Logistics Transportation Routing Research about Agricultural Products based on Improved Genetic Algorithm

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Abstract

In view of the characteristics of agricultural products distribution and logistics path selection in our country, an abstract mathematical model is established according to the characteristics of rural areas and the transportation characteristics of agricultural products in china. Logistics delivery cost minimization is taken as the goal to solve logistics problems. On the basis of the traditional genetic algorithm, the algorithm is optimized in this paper. The triangular cosine function is used to make the crossover probability and mutation probability adaptively change. Finally, the simulation and coding are used to solve the problem. The improved genetic algorithm has faster convergence speed and smaller target value of the optimal solution. The research has a good application prospect and practical value.

Keywords

Genetic algorithm, cosine function, crossover probability, mutation probability.

1. Introduction

The vehicle routing optimization is a classic combinatorial optimization problem and it was first proposed by Dantzig and Ramser in 1959 [1]. Its main work is to establish a mathematical model to determine vehicle routes with minimum cost to serve a set of customers whose geographical coordinates and demands are known in advance. A vehicle is required to visit each customer only once [2]. Typically, vehicles are homogeneous and have the same capacity restriction. So far, the exploration of this problem has not been stopped, people are more concerned about how to solve this problem in real life. Apart from the original characteristics and constraints of agricultural products is easy to be spoiled, not easy to save. In order to optimize the transportation routes of agricultural products, we considered a variety of elements. Besides the characteristics of agricultural products are considered when solving the problem. Agricultural products distribution has the following characteristics:

China is a big agricultural country, so it has a lot of distribution points for agricultural products [3]. Therefore, in the example of the logistics path planning of agricultural products, the scale of data should be expanded as much as possible.

The shelf life of agricultural products is usually relatively short, perishable spoilage. Because of this, the transport time of agricultural products must be reached within the shelf life or customer requirements, which will ensure the freshness of agricultural products and their value [4,5].

The transportation path of agricultural products is more complicated, which leads to the difficulty of transportation and distribution planning [6]. Therefore, it is necessary to optimize and select the transportation routes of agricultural products and we have to choose a suitable optimization algorithm.

In short, when we set up its mathematical model, we must consider the characteristics of agricultural products during transport and its constraints, and then select the appropriate optimization algorithm to solve the problem. In this way we can improve transport efficiency, reduce logistics costs and meet customer needs.

2. Vehicle Routing Problems with Time Windows (VRPTW)

Agricultural logistics and distribution routing problem can be attributed to vehicle routing problem with time windows. The mathematical model of the problem is described that given a distribution center with several delivery vehicles with the same load, there are several users around the distribution center, each with different cargo needs. The vehicle loads a certain amount of goods, delivers the goods within the service window requested by each customer, and finally the transport vehicle is returned to the delivery place. By reasonably arranging delivery routes and orders, delivery costs are minimized [7].

We can use mathematical graph theory to describe this problem. Let G = (P, A) be a complete graph, where P = {0,1,2 ... n} is a vertex set, vertex 0 is denoted as a distribution center, and A is an arc set. Vertex j corresponds to the customer. Each customer has a known non-negative demand.

$$\min C = \alpha \sum_{i=0}^{n}\sum_{j=0}^{n}\sum_{k=0}^{m} c_{ij} x_{ijk} + \beta \sum_{k=0}^{m}\sum_{j=0}^{n} x_{0jk} + \sum_{k=0}^{n} \sigma_{ik} \tag{1}$$

s. t.

$$\sum_{k=1}^{m}\sum_{j=1}^{n} x_{ijk} \le m, i = 0 \tag{2}$$

$$\sum_{i=1}^{n} d_i s_{ik} \le M, k = 1,2\ldots m \tag{3}$$

$$\sum_{i=0, i\ne j}^{n} x_{ijk} = s_{jk}, j = 1,2\ldots n, \forall k \tag{4}$$

$$\sum_{j=0, i\ne j}^{n} x_{ijk} = s_{ik}, i = 1,2\ldots n, \forall k \tag{5}$$

$$\sum_{k=1}^{m} s_{ik} = 1, i = 1,2\ldots n \tag{6}$$

$$\sum_{i=1}^{n}\sum_{k=1}^{m} s_{ik} = n \tag{7}$$

$$x_{ijk} = \{0,1\}, \forall i, j \in P \tag{8}$$

$$s_{ik} = \{0,1\}, \forall i \in P, \forall k \in K \tag{9}$$

$$\sigma_{ik} = \begin{cases} \eta_1 \sum_{i=0}^{n} s_{ik}[T_1(i) - T_{ik}], T_{ik} < T_1(i) \\ 0, T_1(i) \le T_{ik} \le T_2(i) \\ \eta_2 \sum_{i=0}^{n} s_{ik}[T_{ik} - T_2(i)], T_{ik} > T_2(i) \end{cases} \tag{10}$$

