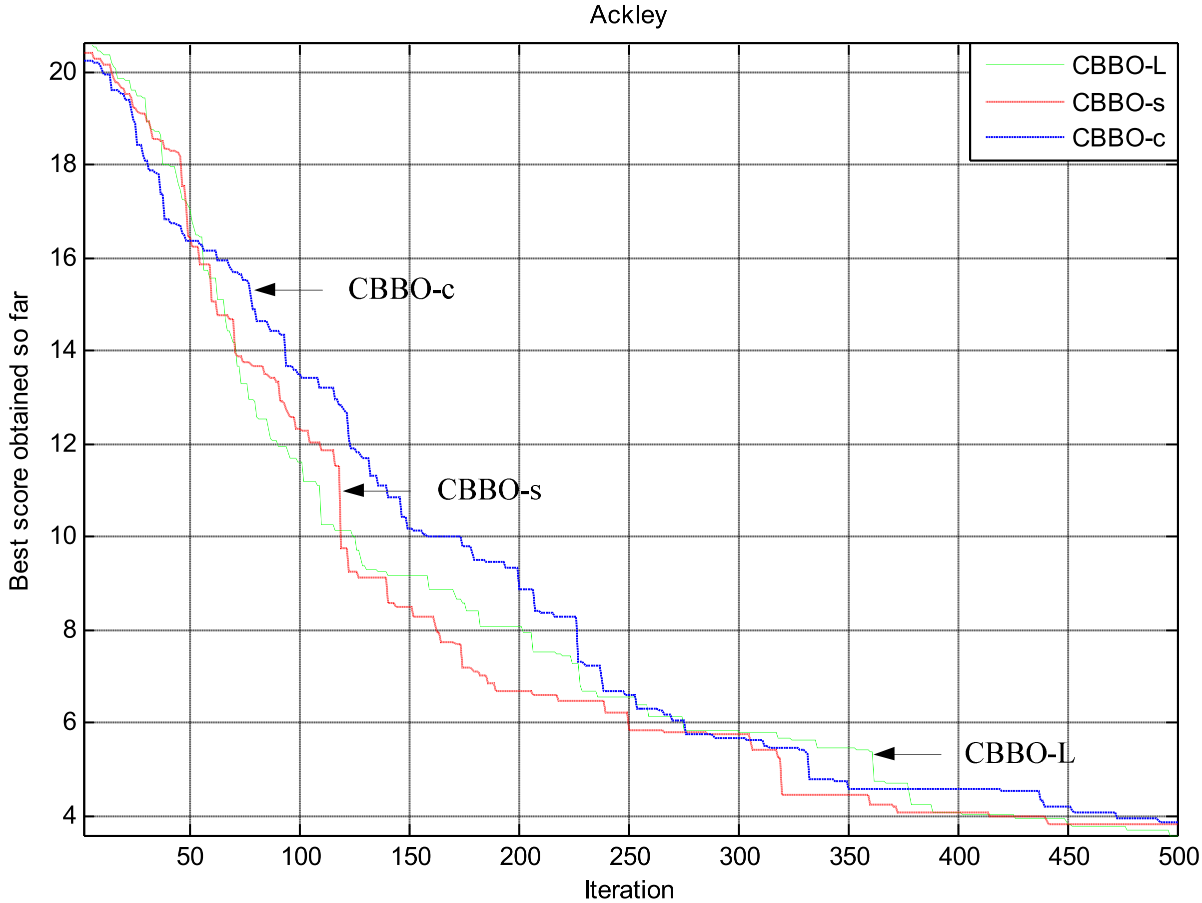
Function	Chaotic map	Gauss/mouse		Sine		Chebyshev	
		Optimum	Mean	Optimum	Mean	Optimum	Mean
Griewank	CBBO-L	1.763	1.836	12.227	14.306	4.075	27.005
	CBBO-s	1.636	1.809	12.896	13.114	4.387	13.029
	CBBO-c	1.729	2.082	12.588	13.786	4.337	10.245
Quartic	CBBO-L	3.381e-4	42.853e-3	0.130	1.537	9.467e-3	9.904e-3
	CBBO-s	3.065e-4	74151e-3	0.102	0.170	8.218e-3	11.797e-3
	CBBO-c	2.859e-4	4.094e-3	0.061	3.284	5.365e-3	2.592
Ackley	CBBO-L	3.594	4.023	9.120	9.374	5.774	6.394
	CBBO-s	3.832	3.838	9.375	10.978	5.535	6.966
	CBBO-c	3.857	4.296	9.396	11.865	5.835	6.168
Rastrigin	CBBO-L	0	0.033	8	13.433	1	1.033
	CBBO-s	0	0.033	7	8.033	0	0.566
	CBBO-c	0	0	7	8.233	0	0.333



