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Swarm Intelligence Algorithm Inspired by Route Choice Behavior

Daxin Tian^{1,2,6}, Junjie Hu¹, Zhengguo Sheng³, Yunpeng Wang^{1,2}, Jianming Ma⁴, and Jian Wang⁵

¹Beijing Advanced Innovation Center for Big Data and Brain Computing, Beihang University, Beijing, 100191, China

²School of Transportation Science and Engineering, Beijing Key Laboratory for Cooperative Vehicle Infrastructure Systems and Safety Control, Beihang University, Beijing, 100191, China

³University of Sussex, Department of Engineering and Design, Brighton, BN1 9RH, United Kingdom

⁴The Texas Department of Transportation, 10016 Liriope Cove, Austin, TX 78750, United States

⁵College of Computer Science and Technology, Jilin University, Changchun, 130012, China

⁶Jiangsu Province Collaborative Innovation Center of Modern Urban Traffic Technologies, No.2 SiPaiLou, Nanjing, 210096, China

Corresponding author: Jian Wang

E-mail: wangjian591@jlu.edu.cn

Abstract

Travelers' route choice behavior, a dynamical learning process based on their own experience, traffic information, and influence of others, is a type of cooperation optimization and a constant day-to-day evolutionary process. Travelers adjust their route choices to choose the best route, minimizing travel time and distance, or maximizing expressway use. Because route choice behavior is based on human beings, the most intelligent animals in the world, this swarm behavior expects to incorporate more intelligence. Unlike existing research in route choice behavior, the influence of others travelers is considered for updating route choices on account of the reality, which makes the route choice behavior from individual to swarm. A new swarm intelligence algorithm inspired by travelers' route choice behavior for solving mathematical optimization problems is introduced in this paper. A comparison of the results of experiments with those of the classical global PSO algorithm demonstrates the efficacy of the Route Choice Behavior Algorithm (RCBA). The novel algorithm provides a new approach to solving complex problems and new avenues for the study of route choice behavior.

Key words: Swarm Intelligence, Route Choice Behavior, Particle Swarm Optimization, Mathematical Optimization

1. Introduction

Swarm intelligence algorithms originate from swarm intelligence behavior. Scholars have studied some swarm intelligence phenomena in nature to propose new methods for solving complex optimization problems that are difficult to solve using classical optimization algorithms. Holland [1] proposed genetic algorithms (GAs) in

1975 as a simulation of natural selection and the genetic mechanism of Darwin's theory of biological evolution. Other examples include the ant colony optimization (ACO) [2,3], the particle swarm optimization (PSO) [4-8], the artificial fish swarm algorithm (AFSA) [9], , the quantum multi-agent evolutionary algorithm (QMAEA) [10], the firefly algorithm (FA) [11], and the bacteria foraging optimization (BFO) [12]. Tao et al.[13,14] proposed the idea of configurable intelligent optimization algorithms (CIOA), and a framework for CIOA have been studied and a series of algorithms have been developed based on the idea and framework, which are employed for addressing green material selection [15], dynamic migration of virtual machines [16], energy-aware cloud service scheduling [17], multi-objective service composition and optimal-selection [18-20], and so on. All these swarm intelligence algorithms were inspired by swarm behaviors and formulated by simulating those behaviors and learning the evolutionary mechanisms. However, nearly all those swarm behaviors are those of microorganisms or animals. Very few researchers have utilized human swarm behavior as the basis of a swarm intelligence algorithm[21]. Kaur et al.[22] proposed a new optimization algorithm for complex optimization problems based on human opinion formation models. Route choice behavior is one of the most important aspects of transportation systems for traffic prediction and management. As easily observed in recent research, route choice behavior is a constant day-to-day evolutionary process [23,24].

