J. Meas. Sci. Instrum., 2024, 15(3): 369-378.
DOI: 10.62756/jmsi.1674-8042.2024038

http://jmsi.publish.founderss.cn/
jmsi@nuc.edu.cn

Vehicle routing optimization algorithm based on time windows and dynamic demand

LI Jun*, DUAN Yurong, ZHANG Weiwei, ZHU Liyuan

School of Electronic and Information Engineering, Lanzhou Jiaotong University, Lanzhou 730070, China

***Corresponding author:** LI Jun (lijane@mail.lzjtu.cn)

Received: September 19, 2023 **Revised:** December 6, 2023 **Accepted:** December 11, 2023

Abstract: To provide the supplier with the minimizum vehicle travel distance in the distribution process of goods in three situations of new customer demand, customer cancellation service, and change of customer delivery address, based on the ideas of pre-optimization and real-time optimization, a two-stage planning model of dynamic demand based vehicle routing problem with time windows was established. At the pre-optimization stage, an improved genetic algorithm was used to obtain the pre-optimized distribution route, a large-scale neighborhood search method was integrated into the mutation operation to improve the local optimization performance of the genetic algorithm, and a variety of operators were introduced to expand the search space of neighborhood solutions; At the real-time optimization stage, a periodic optimization strategy was adopted to transform a complex dynamic problem into several static problems, and four neighborhood search operators were used to quickly adjust the route. Two different scale examples were designed for experiments. It is proved that the algorithm can plan the better route, and adjust the distribution route in time under the real-time constraints. Therefore, the proposed algorithm can provide theoretical guidance for suppliers to solve the dynamic demand based vehicle routing problem.

Key words: vehicle routing problem; dynamic demand; genetic algorithm; large-scale neighborhood search; time windows

0 Introduction

In recent years, with the rapid development of world logistics industry, logistics distribution has brought a comfortable and convenient life experience for people, especially for small and medium-sized retail industry such as convenience stores and various specialty stores. These convenience stores and various specialty stores have the characteristics of small scale and high density, and their own inventory capacities are small. Therefore, they need to be supplied by regional suppliers at any time. Considering the ordering demands of retailer customers are dynamic and uncertain, i.e., cancellation and addition of orders, change of customer's delivery address, and uncertain delivery time, it becomes difficult for suppliers to plan their distribution schemes. Therefore, designing a perfect distribution system and planning a reasonable distribution scheme have become important issues that logistics companies need to solve urgently.

The vehicle optimization scheduling problem, abstracted as vehicle routing problem[1] (VRP), is a classical combinatorial optimization problem. In the process of delivering goods to retailer customers by suppliers, the problem of changing demands is called dynamic demand based vehicle routing problem (DDVRP)[2]. The combination of DDVRP and vehicle routing problem with time windows (VRPTW)[3] is called dynamic demand based vehicle routing problem with time window (DDVRPTW).

Regarding DDVRP without time window constraint, Li et al.[4] proposed a periodic customer real-time reset strategy based on delayed service by dividing the working hours of distribution center into several time slices with continuous updating of customer information. Based on this, a hybrid variable neighborhood artificial bee colony algorithm was proposed. Zhang et al.[5] established a two-stage mathematical model of multi-vehicle open DDVRP for the emergence of new customers and demand changes of old customers in the service process, designed a solution strategy of pre-optimized route scheduling combined with real-time dynamic scheduling, and proposed a hybrid 2-OPT quantum evolutionary algorithm. Fan et al.[6] built a multi-vehicle DDVRP model by considering the dynamic changes of customer demand and the impact of vehicle speed change on the whole distribution process. Based on it, they proposed an improved adaptive genetic algorithm by combining the ideas of pre-optimization and dynamic adjustment.

As for DDVRPTW, scholars have designed various models and proposed a variety of solution methods, which are mainly classified into the exact algorithm and the heuristic algorithm[7]. for the exact algorithm, it can obtain the optimal solution at the initial stage. However, as time goes on, when the customer needs change, the algorithm cannot find a stable and better solution at the dynamic adjustment stage. Additionally, when the customer size increases, the exact algorithm will take a long solution time, which cannot meet the instantaneous requirement of the algorithm. To solve the above-mentioned problems, the heuristic algorithm was proposed. Wang et al. [8] established a multi-objective optimization model for DDVRPTW, and proposed an ensemble learning based multi-objective evolutionary algoritm (EL-DMOEA) based on population-based prediction strategy, migration strategy and stochastic strategy to improve the performance of the algorithm. Nan et al. [9] constructed a two-stage solution model for the mixed distribution mode of fuel and electric vehicles and designed an improved adaptive large-scale neighborhood search algorithm, which can minimize the distribution cost. Zhang et al.[10] established a DDVRP model with soft time window constraints, and adopted a two-stage solution strategy, that is, an improved genetic algorithm at the initial stage and a simulated annealing algorithm at the dynamic adjustment stage. Yang et al.[11] established a mathematical model for the DDVRP with soft time window, and proposed an improved Riemannian trust-region (RTR) algorithm at the initial planning stage and a plug-in real-time route planning algorithm at the real-time optimization stage. Schyns[12] constructed a mathematical model considering various dynamic factors, such as customer demand change, new customer demand, customer cancellation of service, and service time window change. Lu et al. [13] used a competitive co-evolutionary algorithm to solve the DDVRP. In addition, there are many intelligent optimization algorithms to solve dynamic vehicle routing problems, including improved artificial ant colony algorithm[14], adaptive large neighborhood search algorithm[15], hybrid particle swarm algorithm[16], etc.