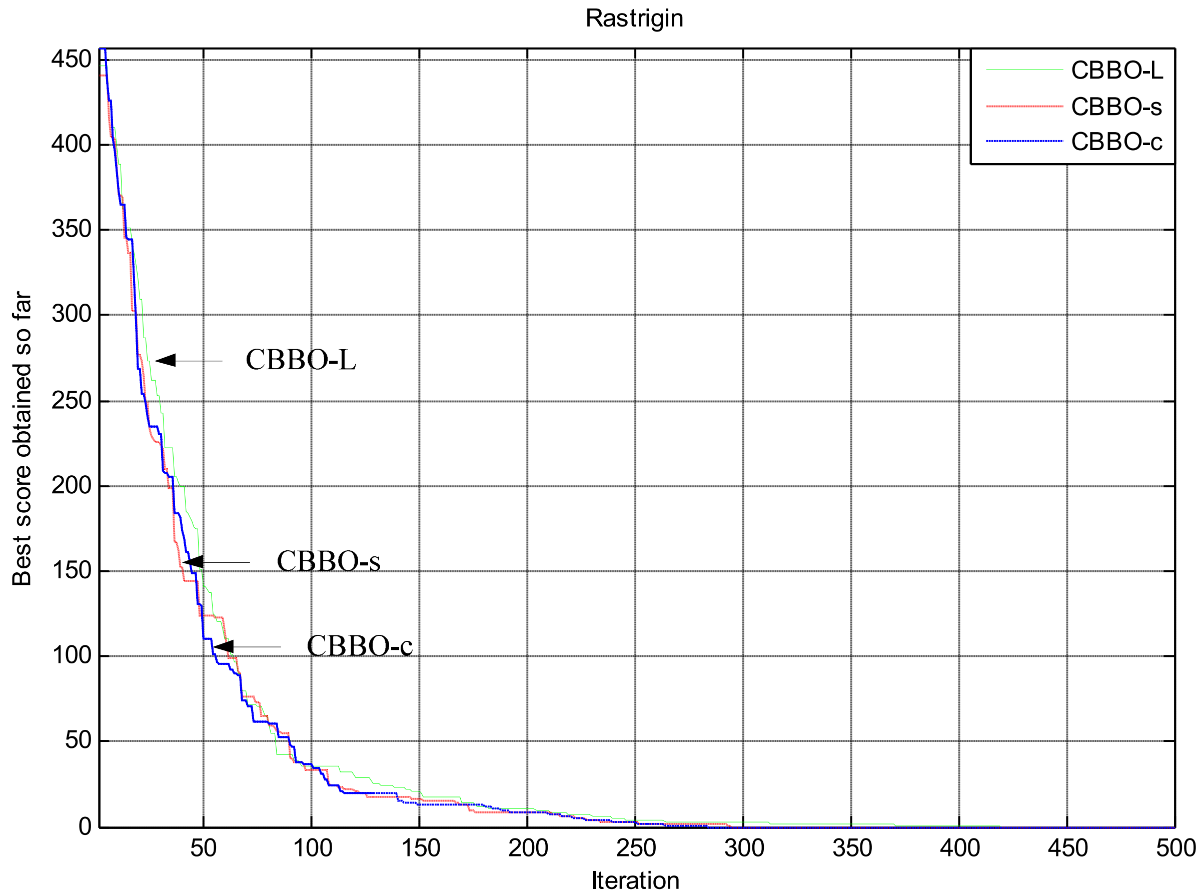
(a) Griewank



(b) Quartic

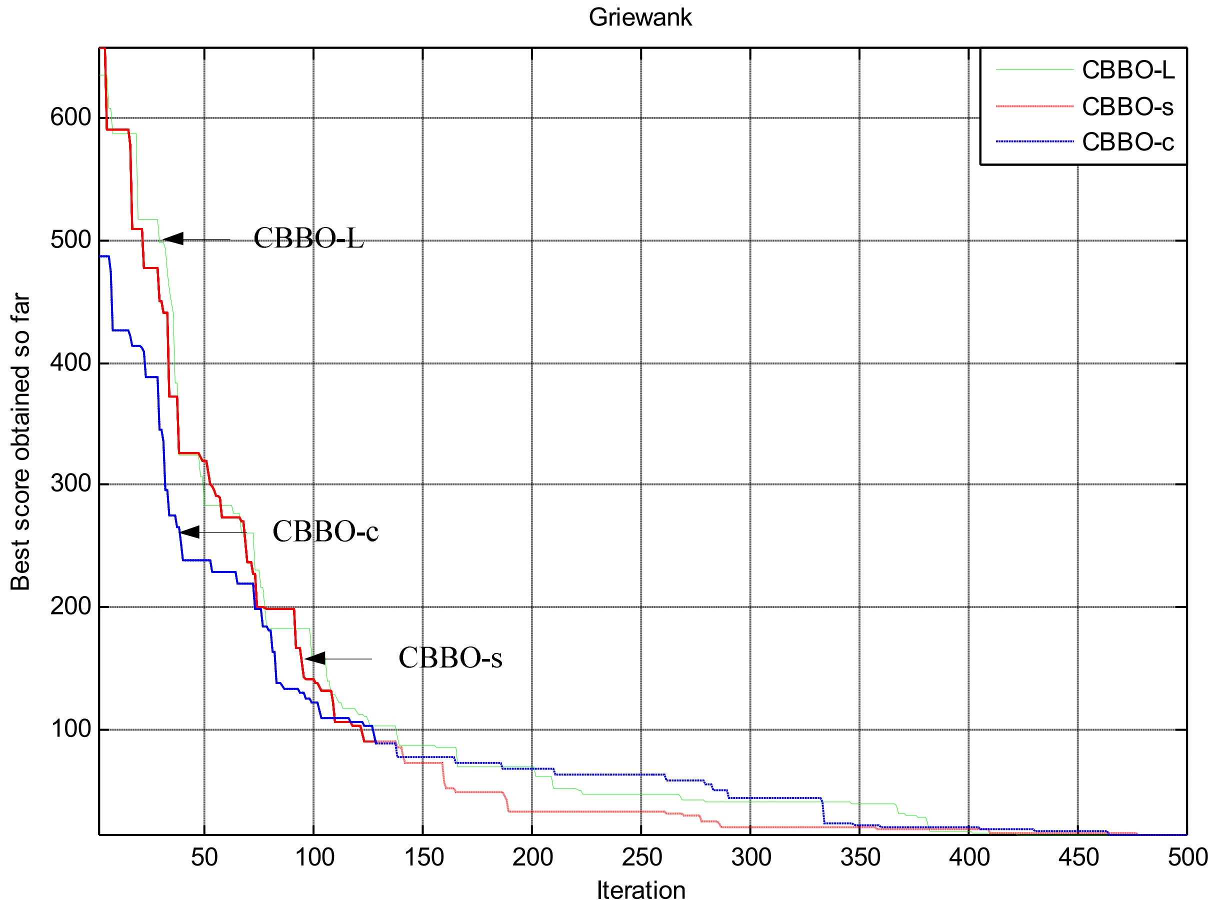


