Analysis of logistics distribution path optimization planning based on traffic network data

H.H. Li [1], *H.R. Fu* [2], *W.H. Li* [3]
[1] *Anyang University, Anyang, Henan 455000, China,*
[2] *Anyang Normal University, Anyang, Henan 455000, China,*
[3] *School of Transportation, Southeast University, Nanjing, Jiangsu 211189, China*

Abstract

With the development of economy, the distribution problem of logistics becomes more and more complex. Based on the traffic network data, this study analyzed the vehicle routing problem (VRP), designed a dynamic vehicle routing problem with time window (DVRPTW) model, and solved it with genetic algorithm (GA). In order to improve the performance of the algorithm, the genetic operation was improved, and the output solution was further optimized by hill climbing algorithm. The analysis of example showed that the improved GA algorithm had better performance in path optimization planning, the total cost of planning results was 31.44 % less than that of GA algorithm, and the total cost of planning results increased by 11.48 % considering the traffic network data. The experimental results show that the improved GA algorithm has good performance and can significantly reduce the cost of distribution and that research on VRP based on the traffic network data is more in line with the actual situation of logistics distribution, which is conducive to the further application of the improved GA algorithm in VRP.

Keywords: traffic network data, logistics distribution, path optimization, genetic algorithm, time window.

Citation: Li HH, Fu HR, Li WH. Analysis of logistics distribution path optimization planning based on traffic network data. Computer Optics 2021; 45(1): 154-160. DOI: 10.18287/2412-6179-CO-732.

Introduction

With the development of economy, logistics industry, as an auxiliary industry, has been developing very fast, and its service level is constantly improving, but the high cost of logistics is still a problem of great concern. The cost of logistics distribution accounts for a large proportion in the whole logistics cost. If the path can be reasonably planed and optimized to reduce the distribution cost time and cost, the logistics cost can be reduced. Vehicle routing problem (VRP) has been widely discussed and studied [1]. Xia et al. [2] proposed a discrete differential evolution algorithm for the VRP problem in Business to Customer (B2C) and obtained the shortest path using the sequential coding method and embedding the FLOYD operator. Norouzi et al. [3] studied the VRP problem in the competition, aiming to minimize the cost, maximize the sales volume and reach the customer point before the competitors. They designed an improved particle swarm optimization algorithm and found through experiment that the method had good accuracy. Yahyaoui et al. [4] aimed at minimizing the total driving distance of vehicles, combined adaptive variable neighborhood search method with genetic algorithm (GA), and found through instance analysis that the method had good quality. Ezugwu et al. [5] improved the intelligent water drop algorithm and optimized it by simulated annealing algorithm and found through experiments that the method had advantages in both quality and time. In this study, VRP problem was studied, and an improved algorithm was designed to solve the problem, in order to find a path optimization planning method which has high performance and is in line with the actual situation. The present study makes some contributions to improve the logistics efficiency and benefits.

Traffic network data

City has a huge demand for logistics and distribution [6], and improving its efficiency plays a very important role in the development of city [7]. Under the influence of urban traffic network, the route of logistics distribution is very complex. With the construction of economic development road and the popularization of means of transportation, more and more problems such as congestion and traffic accidents appear in urban traffic, which brings a lot of inconveniences to people's travel and urban development. Traffic accidents, congestion, delay, control, etc. will affect logistics distribution [8], which brings great challenges to the development of logistics enterprises [9] Therefore, it is necessary to study the VRP problem based on the traffic network data [10].

In this study, the real-time traffic situation was represented by the vehicle speed in the traffic network. The traffic network data collected mainly includes:

(1) daily road conditions which is collect through radar speed detector and camera of each road section;

(2) floating car (bus, taxi, etc.) which is collected through GRS data collection;

(3) emergencies (road construction, control, accidents, etc.) which is collected through the transport sector.

Establishment and solution of logistics distribution path optimization planning model

1. Model establishment

When VRP is studied on the basis of traffic network data, there are some uncertainties in the network data, such as changes in customer demand, vehicle number, road condition information, etc., and there is time window demand for service [11]. In the actual logistics distribution, as long as it can be delivered within the specified time window, the customer can allow some delays. Therefore, the VRP problem was solved on the basis of soft time window in this study, and the dynamic vehicle routing problem with time windows (DVRPTW) model was established considering the dynamic traffic network data.

The dynamic traffic data refers to the traffic flow at different time and in different road sections. The data collection methods include obtaining the basic road conditions through the radar speedometer camera arranged on the road, obtaining the traffic control and traffic accident conditions through the on-site collection of the traffic police, and obtaining the floating car conditions through the GPS data of bus and taxis.

