An Application Study on Vehicle Routing Problem Based on Improved Genetic Algorithm

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Abstract. The Vehicle Routing Problem of Logistics and Distribution is a hot and difficult issue in current field of combinatorial optimization, therefore this paper presents an improved genetic algorithm. The algorithm which applied the idea of Saving Algorithm to the initialization of groups, and improved algorithm on selection operator and cross operator, In the meantime, it proposes a new way to calculate the adaptive probability in the cross operator. In addition, it also introduces a novel CX crossover operator .By the way of simulating experiments of the Vehicle Routing Problem, it demonstrates that the improved genetic algorithm enhanced the ability of global optimization, moreover it can significantly speed up convergence efficiency.

Keywords: logistics and distribution, Vehicle Routing Problem, calculate adaptive probability, genetic algorithm.

1 Introduction

With the rapid development of e-commerce, the logistics industry is becoming more and more important, which attracts extensive concern of various industries as the third profit source. The vehicle routing problem holds the count for much status in logistics, which has become the most important research to low the distribution cost. Therefore, the optimization of vehicle routing has been a hot area of research in the field of logistics and distribution. The Vehicle routing problem (VRP) was first proposed by Dantzig and Ramser in 1959, belonging to a class of problems of combinatorial optimization field with multiple constraints. VRP can be described as such a problem that the vehicle can pass a series of customer points by organizing proper driving route, meanwhile satisfying the constraints(such as goods demand, vehicle capacity restriction, etc.), which is to reach a certain goal (such as the shortest distance, cost at least, etc.).In recent years, Domestic and foreign scholars utilized the heuristic algorithms and intelligent algorithm to solve VRP [1]. As a result of the particular frequency use of genetic algorithms, researchers attempted to overcome the 'premature convergence' issue by improving the genetic algorithm [2].

Because genetic operator is the key to the genetic algorithm, improving the operation of the genetic operators becomes the most important part of improved genetic algorithm. The CX crossover operator was cited in [3], the thought of the crossover operator, which is still able to produce a new individual even if two of the

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same individual cross, meets the requirements of the traditional crossover operator in the diversity of the population, while avoiding the precocious phenomenon, and reducing the possibility of local optimal solution. In [4], a new selection strategy was proposed to control a specific number of individuals, which accelerates the speed of the convergence rate based on maintaining the diversity of the population. Abbattista F firstly proposed the idea of the integration of genetic algorithm and ant colony algorithm, Reference [5] proposed an improved ant colony and genetic integration of optimization algorithms, which apply adaptive crossover probability.

However, in population initialization process, randomly generating the initial population with a random number generator is customarily adopted. The resulting individual has the features of random and multi-point investigation, which is not easy to fall into the regional optimal when solving the optimal solution. Whereas randomly generated initial population has great influence on the convergence rate [6]. Mileage-saving method, also known as VSP (Vehicles Scheduling Program), applies to the situation that the satisfying quasi optimum value or the approximate value of all optimal solutions, not necessarily the optimal value is required in a practical application [7]. The author who combines the idea of saving mileage algorithm, proposed a new initialization way trying to accelerate the convergence speed. As the key link of genetic algorithm, crossover operator maintains the excellent individual characteristics in the original group to some extent, as well as enabling the algorithm to search the new solution space ensuring the diversity of individuals in a population. Therefore the selection of Crossover Concept will directly affect the convergence of genetic algorithm. Also, we present a new computational method for adaptive crossover probability based on the recent one in reference [6]. The final part of this paper is the test of the performance of the algorithm by the MATLAB simulations and experiments.

2 Vehicle Routing Problem Description

2.1 Specific Description

The name of vehicle routing problem was first proposed in the late 1950s by two linear programming masters Dantzig and Ramser, it is mainly used to solve the problem that how to send a car and how many cars should be sent and what kind of route should the cars take to ensure that meeting the customer requirements and making the cost lowest when the customer location and demand for goods was given.

The vehicle routing problem expressed as follows: The number of car in distribution centers is K, and the vehicle's maximum load is Q, the existing transport task of the N client nodes (1,2, ..., N) need to be completed, the demand for the client node of i is d_i (i = 1, 2, ..., N) and $\max d_i \le Q$,and each client is just only served by one car once transported tasks. Each vehicle will start from the distribution center, and return the distribution center after the completion of certain tasks. The ultimate goal is to calculate the minimum distribution costs of vehicle routing under the vehicle capacity constrains using as few vehicles as possible [1]. The VRP with one distribution be shown in the Figure 1.