(c) Ackley

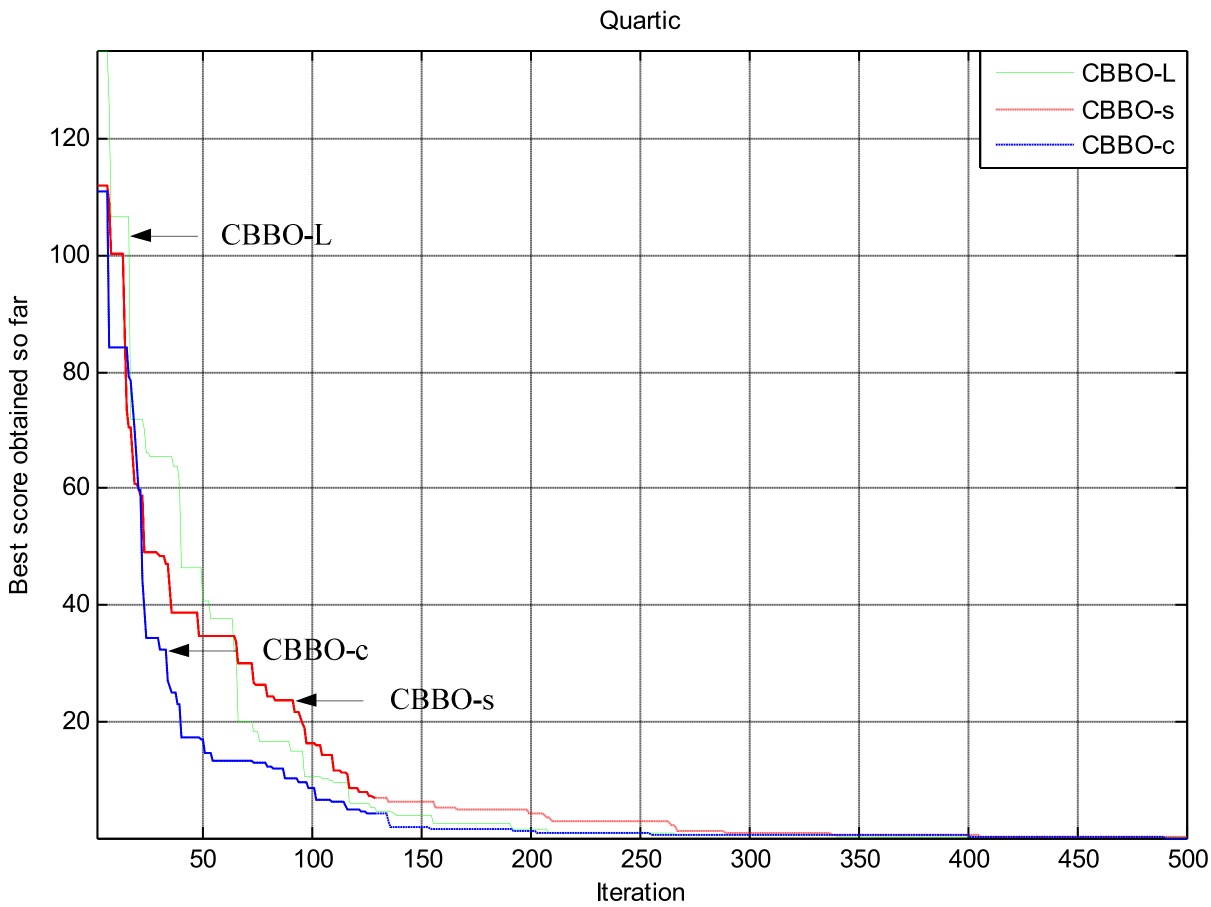


(d) Rastrigin