It was assumed that there was only one distribution center, all distribution vehicles were the same, the customer demand, time window, coordinates, etc. were known, the distance between every two customers and between customer and distribution center was the shortest, and each customer can only accept the service of one vehicle without considering issues such as vehicle failure. The parameters related to the establishment of DVRPTW model are shown in tab. 1.

Table 1. Model related parameters

Parameter	Meaning	Parameter	Meaning
Z	Objective function	s_i	Time of vehicle arriving at customer point i
$N(i=1,2,\ldots,N)$	Customer set	t_i	Time of vehicle serving at customer point i
$M(k=1,2,\ldots,M)$	Vehicle set	t_{ij}	Time of vehicle from customer point i to j
Q	Maximum load capacity of each vehicle	E_j	Earliest arrival time allowed by the customer
r_i	Demand of customer i	L_j	Latest arrival time allowed by the customer
c_1	Start up cost per vehicle	f_w	Waiting cost of vehicles arriving ahead of time
d_{ij}	Distance between customer i and j	f_l	Penalty cost of vehicle delay
c_2	Driving cost per vehicle	o	Penalty coefficient of vehicle overload
s_0	Departure time of vehicle at distribution center	B	Time dependent function

Aiming at minimizing the total cost, the DVRPTM model can be expressed as:

$$\min Z = c_1 M + c_2 \sum_{i=0}^{N}\sum_{j=0}^{N}\sum_{k=1}^{M} d_{ij} x_{ijk} + \\ + o\sum_{k=1}^{M}\max\left(\sum_{i=1}^{N} r_i y_{ik} - Q, 0\right) + \\ + f_w \sum_{j=1}^{N}\max\left(E_j - s_j, 0\right) + f_1 \sum_{j=1}^{N}\max\left(s_j - L_j, 0\right). \tag{1}$$

Constraint conditions include:

$$\sum_{k=1}^{M} y_{ik} = 1, i = 1,2,\cdots,N, \tag{2}$$

$$\sum_{i=1, i\neq j}^{N} x_{ijk} = y_{jk}, j = 1,2,\cdots,N, k = 1,2,\cdots,M, \tag{3}$$

$$\sum_{j=0, i\neq j}^{N} x_{ijk} = y_{ik}, i = 1,2,\cdots,N, k = 1,2,\cdots,M, \tag{4}$$

$$x_{ijk} \in \{0,1\}, i = 1,2,\cdots,N, j = 1,2,\cdots,N, k = 1,2,\cdots,M, \tag{5}$$

$$y_{ik} \in \{0,1\}, i = 1,2,\cdots,N, k = 1,2,\cdots,M, \tag{6}$$

$$s_0 = 0, \tag{7}$$

$$s_j = s_i + t_i + t_{ij}, i = 1,2,\cdots,N, j = 1,2,\cdots N, i \neq j, \tag{8}$$

$$E_j \le s_j \le L_j, j = 1,2,\cdots,N, \tag{9}$$

$$\sum_{i\neq j}\sum_{b=1}^{B} x_{ijk}^{b} \le N-1, i = 1,2,\cdots N, j = 1,2,\cdots,N, \tag{10}$$

where x_{ijk} and y_{ik} are decision variables. Meanings of equation (2) to (10) are as follows.

Equation (2): customer i is served by vehicle k;

Equation (3): vehicle k which serves customer j comes from customer i;

Equation (4): the vehicle arriving at customer i is k,

Equation (5): if there is vehicle k driving from customer i to j, then $x_{ijk}=1$; otherwise $x_{ijk}=0$;

Equation (6): if there is customer i served by vehicle k, then $y_{ik}=1$; otherwise $y_{ik}=0$;

Equation (7): all vehicles start from the distribution center;

Equation (8): the composition of time spent by vehicle k arriving customer j;

Equation (9): time of vehicle k arriving customer j should satisfy time window $[E_j, L_j]$;

Equation (10): avoid forming sub-loops in the customer set; x_{ijk}^{b} refers to that if there is vehicle k driving from customer i to customer j at time period b, then $x_{ijk}^{b}=1$; otherwise $x_{ijk}^{b}=0$.

2. Improved GA

In this study, the VRP problem was solved by GA. The basic operation of GA is as follows.