$$s_{ik} = \begin{cases} 1, \text{node i is provided service by} \\ \quad \text{the transport vehicle k} \\ 0, otherwise \end{cases} \tag{11}$$

$$x_{ijk} = \begin{cases} 1, \text{the transport vehicle k drives} \\ \quad \text{from node i to node j} \\ 0, otherwise \end{cases} \tag{12}$$

where α : Unit cost of delivery vehicles

β : Unit cost of transportation vehicles enabled

c_{ij} : Customer i to customer j distance

n : Number of clients

m : Number of transport vehicles

$[T_1(i), T_2(i)]$:Customer i requires a time window

T_{ik} : The time when vehicle k reaches i customer

η_1 : The unit waits for the cost of the vehicle to arrive early

η_2 : Unit penalty cost for delayed arrival of vehicles

σ_{ik} : The penalty cost function of vehicle k serving client i due to time window constraints

M : The maximum carrying capacity of transport vehicles

d_i :The amount of goods that customer i needs

t_i : Service time at customer i

Objective Eq. (1) minimizes the total cost. Constraint (2) indicates that the number of vehicles departing from the distribution center should not exceed the number of vehicles owned by the center. Constraint (3) indicates that the total demand on the route must not exceed the maximum load of the vehicle. Constraints (4) and constraints (5) represent constraints on the path. Constraints (6) indicate that each customer can only have one car service. Constraints (7) indicate that each client must be serviced. Constraints (8) and constraints (9) are both integer constraints.

3. Improved Genetic Algorithm

Genetic Algorithm (GA) is a random search algorithm of model biological evolution mechanism, obeying the objective law of survival of the fittest. This algorithm was first proposed by Professor J. Holland of the University of Michigan in 1975. [8] The simple genetic algorithm process includes initializing population, calculating fitness function, selecting operation, cross operation, mutation operation and termination judgment.

There are two important parameters in genetic algorithm. They are crossover probability and mutation probability. These two parameters have a great influence on the behavior and performance of genetic algorithm. The traditional genetic algorithm with these two parameters is a constant value and the calculation process will not easily change the size of these two values. In this way, when the probability of mutation or crossover probability is too large, it is easy to make good individuals with good fitness in the population destroyed. Therefore, in order to preserve the best individuals in the population and to mutate out some better individuals, it is necessary to optimize these two parameters of the traditional algorithm.

In the simple genetic algorithm (SGA), the crossover probability and mutation probability have been changed as individual fitness changes. Under the condition of keeping the group diversity, the convergence of genetic algorithm is guaranteed [9].

The formula is as follows:

$$p_c = \begin{cases} k_1 \dfrac{f_{\max} - f'}{f_{\max} - f_{\min}}, f' \geq f_{avg} \\ k_2, f' < f_{avg} \end{cases} \tag{13}$$

$$p_m = \begin{cases} k_3 \dfrac{f_{\max} - f}{f_{\max} - f_{avg}}, f \geq f_{avg} \\ k_4, f < f_{avg} \end{cases} \tag{14}$$

where p_c :Cross probability

p_m : Mutation probability

$f_{\max}$: Maximum fitness in each generation

f_{avg} : The average fitness of each generation

f': Greater fitness to be crossed between two individuals

f : The fitness of individuals to be mutated

According to the above formula, it can be seen that when the fitness is greater than the average fitness of the group, it indicates that the individual's performance is good and belongs to the excellent individual. In this case, the crossover probability and mutation probability are at a small value, in order to ensure that the outstanding individuals can be saved to the next generation. When the fitness is less than the average fitness of the population, it indicates that the individual belongs to a non-elite individual, and the crossover probability and mutation probability are at a large value at this time, so as to evolve to the next generation and make it become a better individual. However, a problem that arises is that when the individual's fitness is the same as the group's maximum fitness, the probability of crossover and mutation at this time becomes 0. This method of adjustment is okay for groups that are at an advanced stage of evolution because the individuals in the group are basically the best individuals at this time, which is not conducive to mutation or crossover to change the best individual structure. However, in the early stage of evolution, this mode of adjustment makes the evolutionary process too slow, because the outstanding individuals at this time are not the globally optimal individuals, which leads to the almost superior individuals in the population being in an invariable state, resulting in the local optimum solution.