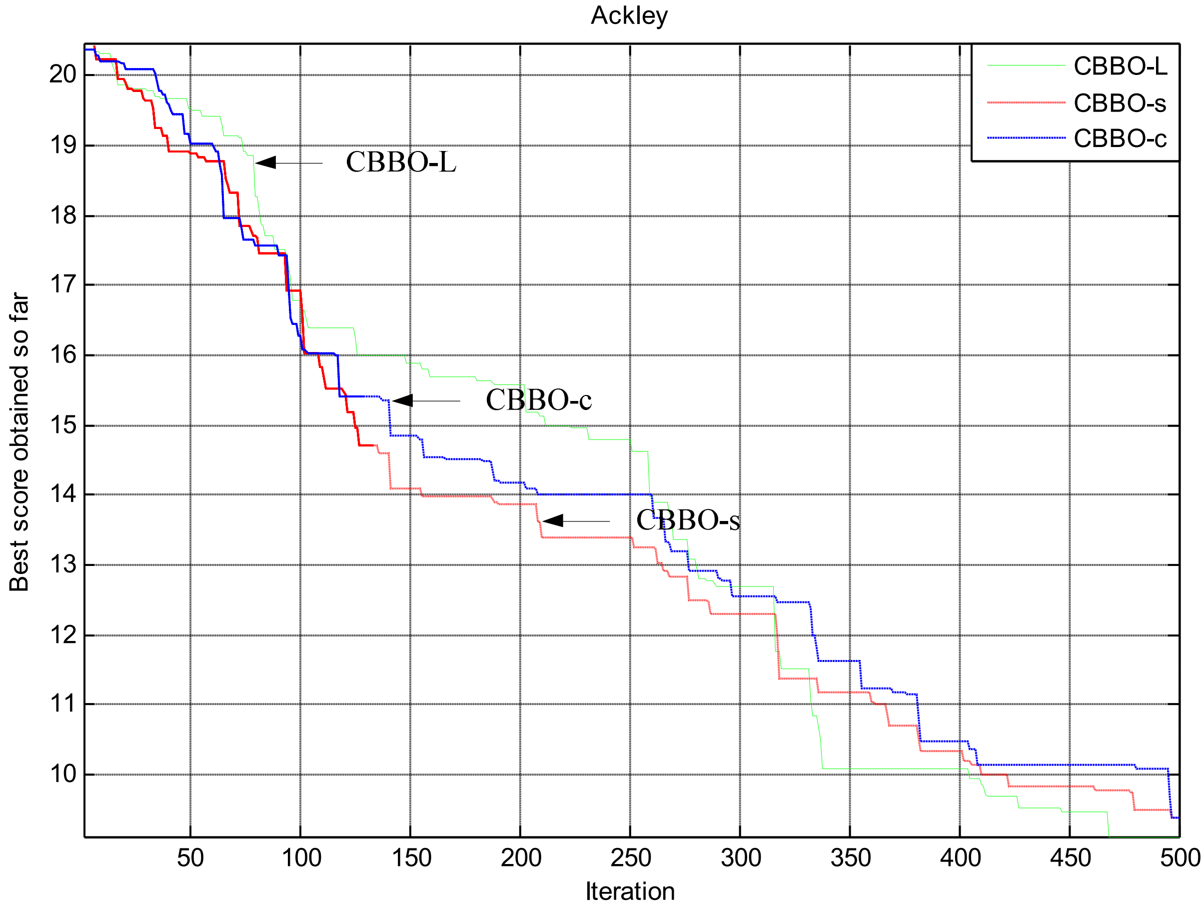
Fig. 6 Simulation Results of CBBO Migration model under Gauss/mouse map.