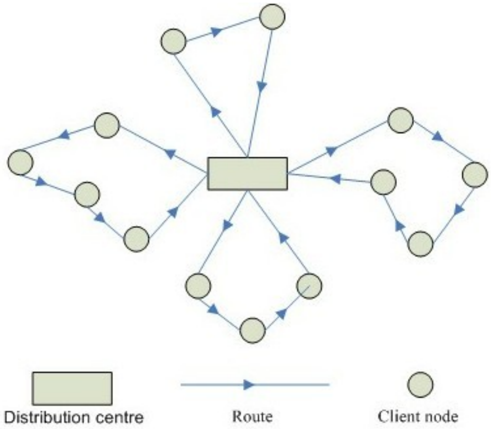

Fig. 1. Schematic Diagram of VRP

2.2 Mathematic Model of Vehicle Routing Optimization

By the above mentioned description, the mathematical model which regards the total cost of the minimum distribution as the objective function establish as follows [3]:

$$\min \quad F(i,\ j,\ k) = \alpha \sum_{k=1}^{k} \sum_{i=0}^{i} \sum_{j=0}^{j} c_{ij} x_{ijk} + \beta \sum_{k=1}^{k} \sum_{j=0}^{j} x_{ojk} \tag{1}$$

$$\sum_{k=1}^{k} \sum_{j=1}^{j} x_{ijk} \le K \qquad i = 0 \tag{2}$$

$$\sum_{j=1}^{N} x_{\mathrm{ijk}} = \sum_{j=1}^{N} x_{\mathrm{jik}} \le 1 \quad i = 0, \mathrm{k} \in \{1,2,\ldots,\mathrm{K}\} \tag{3}$$

$$\sum_{k=1}^{k} \sum_{j=0}^{j} x_{ijk} = 1 \text{ 或 } \sum_{k=1}^{k} \sum_{i=0}^{i} x_{ijk} = 1 \quad i,\ j \in \{1,2,\ldots,\mathrm{N}\} \tag{4}$$

$$\sum_{i=o}^{N} \sum_{j=0}^{N} d_i x_{ijk} \le Q \qquad k \in \{1,2,\ldots,\mathrm{K}\} \tag{5}$$

$$x_{ijk} \in \{0,1\} \quad i,j \in \{1,2,\ldots,\mathrm{N}\}, k \in \{1,2,\ldots,\mathrm{K}\} \tag{6}$$

The formula (1) demonstrates the smallest total distribution cost, which is the objective function. It consists of the costs of vehicle distance and the number of vehicles enabled. Ci, j: the transportation cost of vehicles from customer i to customer j (distance); formula (2) means the number of vehicles from the distribution center is no more than K units; Formula (3) presents that each vehicle starting from the distribution center and eventually return to the distribution center; Formula (4) denotes that each customer point happens to be accessed by a vehicle once; formula

(5) said that the sum of the task assumed by each vehicle does not exceed the load capacity limit of the car the amount of Q(the vehicle's maximum load); formula (6): integer constraint, which restricts the number to be 0 or 1.

3 Improved Genetic Algorithm

3.1 Encoding and Decoding on Chromosome

In the genetic algorithm, the selection of encoding method often depends on the actual situation of the problem to be solved. In vehicle routing problem, feasible solutions should be composed of customers and access path, while the genetic algorithm can not deal directly with the solution data of the solution space. In this paper, in order to calculate conveniently, with the method of natural number encoding mechanism, the form of solutions for the vehicle routing problem is converted to genetic algorithm of genotype string data, and then forms chromosomes.