Route choice behavior can be divided into two types: single choice situations and repeated choice patterns[25]. Several theories have been applied for single choice situations, such as the expected utility theory (EUT) [26], the random utility theory (RUT) [27], and the prospect theory (PT) [28]. A route is chosen in EUT by maximizing the expected utility of potential route choices, and in RUT, a random utility term is added based on EUT to express the uncertainty of travelers. Predictions based on EUT and RUT often disagree with experimental results in real life, but PT, proposed in economics, is applied in route choice decision for its accurate description of decision making in uncertain circumstances. Route choice behavior has been described as a utility maximization or minimization for travelers in single choice behavior. In fact, route choice behavior is not only a utility maximization or minimization, but also an evolutionary process for achieving better route choices[29]. Many other theoretical models have been introduced for describing the repeated choice patterns, such as the

cumulative prospect theory (CPT) [30]. In these models, route choice behavior is described as an iterative process based on travelers' perceptions of road networks and traffic information from transportation systems.

Travelers continually adjust route choice based on their own experience and traffic information regarding better routes. The evolutionary mechanism of route choice behavior can inspire its use for optimization. In fact, a traveler's route choice behavior is not only determined by traffic information and his/her perceptions road networks, but also impacted by other travelers' route choices. What's more, traffic information is based on the aggregated behaviors of travelers. The other travelers' influence and traffic information make the route choice behavior from individual to swarm. In a word, an alternative route set is dependent on travelers' perception of a transportation network, traffic information regarding transportation systems, other travelers' influence, and historical travel information. Travelers cooperate with each other constantly to explore transportation networks and pursue more suitable route choices. Analogous with current swarm intelligence algorithms, such as PSO, these characteristics of route choice behavior encouraged us to propose the Route Choice Behavior Algorithm (RCBA), an evolutionary algorithm for real optimization problems.

2. Route Choice Behavior Algorithm

Routes can be categorized for travelers as guidance, historical, and other. For travelers not familiar with a transportation network, the first need to consider is whether to select guidance routes. From current research, the probability of selecting guidance routes is dependent on market penetration of guidance information systems, guidance information accuracy, and traveler characteristics. When travelers did not choose guidance routes, historical routes were likely to be selected, with a probability based on the gains or losses of selecting the best historical route compared with a reference point. Travelers tend to choose a historical route, when gains or losses are small; otherwise, they select another more satisfying route. When neither guidance nor historical routes are chosen, travelers will consider other routes based on exploration of the transportation network, travelers' preference for unfamiliar routes, or perhaps the influence of other travelers. RCBA is organized into three parts, *the solution space*, *alternative solutions*, and *update of probabilities*, for choosing guidance, historical, and new solutions.

The solution space is the constraint condition for solutions. In route choice behavior models, the solution space consists of the routes from an origin to a destination in a transportation network, with each route separate from others. The evolutionary mechanism of route choice behavior is actually a discrete optimization, hence RCBA requires discretization of a continuous solution space when used for continuous optimization problems, and binary coding is applied for this purpose in this paper.

Alternative solutions are the solution sets that particles can choose at each step. Analogous to alternative routes in route choice behavior, alternative solutions are classified into three kinds: guidance, historical, and new. The global best solution at the previous time t is used as the guidance solution at time $t + 1$, and the best of the historical solutions at previous times represents the historical solution for each particle. New solutions are those in the solution space that have not been visited, but this cannot express the theory of choosing other routes in route choice behavior. In this paper, other routes in the alternative routes are assumed to come from the influence of other travelers, route alteration based on exploration of the transportation network, and selection of unfamiliar routes. Adopting in whole or in part the best route choice of other travelers shows the influence of others in route choice behavior, and RCBA uses hybridization of the route randomly selected from other particles with the best route choice to reflect it. Variation based on the best historical route choice shows route alteration based on exploration of the transportation network, such as finding better parts in the entire route choice when driving, and random initialization of routes expressing unfamiliar routes.