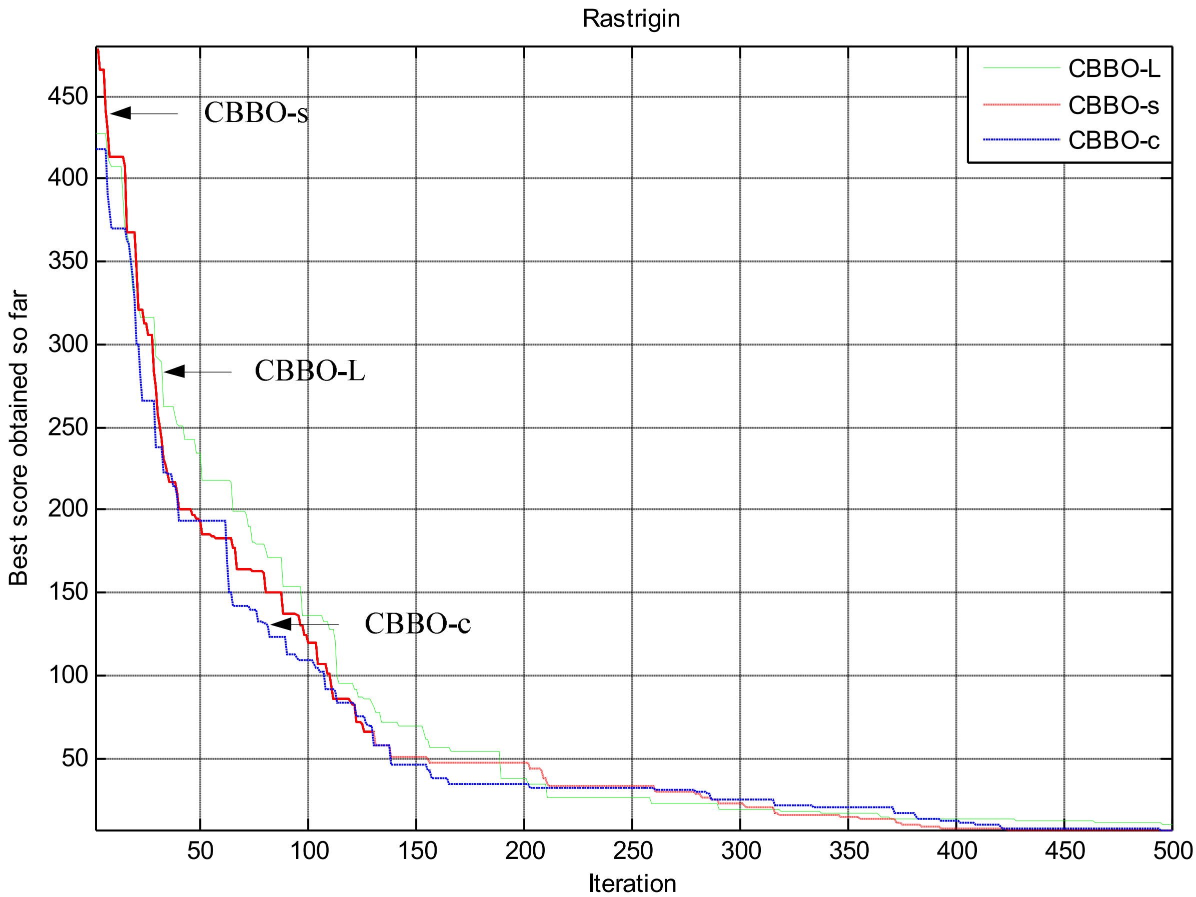
(a) Griewank



(b) Quartic

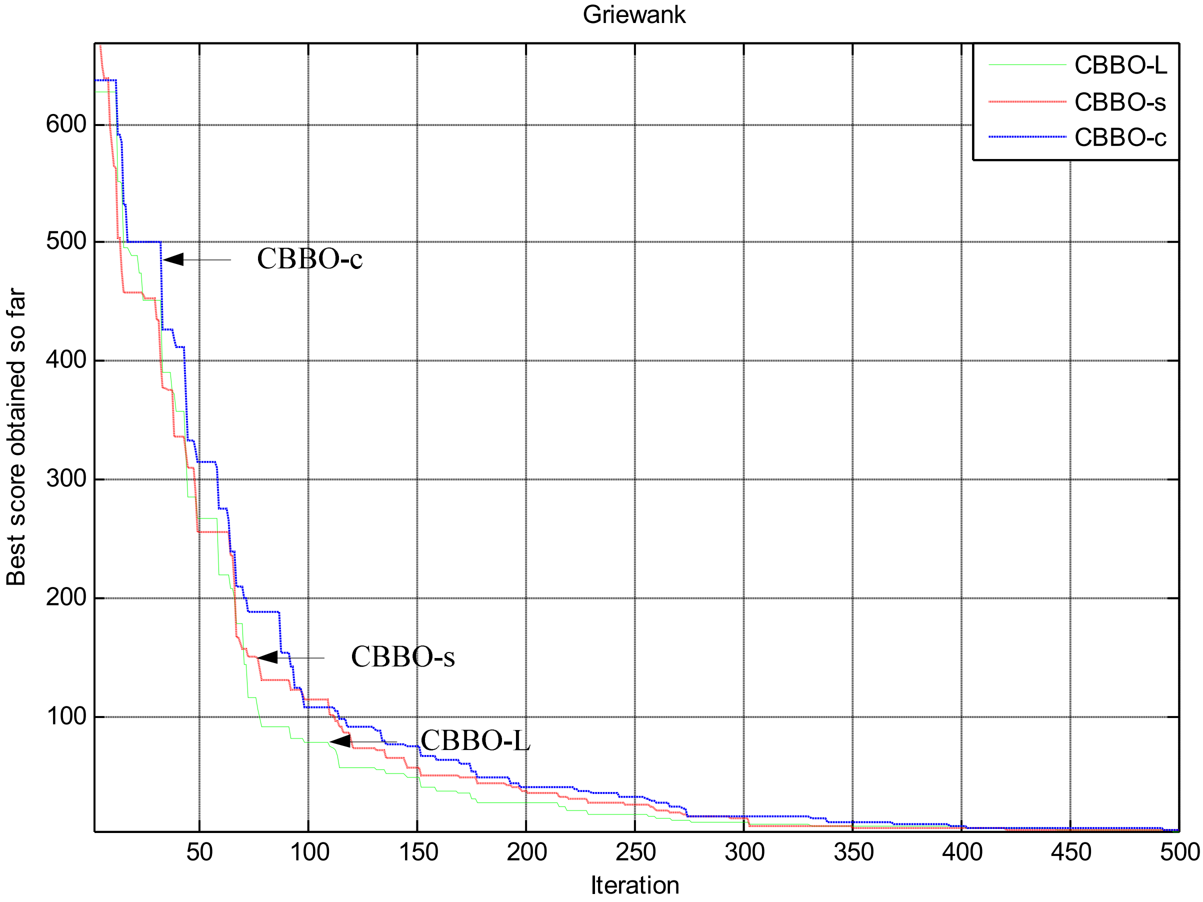