However, there are some shortcomings in the above-mentioned research on DDVRPTW, for example, the algorithm is easy to fall into local optimum and the calculation time is long. In this study, we established a mathematical model based on DDVRPTW to minimize the total distribution distance according to the characteristics of the model, designed an improved genetic algorithm (IGA) to obtain pre-optimized distribution routes, and combined the periodic optimization strategy with various neighborhood search operators to adjust the configuration quantity and distribution routes of vehicles considering the changes of customer demands, so as to provide a theoretical basis for suppliers to obtain a reasonable and effective distribution scheme.

1 Proposed DDVRPTW model

1.1 Problem description

DDVRPTW is based on the traditional VRP, and it considers the impact of the dynamic changes of customer demands on the delivery route planning in the vehicle distribution process.

The problem is described in the context of a single distribution center: there are several vehicles with the same rated load capacity, and the vehicles depart from the distribution center and provide delivery services to each customer within a specific time window according to a pre-optimized delivery route planned for known customers. In the process of vehicle distribution, there may be new customer demands, cancellations of customer service and changes of the customer's delivery address. On the premise that the designed algorithm meets the demands of existing customers, and the distribution scheme can dynamically adjust according to real-time customer information, the total distribution cost is minimum. To establish a DDVRPTW model, the assumptions are as follows:

1) Before the optimization, the customer's demands, service time windows, delivery address and other information of known customers are determined. In the process of vehicle distribution, new customers appear, and their geographic locations, demands and service time windows are also determined.

2) The route is that all vehicles depart from the distribution center with full load, complete the distribution tasks, return to the distribution center, and unload materials if there are any surplus.

3) The distribution center can meet the demands of all customers, multiple vehicles can be used to serve customers at the same time, the maximum demand of each customer does not exceed the rated capacity of the vehicle, and the demand cannot be split; Each customer is only visited once.

4) The time at which the vehicle arrives at the customer's designated location is not earlier or later than

the specified service time window.

5) The vehicles travel at a constant speed and the roads are unobstructed in the delivery process, regardless of unexpected conditions.

1.2 Symbols

To facilitate the construction of DDVRPT model, the corresponding symbols are defined as follows:

N_0: The distribution center;

N_i: The set of customers known to need service, $i\in\{1,2,\cdots,n\}$;

N: The known customers set and distribution center, which is the combination of N_0 and N_i;

K: The vehicles set, $K=\{1,2,\cdots,m\}$;

D_{ij}: The distance from customer i to j, $(i,j\in N)$;

d_i: The demand of customer i;

$[E_i, L_i]$: The time window in which customer i expects to be served;

S_i: The service time required by customer i;

Q: The maximum load capacity of vehicle;

St_i: The start time of service for customer i;

T_{ij}: The time required from customer i to j;

x_{ij}^k: $x_{ij}^k=1$ if vehicle k passes the road between customer i and customer j, otherwise $x_{ij}^k=0$;

y_i^k: $y_i^k=1$ if the vehicle k serves for customer i, otherwise $y_i^k=0$.

1.3 Mathematical model

The strategies of pre-optimization and real-time optimization are combined to solve the DDVRPTW, and the flow chart is shown in Fig. 1. At the pre-optimization stage, the improved genetic algorithm is used to generate a pre-optimized distribution plan. At the real-time optimization stage, the periodic optimization strategy combines various neighborhood search operators to adjust the delivery route in time.

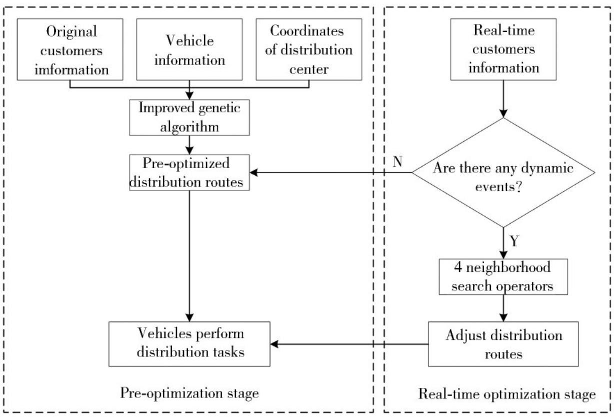

Fig. 1 Flow chart of pre-optimization and real-time optimization strategy

The DDVRPTW model is constructed as

$$\min z=\sum_{i\in N}\sum_{j\in N}\sum_{k\in K}D_{ij}x_{ij}^k, \tag{1}$$

$$\text{s.t.}\sum_{i\in N}\sum_{j\in N_i}x_{ij}^k d_j\leqslant Q,\ \forall k\in K, \tag{2}$$

$$\sum_{i\in N}\sum_{k\in K}x_{ij}^k=1,\ \forall j\in N, \tag{3}$$

$$\sum_{j\in N_i}x_{0j}^k=\sum_{i\in N_i}x_{i0}^k=1,\ \forall k\in K, \tag{4}$$

$$St_j=\begin{cases}St_i+S_i+T_{ij}, & \text{if } E_i<St_i<L_i,\ \forall i\in N_i,\\ E_i+S_i+T_{ij}, & \text{if } St_i\leqslant E_i,\ \forall i\in N_i,\end{cases} \tag{5}$$

where Eq. (1) is the objective function of the model, which is to minimize the total distance; Eq. (2) gives the constraints that the total load on each route cannot exceed the rated load of the vehicle; Eq. (3) means that each customer is served by one vehicle only once; Eq. (4) indicates that the vehicle starts and ends at the distribution center; and Eq. (5) indicates the time window constraint to satisfy the customer.