Update of probabilities for choosing a solution can be divided into three kinds of alternative route choice, the probabilities for guidance, historical and new solutions. In recent research, the most important factors of route choice have been shown to be travelers' perceptions of road networks and guidance information from transportation systems, such as Advanced Traveler Information Systems (ATIS). Perception of road networks is based on travelers' travel experience history, which is constantly updated, while guidance information is provided by real-time traffic information systems. In fact, the influence of guidance information on route choice behavior can be divided into three parts: guidance information acquisition, accuracy, and acceptance. Guidance information acquisition is dependent on market penetration of guidance information systems. The availability of guidance information systems overshadows guidance information accuracy, and traveler characteristics determine guidance

information acceptance. In RCBA, at each step, particles' choice of a solution is also probabilistic, analogous to route choice probabilistic behavior. Accordingly, the probability of guidance solution is based on market penetration of guidance information systems, guidance information accuracy, and traveler characteristics, as shown in equation (1).

$$p_g = \varepsilon \cdot \psi \cdot \left(\frac{k}{N} \right)^4 \quad (1)$$

where ε is the market penetration rate, valued as one for the prosperity of transportation systems, ψ is the accepting guidance ratio, k is the number of interactions in which the guidance solution remains unchanged, and N is a constant for evaluating the guidance solution. k/N is a measure of guidance information accuracy in RBCA. It is easy to determine that the probability of choosing a guidance solution increases with increased k , representing the fact that the longer the guidance information remains unchanged, the larger the probability of choosing the guidance route is.

CPT is introduced to evaluate the historical solution, with the probability of choosing the historical solution depending on gains or losses when compared to a reference point. At each step in RCBA, the guidance solution is used as the reference point. Hence, when choosing the historical solution, losses will occur, whose prospective values can be calculated using equation (2).

$$V(i) = \pi_i^- v(i) \quad (2)$$

where

$$v(i) = -\lambda \left(\frac{|f_h - f_g|}{\text{magnitudes of } \min(f_h, f_g)} \right)^\eta \quad (3)$$

$$\pi_i^- = 1 \quad (4)$$

According to Tversky and Kahneman [31], λ and η are constants with the values 2.25 and 0.88, respectively. f_h and f_g are the mean fitness values of the historical and guidance solutions, respectively, and π_i^- is valued as one, because of a particular fitness value for the solution, according to CPT. Considering the priority of the guidance solution, the probability of choosing the historical solution can be calculated using equation (5).

$$P_h = (1 - P_g) \cdot (1 - H^{v(i)}), \quad H > 1 \quad (5)$$

where H is a constant factor representing the sensitivity of travelers to a loss. The greater the value of H , the more sensitive the loss is to particles, meaning that particles are more likely to be unable to bear the loss to seek better solutions. Moreover, the calculation process shows that a greater loss results in a lower probability of choosing the historical solution.

When travelers do not choose the guidance or historical solution, they choose a new solution. The probability of choosing a solution can be calculated as follows:

$$P_n = (1 - P_g) \cdot (1 - P_h) \quad (6)$$

A uniform distribution is recommended for selecting the three kinds of new solutions, with the result that the probabilities of hybridization, variation, and initialization are each 1/3, as shown in following equation:

$$P_{nh} = P_{nv} = P_{ni} = P_n/3 = (1 - P_g) \cdot (1 - P_h)/3 \quad (7)$$

where P_{nh} , P_{nv} , and P_{ni} represent the probability of selecting hybridization, variation, and initialization, respectively, to generate a new solution.

A simplified diagram of the RCBA algorithm is shown in Figure 1. At each step, solutions of all particles are calculated based on an objective function to acquire a fitness value for each particle. Then, the perception of the road network for each particle is updated based on the fitness values, and alternative solutions are also updated. The guidance solution is selected as the one with the best fitness value of all particles, and individual historical solutions are updated by choosing the best fitness value from the current historical solutions of each particle. New solutions for each particle are generated by hybridization, variation, and initialization, reflecting others' influence, route alteration, and unfamiliar routes, respectively. The probability of choosing each kind of alternative solution can be calculated using the respective equations (1), (5), and (7). The new solutions for the next step can be acquired by selecting probabilistically.