(c) Ackley

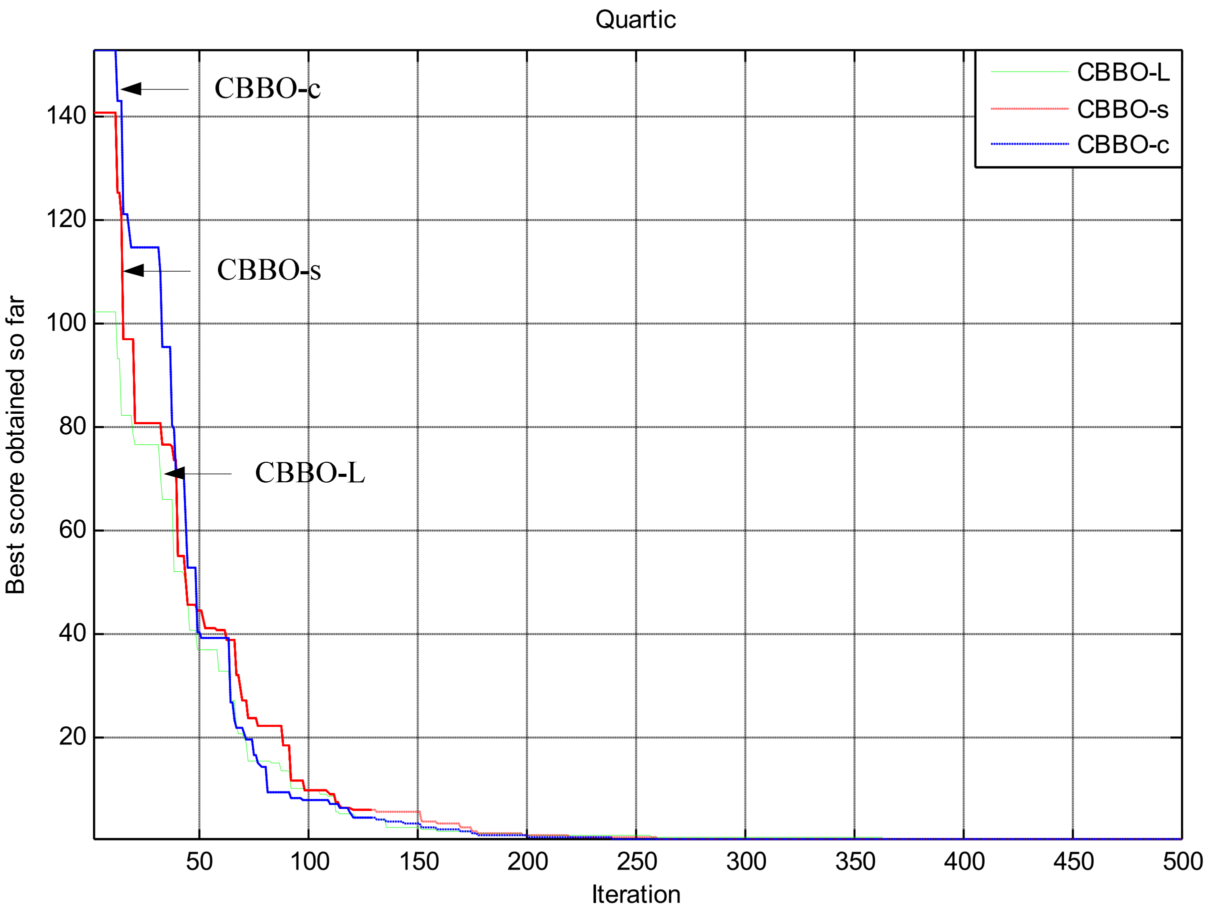


(d) Rastrigin