(1) Coding: natural number coding was adopted, and distribution center was coded as 0, vehicle as K and customer as N; the customers were numbered to randomly generate a chromosome. Taking "021503460" as an example, it refers to two distribution paths, and two vehicles needed to complete the service for six customers; path 1 was $0 \rightarrow 2 \rightarrow 1 \rightarrow 5 \rightarrow 0$, and path 2 was $0 \rightarrow 3 \rightarrow 4 \rightarrow 6 \rightarrow 0$.

(2) Population initialization: N natural numbers were randomly generated to compose different chromosomes, i.e., the initial population.

(3) Fitness calculation: the objective function of VRP problem was to minimize the total cost, and the fitness value could be expressed by its reciprocal, i.e., $Fit(i)=1/Z_i$, where $Fit(i)$ refers to the fitness value and Z_i refers to the total cost of the i-th chromosome.

(4) Selection: The order based selection operator was adopted. Firstly, the individuals were sorted according to the total distance. The sequence number of the individual with the smallest distance was 1, and the sequence number of the individual with the largest distance was N; the fitness value was calculated using $Fit=1000base^{i}$, where $base$ refers to the cardinal number between 0 and 1 and i refers to the sequence number of individual. It was assumed that there were three individuals, X, Y and Z, whose sequence numbers were 1, 4 and 6 respectively and the cardinal number was set as 0.5, then the fitness values of X, Y and Z were respectively

$$Fit_X = 10000 \times 0.5^1 = 5000\,, \quad (11)$$

$$Fit_Y = 10000 \times 0.5^4 = 625\,, \quad (12)$$

$$Fit_Z = 10000 \times 0.5^6 = 156.25\,. \quad (13)$$

It was found that the fitness value of individual X was significantly higher than that of Y and Z, indicating that it was a better individual; after sequence based operation, differences between X, Y and Z were more obvious and easier to be selected quickly.

(5) Crossover: Two parent chromosomes were randomly selected for crossover; for example, for chromosomes A: 12463578 and B: 36712584, the crossover locations were 2, 5 and 3, 6, then the crossover selection regions were A: 1|2463|578 and B: 36|7125|84; the gene which was overlapped with 7125 in A was deleted, and then it was combined with 7125 to form new A': 71254638; the gene which was overlapped with 2463 in B was deleted, and it was combined with 2463 to form new B': 24637158.

(6) Mutation: Mutation refers to replace some genes on the chromosome according to certain mutation probability, and the common methods include site mutation, inversion mutation, etc. In this study, interchange mutation algorithm was used, i.e., two random genes on the chromosome were exchanged. For example, for chromosome 0124503670, the positions of "4" and "7" were exchanged to get a new chromosome: 01250503640.

(7) Termination condition: when the number of iterations reached T, the algorithm ended.

In order to improve the convergence speed of GA and avoid the prematurity of algorithm, it was improved. The mutation results were further optimized using hill climbing algorithm. Hill climbing algorithm has an excellent performance in local optimization [12]. The hill climbing algorithm is as follows:

a. Initial solution X_0 is randomly generated. It is assumed that the current optimal solution is X_i and the optimal solution of the adjacent area is X_n.

b. X_i and X_n are solved. If the performance of X_n is better than that of X_i, then iteration continues; otherwise it indicates that X_i is the optimal solution, and the result is output.

The flow chart of the improved GA algorithm solving VRP problem is shown in fig. 1.

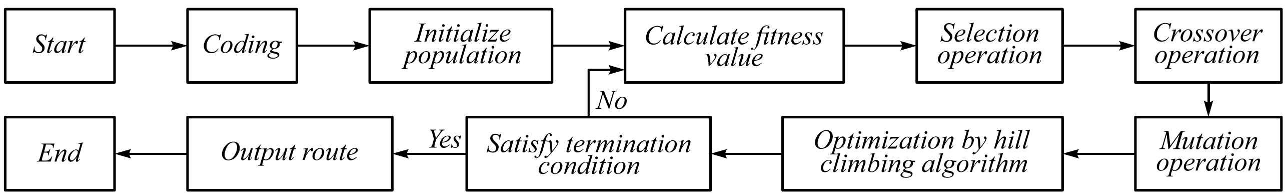

Fig. 1. The flow chart of the improved GA algorithm

Example analysis

1. Experimental data

It was assumed that there was a distribution center with three vehicles of the same vehicle model and 20 customers, and their locations are shown in fig. 2. It was found that the location of customers was relatively scattered and there was no obvious concentration. Customer number, demand (r_i), time window ($[E_j, L_j]$) and service time (t_i) are shown in tab. 2. Sequence number 0 refers to the distribution center, sequence number 1–20 refers to the customer number, and the unit of time window was h (24-hour system).