Supposing there are customers in the distribution center, the resulting production of chromosomes with a length of N, each gene in the chromosome corresponds to a customer; there is no gene locus of separation point between clients. So, there is no need to consider the impact of the separation point in the crossover and mutation operations. When decoding, what need to be done is just to put the customer of the corresponding gene point into the path in order as much as possible until a point against the constraints. For example, eight clients individual coding (51273684) can be interpreted as:

Sub path l: 0-5-1-2-0;

Sub path 2:0-7-3-6-0;

Sub path 3:0-8-4-0; (0 stands for the distribution center)

3.2 Improved Population Initialization

When the population is initialized, we will introduce a new mechanism based on the idea of mileage-saving method in order to produce part of the individual. Saving algorithm is one of the most classic heuristic algorithms for VRP. The idea of the algorithm is that according to the principle of the connection distance between the customers points will be the most economical. Then inserting the absence customer to line in proper order, it will be finished after all points are arranged into the line [7]. The formula to calculate the conservation value between two nodes of the save algorithm was shown in Figure 2, and its significance is shown in Equation (8):

$$S(i,j)=2(d(i,0)+d(0,j))-(d(i,0)+d(0,j)+d(i,j)) \tag{7}$$

That is: $$S(i,j)=d(i,0)+d(0,j)-d(i,j) \tag{8}$$

At the beginning, the algorithm to calculate the savings value of any two nodes and rank conservation values in descending order. Then according to the results, as well as the feasibility conditions, merger path until you can not find a better solution under constraints to some conditions.

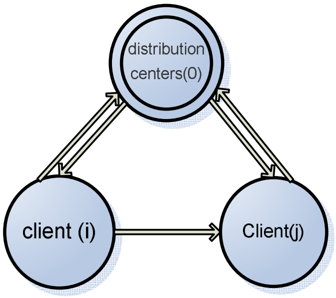

Fig. 2. The idea of Saving Algorithm

For example, for eight customers, we will get three sub paths as follow under the premise that satisfies the constraints by saving algorithm: sub path l: O-5-1-2-0; sub path 2:0-7-3-6-O; sub path 3:0-8-4-0. Then the realignment of three sub paths can produce the following individuals: 51273684, 51284736, 73651284, 73684512, 84736512, 84512736; these will be a part of the initial population, the other part will be randomly generated.

The individuals produced by the saving algorithm is generally more excellent than that produced random, but research shows that when encountering the huge number of customers or a complex service point distributed network, this algorithm will lead to huge computing workload and computational complexity. When facing the small scale, the algorithm shows its superiority comparing with the huge one to be dealt with. Of course, we can also divide the complex network randomly into a number of simple networks. When the problem that the little difference between individuals will easily fall into the "premature convergence" is taken into account, we will also randomly generate initial population as the probability of the saving initialization is too large.

3.3 Genetic Operators

(1) Selection Operator

Selection operator is similar to the natural evolution "natural selection, survival of the fittest". Its purpose is to turn the optimize individual in the population by means of cross-matching or inheriting directly into the next generation, and eliminate the least suitable individuals.

The idea of this paper is based on individual fitness. Part of the individual which have the highest individual fitness will do not participate in the crossing and mutation and directly get into the next generation, but for the individual with a very low degree will directly discarded. This will ensure that the best individual will be able to enter the next generation of genetic manipulation successfully, which can improve the operating efficiency of the algorithm and speed up the convergence rate of the population. For the rest, the roulette wheel selection operator which is easy to operate will be adopted [1].What roulette wheel selection describe is choosing a few individuals from the group, these individuals probability that are selected are proportional to their relative fitness, the higher individual relative fitness value, the greater the probability that is to be selected. But it does not guarantee the individual that has higher relative fitness value can be elected to the next generation, which simply means that it has big probability to be selected. So we directly save the individual that has higher fitness value to the next generation, so that it can make up for the deficiency of the roulette wheel selection to a certain extent.

(2) The Improved Crossover Operator

The crossover operation is the most critical aspect in the genetic algorithm, which mimics the natural evolution process that two chromosomes form a new chromosome by mating to produce a new individual. Not only does the operation provide new individuals, but also it can generate new genes, so that crossover operator protects the individual diversity.

In the process of cross operations, the CX crossover operator is introduced as follow [3]:Randomly generate two bit string cross points, define the area between the two points as intersection, add the intersection in front of the first gene, and then remove the original individual parts of the same genes as the intersection of genes one by one, getting the individual as a result. An example for the crossover process is as follows:

(1) Randomly choose a cross area from parent individuals, If two father generation individual and cross area that were selected are describe as: Parent1="29|1674|538"， Parent2="734|2596|18", in which the symbol "| |" means cross area;
(2) Add the cross area of Parent2 to the front of the Parent1, and adding the cross area of Parent1 to the front of the Parent2, then we can get two provisional individuals: A="2596291674538",B="1674734259618";
(3) In A and B, deleting the same genes as that in cross area in the order after increase area, and then get the final two individual: Child1 = "259617438", Child2 = "167432598".