In view of the shortcomings of adaptive adjustment methods, Ren Ziwu et al. proposed an improved genetic algorithm (IAGA) based on the adaptive genetic algorithm proposed by Srinivas et al [10]. In order to ensure that the elite individuals of each generation are not destroyed, the elitist retention strategy is adopted. That is, if the fitness of the best individual in the next generation is less than the optimal fitness of the current population, the current population is optimized Individuals or individuals whose fitness is greater than the optimal fitness value of the next generation are copied directly to the generation, randomly replacing or substituting a corresponding number of individuals in the worst next generation population. The crossover probability and mutation probability formula are shown below.

$$p_c = \begin{cases} p_{c1} - \dfrac{(p_{c1} - p_{c2})(f - f_{avg})}{f_{\max} - f_{avg}}, f \geq f_{avg} \\ p_{c2}, f < f_{avg} \end{cases} \tag{15}$$

$$p_m = \begin{cases} p_{m1} - \dfrac{(p_{m1} - p_{m2})(f_{\max} - f')}{f_{\max} - f_{avg}}, f' \geq f_{avg} \\ p_{m2}, f' < f_{avg} \end{cases} \tag{16}$$

We know that the crossover probability and mutation probability change with the iterative process, which is a gradual process. On the basis of the simple genetic algorithm (SGA), we must ensure that the crossover probability and the mutation probability can not be zero, which means that the excellent individuals in the early stage of evolution will not be immutable. Finally, the number of iterations is added to the IAGA by Ren Ziwu et al. Improved crossover probability and mutation probability formulas are as follows.

$$p_c = \begin{cases} p_{c1}(1-\cos^2(\frac{f_{\max}-f^{'}}{f_{\max}-f_{avg}+\lambda}-1-\pi/2)),\ f^{'} \geq f_{avg} \\ p_{c1},\ f^{'} < f_{avg} \end{cases} \quad (17)$$

$$p_m = \begin{cases} \frac{1}{\sqrt{n}} p_{m1}(1-\cos^2(\frac{f_{\max}-f}{f_{\max}-f_{avg}+\lambda}-1-\pi/2)),\ f \geq f_{avg} \\ \frac{1}{\sqrt{n}} p_{m1},\ f < f_{avg} \end{cases} \quad (18)$$

In the above formula, firstly, λ is a very small positive number, so as to prevent the occurrence of the case where the maximum fitness and the average fitness in the population are equal. Then we use the function of triangular cosine function in interval and for the selection of mutation probability, we add the number of iterations (n) and correlate the mutation probability with the number of iterations, which is more in line with the factual situation.

The improved crossover probability and mutation probability not only can be adjusted with the change of fitness, but also ensure that the two probabilities will not be 0. They will not be in a state of approximate halt in the evolutionary process. Finally, adding the number of iterations in the mutation probability makes the algorithm more realistic.

4. Calculation and Analysis

4.1 Problem Description

The experimental data shown in Table 1, the use of MATLAB for optimization.

There is a distribution center somewhere, numbered 1. The rest are the demand points of agricultural products customers, the coordinates of each demand point, demand, time window and unit waiting for arrival ahead of schedule cost and penalty costs shown in Table 1. The distribution center has a total of 10 delivery vehicles. The maximum load of all delivery vehicles is 30 and the maximum travel distance is 40. The activation cost per vehicle is 10 and the distance traveled by the vehicle is 1.