Other parameters required for the experiment are shown in Table 3. The start-up cost (c_1) of each vehicle was 8 yuan, the driving cost (c_2) was 10 yuan / km, the waiting cost (f_w) was 0.5 yuan / h, the penalty cost (f_1) was 1.5 yuan/h, and the rest were parameters of GA.

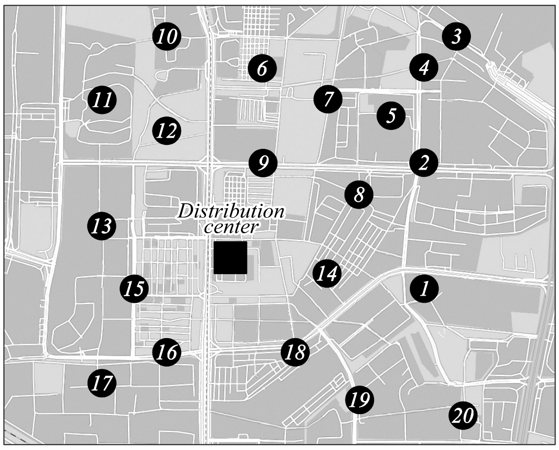

Fig. 2. Location of customers

Table 2. Example data

Sequence number	r_i (piece)	E_j (h)	L_j (h)	t_i (h)
0	0	0	0	0
1	18	3.02	7.01	1.08
2	18	2.12	7.41	0.01
3	15	4.8	6.78	0.44
4	9	3.4	7.93	0.15
5	17	4.1	8.88	0.04
6	10	3.59	8.82	1.22
7	3	3.56	7.43	1.25
8	7	3.44	6.16	0.22
9	1	2.17	7.03	0.18
10	7	3.74	8.34	0.82
11	3	4.7	6.55	0.56
12	10	2.89	7.08	1.78
13	2	3.34	8.7	0.68
14	6	3.32	7.95	1.73
15	6	2.93	7.02	0.87
16	15	2.89	6.01	1.98
17	8	3.91	7.66	1.65
18	2	3.57	8.16	1.6
19	1	4.52	6.18	0.81
20	7	2.27	8.98	1.66

Table 3. Experimental parameters

Parameter	Numerical value
c_1 (yuan)	8
c_2 (yuan/km)	10
f_w (yuan / h)	0.5
f_1 (yuan / h)	1.5
Chromosome length	20
Population size	200
Crossover probability	0.85
Mutation probability	0.01
Times of iterations	100

The traffic network data are shown in Table 4, including average values of data which were monitored in one week in the traffic network, and the data could be used for estimating the real-time condition of road network. The driving speed of vehicles was different in different sections and at different times. The road conditions were different in different sections and at different times. Some roads might be congested due to emergencies, leading to slow driving speed of vehicles, while some roads were smooth all the way, leading to fast driving speed.

Table 4. Traffic network data (km / h)

Time interval	Trunk road	Secondary trunk road	Branch road
8:00-9:00	30.3	25.6	21.2
9:00-11:00	31.3	32.5	33.7
11:00-15:00	34.6	36.7	38.4
15:00-18:00	27.6	19.6	22.5

2. Path optimization planning results

On the basis of traffic network data, the computation performance of algorithms was analyzed firstly, and the DCRPTW model was solved by the ant colony algorithm, GA and improved GA respectively. The computation performance of different algorithms is shown in tab. 5.

Table 5. Comparison of computation performance

	Ant colony algorithm	GA	Improved GA
Times of obtaining optimal solution/n	2	3	9
Average computation time / s	12.3	11.9	10.6

It was seen from Table 5 that the improved GA obtained 9 times of optimal solution in the computation process, showing good optimization performance; in the aspect of computation time, the improved GA only needed 10.6 s, which was 13.82 % faster than the ant colony algorithm and 10.92 % faster than the GA, which showed that the improved GA had excellent computation performance.

The GA and improved GA were used for path planning, and the results are shown in fig. 3 and 4.