The cross operation process is as shown in figure 3.

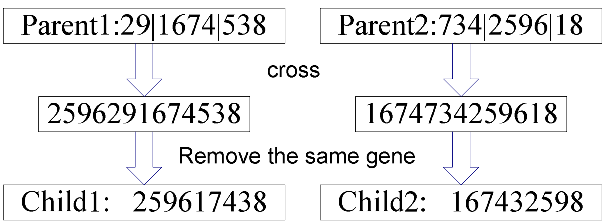

Fig. 3. Crossover operator

Compared with traditional single-point crossover and multi-point crossover, CX Cross ensure that even if two of the same individual cross, it was still able to produce a new individual, So that it gets rid of shortage of the traditional crossover operator on the diversity of the population and avoids premature convergence and reduces the possible results for the local optimal solution.

Studies have shown that the crossover probability of the genetic algorithm have a direct impact on the convergence of the algorithm.

When the value of p_c remain the same, the higher the value, the faster of the new individuals generated by, with a too large p_c ,the possibility of genetic patterns breakage is increased and high-fitness individuals structure will soon be destroyed. If the value is too small, the search process will become slow or even be stagnant. When using adaptive crossover probability, different individuals have different values, as shown in the figure 4. In order to meet the above requirements, the paper uses adaptive crossover probability formula as follow:

$$P_c = \begin{cases} P_k & f < \bar{f} \\ \dfrac{P_k (f_{\max} - f)^2}{(f_{\max} - \bar{f})^2} & f \geq \bar{f} \end{cases} \tag{9}$$

In the above equation, $f_{\max}$ is the maximum fitness value in groups and $\bar{f}$ is the average fitness value of each generation group and f is the individual fitness and P_k is the crossover probability that has preset.

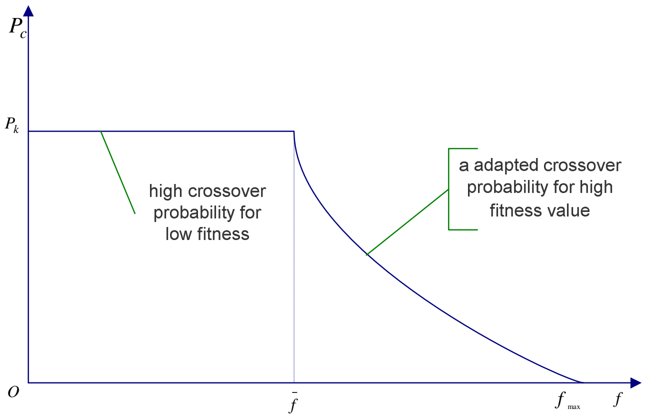

Fig. 4. Adaptive crossover probability

Setting the value of as 0.8, by the formula 9 and Figure 4, we can find that the cross probability is 0.8 when the individual's fitness is less than or equal to the average cross probability; the probability of cross adapt reduced accordingly when the individual's fitness greater than the average cross probability. In this way, we will ensure excellent individuals were reserved to the next generation. On the contrary, the poor individual will be implemented crossover operation with larger probability. The value of can be appropriately adjust according to specific needs in order to achieve the effect of to keep the best individual as much as possible.

(3) Mutation Operator

What the variation describe as randomly select a individual from the population at first, with regard to the selected individuals, randomly changing a string value in the string data structure with a certain probability.The mutation operator of genetic algorithm will be conducive to jump off a fixed area to search a broader space. In this paper, the inversion mutation operator is that selecting two points as the mutation point randomly at first,then invert the area between mutation points into a chromosome and make a new individual. And inversion mutation describe that in the evolutionary process we can effectively adjust the individuals of the population in order to prevent the premature convergence problem, as well as improving the genetic operation of the global optimization performance. The example of inversion mutation process is shown as follows:

(1) Randomly choose two change points in the individuals of father generation, so as to determine a variation area, for example: Temp = "29 | 16745 | 38", in which the symbol "| |" represents variation area;
(2) Inversing gene in genetic variation area, then replace the original position, thus we can obtains the new individual: Temp1 = "295476138";

The mutation process is shown in Figure 5.