1.4 Dynamicity analysis of DDVRPTW

The dynamicity of DDVRPTW refers to the dynamic changes of customer demand information. After the pre-optimization is completed, the distribution center issues a task scheduling instruction. During the process of vehicle distribution, customer demand may dynamically occur. How to reasonably and effectively balance the needs of existing customers and new customers and plan a minimized distribution route is the key problem in this study.

With dynamic change of customer demands, the working time of the distribution center is equally divided into several time slices for periodic optimization, and then sub-problem in each time slice can be regarded as a static vehicle routing problem[17]. The optimization plan is transmitted and adjusted in successive time slices, and finally a complete distribution plan is formed. Supposing that the working time window of the distribution center is $[0, T]$, the number of time slices is n, the deadline for receiving customer change requests is t, where $t=(T+1)/2$, and the duration of each time slice is $(t+1)/n$. At the end of the current time slice, the dynamic request will readjust the distribution route considering the existing route and the information of customers not to be serviced.

2 Algorithm design for DDVRPTW

2.1 Pre-optimization algorithm

In this section, we design an intelligent optimization algorithm called improved genetic algorithm (IGA), which uses large-scale neighborhood search (LNS) to improve the local search ability of genetic algorithm (GA), and introduces multiple removal operators and a repair operator to reconstruct the solution so as to improve the quality of the solution.

2.1.1 Encoding and decoding

The encoding method of the IGA adopts integer encoding. Firstly, m chromosomes are randomly generated and the length of each chromosome is N, where each number in the chromosome represents a customer number. Secondly, the customers in all chromosomes are arranged in ascending order according to the start time window, and the customers in each chromosome are assigned to vehicles in order according to the rated load of the vehicle. Finally, an initial population is generated. Assuming that there are 12 customers to be served, the decoding process of chromosome is shown in Fig.2. According to the order of customers, the customer demand is accumulated from customer 8. Assuming that the vehicle load constraint cannot be met at customer 9, we need record it, insert number 0 (distribution center) in front of customer 9, and rearrange the vehicle at the recorded customer. The above process is repeated until the customer assignment in the chromosome is completed. Then, the number 0 is inserted at the head and tail of the chromosome. So far, the decoding operation is completed. In this way, four distribution routes are generated, namely, route 1: 0-8-1-4-5-0, route 2: 0-9-2-11-7-0, route 3: 0-3-12-6-0, and route 4: 0-10-0.

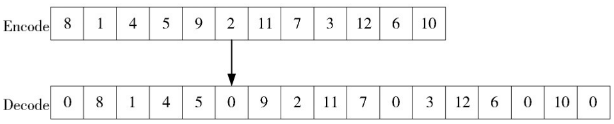

Fig. 2 Chromosome encoding and decoding process

2.1.2 Selection and crossover

To obtain the minimum objective function value in Eq. (1), we adopt the roulette selection strategy to select a number of chromosome individuals with smaller function values (larger fitness values) and retain them. The crossover operation adopts OX crossover method. Firstly, parent generation A and parent generation B are determined, Secondly, two crossover points are selected randomly, and the area between these two crossover points is the crossover segment. Afterwards, we place the crossover segment of parent b in front of that of parent A, and conversely, we place the crossover segment of parent A in front of that of parent B. If the genetic positions in parent A and B are duplicated in the inserted crossover segment, they are marked respectively. Finally, the genetic positions marked in both parents are deleted to create two new offspring individuals. The procedure of crossover operation is shown in Fig.3.

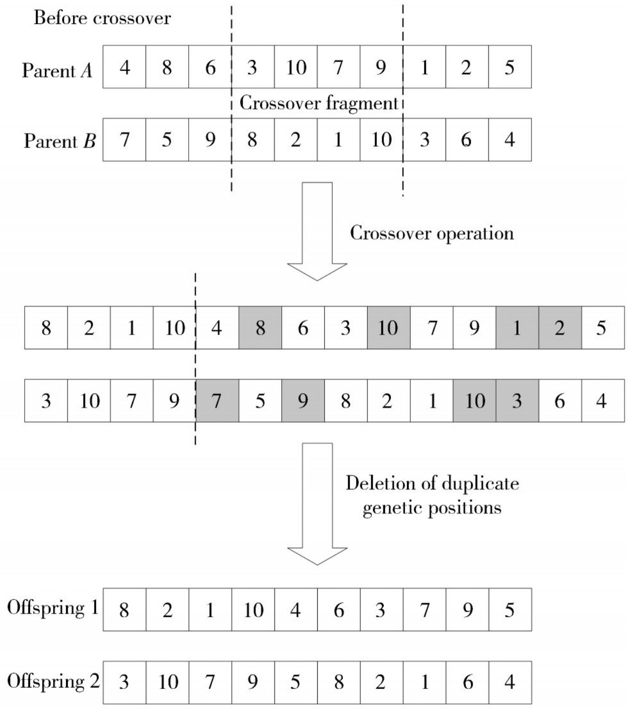

Fig. 3 Crossover operation

2.1.3 Improved mutation operation

To enhance the local exploitation ability of genetic algorithms, large-scale neighborhood search operators are introduced to the mutation operation to adjust the solution in the neighborhood of feasible solution by "destroy" and "repair" operations to obtain a high-quality solution[18]. The "destroy" and "repair" operations are implemented by removal and insertion operators, respectively. Firstly, some customer nodes are removed from the current solution using the removal operators, and then the removed nodes are reinserted into the destroyed solution using the insertion operator, so as to obtain the neighborhood solution of the original feasible solution.

1) Removal operator

Three removal operators are used in this study.