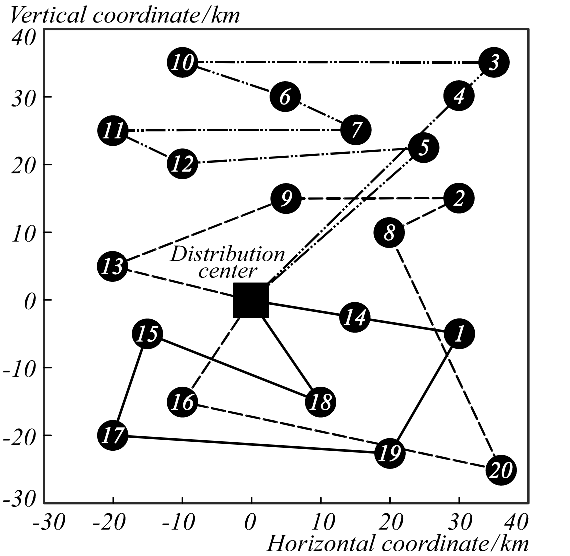

Fig. 3. Planning results of the GA algorithm

In fig. 3 and 4, the three line segments represent the distribution paths of the three vehicles respectively. It was found that the paths of the GA algorithm were staggered, many paths did not choose the customers who were close, but choose the customers who were far away, and the results of the improved GA algorithm planning were more reasonable as it always chose customers who were close preferentially after completing the service of one customer. The total cost of every path was calculated according to equation (1). The performance of the ant colony algorithm, GA algorithm and improved GA algorithm was compared. The specific path and total cost are shown in tab. 6.

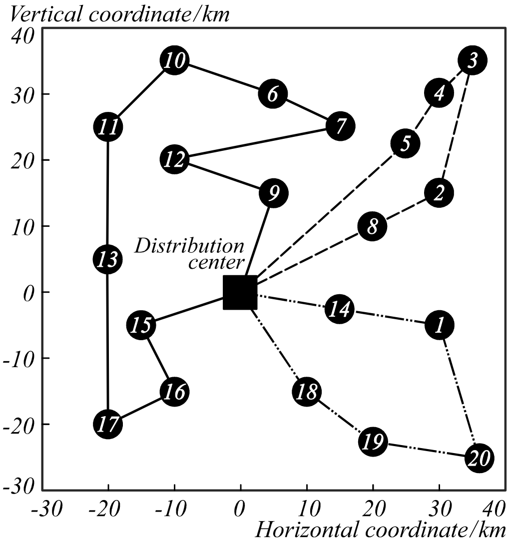

Fig. 4. Planning results of the improved GA algorithm

Table 6. The specific path and cost

		Path	Cost/yuan
Ant colony algorithm	1	0-13-17-15-16-19-18-20-1-14-0	772.63
	2	0-9-6-12-7-10-11-0	599.83
	3	0-4-3-8-2-5-0	407.96
GA algorithm	1	0-14-1-19-17-15-18-0	567.25
	2	0-16-20-8-2-9-13-0	426.56
	3	0-5-12-11-7-6-10-3-4-0	697.68
The improved GA algorithm	1	0-15-16-17-13-11-10-6-7-12-9-0	476.15
	2	0-8-2-3-4-5-0	387.45
	3	0-14-1-20-19-18-0	296.16

It was seen from Table 6 that the cost of the three vehicles under the ant colony algorithm was 772.63, 599.83 and 407.96 yuan respectively, and the total cost was 1780.42 yuan; the cost of the three vehicles was 567.25, 426.56 and 697.68 yuan respectively under the path planned by the GA algorithm, and the total cost was 1691.49 yuan; under the improved GA algorithm, the cost of the three vehicles was 406.15, 347.45 and 286.16 yuan respectively, and the total cost was 1159.76 yuan, which was 34.86 % less than the ant colony algorithm and 31.44 % less than that of the GA algorithm.

On the basis of considering the traffic network data, the total cost of the planning result obtained by the improved GA algorithm was 1159.76 yuan. If the traffic network data was not considered, i.e. the vehicle speed was the same in all time periods, and the vehicle speed was set as 36 km/h, the path planned by the improved GA algorithm is shown in fig. 5.

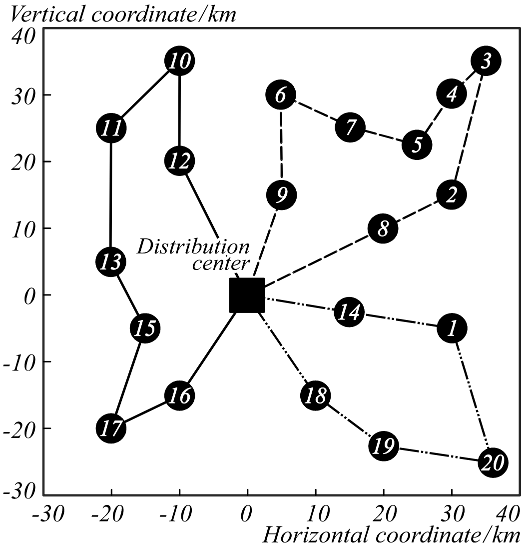

Fig. 5. The planning results without considering traffic network data

At that time, the paths of the three vehicles are as follows:

1: 0-16-17-15-13-11-10-12-0;

2: 0-9-6-7-5-4-3-2-8-0;

3: 0-18-19-20-1-14-0.