Table 1 Customer information

Number	Position	Demand	Service time	Time window	Waiting cost	Penalty cost
1	(18.70,15.29)	0	0	(0,1000)	0	0
2	(16.47,8.45)	3.0	1.8	(5.0,19.5)	5.0	10
3	(20.07,10.14)	2.5	1.0	(4.1,14.9)	6.0	15
4	(19.39,13.37)	5.5	2.3	(1.5,10.9)	14.0	30
5	(25.27,14.24)	3.0	1.8	(6.0,19.6)	5.0	10000
6	(22.00,10.04)	1.5	1.2	(6.5,14.8)	4.0	16
7	(25.47,17.02)	4.0	2.4	(9.9,19.8)	4.0	18
8	(15.79,15.10)	2.5	1.5	(10.1,24.2)	8.0	32
9	(16.60,12.38)	3.0	1.8	(15.5,27.1)	5.0	21
10	(14.05,18.12)	2.0	1.2	(2.5,19.9)	3.0	27
11	(17.53,17.38)	2.5	1.5	(3.2,15.6)	6.0	22
12	(23.52,13.35)	3.5	2.1	(2.0,23.3)	15.0	18
13	(19.41,18.13)	3.0	1.8	(2.3,15.5)	8.0	10000
14	(22.11,12.51)	5.0	2.0	(15.2,24.5)	7.0	25
15	(11.25,11.04)	4.5	2.7	(11.1,28.8)	15.0	31
16	(14.17,9.76)	2.0	1.3	(12.6,24.0)	5.0	10000
17	(24.00,19.89)	3.5	1.2	(8.4,18.5)	4.0	10
18	(12.21,14.05)	4.5	1.5	(10.1,23.2)	6.0	18

4.2 Genetic Algorithm Process

Initialize the population

The key to initialize a population is to construct chromosomes, also known as "strings" that correspond to each living individual in the population. Chromosome is a code string using a specific encoding, where we use natural number encoding according to the characteristics of the problem solving. A chromosome represents a viable path, such as "1 2 3 1 4 5 1 6 7 1" [11]:

Vehicle Route 1: Distribution Center 1-> Customer Point 2-> Customer Point 3-> Distribution Center 1

Vehicle Path 2: Distribution Center 1-> Customer Points 4-> Customer Points 5-> Distribution Center 1

Vehicle Route 3: Distribution Center 1-> Customer Point 6-> Customer Point 7-> Distribution Center 1

Fitness calculation

Fitness value is used to assess and distinguish the merits of chromosomes. The more adaptable chromosomes are more excellent. Fitness values are often based on fitness functions, while fitness functions are based on solving the problem's objective function. For some problems solving the maximum, we can directly apply the objective function defined by the problem as a fitness function. However, the goal of the objective function defined in this paper is to solve the minimum problem, so we use the inverse of the objective function as the fitness function of the problem [12]. From the above formula 1 we can see:

$$fit(i) = \frac{1}{C} \tag{19}$$

Select

The selection operation is also referred to as a copy operation, which is based on the fitness value of the individual to determine its fitness level, and then decide whether it is out in the next generation or genetic. The paper uses roulette selection method and elite retention strategy [13]. The basic operation of the roulette method is as follows:

The fitness of each individual in the population is calculated according to Equation 19, where M is the size of the population.

Calculate the probability of each individual being passed on to the next generation.

$$P(x_i) = \frac{fit(x_i)}{\sum_{j=1}^{M} fit(x_j)} \tag{20}$$

Calculate the cumulative probability of each individual.

$$q_i = \sum_{j=1}^{i} P(x_j) \tag{21}$$

Generate a uniformly distributed pseudo-random number r in the [0,1] interval

If $r < q[1]$, we choose individual 1; otherwise, we choose individual k such that $q[k-1] < r < q[k]$ holds;

Repeat step iv and step v, a total of M times

Cross and mutation

The crossover and mutation operations in genetic algorithms are very important for the experimental results. Based on the deficiency of the traditional adaptive genetic algorithm and the merits of the genetic algorithm, this paper optimizes the choice of crossover and mutation probability so that it can be dynamically adjusted during the iterative process. In this way, we prevent the algorithm from stalling later in the algorithm iteration and can increase the diversity of the population. The crossover probability and mutation probability are adjusted as shown in Equation 17 and Equation 18.

4.3 Experimental Results and Analysis

In this paper, we use MATLAB to carry out experiments. The parameters are set as follows: the population size is 80, the maximum number of iterations is 1000 and the crossover and mutation probabilities are calculated according to the adaptive probabilities mentioned in the improved algorithm.

There are MATLAB operation results, shown as follows.

