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Origin-Oriented Shuffled Frog Leaping Vehicle Routing Multiobjective Optimization Algorithm

Liqun Liu, Gansu Agricultural University, China*
Renyuan Gu, Gansu Agricultural University, China
Jiuyuan Huo, Lanzhou Jiaotong University, China
Yubo Zhou, Gansu Agricultural University, China

ABSTRACT

Shuffled frog leaping algorithm is a biological swarm intelligent optimization algorithm and improved into capacity-limited vehicle routing problem. However, the optimization performance is limited with improvement strategies in major of the improvement algorithm. A novel framework of algorithm is proposed to solve capacity-limited vehicle routing problem, including three modules such as origin oriented shuffled frog leaping algorithm strategy, origin oriented shuffled frog leaping vehicle routing multiobjective optimization algorithm strategy, and output module. The frog individuals gather near the origin with the maximum probability and in the area circle, with the frog leaping radius or frog-oriented radius, as the neighborhood. The negative value of the maximum entropy and the shortest total path length of the vehicle are selected as the fitness. The performance test shows that it overcomes the defect of slow convergence compared with other five algorithms. It performs well to solve vehicle routing problems.

KEYWORDS

Frog Leaping Radius, Frog Oriented Radius, Improvement Strategy, Multiobjective, Multiobjective Fitness, Optimized Application, Optimization Performance, Origin Oriented

INTRODUCTION

The shuffled frog leaping algorithm (SFLA) originated from the biological swarm intelligent optimization algorithm. The authors of Eusuff et al. (2003) and Sun et al. (2021) showed in their previous work that it has the advantages of the frog swarm optimization strategy of cyclic sorting and grouping and the frog individual jump optimization in the Group. He et al. (2021) discuss it has been largely applied to solve numerical problems. The results in the research of Lei et al. (2021) showed SFLA has the shortcomings of relying on the inertial guidance of the original position and the limitation of step size. The capacity-limited vehicle routing problem (CVRP) is a non-deterministic

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*Corresponding Author

polynomial problem, usually be considered as a multiobjective optimization problem. However, most of existing technology using heuristic algorithm to solve CVRP has the defects of long running time and easy to fall into premature convergence.

Related Work in Field of Shuffled Frog Leaping Algorithm

Scholars have improved the defects of SFLA and applied it to different fields. In the research of Wang et al. (2021), it introduced the intermediate factor and acceleration factor based on the idea of dichotomy search in mathematics. Shen et al. (2021) proposed a personalized tourism route recommendation method based on an improved hybrid leapfrog algorithm. Al-Ghussain et al. (2020) used shuffled frog leaping and pattern search to model a photovoltaic system. Cai et al. (2021) proposed a modified shuffled frog leaping algorithm with a ternary quantum. You et al. (2020) used an improved hybrid leapfrog algorithm to optimize fault diagnosis in a support vector machine.

The above research adopted different strategies to improve the performance of SFLA. However, the above methods all have defects of themselves. In this article, in the view of a local mechanism in the area with the origin as the center and the individual step size as the radius, the definitions of the frog leaping radius and frog oriented radius are defined. The frog's current position inertia and jump step in the local search are discarded so that the frog individuals gather near the origin with the maximum probability and in the area circle with the frog leaping radius or frog oriented radius as the neighborhood.

Related Work in Field of Capacity-Limited Vehicle Routing Problem

In the research of Yan (2015), it shows that the capacity-limited vehicle routing problem is a typical NP-hard problem. Yang et al. (2020) proposed a multigroup multistrategy sine cosine algorithm to solve the CVRP. Mohammed et al. (2017) used a genetic algorithm (GA) to solve the route of the vehicle routing problem (VRP). Sajid et al. (2021) proposed an operator of giant tour best cost crossover for CVRP solutions. Faust et al. (2020) used the ant colony optimization (ACO) algorithm with optimized parameters from the GA to compute the CVRP. Li et al. (2021) proposed a new ACO algorithm based on an improved greedy strategy for path planning problem. Dhanya et al. (2018) provided a hybrid relay algorithm, which involved ACO and the Crow Search Algorithm (CSA) to solve the CVRP. Gupta et al. (2018) proposed a CVRP solution using improved ACO algorithm. Yang et al. (2019) proposed a generating sparks mechanism in the fireworks algorithm (FWA) to apply in the benchmark CVRP. Kussman et al. (2020) proposed the hybrid bat algorithm to solve the CVRP. Luo et al. (2011) proposed the shuffled frog leaping algorithm on real coding mode using the method of power law external optimization to solve the CVRP. Wan et al. (2011) used a different local search mechanism in the SFLA for the improvement efficiency of CVRP. Hannan et al. (2018) computed the route optimization solutions in the CVRP model with more efficient particle swarm optimization (PSO) algorithm. Kao et al. (2013) developed a discrete PSO with Simulated Annealing (SA) to compute the CVRP. Kao et al. (2012) proposed a new algorithm combining ACO and PSO for the CVRP. Ahmed et al. (2018) developed a new PSO algorithm with a bilayer local search mechanism for decoding the CVRP. ElMousel et al. (2021) introduced the discrete whale optimization algorithm to solve the CVRP. Altabeeb et al. (2019) proposed the firefly algorithm (FA) to solve the CVRP. The above research adopted different improved swarm intelligence algorithms to solve the CVRP. The research results show that using better strategy to improve the swarm intelligence algorithm and applying into the CVRP problem is a good solution. However, the optimization performance is limited with improvement strategies in major of the improvement algorithm.

Considering that the optimization performance is limited with improvement strategies in major of the improvement algorithm, an origin oriented shuffled frog leaping algorithm (OPSFLA) is proposed, which greatly improves the convergence performance of the original SFLA. The proposed OPSFLA is implemented to solve the CVRP, and an origin oriented shuffled frog leaping vehicle routing multiobjective optimization algorithm (OPSFLA-MOVRP) is proposed to achieve good results.

Contributions

The contributions in this article are summarized as follows:

First, the framework of algorithm is proposed to solve the CVRP, including three modules such as OPSFLA strategy, OPSFLA-MOVRP strategy and output module.

Second, OPSFLA algorithm is proposed to improve the efficiency of SFLA. The purpose of the frog leaping radius and frog oriented radius is to limit the frog's current position inertia and jump step in the local search so that the frog individuals gather near the origin with the maximum probability and in the area circle with the frog leaping radius or frog oriented radius as the neighborhood. The CEC2017 benchmark function experiment shows that the OPSFLA overcomes the defect of slow convergence of the original SFLA.

Third, taken the CVRP problem as a multiobjective optimization problem, OPSFLA-MOVRP is proposed to solve CVRP. The negative value of the maximum entropy and the shortest total path length of the vehicle are selected as the multiobjective fitness. The small-scale data and large-scale standard test results show that the OPSFLA-MOVRP algorithm reflects the good effect of multiobjective path optimization.

Paper Structure

The structure in this article is summarized as follows.

In introduction section, the original shuffled frog leaping algorithm is introduced. In related work section, two fields are described. In contributions section, three contributions are clarified. In paper structure section, the structure of this paper is given out. In origin oriented shuffled frog leaping algorithm section, the framework, definition, idea, convergence analysis and algorithm efficiency analysis are given out. In origin oriented shuffled frog leaping vehicle routing multiobjective optimization algorithm section, the multiobjective optimization strategy, algorithm idea, and algorithm efficiency analysis are given out. In test experiment section, two types of test are given out, including OPSFLA algorithm optimization performance test, and optimization application experiment of vehicle routing problem. In the end section, the conclusion of this paper is given out.

ORIGIN ORIENTED SHUFFLED FROG LEAPING ALGORITHM

Framework of Algorithm

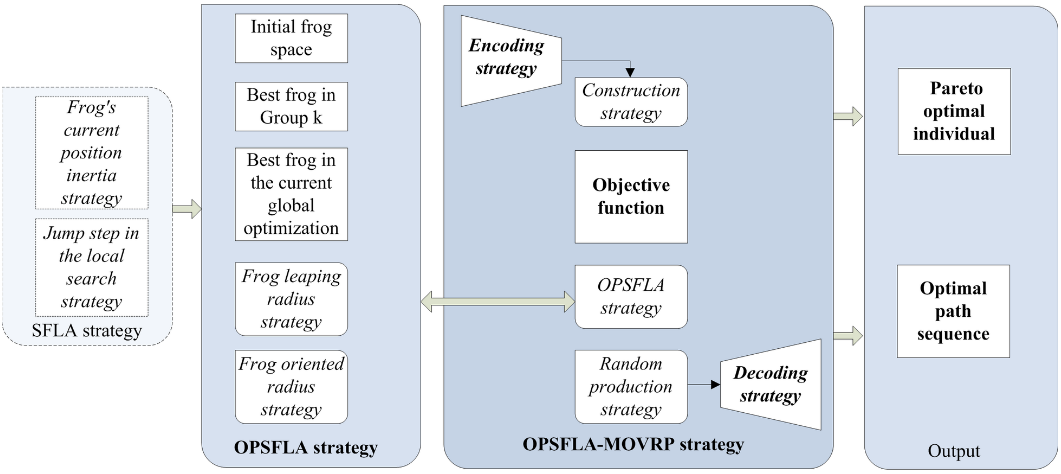
Aiming at the weaknesses of tending to get into grouping convergence caused by the original SFLA frog's dependence on the original position inertial guidance and step size limitation, this paper proposes an origin oriented shuffled frog leaping algorithm. And an origin oriented shuffled frog leaping vehicle routing multiobjective optimization algorithm is proposed to solve the CVRP. The framework of algorithm is descripted in Figure 1.

As shown in Figure 1, the SFLA strategy is discarded, including the frog's current position inertia strategy and jump step in the local search strategy. Instead of it, a novel framework of algorithm is proposed to solve the CVRP, including three modules. First, the OPSFLA strategy is proposed, including five definitions and two improvement strategies. And then, the OPSFLA strategy is adopted into the OPSFLA-MOVRP strategy to solve CVRP. At last, the output module is used to output pareto optimal individual and optimal path sequence.

Background of Origin Oriented Shuffled Frog Leaping Algorithm

Based on the idea of a local mechanism in the area with the origin as the center and the individual step size as the radius, the definitions of the frog leaping radius and frog oriented radius are defined as follows:

Figure 1. Framework of algorithm



Definition One: The initial frog space is represented as X_p. The initial frog population is p, the number of groups is m, the number of frogs in the group is n, and each frog has s dimensions. Set the number of optimizations within the group as T_1 and the number of global optimizations as T_2.