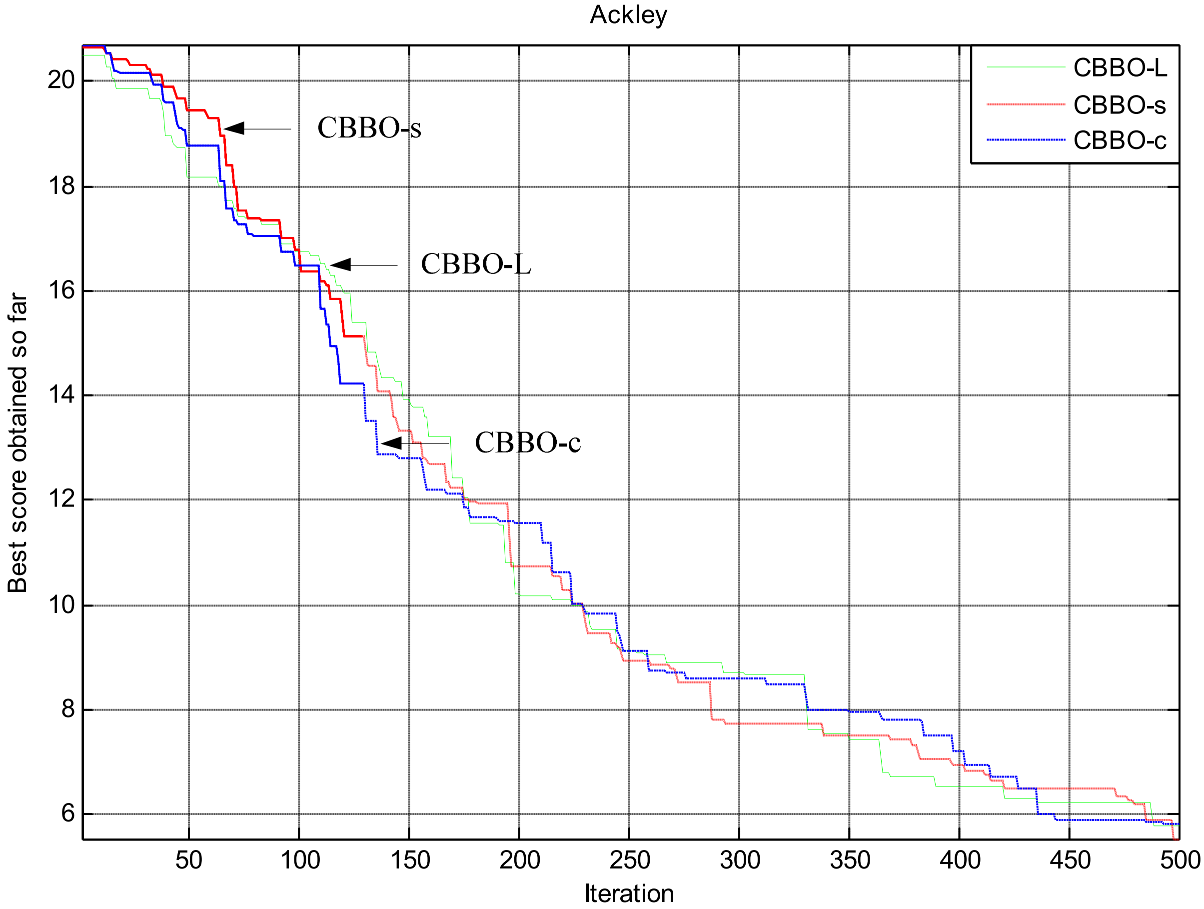
Fig. 7 Simulation results of CBBO Migration model under Sine map.