① Random removal operator

The removal operator randomly removes m customers with equal probability in each route, where m is a random positive integer, $m \in \{1, 2, \cdots, m_{\max}\}$, the selection probability of m is $1/m_{\max}$.

② Similarity removal operator

Firstly, the similarity removal operator randomly selects customer i and removes it from the existing distribution scheme. Then, the similarity $R(i, j)$ between other customers and customer i in the scheme is calculated. Finally, the customer with the smallest $R(i, j)$ (the customer with the largest similarity) is removed. The above operations are repeated until m customers are removed. The calculation formula is

$$R(i,j)=\gamma_1\frac{D_{ij}}{\max\limits_{i,j\in N}D_{ij}}+\gamma_2\frac{\left|E_i-E_j\right|}{\max\limits_{i,j\in N}\left(\left|E_i-E_j\right|\right)}+\gamma_3\frac{\left|d_i-d_j\right|}{\max\limits_{i,j\in N}\left(\left|d_i-d_j\right|\right)},\tag{6}$$

where N is the set of all customers requiring service; D_{ij} represents the distance between customer i and customer j; $\left|E_i-E_j\right|$ represents the difference between the earliest service time of customer i and j; $\left|d_i-d_j\right|$ represents the demand difference between customer i and customer j; the distance between customers, the earliest service time difference between customers and the demand difference of customers will affect the measurement of similarity. Parameters γ_1, γ_2 and γ_3 represent the weights of different influencing factors to normalize the measurement results.

③ Removal operator of high-cost customers

The method of removing customers with higher cost can greatly reduce the distribution cost. The specific operations are as follows: Firstly, the cost of customer i is defined as $w_i(i,s)=f(s)-f_{-i}(s)$, where s represents a current solution, $f(s)$ represents the current cost, and $f_{-i}(s)$ represents the cost after removing customer i from s; Then, each customer is arranged in descending order according to the value of $w(i, s)$; Finally, m customers with higher cost are selected to remove.

2) Insertion operator

In this study, a greedy insertion operator acts as a repair operator, so that the generated neighborhood solutions can satisfy the constraints and better solution can be obtained to a large extent. This method minimizes the increase in total cost by reinserting the removed customers into the optimal position in the route. The specific operations are as follows:

Assuming that the set of removed customers is O, the algorithm randomly selects customer i from set O, traverses each route, finds all the insertion positions that satisfy the customer service time window constraint and vehicle load constraint, and calculates the distance increment between customer j and customer $j+1$ inserted by customer i into route p by

$$D_{pj}=D_{ji}+D_{i(j+1)}-D_{j(j+1)}.\tag{7}$$

Thus, the position with the smallest distance increment can be found, which is the best insertion location.

If the position to be inserted that meets time window and vehicle load constraints cannot be found after all routes being travelled, a new route will be constructed and the customers to be inserted are added to it. Repeat the above steps until all the customers in set O are reinserted into the route.

2.2 Real-time optimization

2.2.1 Construction of initial solution

At the pre-optimization stage, we use IGA to generate a pre-optimized distribution scheme based on known customer information and related parameters. It is a complete scheme and can dispatch instructions to all the vehicle to start their respective distribution tasks. At the end of time slice, the distribution path needs to be adjusted instantly with dynamic customer information. Firstly, the sub-paths in the planned distribution path are filtered and tracked, and the served customers and next customers close to the service start time are set as unchangeable customers. Then, the remaining paths in sub-paths are operated. For the customers who cancel service, they are directly deleted from the route; For the customers who change delivery address, they are deleted from the route and considered as new demand customers. The adjustment of distribution routes results from the customers who have new demands. The new customers are inserted into the route by the greedy insertion method. When all the new customers are added to the path, the initial solution is constructed completely.

2.2.2 Optimization of initial solution

Since the initial solution may not be optimal, it need to be optimized. Four neighborhood search operators are used for fast local optimization of feasible solutions.

1) 2-opt operator in path

It randomly selects two customers as two points in the same path, and flips all the customers between the two points, as shown in Fig.4.

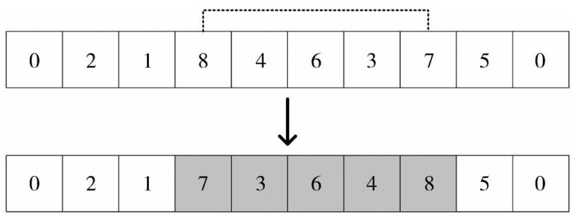

Fig. 4 2-opt operator in path

2) Point insertion operator between paths

It selects a random customer point in two different paths, respectively, and inserts one customer point to the position behind the other customer point, as shown in Fig.5.

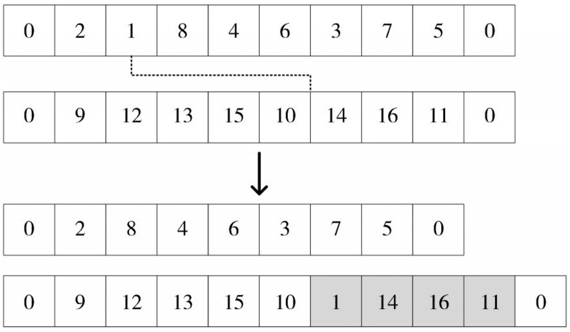

Fig. 5 Point insertion operator between paths

3) Points exchange operator between paths

It selects a random customer point in two different paths, respectively, and exchanges their positions, as shown in Fig.6.