Definition Two: The best frog in Group k is recorded as $x(k)_b = (x(k)_{b1}, x(k)_{b2}, \cdots, x(k)_{bS})$.

Definition Three: The best frog in the current global optimization is recorded as $x(g)_b = (x(g)_{b1}, x(g)_{b2}, \cdots, x(g)_{bS})$.

Definition Four: The frog leaping radius (Leap_radius) in Group k is defined as the difference between the best frog and the worst frog in the current group k, which is recorded as $Ls = x(k)_b - x(k)_w$. $x(k)_w$ represents the worst frog in group k.

Definition Five: The frog oriented radius (Oriented_radius) in Group k is defined as the difference between the best frog and the worst frog in the current group k, which is recorded as $Os = x(g)_b - x(k)_w$. $x(k)_w$ represents the worst frog in group k.

Frog Leaping Radius Strategy Based on Original Point

In one iteration of frog group optimization, the worst frog component $x(k)_{wi}, i = 1, 2, \cdots, S$ in Group k will take the origin (0,0) as the center and search with radius Ls, as shown in equation (1).

$$x(k)^{new}{}_{wi} = rand(0,1)[x(k)_{bi} - x(k)^{old}{}_{wi}] \tag{1}$$

In equation (1), the frog's current position inertia and jump step in the local search are discarded so that the frog individuals gather near the origin with the maximum probability and in the area circle with the frog leaping radius as the neighborhood. The origin is used as the center to guide the direction of individual frog jumping, and then the frog leaping radius is used to guide the speed of individual frog jumping so that individual frogs gather near the origin with maximum probability, which improves the search ability.

Frog Oriented Radius Strategy Based on Original Point

In one iteration of frog group optimization, if the optimization requirements are not met, the worst frog component $x(k)_{\mathrm{w}i}, i = 1, 2, \cdots, \mathrm{S}$ in Group K will take the origin (0,0) as the center and search with radius Os_w , as shown in equation (2).

$$x(k)^{new}{}_{wi} = rand(0,1)[x(\mathrm{g})_{bi} - x(k)^{old}{}_{wi}] \tag{2}$$

In equation (2), the frog's current position inertia and jump step in the local search are discarded so that the frog individuals gather near the origin with the maximum probability and in the area circle with the frog oriented radius as the neighborhood. The origin is used as the center to guide the direction of individual frog jumping, and then the frog oriented radius is used to guide the speed of individual frog jumping so that individual frogs gather near the origin with maximum probability, which improves the search ability.

Idea of Origin Oriented Shuffled Frog Leaping Algorithm

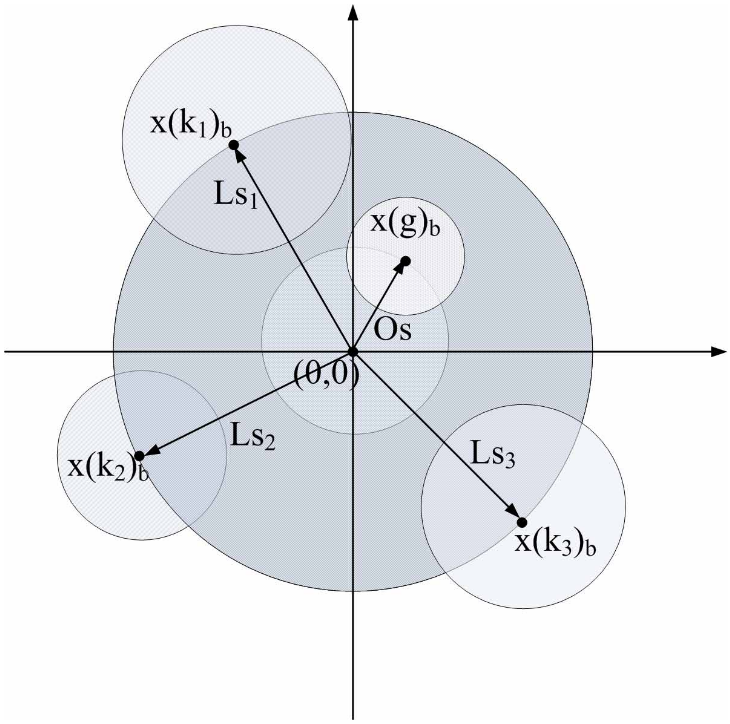
The frogs jump as follows in SFLA. First, select the worst one in the group. Second, let the worst one jump to the best one in the group. Third, if the updated value is worse than the former value, let the worst value jump to the global optimum. Fourth, if the updated value is still worse than the former value, it will jump randomly once. In this way, the frog's jump is limited by the step size. Therefore, the frog will carry out the optimal convergence within the population step by step and then carry out the optimal convergence between the populations. Thus, the evolution performance is poor, and it tends to enter the extreme of grouping convergence.

According to the no free lunch theory in the research of Wolpert et al. (1997), that is, from the perspective of solving practical problems, it is assumed that the optimal algorithm has the same average performance as the simple algorithm, which is as well as shown in the research of Goodfellow et al. (2017). Therefore, in the origin oriented shuffled frog leaping algorithm, discarding the inertial guidance of the individual's original position and the step size limit in the group search will produce the following results. First, select the worst one in the group. Second, the worst one jumps into an area that is a circle with (0,0) as the center and the frog leaping radius as the neighborhood. Third, if it is inferior to the original value, it jumps into an area that is a circle with (0,0) as the center and the frog oriented radius as the neighborhood. Fourth, if it is still inferior to the original value, it will jump randomly. The principle of the OPSFLA algorithm is shown in Figure 2. The origin (0,0) is used as the center to guide the direction of individual frog jumping, and then the frog leaping radius and frog oriented radius are used to guide the speed of individual frog jumping so that individual frogs gather near the origin (0,0) with maximum probability, which improves the search ability.

Convergence Analysis

The Origin Oriented Shuffled Frog Leaping Algorithm mainly aims at the defects that the original SFLA group optimization depends too much on the original position inertial guidance and step size limit. In the group optimization, two optimization strategies, including the frog leaping radius strategy based on the original point and the frog oriented radius strategy based on the original point, are used to evolve the worst frogs in the group, jumping to the optimal frog in the group with Ls as the radius and jumping to the global optimal frog with Os as the radius. Taking the (0,0) origin as the center and the improved individual step size as the radius, evolutionary optimization can promote frog individuals to gather near the origin (0,0) in the way of maximum probability, which greatly modifies the convergence performance of the original SFLA.

Figure 2. Principle of origin oriented shuffled frog leaping algorithm



Algorithm Efficiency Analysis

The space-time complexity of the SFLA and improved OPSFLA algorithms are $O(T_1 \times T_2 \times m \times S)$ and $O(m \times n \times S)$, respectively. The OPSFLA does not add additional computational complexity and cost.

ORIGIN ORIENTED SHUFFLED FROG LEAPING VEHICLE ROUTING MULTIOBJECTIVE OPTIMIZATION ALGORITHM

Multiobjective Optimization Strategy of Vehicle Routing

The CVRP problem is taken as a multiobjective optimization problem, OPSFLA-MOVRP is proposed to solve CVRP. In this multiobjective optimization problem, the customer number is coded as the initial frog individual, and the negative value of the maximum entropy and the shortest total path length of the vehicle are selected as the fitness.

Encoding and Decoding Strategy

A customer number is encoded as an initial individual component, and the S-dimensional component is the number of S customers. Decode the individual into the vehicle routing sequence and customer number.

Random Production Strategy

In a grouping evolution, if the updated value of the evolution strategy in two groups is still worse than the original value, equation (3) is used.

$$x(k)_i^{new} = r\%\mathrm{S} + 1 \tag{3}$$

Objective Function of the Capacity-Limited Vehicle Routing Multiobjective Optimization Problem

In practical applications, the CVRP problem can be regarded as a multiobjective problem. The fitness expression is shown in equation (4). Two functions, the negative value of the maximum entropy $H(X)$ and the shortest total path length of the vehicle $D(i,j)$, are selected as the multiobjective fitness. Among them, the value of the maximum entropy $H(X)$ represents the maximum value of information included in the transportation. And, the shortest total path length of the vehicle $D(i,j)$ represents the minimum summary value of vehicle path in the transportation.

$$\begin{aligned}
&\min f(i,j) = \min\{f_1, f_2\} \quad (4.1)\\
&f_1 = D(i,j) = \sum_{i=0}^{N}\sum_{j=0}^{N}\sum_{s=1}^{K} c_{ij} x_{ijs} \quad (4.2)\\
&f_2 = -H(i,j) = \sum_{i=0}^{N}\sum_{j=0}^{N} p_{ij}\log p_{ij} \quad (4.3)\\
&s.t.\begin{cases}
\sum_{i=0}^{N} x_{ijs} = y_{js}, j = 1,2,\cdots,N; s = 1,2,\cdots,K \quad (4.4)\\
\sum_{j=0}^{N} x_{ijs} = y_{is}, i = 1,2,\cdots,N; s = 1,2,\cdots,K \quad (4.5)\\
\sum_{i=0}^{N} q_i y_{is} \le q_s, s = 1,2,\cdots,K \quad (4.6)\\
\sum_{s=1}^{K} y_{is} = \begin{cases} 1, i = 1,2,\cdots,N \\ K, i = 0 \end{cases} \quad (4.7)
\end{cases}\\
&\sum_{i=0}^{N} p_i = 1, i = 1,2,\cdots,N \quad (4.8)\\
&\sum_{j=0}^{N} p_j = 1, j = 1,2,\cdots,N \quad (4.9)\\
&p_{ij} = \frac{c_{ij}}{D(i,j)} \quad (4.10)
\end{aligned} \tag{4}$$

Construction Strategy of the Multiobjective Nondominated Solution Set

In this problem, the advantages and disadvantages of individuals are judged by the dominant relationship and density of solutions. The grid construction technology is used to check the density of the Pareto data set to ensure that the distribution between Pareto optimal solutions is not too dense. Equation (5) is used as the condition of multiobjective nondominated solution ranking.

$$f_{T\arg et=1}(x(j)) < f_{T\arg et=1}(x(j+1)) and f_{T\arg et=2}(x(j)) < f_{T\arg et=2}(x(j+1)) \tag{5}$$

Algorithm Idea

Step 1: Set the number of optimizations within the group to T_1, the number of global optimizations to T_2, the number of objective functions to target = 2, and the number of nondominated solutions to Pare.
Step 2: Calculate the frog fitness according to equation (4), judge whether there is a dominant relationship within the initial frog, and construct a nondominant solution set.