Figure 1: RCBA optimization process

The pseudocode of RCBA is as follows:

- 1) Initialize solutions of all particles by binary coding for every dimension d
- 2) $iter=0$
- 3) While ($iter < max_iter$) DO
- 4) $iter=iter+1$;
- 5) $Solutions_decimal=decode(solutions)$;
- 6) $FitnessValue = EvaluateFitnessFcn(Solutions_decimal)$; // *evaluate solutions using objective functions*
- 7) $[f_g, g]=updatefg(FitnessValue, solutions)$; // *select the best solution as guidance solution g*
- 8) For each particle I DO
- 9) $[f_{pi}, p_i]=updatefp(FitnessValue(i), solutions(i))$; // *select the best solution in historical solutions of each particle i as historical solution p_i*
- 10) $nh_i=single_point_cross(p_i, p_j)$; // *acquire a new solution by single-point crossover with other historical solution*
- 11) $nv_i=one_point_variation(p_i)$; // *acquire a new solution by single-point variation of historical solution*
- 12) $ni_i=Initialize$; // *acquire a new solution by random initialization*
- 13) calculate $P_g, P_{hi}, P_{nhi}, P_{nvi}, P_{nii}$ for particle i to choose kinds of alternative solutions
- 14) generate new solution for particle i according to probabilities

3. Experiments

3.1 Benchmark Functions

The proposed RCBA is tested by comparing with the global PSO based on eight benchmark functions in 10, 30, and 50 dimensions, using four unimodal and four multimodal functions. In the benchmark functions, n stands for the dimension of each function. The reasons for using the global PSO are to ensure the use of the same complete information sharing and global optimal guidance as for RCBA. All the benchmark functions are minimization problems and have properties such as multi-modality and non-separability that are too complex to be solved by classical optimization methods. The benchmark functions are of two types, namely unimodal (f_1, f_2, f_3, f_4) and multimodal (f_5, f_6, f_7, f_8), and can demonstrate the local and global optimization capabilities, respectively, of the algorithms. The mathematical description of the eight benchmark functions is as follows:

Quadric function (unimodal):

$$f_1(x) = \sum_{i=1}^n \left(\sum_{j=1}^i x_j \right)^2, \quad -100 \leq x_j \leq 100$$

Quartic function (unimodal):

$$f_2(x) = \sum_{i=1}^n ix_i^4, \quad -1.28 \leq x_i \leq 1.28$$

Spherical function (unimodal):

$$f_3(x) = \sum_{i=1}^n x_i^2, \quad -5.12 \leq x_i \leq 5.12$$

HyperEllipsoid function (unimodal):

$$f_4(x) = \sum_{i=1}^n ix_i^2, \quad -5.12 \leq x_i \leq 5.12$$

Ackley function (multimodal):

$$f_5(x) = 20 + e - 20 \exp \left(-0.2 \sqrt{\frac{1}{n} \sum_{i=1}^n x_i^2} \right) - \exp \left(\frac{1}{n} \sum_{i=1}^n \cos(2\pi x_i) \right), \quad -32.768 \leq x_i \leq 32.768$$

Griewank function (multimodal):

$$f_6(x) = 1 + \frac{1}{4000} \sum_{i=1}^n x_i^2 - \prod_{i=1}^n \cos \left(\frac{x_i}{\sqrt{i}} \right), \quad -600 \leq x_i \leq 600$$

Rastrigin function (multimodal):

$$f_7(x) = 10n + \sum_{i=1}^n \left[x_i^2 - 10 \cos(2\pi x_i) \right], \quad -5.12 \leq x_i \leq 5.12$$