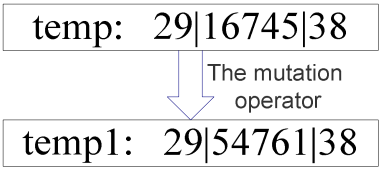

Fig. 5. Mutation operator

4 The Flowchart of Genetic Algorithm

The execution process of genetic algorithm is typical of iteration process, as shown in figure 6, and the process is described below:

Setp1 : Construct chromosomes satisfying the criteria. Genetic algorithm can not directly handle the solution space, so it must express the solution of the space as the corresponding chromosome by means of encoding. There are many chromosomes encoding method in practical problems, and natural number coding mode is adopted in this paper.

Setp2 : Generate the initial population and select the appropriate number, then set the relevant parameters. Such as the maximum generation, population size (N), crossover probability (Pc), mutation probability (Pm), and the dead-weight of every vehicle (Q) and so on.

Setp3 : Calculate the fitness of chromosomes. As an important evaluating index reflecting the quality of chromosomes, fitness is associated with the solution, and the individual with the largest fitness is the optimal solution of the genetic algorithm to be solved.
Setp4 : Produce new individuals by means of using selection, crossover and mutation operator.
Setp5 : Repeat step 3 and step 4, stopping evolution until meeting termination conditions, and then get the final result.

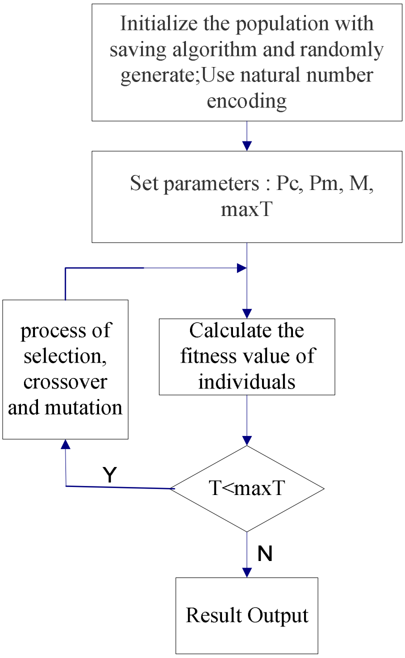

Fig. 6. The flowchart of Genetic algorithm

5 The Experimental Results and Analysis

In order to verify the feasibility of the algorithm, Benchmark Problems R101 examples designed by Solomon were selected as test data in this experiment. The basic parameters of the experiments be used in table 1 , and the test data showed in table 2. The first column figures in Table 2 represent distribution centers and customer node numbers, the figure 0 stands for distribution center; Data in the second and the third column represent x-axis and y-axis of distribution center or customer respectively, the fourth column figures mean the customers demand for goods . Each set of data is corresponding with one node shown in figure 7.

Table 1. Relevant parameter

Parameters	value
maximum generation	200
population size (N)	100
The number of customers	25
crossover probability(Pc)	0.8
mutation probability(Pm)	0.01
The unit cost	1.5
Enable fixed costs	10
Deadweight（Q）	60

Table 2. The Message of clients

Client (i)	Axis (x)	Axis (y)	Demand (Gi)	Client (i)	Axis (x)	Axis (y)	Demand (Gi)
0	35	35	0	13	30	25	23
1	41	49	10	14	15	10	20
2	35	17	7	15	30	5	8
3	55	45	13	16	10	20	19
4	55	20	19	17	5	30	2
5	15	30	26	18	20	40	12
6	25	30	3	19	15	60	17
7	20	50	5	20	45	65	9
8	10	43	9	21	45	20	11
9	55	60	16	22	45	10	18
10	30	60	16	23	55	5	29
11	20	65	12	24	65	35	3
12	50	35	19	25	65	20	6

Table 3. Experimental results

Objective / results	The best value	Generation number	Vehicle number
Calculation results	912	89	7
path number	Service order		
1	0-19-4-22-0		
2	0-15-11-1-23-0		
3	0-24-5-2-9-0		
4	0-13-20-7-14-0		
5	0-25-12-21-3-0		
6	0-18-17-16-10-8-0		
7	0-6-0		

After several tests, we list the optimal experimental results in the table 3 and the corresponding distribution path scheme be shown in Figure 7. From the table 3 we can see that we get the optimal solution 912 in the 89th generation.