The distribution cost of the three paths was 409.55, 362.87 and 254.19 yuan respectively, with a total cost of 1026.61 yuan. In tab. 5, the total cost of the improved GA algorithm was 1159.76 yuan, which had an increase of 11.48 % compared with the situation without considering the traffic network data. It was found that the distribution time was different, the probability of delay is larger, and the total cost of distribution is larger when traffic network data was considered as the speed of different vehicles was different, which was closer to the actual situation.

Discussion

The background of economic development and technological innovation, especially the development of e-commerce enterprises, greatly promote the development of the logistics industry [13]. In order to meet the growing market demand, the logistics industry needs to invest a lot of vehicles for distribution. However, China's distribution is still in a relatively extensive stage, the utilization rate of vehicles is not high, and the efficiency of distribution is also low, which is not conducive to the long-term development of the logistics industry. Therefore, research on VRP problem has a very important practical value [14].

In this study, based on the general VRP problem, the time window of customers was considered, then a DVRPTW model was designed with the traffic network data, the objective function and constraints were analyzed, and an improved GA algorithm was designed to solve the model. It was found from the example analysis that the improved GA algorithm had better performance in solving DVRPTW problem through further optimization of genetic operation and solution. First of all, the comparison between the GA algorithm and improved GA algorithm demonstrated that the path obtained by the GA algorithm (fig. 4) was complex, some planning results even did not conform to the actual situation and might increase the transportation cost, and the results of the improved GA algorithm were more concise, efficient and reasonable. The comparison of total distribution cost demonstrated that the total cost of the GA algorithm was 1691.49 yuan, while the total cost of the improved GA algorithm was 1691.49 yuan, which showed that the path planning result obtained by the improved GA algorithm was better and more conducive to reducing the distribution cost. In addition, in order to verify the necessity of studying VRP problem on the basis of traffic network data, this study compared the difference of planning results when considering and not considering traffic network data. The results showed that the total cost of the planning results was less when not considering traffic network data, which was 1026.61 yuan, which showed that traffic network data had an effect on VRP problem. In the actual situation, there were some differences in the speed of different periods, so it is necessary to take it into consideration in VRP problem.

Although some achievements have been made in the research of VRP, there are still some problems that need to be solved in the future work:

(1) the study of VRP problem of multi-distribution center;

(2) the further improvement of the performance of GA algorithm;

(3) further expansion of the number of customers and the complexity of the path;

(4) the analysis of the performance of algorithm in the practical application.

Conclusion

This study designed a DVRPTW model based on the traffic network data, improved the GA algorithm by improving the genetic operation and combining with the mountain climbing algorithm, and solved the model. The results suggested that:

(1) the path planning result of the GA algorithm was not reasonable;

(2) compared with the GA algorithm, the total cost of the improved GA algorithm reduced by 31.44 %;

(3) the cost of planning results considering traffic network data was 11.48 % higher than that without consideration.

The experimental results verified the effectiveness of the improved GA algorithm and the necessity of considering traffic network data, which provides some theoretical bases for solving VRP problems.

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Authors' information

Huahui Li (b.1988) is a master's degree candidate in the School of Mathematics and Statistics of Yunnan Universty (China). Her current research interests include operational research and cybernetics, and supply chain management.
E-mail: 001229@ayxy.edu.cn .

Haoran Fu (b.1990) is a master's degree candidate in College of Mechanical Engineering Chongqing Universty (China). His current research interests include logistics optimization and electronic commerce logistics.
Email: *haoranfu@aynu.edu.cn* .

Wenhao Li (b. 1993) is a Ph.D. candidate at School of Transportation of Southeast University (China). His current research interests include traffic big data analysis and application with machine learning algorithms, urban road network analysis and modeling, and intelligent transportation systems. He is also interested in data mining in various domains, e.g. agriculture, medical science, and manufacturing. E-mail: *lwy70r@163.com* .

Received April 10, 2020. The final version – August 26, 2020.