EggHolder function (multimodal):

$$f_8(x) = \sum_{i=1}^{n-1} \left[- (x_{i+1} + 47) \sin \left(\sqrt{\left| x_{i+1} + \frac{x_i}{2} + 47 \right|} \right) - x_i \sin \left(\sqrt{|x_i - (x_{i+1} + 47)|} \right) \right], \quad -512 \leq x_i \leq 512$$

3.2 Parameters Setting

The parameters used in RCBA and the global PSO are shown in Table 1. The two algorithms use complete information sharing, in which each particle can acquire information from others; hence, global PSO is chosen for the comparison experiments. We have considered 10, 30, and 50 dimensions for all benchmark functions, to analyze the effect of dimension on algorithms, with popsize valued as 25, 36, and 60, respectively. The stopping condition for the two algorithms is attainment of Max_iter, which is valued as $100 \times d$. In global PSO, parameters are introduced from [32], where $\omega = 0.729$, and $c_1 = c_2 = 1.49445$. Throughout the experiments, the parameters are held constant for all benchmark functions to maintain consistency, and each function is conducted for 30 independent runs in 10, 30, and 50 dimensions, respectively.

Table 1. The values of parameters for RCBA and the global PSO.

Topological structure	Complete information sharing
Popsiz	25, d = 10; 36, d = 30; 60, d = 50
Initialization	Uniform random distribution
Max_iter	$100 \times d$
Stopping condition	Max_iter
Number of independent runs	30
ψ'	0.5
N	Max_iter
H	100
ω	0.729
c_1, c_2	1.49445

3.3 Experimental Results and Analysis

The experimental results are shown in Tables 2, 3, and 4. Several statistical indicators are introduced to demonstrate the availability of the algorithms: frequency of falling into a local optimum, maximum, minimum, average, and relative standard deviation (RSD). Falling into a local optimum indicates that the result is very much larger than the function's optimum; this is considered to be an unsuccessful operation, and the maximum in the

tables shows examples of falling into local optima when they exist. The success rate of an operation for each algorithm can be determined from the frequency of falling into a local optimum, and the effectiveness of successful operation results for algorithms can be verified by analyzing the minimum, average, and RSD of operation results. The accuracy and stability of successful results can be determined from the average and RSD, respectively, which are both calculated next to the results of falling into a local optimum. The minimum is the least accuracy that can be obtained. To observe the experimental results more directly, convergence curves of the fitness values nearest to the averages for the unimodal and multimodal functions in each dimension are described in Figures 2 and 3, respectively.

Unimodal functions: Tables 2–4 show the experimental results of the unimodal functions (f1–f4) obtained by RCBA and global PSO in each dimension. Considering the operation success rate for each algorithm, it can be found that RCBA is similar to global PSO in function f1 and absolutely superior to global PSO in functions f2–f4. Unsuccessful operation results are usually obtained by global PSO in functions f2–f4. Only two successful operations are obtained by global PSO for function f4 in 50 dimensions, the worst results among the unimodal functions, indicating extremely poor performance by global PSO. As for RCBA, successful operations are steadily achieved for all of the unimodal functions in each dimension. On the other hand, the results shown in Figure 2 are the fitness values nearest to the average. RCBA mostly performs better than global PSO on the stability of results, as shown by RSD. Only the results on function f2 in 10 dimensions show a slight disadvantage of RCBA compared to global PSO. In fact, considering the low success rate of operation for global PSO in 30 and 50 dimensions, RCBA is more suitable than global PSO in higher-dimensional unimodal optimization problems.

Multimodal functions: As shown in Tables 2–4, RCBA performs slightly better than global PSO in terms of operation success rate of all of the operations of RCBA, with unsuccessful operations appearing only in global PSO when performed on f6 in 30 and 50 dimensions. With regard to the accuracy and stability of successful results, RCBA mostly performs better than PSO, as shown in Figure 3 and Tables 2–4. In particular, on f6 in 50 dimensions, RCBA performs absolutely better than global PSO on accuracy of successful operations. Similarly, nearly all of the RSD values obtained in the experiments show the superiority of RCBA. Summarizing, when

considering multimodal functions, RCBA performs better than global PSO, with regard to the success rate of operation as well as the accuracy or stability of successful results.