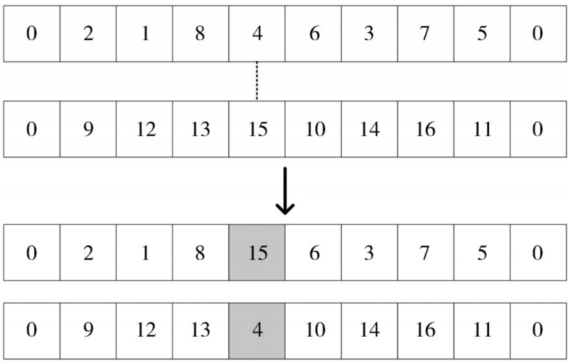

Fig. 6 Points exchange operator between paths

4) Fragments exchange operator between paths

It randomly selects the customer segments in two different paths and changes their positions, as shown in Fig.7.

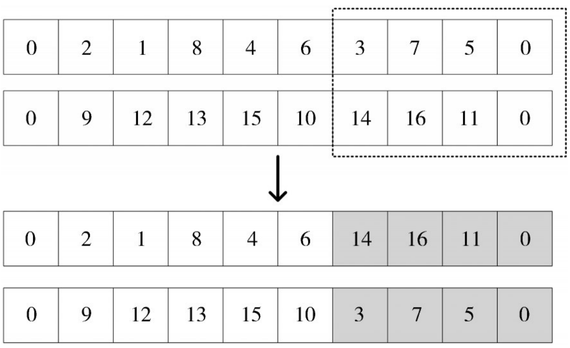

Fig. 7 Fragments exchange operator between paths

3 Simulation

The simulation was conducted by use of Matlab (R2016a) on a computer with Intel (R) Core (TM) i5-7300HQ CPU@2.50 GHZ.

To verify the effectiveness of the proposed algorithm, two simulations with different customer scales were designed. In the IGA, the population size was set to be 100, the maximum number of iterations was 100, the crossover probability was 0.9, and the mutation probability was 0.05.

3.1 Small-scale simulation

The coordinates of distribution center were (0, 0), the working time window of distribution center was [7, 18], the deadline for receiving customer change demand was 13, the time window of real-time optimization was [7, 13], the initial customer demand information was referred to Ref. [10], there were 24 initial customers, the load capacity of the vehicle was set to be 60, and the average driving speed of the vehicle was 40 km/h. This was a small-scale simulation with 29 customers. Since the transport distance and total distance of each vehicle based on experimental results retain two significant places after the decimal point, the accumulated processed transport distance may have a very small error with the total distance, which is unavoidable, and the following situations are the same.

The pre-optimized distribution scheme is listed in Table 1, and the distribution route is shown in Fig.8.

Table 1 Pre-optimized distribution scheme

Vehicle No.	Distribution route	Transport distance/km	Total distance /km
1	1-20-21-22-19-18	44.04	135.25
2	4-10-11-12-13-14-15-16	47.72	
3	5-9-7-8-6-17	21.10	
4	3-2-23-24	22.39	

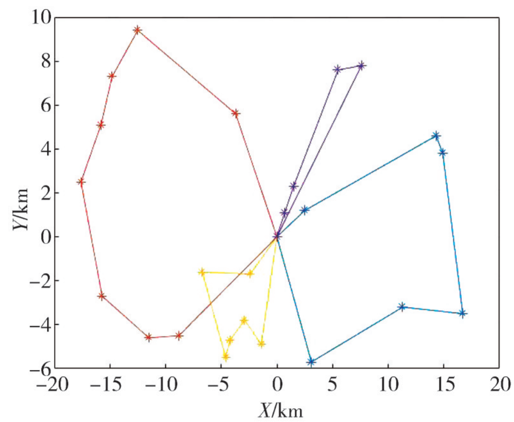

Fig. 8 Pre-optimized distribution route

When the vehicle is fully loaded and starts delivery service from the distribution center, the dynamic service is also opened. It receives new customer demand and original customer change information, and then starts real-time optimization. The time interval of periodic optimization is 1 h, and there are 6 time slices, namely, [7, 8], [8, 9], [9, 10], [10, 11], [11, 12], and [12, 13].

The dynamic customer demand information received by the vehicle in the distribution process is shown in Table 2 and Table 3.

Table 2 Change information of original customers

Customer No.	Variation type	New address	Present moment
24	Change address	(3,8.2)	9:35
19	Change address	(−4.6,10)	11:24
17	Cancel service	—	11:33

Table 3 New customer demands information

Customer No.	Coordinates	Demand	Service time window	Length of service time/h	Present moment
25	(5.9,3.4)	15	[14,16]	0.66	8:12
26	(−8.3,3.2)	10	[11,13]	0.50	9:15
27	(4.7,−3.6)	10	[11,14]	0.33	9:42
28	(9.6,2.3)	6	[11.5,15.5]	0.33	11:08
29	(−6.5,5.7)	12	[14,17]	0.83	11:46

The above-mentioned dynamic events mainly occur in the time windows [8, 9], [9, 10] and [11, 12]. At 9:00, the distribution status of each vehicle is shown in Table 4.

Table 4 Distribution of vehicles at 9:00

Vehicle No.	Vehicle location	Remaining load
1	On the road from customer 1 to customer 20	49
2	Serving customer 10	50
3	Serving customer 5	60
4	Has not departed from distribution center	0

It can be seen from Table 3 that there are new customers requests in the time slice [8, 9]. At 9:00, new customers and undelivered customers need to be routed again. The distribution scheme is shown in Table 5, and the distribution route is shown in Fig.9.