Step 3: Sort the nondominated solution according to $f_{T\arg et}(x(j))$, determine the Pareto optimal frog in this evolution, and the frog cycle enters the grouping.
Step 4: In each group, sort the nondominated solution of frog individuals in the group according to the fitness, find the Pareto optimal frog in group $k = 1,2,\cdots,\mathrm{m}$, and evolve each one-dimensional weight $x(k)_i, i = 1,2,\cdots,\mathrm{S}$ of different frog individuals $x(k)$ through the frog leaping radius strategy based on the original point of equation (1). Judge the dominating relationship of the current nondominating solution set. If there is a dominating solution, delete it; otherwise, replace $x(k)_i^{old}$ with $x(k)_i^{new}$. Judge the grid density and delete the dense solution.
Step 5: The frog oriented radius strategy based on the original point of equation (2) is used for evolution. Judge the dominant relationship of the current nondominant solution set and delete it if it is dominant. Judge the grid density.
Step 6: Use equation (3) to randomly generate a new nonrepeating frog individual component. Judge the dominant relationship of the current nondominant solution set and delete it if it is dominant.
Step 7: Judge that T_1 is reached in the group; otherwise, go to Step 4 to continue group information exchange.
Step 8: Otherwise, the judgment reaches T_2 or convergence accuracy; otherwise, go to Step 3, mix all frogs, sort the nondominated solution again according to the fitness, and then continue to evolve. Otherwise, the algorithm stops outputting the result $f_{T\arg et}(x(j))$.
The algorithm flow is shown in Figure 3.

Algorithm Efficiency Analysis

The space-time complexity of OPSFLA-MOVRP is $O(T_1 \times T_2 \times m \times n \times T\arg et \times Pare \times S \times K)$ and $O(m \times n \times S \times T\arg et \times Pare \times N + K)$, respectively. S, N and K will vary with the size of the data set.

TEST EXPERIMENT

OPSFLA Algorithm Optimization Performance Test Experiment

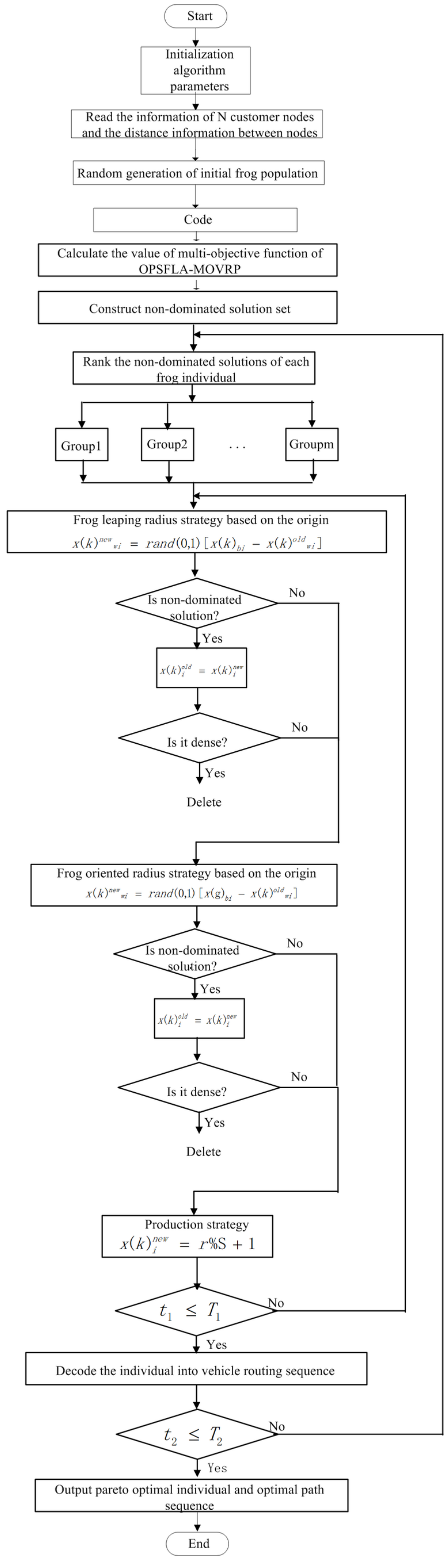
The experiment adopts the CEC2017 test set functions which were listed in the research of Awad et al. (2016). The optimization performance of the following six algorithms is tested: OPSFLA, shuffled frog leaping algorithm with memory (MSFLA) which was proposed by Dai et al. (2011), shuffled frog leaping algorithm based on global sharing factor (GSF^{2}LA) which was proposed by Liu et al. (2013), SFLA, harmony search algorithm (HSA) which was proposed by Geem et al. (2001), and artificial bee colony algorithm (ABCA) which was proposed by Karaboga et al. (2007). Twenty benchmark functions of CEC2017 test set are chosen in this paper, including nine unimodal functions, and nine multimodal functions, and two composition functions. Among them, P = 200, M = 20, n = 10, S = 30, T_1 = 10, and T_2 = 200.

The iterative results are shown in Figure 4 ~ Figure 23. The results show that, except for the optimization results of two multipeak functions f_8 and $f_{18,}$ which are not ideal, the OPSFLA performs well in the convergence accuracy of the single peak function, multipeak function and composite functions f_{19} and f_{20}. The OPSFLA overcomes the defect of slow convergence of the original SFLA.

Single Objective Optimization Application Experiment of Vehicle Routing Problem

The experiments are conducted on the following four algorithms OPSFLA, MSFLA, GSF^{2}LA, and SFLA for single objective optimization of the vehicle routing problem. The shortest path value is adopted to be the fitness of single objective optimization. Four algorithms are obtained, including OPSFLA-MOVRP, shuffled frog leaping algorithm with memory for Capacity-Limited vehicle routing problem (MSFLA-CVRP), shuffled frog leaping algorithm based on global sharing factor

Figure 3. Flow chart of OPSFLA-MOVRP



for capacity-limited vehicle routing problem (GSF²LA-CVRP), shuffled frog leaping algorithm for capacity-limited vehicle routing problem (SFLA-CVRP).

The RC101 data set from the Solomon website is adopted to test the performance of the CVRP using the above four algorithms. The RC101 data set could be available from http://web.cba.neu.edu/~msolomon/problems.htm. Where p = 100, M = 10, n = 10, S = 8, T_1 = 10, T_2 = 30, n = 100, S = 100, K = 2 and K = 4, q_s = 200. When K = 2, the optimized vehicle route results are shown in Table 1. When K = 4, the results are shown in Table 2.