Effect of dimension: Similarly, the effect of dimension is introduced in three aspects, success rate of operation and the accuracy and stability of successful results. First, it is easy to find from Table 2-4 that a higher dimension results in a worse global PSO success rate of operation, particularly in f2, f3, f4, and f6. Global PSO falls into a local optimum 4 and 15 times in 30 and 50 dimensions, respectively, in f2, 4 and 10 times in f3, 20 and 28 times in f4, and 1 and 12 times in f6. Global PSO usually performs unsuccessfully in higher dimensions, while RCBA maintains steadily successful operations with increased dimension. Accuracy of successful results remains basically unchanged for nearly all functions with increased dimension, but when considering f1 and f5, global PSO performs absolutely poorly in 30 and 50 dimensions, while RCBA still remains basically unchanged. Moreover, as shown in Figures 2 and 3, only the results for f8 show that RCBA is better than global PSO on accuracy of successful results in 10 dimensions, while in 30 and 50 dimensions, the results of four functions show the superiority of RCBA. In particular, for f6 in 50 dimensions, RCBA can achieve a precision of 10^{-7} , with global PSO achieving only 10^{-2} . In general, RCBA performs better than global PSO on accuracy of successful results with increased dimension. Finally, as shown in the analysis of unimodal and multimodal functions, nearly all of the RSD values in Tables 2-4 show the superiority of RCBA over global PSO on stability of successful results. It is not difficult to see that RCBA performs better than global PSO with increase of dimension. Moreover, the higher the dimension is, the smaller the RSD of all functions other than f6 based on RCBA is, indicating that RCBA performs better with increase of dimension. In addition, there is no such character in global PSO. Summarizing, RCBA performs better than global PSO with increase of dimension, and RCBA is more suitable than global PSO for high-dimensional optimization problems.

Table 2: Experimental results of the two algorithms in 10 dimensions.

Objective Function	Algorithm	Frequency of local optimum	Minimum	Average	Maximum	RSD
f1:Quadric	PSO	1	4.38E-21	7.36E-17	5000	3.52
	RCBA	0	5.80E+01	1.13E+03	3.08E+03	0.58
f2:Quartic	PSO	0	4.19E-91	2.00E-83	3.23E-82	3.04
	RCBA	0	1.28E-16	4.64E-13	1.30E-11	5.20
f3:Spherical	PSO	0	1.45E-48	1.29E-45	3.31E-44	4.66
	RCBA	0	2.44E-07	9.68E-07	7.67E-06	1.72
f4:HyperEllipsoid	PSO	0	6.52E-49	1.95E-45	1.88E-44	2.07
	RCBA	0	1.34E-06	1.69E-06	7.40E-06	0.70
f5:Ackley	PSO	0	2.66E-15	3.14E-15	6.22E-15	0.39
	RCBA	0	0.0041	1.9252	3.2264	0.55
f6:Griewank	PSO	0	0.0123	0.0887	0.1993	0.59
	RCBA	0	0.0174	0.1871	0.7475	1.00
f7:Rastrigin	PSO	0	2.9849	8.3245	28.8536	0.57
	RCBA	0	5.7869	14.2457	24.3351	0.34
f8:EggHolder	PSO	0	-6.45E+03	-5.46E+03	-4.44E+03	0.10
	RCBA	0	-6.95E+03	-6.01E+03	-4.68E+03	0.10

Table 3: Experimental results of the two algorithms in 30 dimensions.