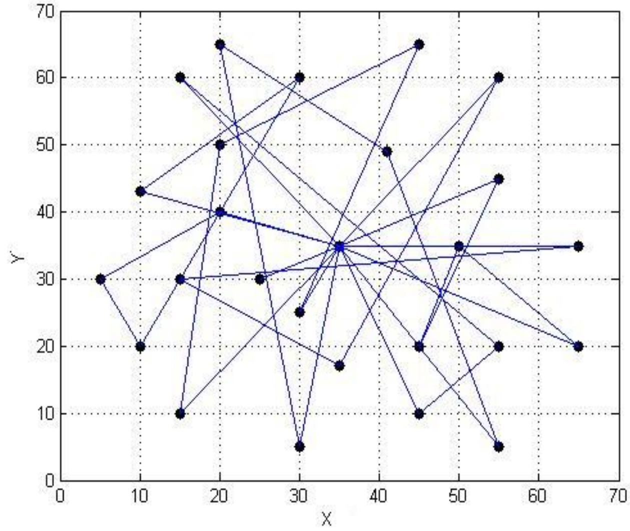

Fig. 7. Distribution path

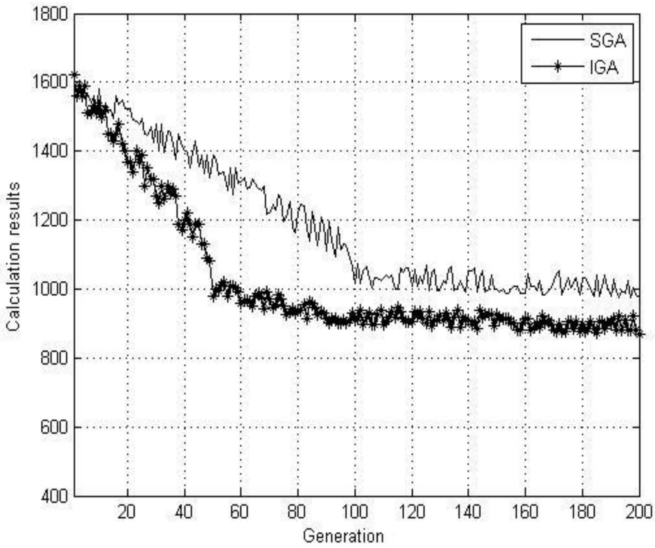

Fig. 8. Compared with the basic algorithm

From the Figure 8 we can see that, in the beginning stage of the optimizations in the process the curve falls relatively steep. Carry on with the conduct of the process, the curve which is optimized would become flatten and get the optimal solution 912 in the 89th generation. Since initial population is generated randomly, fitness of population in the beginning stage of the optimizations in the process is poor. Carry on with the conduct of the process, the mechanism which can find best solution automatically would conduct the convergence procedure convergent to the direction which is more optimized so that the solution would approach the optimal solution gradually. Since 60th generation, the volatility of the solution got relatively stable, and got the optimal solution in 89th generation.

We can find that the improved genetic algorithm is superior to the basic genetic algorithm in solution quality, speed, and stability, and it is a feasible and effective way to solve a vehicle routing problem. Additionally, different parameters may obtain different performance during solving process, therefore generally require repeated adjustments or setting the parameters according rule of thumb because of their great unpredictability. The reason is that the genetic algorithm is guidance of a randomized search technical. The operation of the genetic operators needs to randomly generate the corresponding random number. The good or bad numbers have effect on the research performance of genetic algorithm to some extent. So even if the same question, we may get different test results by using the same parameter setting. Additionally, because different parameters may obtain different performance during solving process , generally require repeated adjustments or according rule of thumb to set the parameters, As a result, the search solutions become great uncertain.