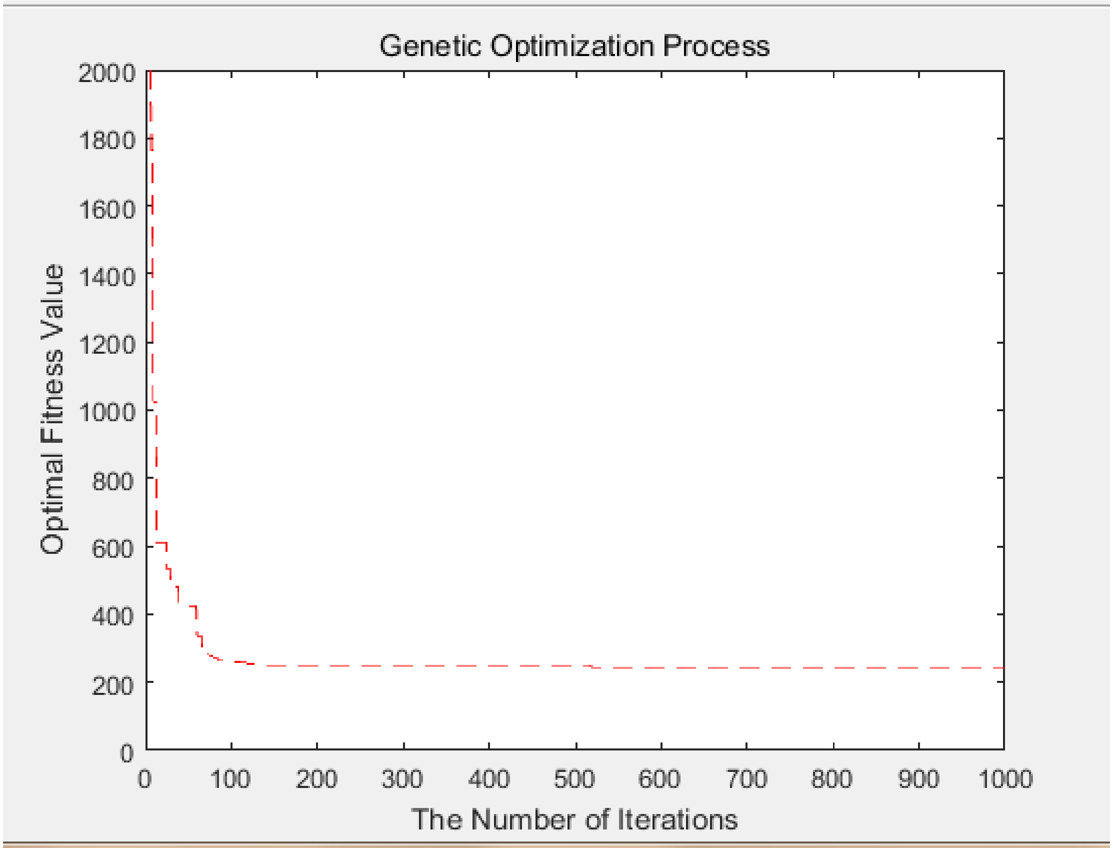

Fig. 1 Optimization process of traditional genetic algorithm

We can see from Figure 1 that the traditional genetic algorithm is stable at about 90 times, reaching the optimal state, and the optimal cost is 239.7012.

There are results, shown as follows.

Vehicle Route 1: Distribution Center 1-> Customer Point 13-> Customer Point 8-> Customer Point 9->Distribution Center 1

Vehicle Route 2: Distribution Center 1-> Customer Points 15-> Distribution Center 1

Vehicle Route 3: Distribution Center 1-> Customer Point 6-> Customer Point 14-> Distribution Center 1

Vehicle Route 4: Distribution Center 1-> Customer Point 2-> Customer Point 16-> Distribution Center 1

Vehicle Route 5: Distribution Center 1-> Customer Points 12-> Customer Points 17-> Distribution Center 1

Vehicle Route 6: Distribution Center 1-> Customer Point 11-> Distribution Center 1

Vehicle Route 7: Distribution Center 1-> Customer Point 10-> Customer Point 18-> Distribution Center 1

Vehicle Route 8: Distribution Center 1-> Customer Points 3-> Distribution Center 1

Vehicle Route 9: Distribution Center 1-> Customer Point 5-> Customer Point 7-> Distribution Center 1

Vehicle Route 10: Distribution Center 1-> Customer Point 4-> Distribution Center 1