Objective Function	Algorithm	Frequency of local optimum	Minimum	Average	Maximum	RSD
f1:Quadric	PSO	0	5.00E+03	9.73E+03	2.00E+04	0.51
	RCBA	0	8.24E+03	1.54E+04	2.44E+04	0.26
f2:Quartic	PSO	4	9.66E-94	2.02E-86	2.15E+01	4.29
	RCBA	0	1.08E-15	3.13E-15	3.74E-14	2.17
f3:Spherical	PSO	4	2.72E-59	9.14E-52	26.2144	4.73
	RCBA	0	7.32E-07	1.49E-06	4.05E-06	0.63
f4:HyperEllipsoid	PSO	20	3.28E-58	8.91E-48	262.144	3.13
	RCBA	0	1.14E-05	1.16E-05	1.39E-05	0.06
f5:Ackley	PSO	0	9.31E-01	3.1063	14.3936	0.84
	RCBA	0	1.7869	2.4993	2.899	0.09
f6:Griewank	PSO	1	0.0074	0.0382	90.1501	1.01
	RCBA	0	4.44E-06	0.0259	0.0625	0.76
f7:Rastrigin	PSO	0	58.7025	119.4253	191.1732	0.26
	RCBA	0	44.0972	56.1349	73.1088	0.15
f8:EggHolder	PSO	0	-1.83E+04	-1.50E+04	-1.18E+04	0.10
	RCBA	0	-1.89E+04	-1.70E+04	-1.44E+04	0.06

Table 4: Experimental results of the two algorithms in 50 dimensions.

Objective Function	Algorithm	times of local optimum	Minimum	Average	Maximum	RSD
f1:Quadric	PSO	0	5.00E+03	2.54E+04	8.67E+04	0.80
	RCBA	0	2.18E+04	3.46E+04	4.89E+04	0.16
f2:Quartic	PSO	15	1.02E-91	4.16E-85	42.9497	3.21
	RCBA	0	2.97E-15	2.97E-15	2.97E-15	0.00
f3:Spherical	PSO	10	1.28E-56	1.65E-47	26.2144	4.03
	RCBA	0	1.22E-06	1.65E-06	5.71E-06	0.62
f4:HyperEllipsoid	PSO	28	7.20E-54	8.25E-51	1.44E+03	1.41
	RCBA	0	3.11E-05	3.13E-05	3.56E-05	0.03
f5:Ackley	PSO	0	1.471	8.6892	16.855	0.63
	RCBA	0	2.1493	2.5136	3.0702	0.09
f6:Griewank	PSO	12	0.0099	0.0489	90.9923	0.65
	RCBA	0	2.06E-07	0.0158	0.0866	1.51
f7:Rastrigin	PSO	0	164.2387	243.2615	365.5032	0.20
	RCBA	0	75.9001	93.582	116.4303	0.13
f8:EggHolder	PSO	0	-2.83E+04	-2.43E+04	-2.06E+04	0.08
	RCBA	0	-3.15E+04	-2.86E+04	-2.59E+04	0.05

(a) f1: Quadric

(b) f2: Quartic

(c) f3: Spherical

(d) f4: HyperEllipsoid

Figure 2: Convergence curves of RCBA and global PSO for unimodal functions (f1–f4).

Figure 3: Convergence curves of RCBA and global PSO for multimodal functions (f5–f8).

4. Conclusion

In daily life, people constantly adjust their route choice to find a better one on each trip based on their own experience, guidance information, and the influence of others. This is a learning optimization process, and it inspired us to utilize it for optimization. RCBA is proposed in this paper based on route choice behavior. Experimental results show the superiority of RCBA over the global PSO, especially in higher dimensions, and an analysis of the influence of dimension on RCBA and global PSO shows that the higher the dimension is, the better RCBA performs relative to global PSO. Since the parameters in RCBA correspond to aspects of route choice behavior with practical significance, in the future, we also can match impact factors of route choice with parameters in RCBA and analyze the influence of impact factors on route choice behavior by studying the influence of the corresponding parameters on RCBA, such as studying the influence of the parameter ψ on RCBA to analyze the accepting guidance ratio in route choice behavior.

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