6 Conclusion and Future Work

This paper mainly studies the application of the genetic algorithm for vehicle routing optimization problems. Aimed at the characteristics of the VRP problem based on the results of many researchers, we modifie the process of initial population and cross operator, and proposes a new adaptive adjustment method for crossover probability, moreover puts forward the improved genetic algorithm. The experimental results show that the improved method proposed in this paper can effectively speed up the convergence and reduce the possibility of the results for the local optimal solution. But in the course of the study, we did not consider the influence of real-time traffic information and personalized service time requirements for the customer, but to analyze the feasibility of the proposed algorithm from a theoretical point of view. We will focus on analyzing the superiority of the algorithm from the point of view of practical application in the next research.

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References

1. Jiang, B.: Study of Vehicle Routing Problem with Time Windows Based on Genetic Algorithm. Beijing Jiaotong University (2010)
2. Cai, Z.: Research on logistics vehicle routing problem based on genetic algorithm. In: 2011 IEEE 3rd International Conference on Communication Software and Networks (ICCSN), pp. 232–235 (2011)
3. Huang, X., Zou, S., Zhang, H.: Improved genetic algorithm and its application to the optimization of physical distribution routing. Journal of Southwest University for Nationalities (Natrual Science Edition) 34(4) (2008)
4. Ren, C., Wang, X.: Research on Vehicle Scheduling Problem Based on Improved Genetic Algorithm for Electronic Commerce. In: 2007 Second IEEE Conference on Industrial Electronics and Applications, pp. 1887–1891 (2007)
5. Gong, G., Hu, X.-T., Wei, K.-X., Hao, G.-S.: Optimized Performance Research of the Vehicle Routing Problem in Industry Logistics. Computer Science & Engineering (2011)
6. Lang, M.X.: Study of the optimizing of physical distribution routing problem based on genetic algorithm. China Journal of Highway and Transport 15(3) (2002)
7. Zhang, Y.-M.: Research on Routing Optimization of Logistics Distribution Based on Saving Algorithm and its Improved. South China Normal University of Zengcheng College, Guangzhou (2011)
8. Lang, M.: Vehicle routing problem model and algorithm. Publishing House of Electronics Industry, Beijing (2009)
9. Kunkel, M., Schwind, M.: Vehicle Routing with Driver Learning for Real World CEP Problems. In: 2012 45th Hawaii International Conference on System Science (HICSS), pp. 1315–1322 (2012)
10. Calvete, H.I., Gale, C., Oliveros, M.J.: A goal programming approach to vehicle routing problems with soft time windows. European Journal of Operational Research 177, 1720–1733 (2007)
11. Alvarenga, G.B., Mateus, G.R., de Tomi, G.: A genetic and set portioning two-phase approach for the vehicle routing problem with time windows. Computers & Operations Research 34, 1561–1584 (2007)
12. Ge, H., Wang, Y.: Improved simulated annealing genetic algorithm for VRPSDP problem. Computer Engineering and Applications 46(30), 36–39 (2010)
13. Nazif, H., Lee, L.S.: Optimized crossover genetic algorithm for vehiclerouting problem with time windows. Amer. J. Appl. Sci. 7(1), 95–101 (2010)
14. Ghoseiri, K., Ghannadpour, S.F.: Hybrid genetic algorithm for vehicle routing and scheduling problem. J. Appl. Sci. 9(1), 79–87 (2009)
15. Kulkarni, R.V., Venayagamoorthy, G.K.: Bio-inspired algorithms for autonomous deployment and localization of sensor nodes. IEEE Trans.Syst., Man, Cybern. C, Appl. Rev. 40(6), 663–675 (2010)
16. Amini, S., Javanshir, H., Tavakkoli-Moghaddam, R.: A PSO approach for solving VRPTW with real case study. Int. J. Res. Rev. Appl. Sci. 4(3), 118–126 (2010)
17. Cheng, L., Wang, J.: Improved gentic algorithm for vehicle routing problem. Computer Engineering and Applications 46(36), 219–221 (2010)
18. Zhang, J., Fang, W.: Improved gentic algorithm for vehicle routing problem with time window. Computer Engineering and Applications 46(32), 228–231 (2010)
19. Gendreau, M., Tarantilis, C.D.: Solving large-scale vehicle routing problems with time windows - the state-of-the-art. Technical report, Universite de Montreal, CIRRELT (2010)