Table 5 Optimized distribution scheme at 9:00

Vehicle No.	Distribution route	Transport distance/km	Total distance/km
1	1-20-21-22-19-18	44.04	135.88
2	4-10-11-12-13-14-15-16	47.72	
3	5-9-7-8-6-17	21.10	
4	3-2-23-24-25	23.02	

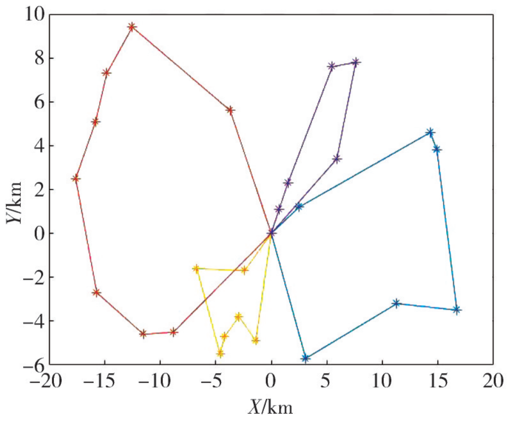

Fig. 9 Optimized distribution route at 9:00

It can be seen from Table 2 and Table 3 that in the time slice [9, 10], customer 24 changes the delivery address and customers 26 and 27 are added. The distribution route is adjusted at 10:00, the distribution scheme is shown in Table 6, and the re-optimized distribution route is shown in Fig.10.

It can be seen from Table 2 and Table 3 that in the time slice [11, 12], customer 19 changes the delivery address, customer 17 cancels the service, and customers 28 and 29 are added. At 12:00, the distribution route is adjusted again. The final distribution scheme is shown in Table 7, and the distribution route is shown in Fig.11.

Table 6 Optimized distribution scheme at 10:00

Vehicle No.	Distribution route	Transport distance/km	Total distance/km
1	1-20-21-22-19-27-18	44.72	153.62
2	4-10-11-12-13-14-15-16	47.72	
3	5-9-7-8-6-17	21.10	
4	3-26-2-24-23-25	40.07	

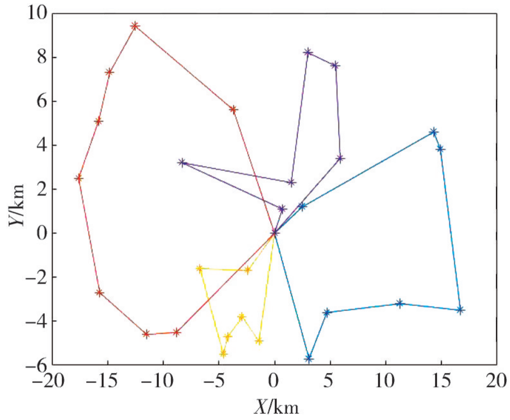

Fig. 10 Optimized distribution route at 10:00

Table 7 Optimized distribution scheme at 12:00

Vehicle No.	Distribution route	Transport distance/km	Total distance/km
1	1-20-21-22-18-27-28-6	66.35	193.07
2	4-10-11-12-13-14-15-16	47.72	
3	5-9-7-8-29-19	38.93	
4	3-26-2-24-23-25	40.07	

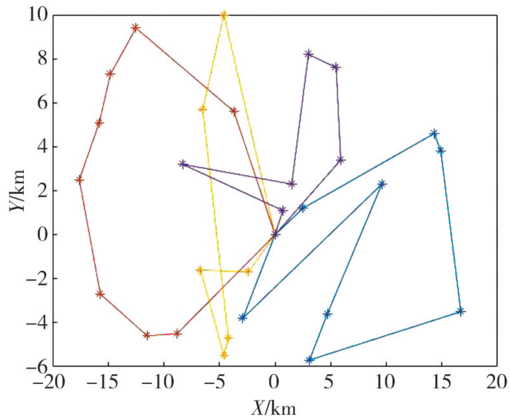

Fig. 11 Optimized distribution route at 12:00

3.2 Large-scale simulation

The coordinates of the distribution center were (40, 50), and there were 100 initial customers to be served.

The information of these 100 customers came from the C101 example in the classical Solomon dataset with a specific time window for the customers. To test the performance of the algorithm more scientifically, the original time window was not adjusted, which resulted in longer working time window of the distribution center, [0, 21]. Therefore, two drivers took turns to serve customers. The continuous service time of customers was a random number between 10 and 30, the vehicle load was 200, the average speed was 40 km/h, the time interval for periodic optimization was 1 h, and the deadline for receiving customer change requests was 11, so [0, 11] was the real-time optimization stage. The vehicle departed from the distribution center with full load, and served each customer in turn according to the pre-optimized distribution scheme shown in Table 8. Thus, the distribution route is shown in Fig.12.

Table 8 Pre-optimized distribution scheme

Vehicle No.	Distribution route	Transport distance/km	Total distance/km
1	20-24-25-27-29-30-28-26-23-22-21	50.80	828.94
2	90-87-86-83-82-84-85-88-89-91	76.07	
3	5-3-7-8-10-11-9-6-4-2-1-75	59.62	
4	81-78-76-71-70-73-77-79-80	127.30	
5	98-96-95-94-92-93-97-100-99	95.94	
6	32-33-31-35-37-38-39-36-34	97.23	
7	67-65-63-62-74-72-61-64-68-66-69	59.40	
8	13-17-18-19-15-16-14-12	95.88	
9	57-55-54-53-56-58-60-59	101.88	
10	43-42-41-40-44-46-45-48-51-50-52-49-47	64.81	

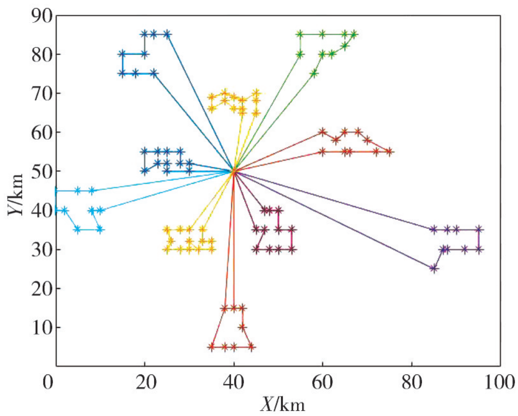

Fig. 12 Pre-optimized distribution route

In the process of vehicle distribution, customer demands were constantly changing, and the dynamic information is shown in Table 9 and Table 10.