Figure 4. Iterative results of f1

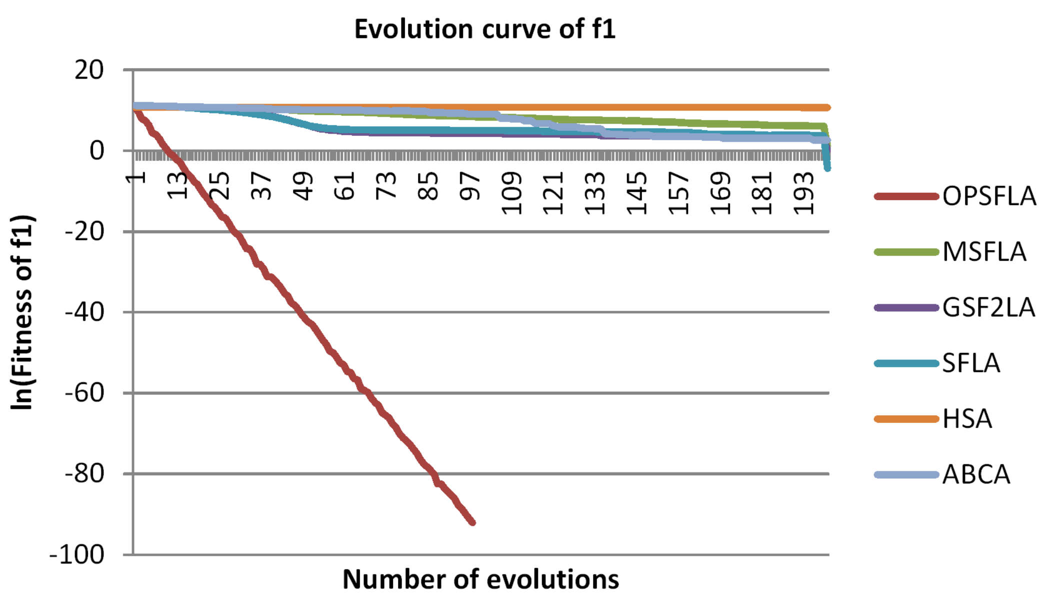


Figure 5. Iterative results of f2

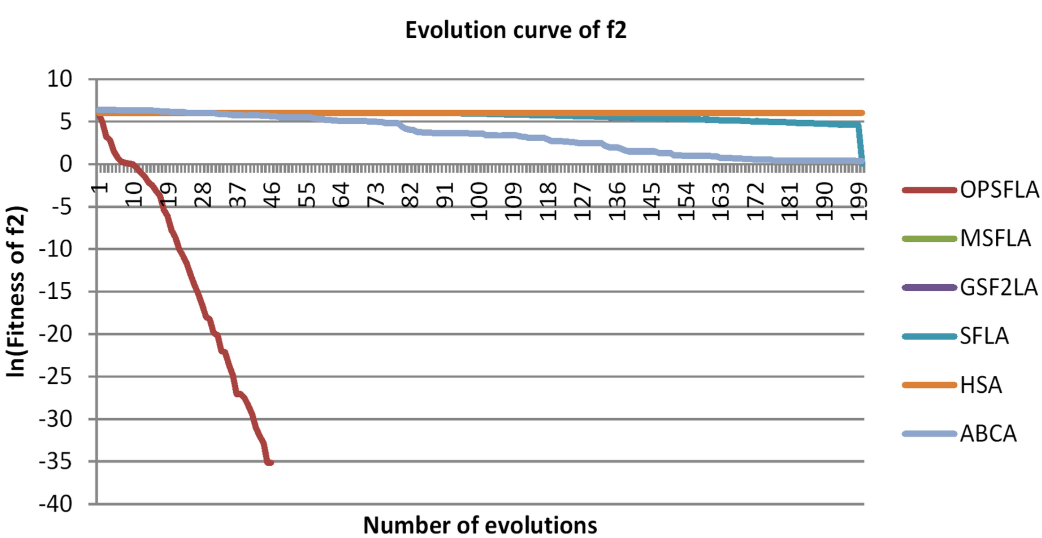


Figure 6. Iterative results of f3

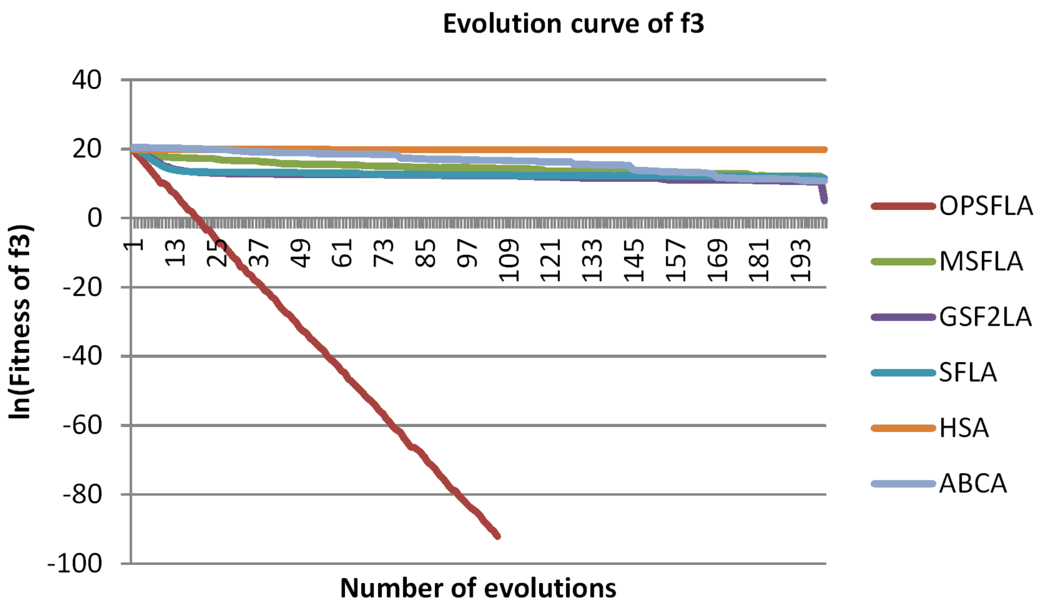
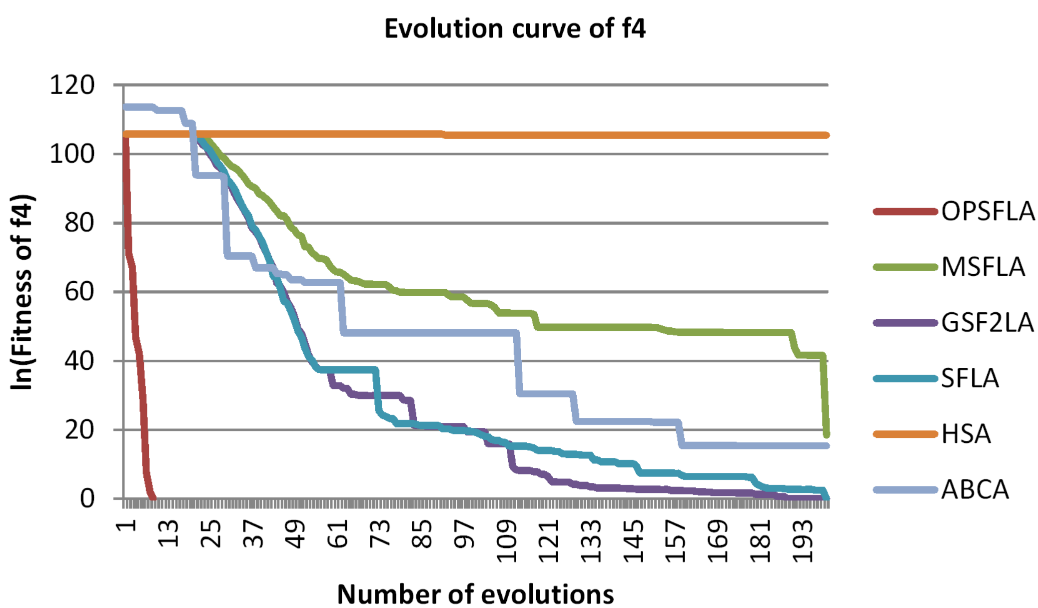


Figure 7. Iterative results of f4



Multiobjective Optimization Application Experiment of Vehicle Routing Problem

Small-scale Data Application Experiment

The proposed OPSFLA-MOVRP algorithm is tested with small-scale data which is come from the research of Yan et al. (2015). The distance and demand between customers are set similar to the

Figure 8. Iterative results of f5

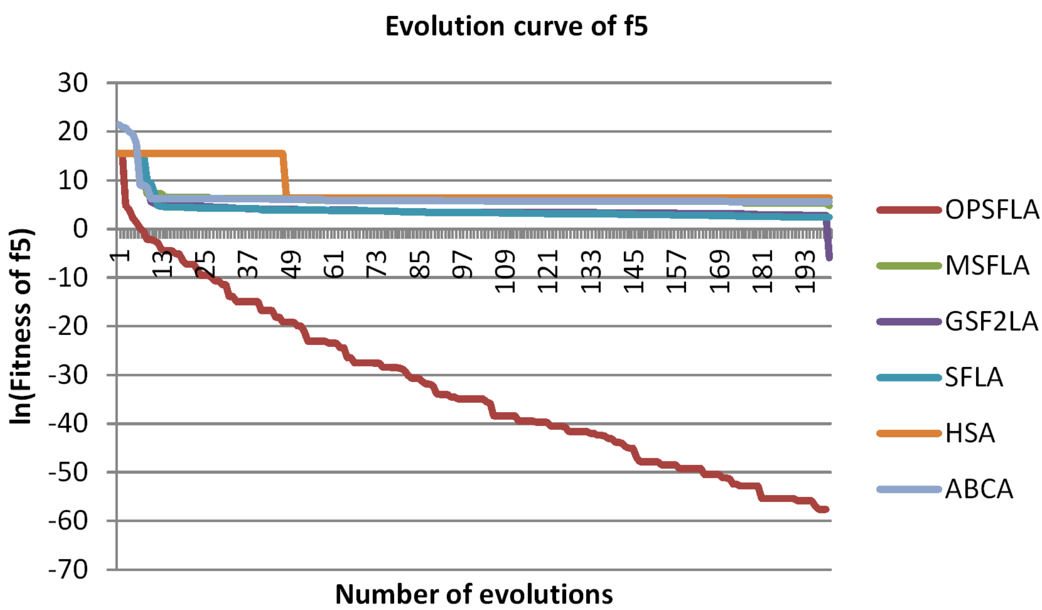
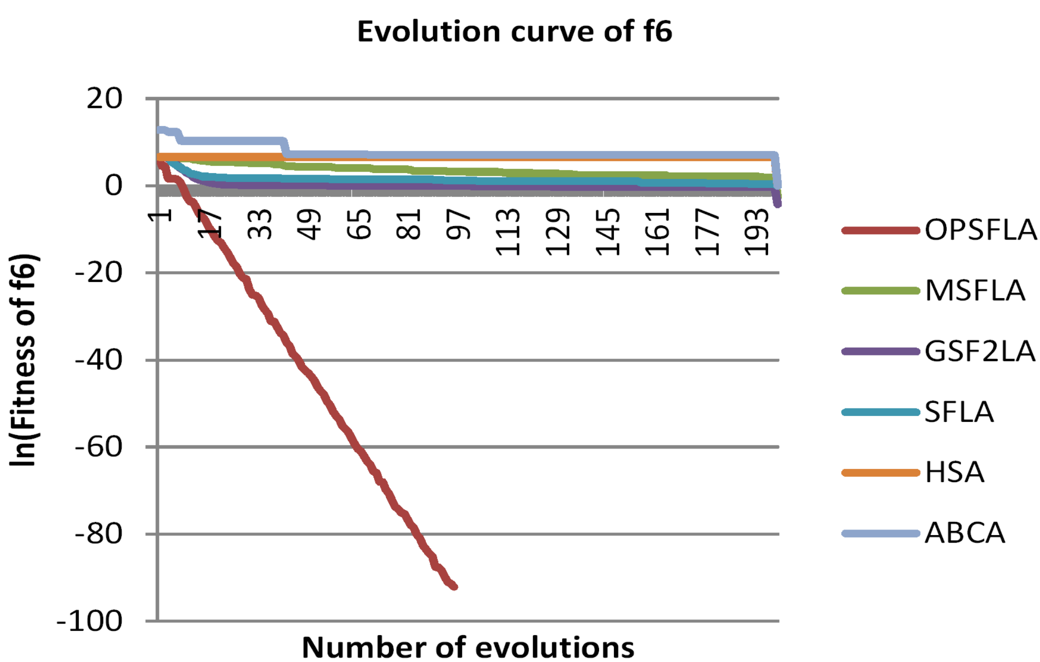


Figure 9. Iterative results of f6



research of Yan et al. (2015). Where p = 100, M = 10, n = 10, S = 8, T_1 = 10, T_2 = 100, n = 8, S = 8, and K = 2. The optimized vehicle route results are shown in Figure 24 and Table 3.