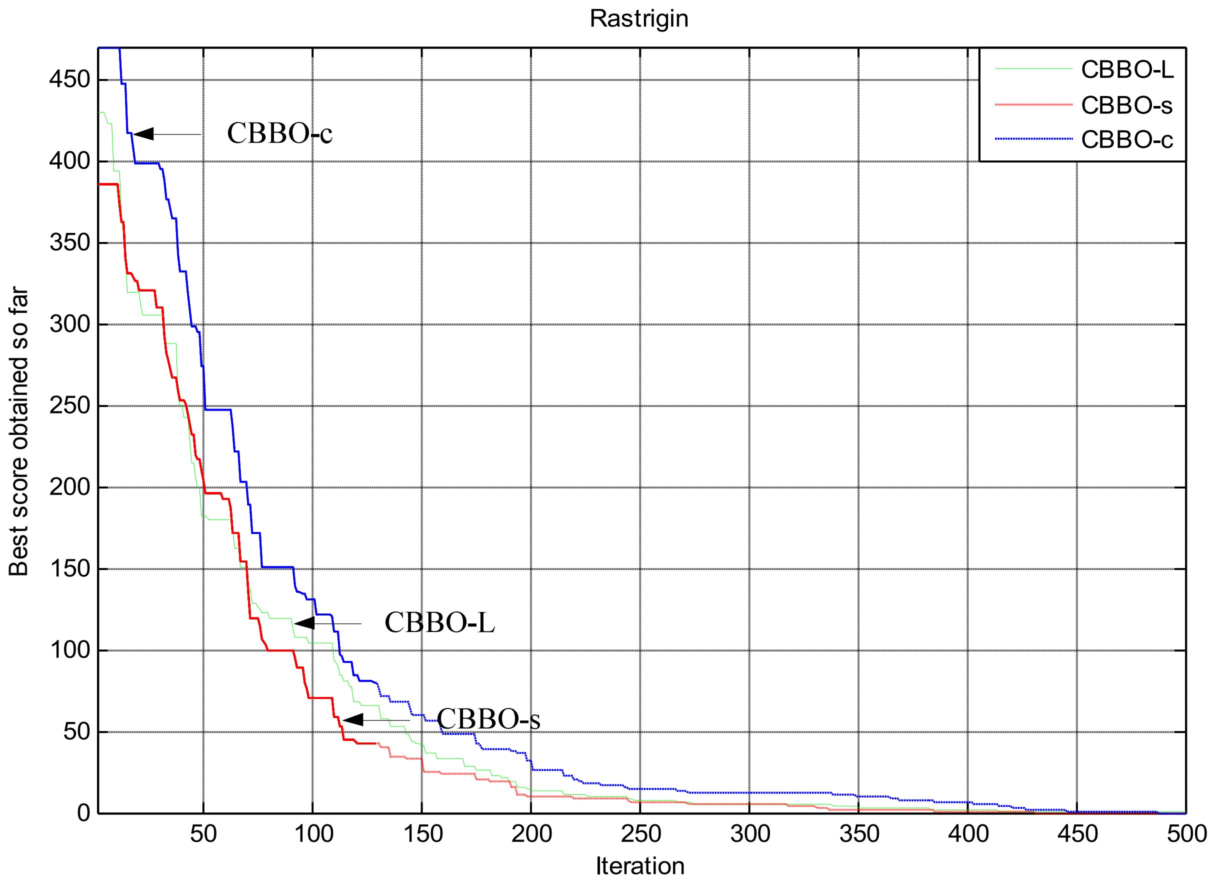
(a) Griewank



(b) Quartic



(c) Ackley



(d) Rastrigin

Fig. 8 Simulation results of CBBO Migration model under Chebyshev map.

V. Conclusion

The optimal chaotic mapping strategy and the optimal BBO migration models are combined in this paper. The simulation results show that the optimization performance of three chaotic mapping methods is in accordance with the following rule: Gauss/mouse < Chebyshev <Sine. Overall, the convergence velocity and optimization accuracy of CBBO-c and CBBO-s are better than CBBO-L. This shows the CBBO algorithm with the optimal chaos mapping strategy has better optimization effect due to its proximity to the migration model under natural law.

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