Table 9 Change information of original customers

Customer No.	Variation type	New address	Present moment
6	Cancel service	—	7:05
14	Change delivery address	(46,10)	7:23
47	Cancel service	—	9:07
21	Change delivery address	(41,82)	9:20

Table 10 New customer demands information

Customer No.	Coordinates	Demand	Service time window	Length of service time/h	Present moment
101	(70,80)	15	[17,18]	0.25	7:20
102	(80,31)	10	[11,13]	0.2	7:25
103	(30,40)	12	[11,14]	0.3	9:10
104	(85,20)	10	[11.5,15.5]	0.3	9:11
105	(10,80)	12	[16,17]	0.3	9:45
106	(71,8)	20	[14.5,16]	0.4	9:47
107	(7,90)	11	[18.5,19]	0.25	9:59

It can be seen from Table 9 and Table 10 that in the time slice [7, 8], there are two new customers, customer 6 cancels the service, and customer 14 changes the delivery address. The distribution route was planned at 8:00 again, the distribution scheme is shown in Table 11, and the re-optimized distribution route is shown in Fig.13.

Table 11 Optimized distribution scheme at 8:00

Vehicle No.	Distribution route	Transport distance/km	Total distance/km
1	20-24-25-27-29-30-28-26-23-22-21	50.80	931.38
2	90-87-86-83-82-84-85-88-89-91	118.50	
3	5-3-7-8-10-11-9-6-4-2-1-75	59.61	
4	81-78-76-71-70-73-77-79-80	136.79	
5	98-96-95-94-92-93-97-100-99	95.94	
6	32-33-31-35-37-38-39-36-34	97.23	
7	67-65-63-62-74-72-61-64-68-66-69	59.40	
8	13-17-18-19-15-16-14-12	95.88	
9	57-55-54-53-56-58-60-59	101.88	
10	43-42-41-40-44-46-45-48-51-50-52-49-47	115.33	

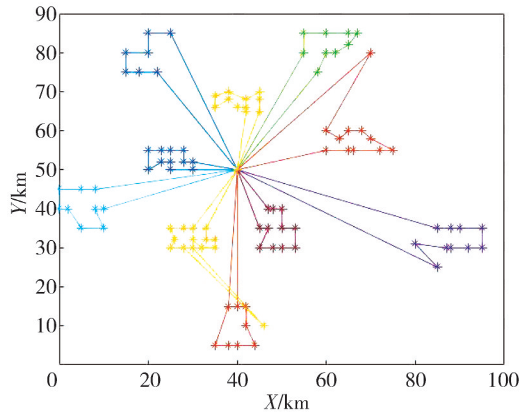

Fig. 13 Optimized distribution route at 8:00

It can be seen from Table 9 and Table 10 that in the time slice [9, 10], there are five new customers, customer 47 cancels the service, and customer 21 changes the delivery address. The distribution route was adjusted at 10:00 again. The distribution scheme is shown in Table 12, the distribution route is shown in Fig.14.

Table 12 Optimized distribution scheme at 10:00

Vehicle No.	Distribution route	Transport distance/km	Total distance/km
1	20-24-25-27-29-30-28-26-23-22-21	134.19	1 066.05
2	90-87-86-83-82-84-85-88-89-91	118.50	
3	5-3-7-8-10-11-9-6-4-2-1-75	59.62	
4	81-78-76-71-70-73-77-79-80	162.05	
5	98-96-95-94-92-93-97-100-99	95.94	
6	32-33-31-35-37-38-39-36-34	97.23	
7	67-65-63-62-74-72-61-64-68-66-69	58.14	
8	13-17-18-19-15-16-14-12	106.10	
9	57-55-54-53-56-58-60-59	101.88	
10	43-42-41-40-44-46-45-48-51-50-52-49-47	132.40	

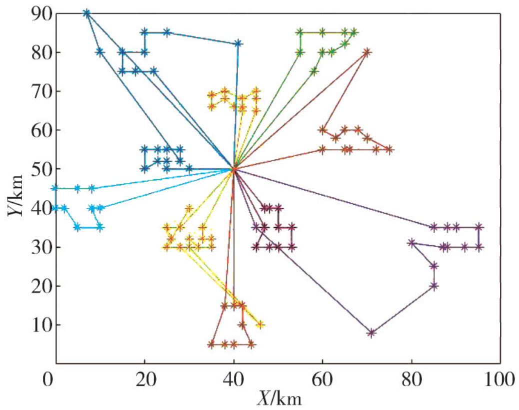

Fig. 14 Optimized distribution route at 10:00

4 Conclusions

In actual logistics distribution, dynamic changes in customer demands are very common. To reduce the distribution cost, it is important to seek better optimization strategies with stronger solving performance. Based on DDVRPTW, considering new customers, original customers canceling services, changes in the original customer's delivery address, and customer's service time window, a mathematical model with the minimized total distribution cost was established. At the pre-optimization stage, the initial distribution scheme was planned by the propoed IGA . At the real-time optimization stage, the distribution scheme was quickly adjusted by combining the periodic optimization strategy with the neighborhood search method. The simulation shows that the algorithm can respond to the dynamic demand information of customers quickly, and provide reasonable and effective decision supports for logistics enterprises. The main work in the future is to design a model considering more factors such as carbon emissions and customer satisfaction on the basis of this study.