Figure 10. Iterative results of f7

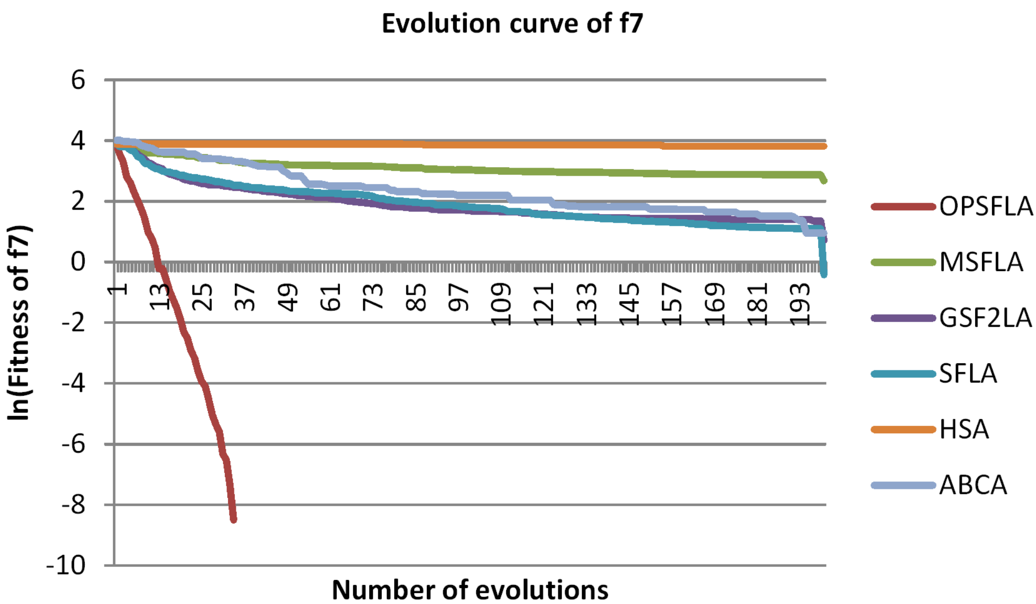
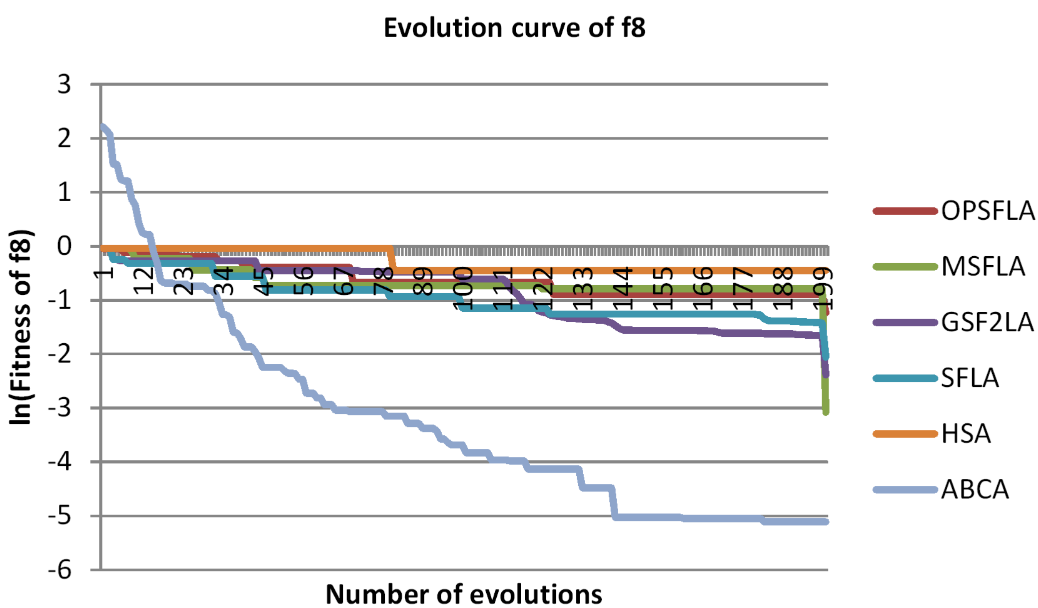


Figure 11. Iterative results of f8



Large-Scale Data Application Experiment

In this test, to expand the data scale, the large-scale test set C202 data is used for the performance test. The C202 data set could be available from http://web.cba.neu.edu/~msolomon/problems.htm. Where p = 100, M = 10, n = 10, S = 100, $T_1 = 10$, $T_2 = 80$, n = 100, S = 100, K = 3 and K = 4, q_s

Figure 12. Iterative results of f9

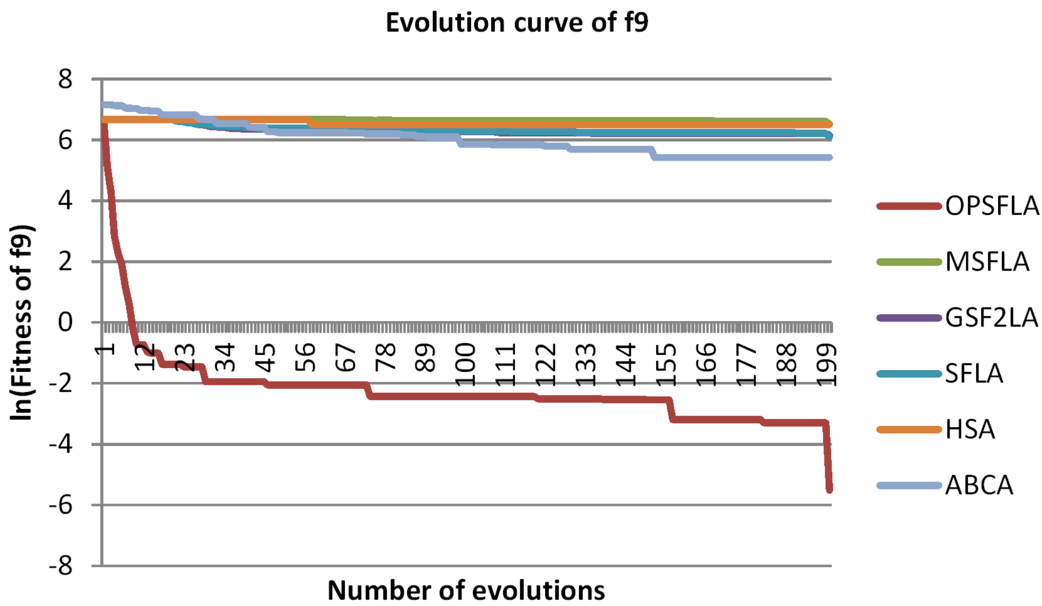
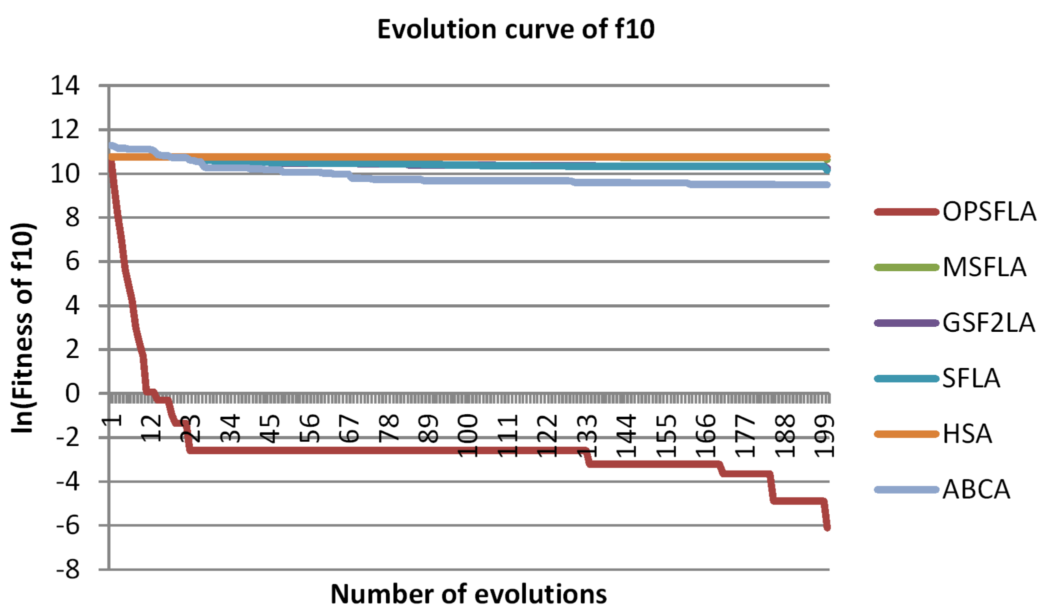


Figure 13. Iterative results of f10



= 700. The optimized vehicle route is shown in Figure 25 ~ Figure 26. When K = 3, the route optimization results are shown in Table 4.

The results show that the OPSFLA-MOVRP algorithm reflects the good effect of multiobjective path optimization, whether it is small-scale data or large-scale standard test data. In the small-scale data experiment, five solutions meet the requirements of path optimization. As seen from figure 24,

Figure 14. Iterative results of f11

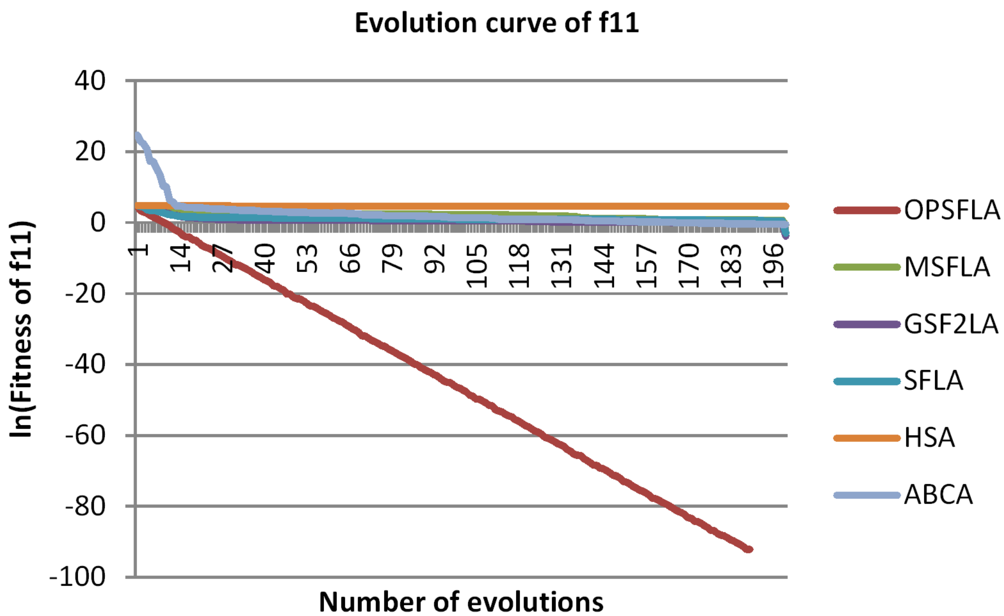
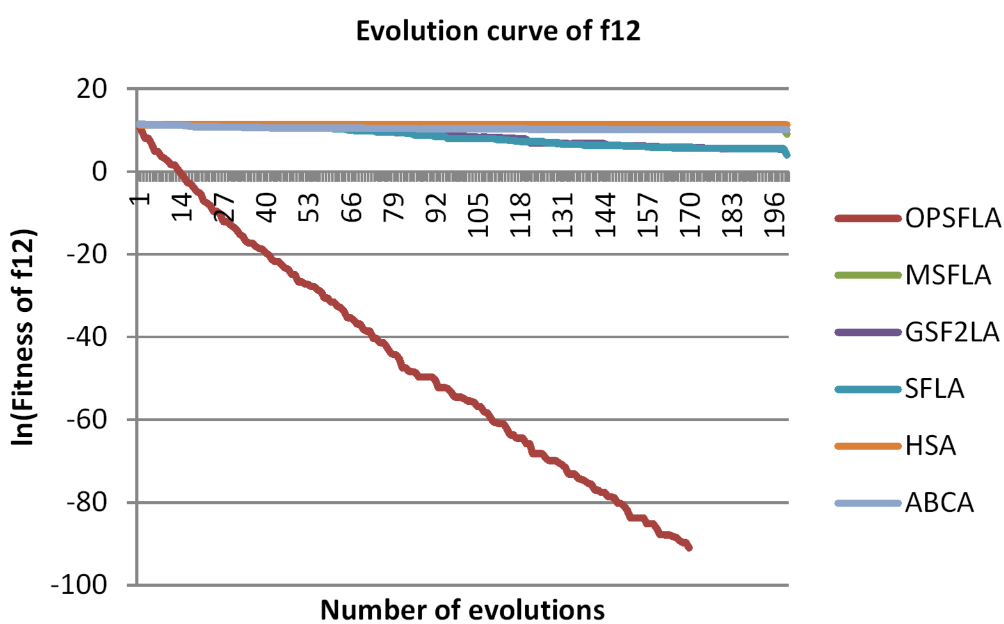