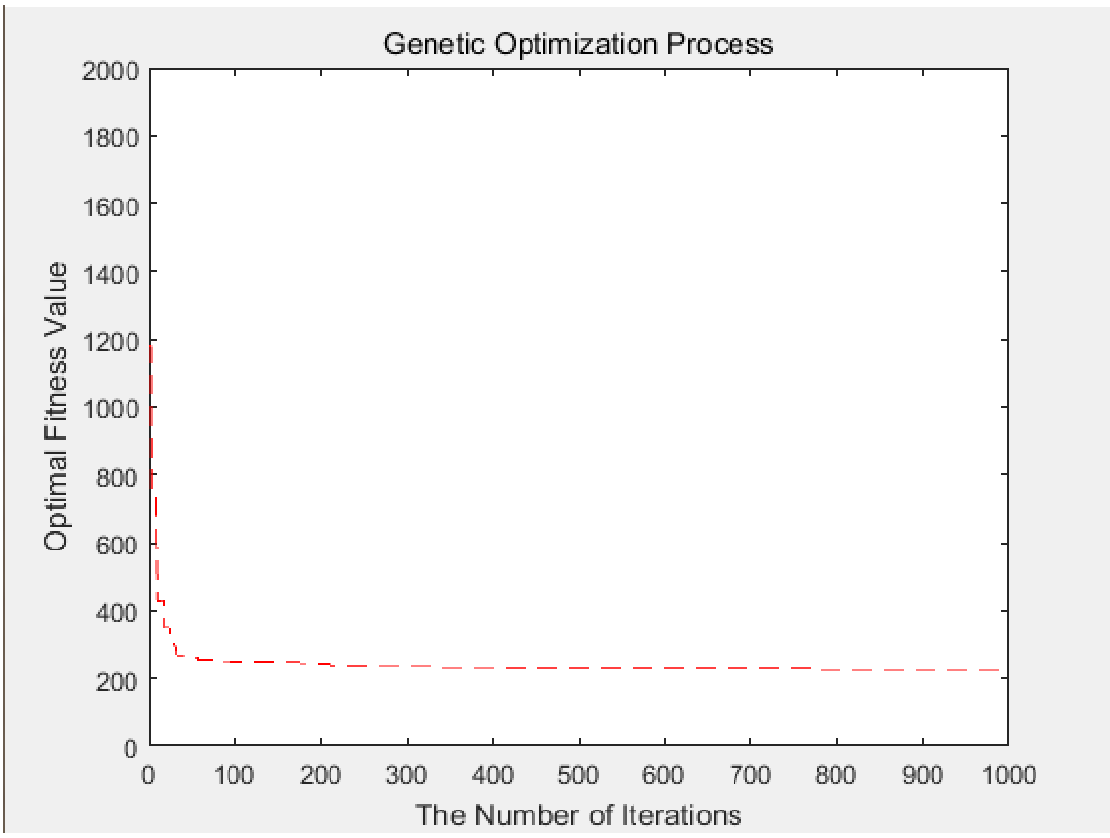

Fig. 2 Optimization process of improved genetic algorithm

We can see from Figure 2 that the improved genetic algorithm is stable at about 60 times, reaching the optimal state, and the optimal cost is 227.0115.

There are results, shown as follows.

Vehicle Route 1: Distribution Center 1-> Customer Point 17-> Customer Point 7-> Distribution Center 1

Vehicle Route 2: Distribution Center 1-> Customer Points 2-> Customer Points 16-> Distribution Center 1

Vehicle Route 3: Distribution Center 1-> Customer Point 6-> Customer Point 9-> Distribution Center 1

Vehicle Route 4: Distribution Center 1-> Customer Point 5-> Customer Point 14-> Distribution Center 1

Vehicle Route 5: Distribution Center 1-> Customer Points 12-> Distribution Center 1

Vehicle Route 6: Distribution Center 1-> Customer Point 4-> Customer Point 18-> Distribution Center 1

Vehicle Route 7: Distribution Center 1-> Customer Point 10-> Customer Point 8-> Distribution Center 1

Vehicle Route 8: Distribution Center 1-> Customer Points 13-> Customer Points 11-> Distribution Center 1

Vehicle Route 9: Distribution Center 1-> Customer Point 3-> Distribution Center 1

Vehicle Route 10: Distribution Center 1-> Customer Point 15-> Distribution Center 1

5. Conclusion

From the experimental results, the improved genetic algorithm does optimize the transportation cost, reduce the transportation cost and speed up the process of convergence. It is proved that the genetic algorithm is effective to improve the genetic algorithm.

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