Acknowledgement

This work was supported by Natural Science Foundation Project of Gansu Provincial Science and Technology Department (No. 1506RJZA084); Gansu Provincial Education Department Scientific Research Fund Grant Project (No.1204-13).

Declaration of conflicting interests

The authors have no conflict of interests related to this publication.

References

[1] DANTZIG G B, RAMSER J H. The truck dispatching problem. Management Science, 1959, 6(1): 80-91.

[2] ZHOU X C, WANG L, ZHOU K J, et al. Research progress and development trend of dynamic vehicle routing problem. Control and Decision, 2019, 34(3): 449-458.

[3] LI J, HAO L Y, HE Y T, et al. Improved bacterial foraging algorithm for solving vehicle routing optimization problem with time windows. Computer Engineering, 2021, 47(11): 44-53.

[4] LI Y, FAN H M, ZHANG X N. A periodic optimization model and solution for capacitated vehicle routing problem with dynamic requests. Chinese Journal of Management Science, 2022, 30(8): 254-266.

[5] ZHANG J L, ZHAO Y W, WANG H Y, et al. Modeling and algorithms for a dynamic multi-vehicle routing problem with Customers' dynamic requests. Computer Integrated Manufacturing Systems, 2010, 16(3): 543-550.

[6] FAN H M, ZHANG Y G, TIAN P J, et al. Dynamic vehicle routing problem of heterogeneous fleets with time-dependent networks. System Engineering-Theory & Practice, 2022, 42(2): 455-470.

[7] PANG Y, LUO H L, XING L N, et al. A survey of vehicle routing optimization problems and solution methods. Control Theory & Applications, 2019, 36(10): 1573-1584.

[8] WANG F, LIAO F S, LI Y X, et al. An ensemble learning based multi-objective evolutionary algorithm for the dynamic vehicle routing problem with time windows. Computers & Industrial Engineering, 2021, 154: 107131.

[9] NAN L J, CHEN Y R, ZHANG Z C. Electric vehicle routing problem with time windows and mixed fleet considering dynamic demands. Application Research of Computers, 2021, 38(10): 2926-2934.

[10] ZHANG W B, SU Q, CHENG G L. Vehicle routing problem with time windows based on dynamic demands. Industrial Engineering and Management, 2016, 21(6): 68-74.

[11] YANG Y, ZHANG J. Vehicle routing problem with soft time windows based on dynamic demands// 2019 4th International Conference on Intelligent Transportation Engineering, September 5-7, 2019, Singapore. New York: IEEE, 2019: 222-226.

[12] SCHYNS M. An ant colony system for responsive dynamic vehicle routing. European Journal of Operational Research,

2015, 245(3): 704-718.

[13] LU X F, TANG K, MENZEL S, et al. A competitive co-evolutionary optimization method for the dynamic vehicle routing problem//2020 IEEE Symposium Series on Computational Intelligence, December 1-4, 2020, Canberra, ACT, Australia. New York: IEEE, 2020: 305-312.

[14] EUCHI J, YASSINE A, CHABCHOUB H. The dynamic vehicle routing problem: Solution with hybrid metaheuristic approach. Swarm and Evolutionary Computation, 2015, 21: 41-53.

[15] CHEN S F, CHEN R, WANG G G, et al. An adaptive large neighborhood search heuristic for dynamic vehicle routing problems. Computers & Electrical Engineering, 2018, 67: 596-607.

[16] OKULEWICZ M, MAŃDZIUK J. A metaheuristic approach to solve Dynamic Vehicle Routing Problem in continuous search space. Swarm and Evolutionary Computation, 2019, 48: 44-61.

[17] HE X H. Research on dynamic vehicle routing problem with soft time window and system implementation. Harbin: Harbin Institute of Technology, 2017.

[18] JIANG D J, LIU X W. Two-echelon vehicle routing optimization with time windows and "gray zone" customers based on LNS alogorithm. Journal of Chongqing Normal University (Natural Science), 2020, 37 (4): 15-23.

基于时间窗和动态需求的车辆路径优化算法

李 珺*, 段钰蓉, 张维维, 朱利圆

兰州交通大学 电子与信息工程学院, 甘肃 兰州 730070

摘 要: 为了满足供应商在货物配送过程中, 面对新增客户需求、客户取消需求和客户改变收货地址三种信息更新的情况, 能够实现最小化车辆行驶距离的目标, 结合预优化与实时优化的思想, 建立了带时间窗约束的动态需求车辆路径问题的两阶段规划模型。在预优化阶段, 采用改进的遗传算法获得预优化配送路径, 在变异操作中融合大规模邻域搜索方法提升遗传算法的局部寻优能力, 并引入多种操作算子扩大邻域解的搜索空间。在实时优化阶段, 采用周期性优化策略, 将复杂的动态问题转化为若干个静态问题, 采用四种邻域搜索算子实现路径快速调整。设计了两种不同规模的算例进行实验, 证明了该算法能够规划出较优路径, 且在满足实时性约束下, 能及时调整配送路线。该方法为供应商解决动态需求下的车辆路径问题提供了理论指导。

关键词: 车辆路径; 动态需求; 遗传算法; 大规模邻域搜索; 时间窗

引用格式: LI Jun, DUAN Yurong, ZHANG Weiwei, et al. Vehicle routing optimization algorithm based on time windows and dynamic demand. Journal of Measurement Science and Instrumentation, 2024, 15(3): 369-378.