Figure 15. Iterative results of f12



multiple paths start and end with the distribution center after passing through three customers. In large-scale data experiments, when K = 3, the result is Pare = 4, and when K = 4, the result is Pare = 9. With the number of customers rising and the vehicle capacity adding, the number of multiple

Figure 16. Iterative results of f13

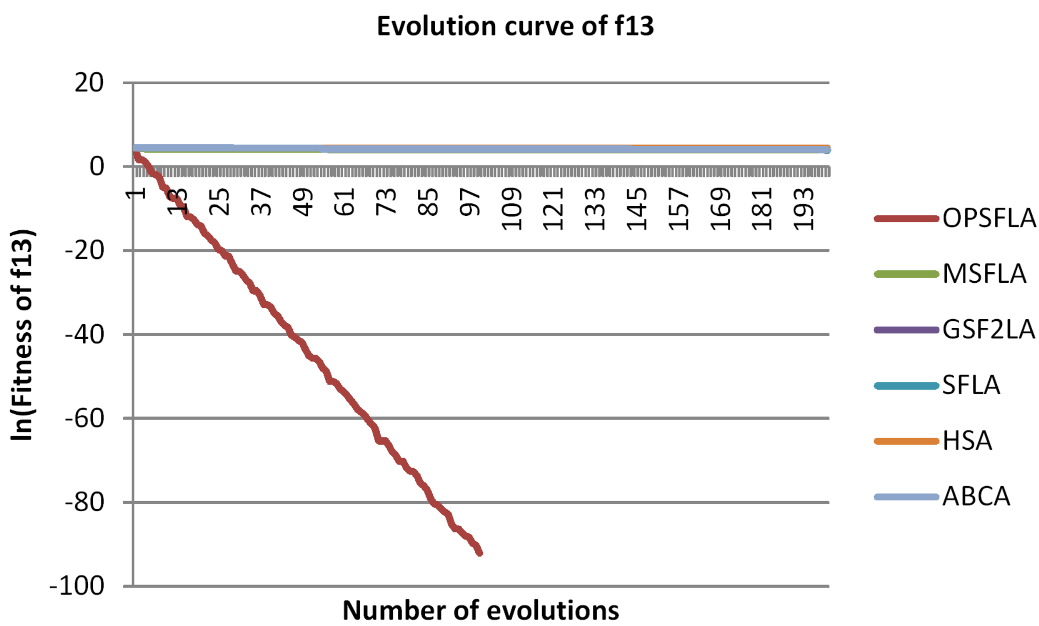
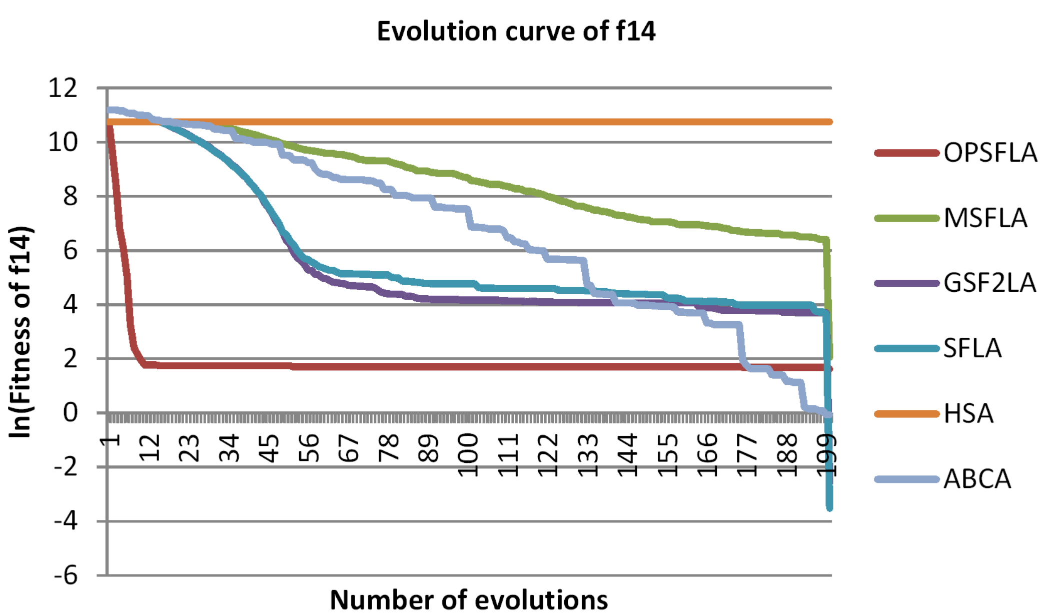


Figure 17. Iterative results of f14



solutions increases, as does the number of corresponding paths, showing the trend of multiple path optimization.

In conclusion, the two types of experiments results are summarized as follows:

Figure 18. Iterative results of f15

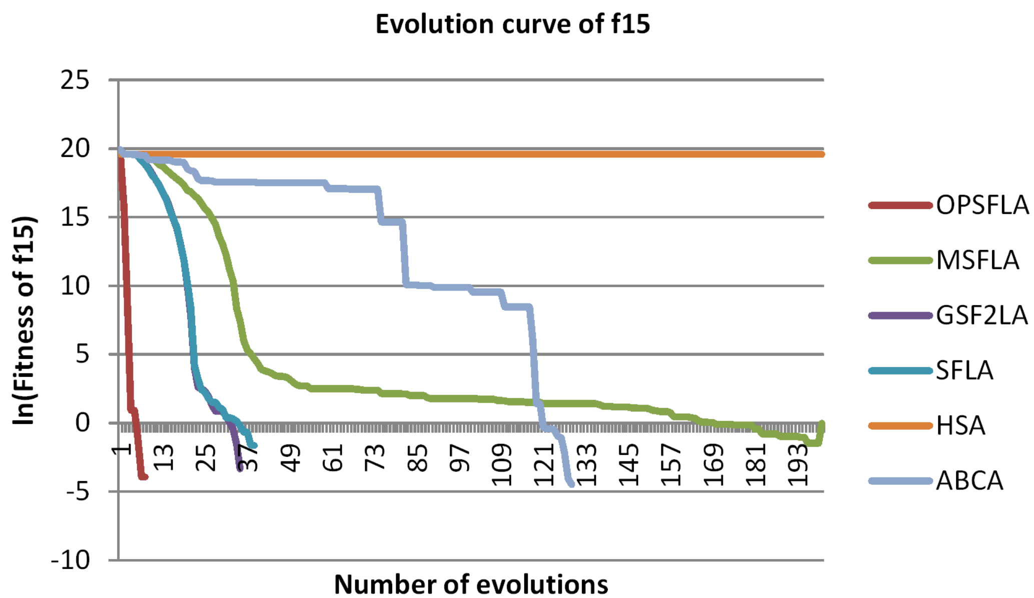
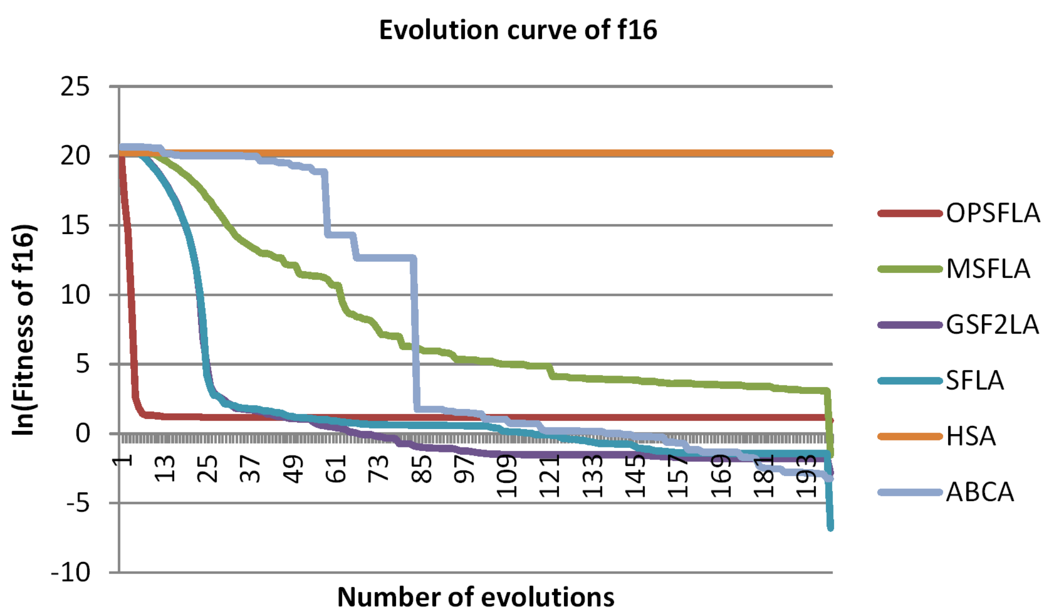


Figure 19. Iterative results of f16



First, the CEC2017 benchmark function experiment shows that the OPSFLA overcomes the defect of slow convergence of the original SFLA compared with other five algorithms.

Second, the small-scale data and large-scale standard test results show that the OPSFLA-MOVRP algorithm reflects the good effect of multiobjective path optimization compared with other three algorithms.

Figure 20. Iterative results of f17

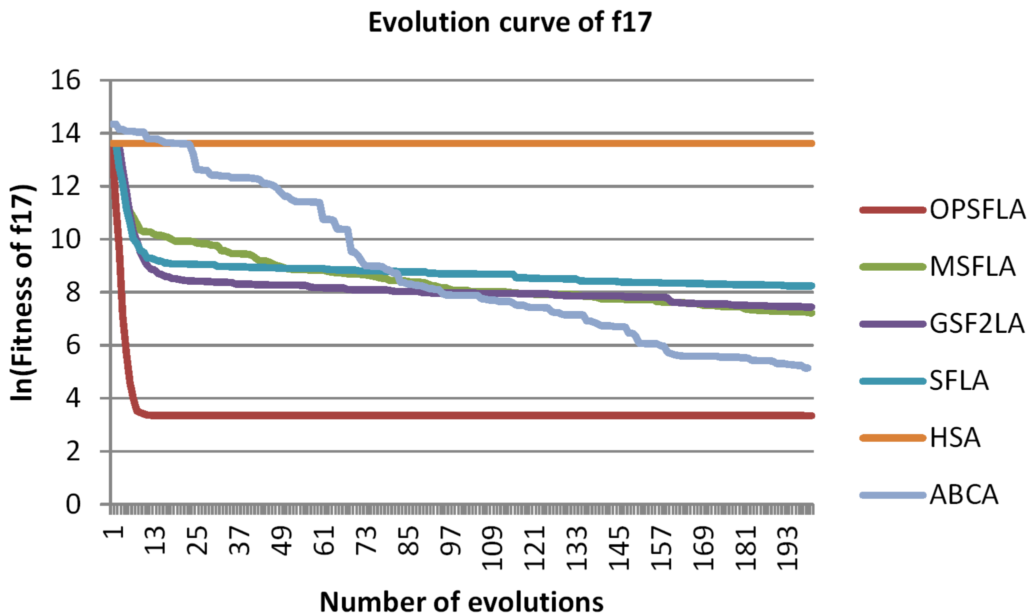
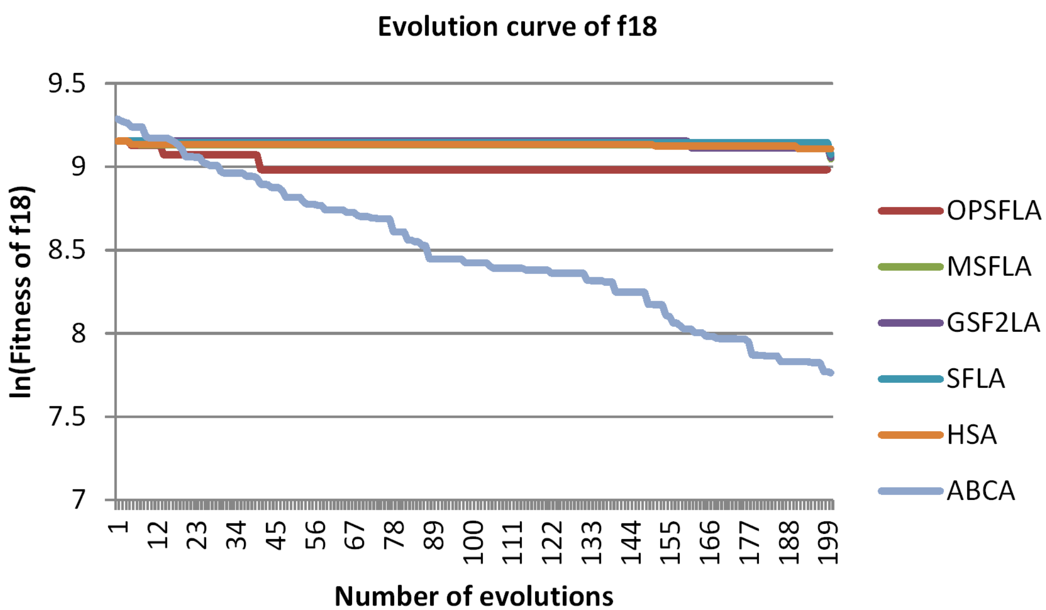


Figure 21. Iterative results of f18



As the CVRP problem is NP-hard problem, it is difficult to find the optimal solution within the polynomial time complexity. A novel framework of algorithm is proposed to solve capacity-limited vehicle routing problem. In the proposed origin oriented shuffled frog leaping algorithm strategy, the frog individuals gather near the origin with the maximum probability and in the area circle with the

Figure 22. Iterative results of f19

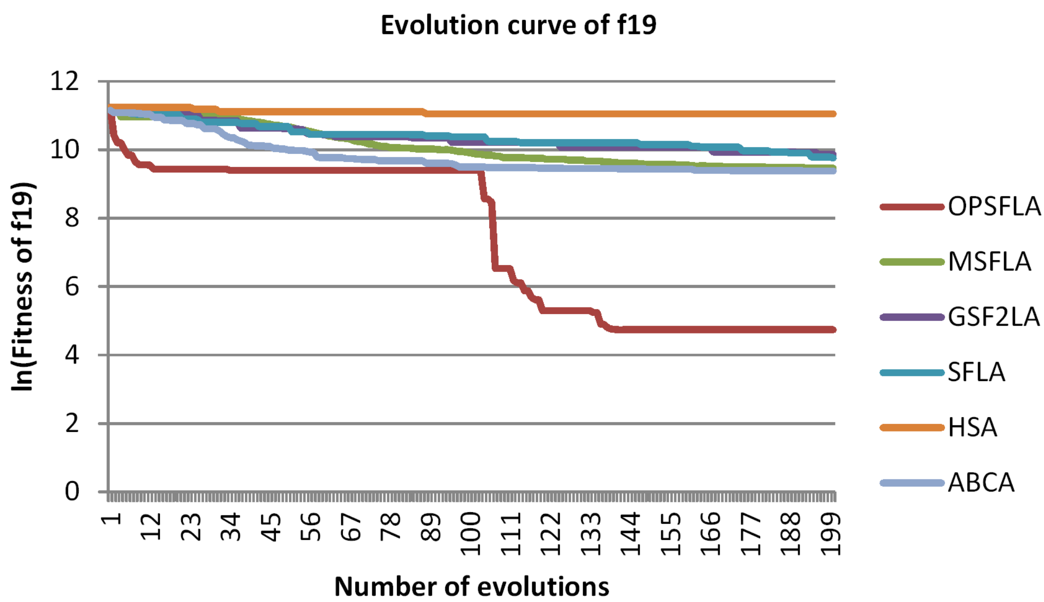
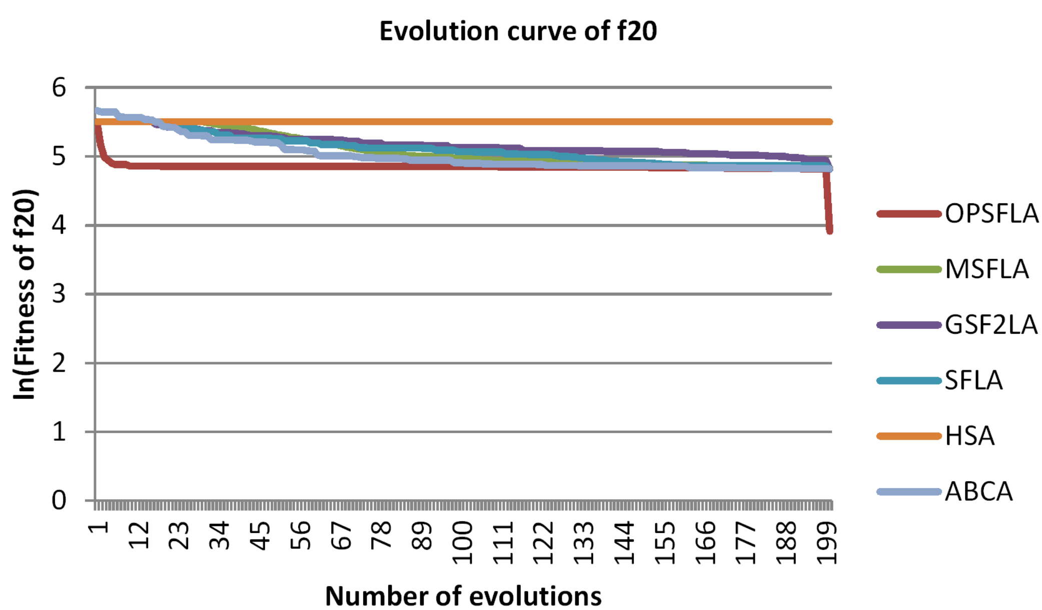


Figure 23. Iterative results of f20



frog leaping radius or frog oriented radius as the neighborhood. The negative value of the maximum entropy and the shortest total path length of the vehicle are selected as the fitness. The results show that OPSFLA-MOVRP algorithm has high robustness and reliability, and can still meet the actual needs of multiple customers under the condition of multiple vehicles.

Table 1. Comparisons of the RC101 data set when K = 2

Algorithms	Shortest Path Value	Vehicle 1 Optimized Route	Vehicle 2 Optimized Route
OPSFLA-MOVRP	616.90	83-75-57-19-91-89-22	11-5-42-80-69-12-71-88-98
MSFLA-CVRP	629.68	59-46-4-81-9-11-67-94	22-1-3-50-88-82-95-87
GSF²LA-CVRP	634.21	98-16-4-17-58-67-53-65-82	38-59-11-75-32-69-8-12
SFLA-CVRP	647.69	56-79-85-22-58-18-57-86-74	12-96-78-11-5-50-31-29

Table 2. Comparisons of the RC101 data set when K = 4

Algorithms	Shortest Path Value	Vehicle 1 Optimized Route	Vehicle 2 Optimized Route	Vehicle 3 Optimized Route	Vehicle 4 Optimized Route
OPSFLA-MOVRP	1530.84	98-50-61-53-86-78-13-22-15-41	68-99-8-74-43-79-9-59-2-67	40-21-34-30-19-63-62-29-77	85-16-11-3-75-83-95-31
MSFLA-CVRP	1552.84	87-97-17-68-36-89-85-57-65	12-58-16-27-34-95-33-30-35-83	90-64-74-46-60-75-28-21-53-98-18-80	11-86-94-56-22-26-38
GSF²LA-CVRP	1566.62	64-21-15-80-5-87-53-36-92-83-52	96-89-42-85-93-94-25-44-6-17	23-76-97-73-49-30-33-40-69-65	10-38-61-18-68-75-95
SFLA-CVRP	1578.83	86-7-85-11-82-45-90-50-8-3	95-36-49-34-22-93-66	78-21-73-96-57-62-87-24-23-48	38-26-46-13-97-61-35-70-91-68-55

Figure 24. Small-scale data vehicle route optimization curve

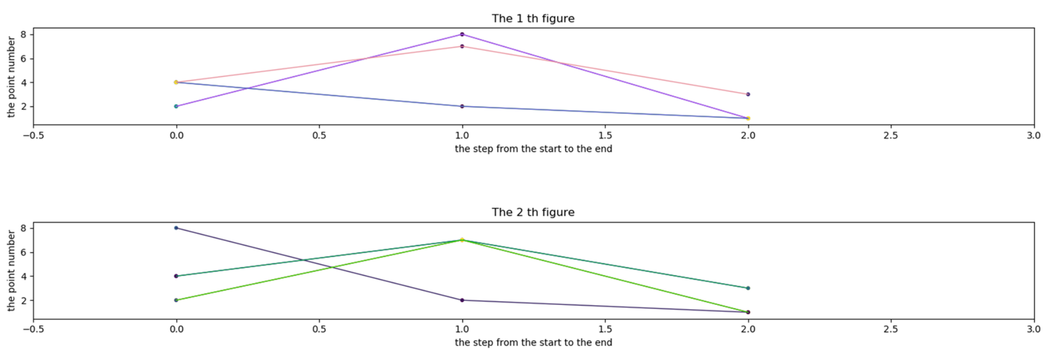


Table 3. Small-scale vehicle route optimization data

Pareto Solution	Shortest Path Value	Entropy	Vehicle 1 Optimized Route	Vehicle 2 Optimized Route
1	62.5	2.48	2-8-1	6-4-3
2	63.0	2.51	4-2-1	6-7-3
3	61.0	2.38	4-7-3	6-2-1
4	63.5	2.67	2-7-1	6-7-4
5	59.5	2.36	8-2-1	6-4-3

Figure 25. Large-scale data vehicle route optimization curve when K=3

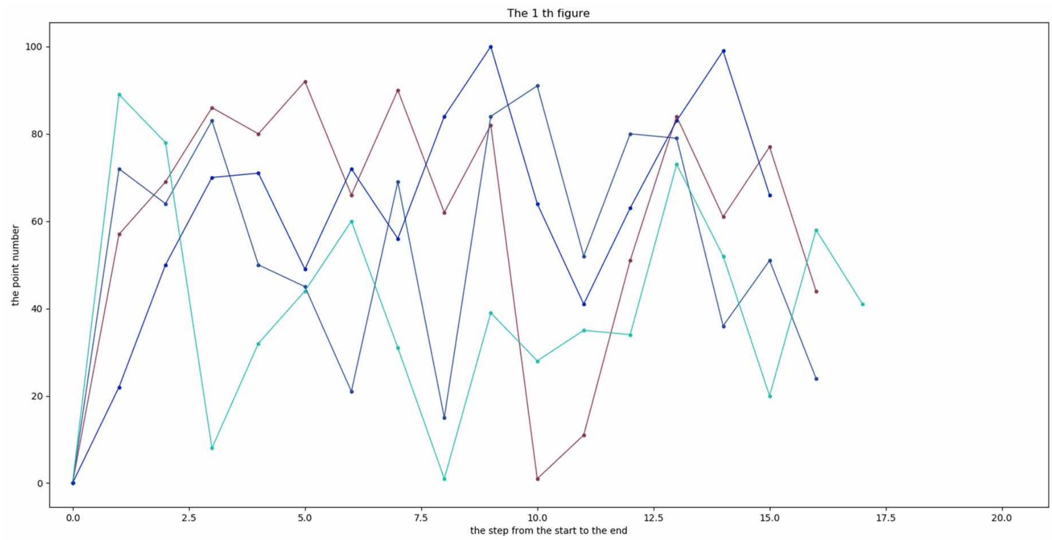
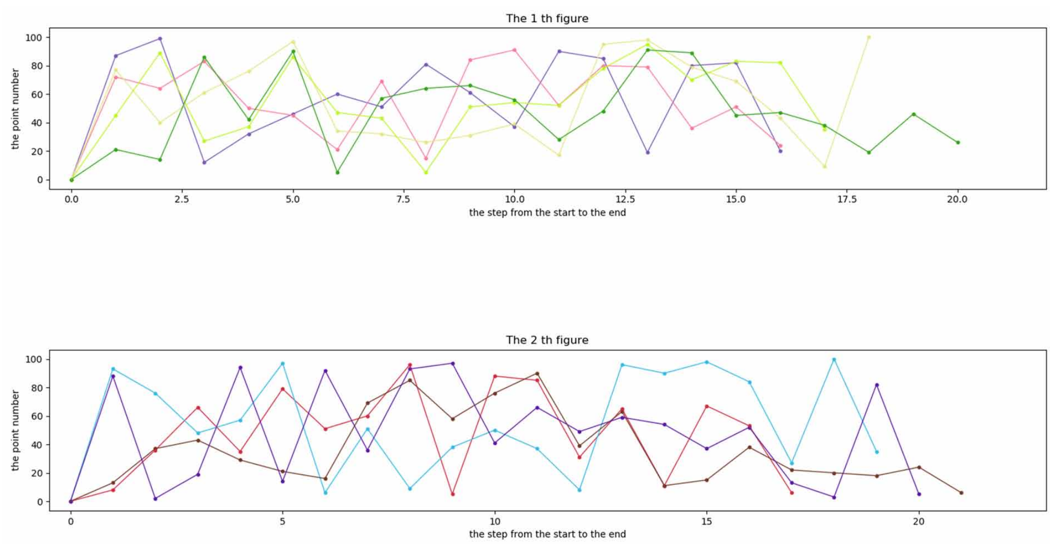


Figure 26. Large-scale data vehicle route optimization curve when K=4



CONCLUSION

Considering that the optimization performance is limited with improvement strategies in the improvement algorithm, a novel framework of algorithm is proposed to solve the CVRP, including three modules such as OPSFLA strategy, OPSFLA-MOVRP strategy and output module. And a new origin oriented shuffled frog leaping algorithm is proposed and applied into the CVRP path optimization problem. An origin oriented shuffled frog leaping vehicle routing multiobjective optimization algorithm is proposed. The improved idea comes from the no free lunch theory in the field of optimization research, discarding the inertial guidance of the original position of group search

Table 4. Large-scale vehicle route optimization data when K = 3

Pareto solution	Shortest path value	Entropy	Vehicle 1 Optimized Route	Vehicle 2 Optimized Route	Vehicle 3 Optimized Route
Solution 1	2432.44	11.07	57-69-86-80-92-66-90-62-82-1-11-51-84-61-77-44	99-95-54-75-58-43-41-56-78-22-55-31-28-18-27-81-50-13	73-2-15-17-35-9-40-42-7-93-32-65-76-97-85-25-39-21-33-53-74-63-29-34-59-10-30-46-67-38-45
Solution 2	2289.81	9.60	72-64-83-50-45-21-69-15-84-91-52-80-79-36-51-24	70-67-76-68-32-33-16-100-62-81-2-12-4-20-3-71-77	28-14-10-22-46-86-87-88-73-74-93-40-59-61-55-49-57-60-47-85-53-63-19-11-94-9-98-44-56-54-13-43-82-78-66
Solution 3	2309.46	10.23	89-78-8-32-44-60-31-1-39-28-35-34-73-52-20-58-41	97-71-66-55-59-61-70-64-79-62-53-7-29-6	13-45-94-18-48-87-25-24-17-95-91-26-30-33-43-36-65-37-69-47-46-23-15-27-16-93-68-54-76-96-85-63-9-88
Solution 4	2336.31	11.01	22-50-70-71-49-72-56-84-100-64-41-63-83-99-66	98-58-77-45-68-61-26-30-52-36-43-67-55-73-42-88-9-89	85-7-15-93-20-25-5-14-69-65-18-27-23-59-2-8-29-79-90-78-16-24-32-97-46-82-86-60-44-6-39-54-91

and the limitation of step size. Two strategies, including the frog leaping radius strategy based on the original point and the frog oriented radius strategy based on the original point are proposed to improve the search strategy of shuffled frog jumping. In this way, the individual frog jumps into an area with (0,0) as the center and the individual step size as the radius. This increases the probability of gathering near the origin (0,0) and improves the search ability. The tests show that the proposed origin oriented shuffled frog leaping algorithm has good convergence performance, and the origin oriented shuffled frog leaping vehicle routing multiobjective optimization algorithm meets the requirements of multipath optimization. However, the results of two multipeak functions are not ideal of the proposed OPSFLA-MOVRP algorithm. In the future research, the improvement strategies will be further researched to make the algorithm more efficient. In addition, the method of deep learning can be considered in future research.

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Liqun Liu and Renyuan Gu designed and wrote the paper. Renyuan Gu, Jiuyuan Huo and Yubo Zhou collected data and analyzed the experiments. All authors read and approved the final manuscript.

CONFLICT OF INTEREST

The authors of this publication declare there is no conflict of interest.

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Liqun Liu received a master's degree, and she is an Associate Professor. Her research interests include intelligent computing, deep learning and computer vision, etc.

Renyuan Gu is a postgraduate, 2021 Software Engineering major. His research interests include deep learning, computer vision, etc.

Jiuyuan Huo received a doctor's degree, and he is a Professor. His research interests include intelligent computing, computer vision, etc.

Yubo Zhou is a postgraduate, 2020 Software Engineering major. His research interests include image processing, computer vision, etc.