Journal of Measurement Science and Instrumentation
测试科学与仪器(英文版)
ISSN 1674-8042,CN 14-1357/TH

《Journal of Measurement Science and Instrumentation》网络首发论文

题目：　基于时间窗和动态需求的车辆路径优化算法(英文)
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网络首发日期：　2023-12-14
引用格式：　李珺，段钰蓉，张维维，朱利圆．基于时间窗和动态需求的车辆路径优化算法(英文)[J/OL]．Journal of Measurement Science and Instrumentation.
https://link.cnki.net/urlid/14.1357.th.20231213.1717.004

Published online：2023-12-14 10:41:29
URL：https://link.cnki.net/urlid/14.1357.th.20231213.1717.004

Vehicle routing optimization algorithm based on time window and dynamic demand

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Abstract: In order to satisfy the supplier in the process of goods for distribution, there are three kinds of situations of new customer demand, customer cancellation service and customer change of delivery address, with the goal of minimizing the vehicle travel distance and the idea of combining pre-optimization and real-time optimization, a two-stage planning model of dynamic demand based vehicle routing problem with time windows is established. In the pre-optimization stage, the improved genetic algorithm is used to obtain the pre optimized distribution route, the large-scale neighborhood search method is integrated in the mutation operation to improve the local optimization performance of the genetic algorithm, and a variety of operators are introduced to expand the search space of neighborhood solutions; In the real-time optimization stage, the periodic optimization strategy is adopted to transform the complex dynamic problem into several static problems, and four neighborhood search operators are used to quickly adjust the route. Two different scale examples are 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, which can provide theoretical guidance for suppliers to solve the dynamic demand based vehicle routing problem.

Keywords: vehicle routing problem; dynamic demand; genetic algorithm; large-scale neighborhood search; time window

0 Introduction

In recent years, with the rapid development of China's logistics industry, logistics distribution has brought a comfortable and convenient life experience for people, while also providing great convenience for small and medium-sized retail industry, including convenience stores and various specialty stores. With the characteristics of small scale and high density, small and medium-sized retail stores have become an important part of people's life. However, its own inventory capacity is small and needs to be supplied by regional suppliers at any time. The ordering demand of retailer customers will be dynamic and uncertain with the personalized demand of consumers. After the goods have been distributed, there will still be new customer orders, customer cancellations of orders, and changes in the customer's delivery address. At the same time, in order to ensure the normal operation of retail stores, retail customers usually ask for delivery time. These situations make it 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 [2](DDVRP). The combination of DDVRP and Vehicle Routing Problem with Time Windows[3] (VRPTW) is called Dynamic demand based Vehicle Routing

Foundation items: Natural Science Foundation Project of Gansu Provincial Science and Technology Department(1506RJZA084); Gansu Provincial Education Department Scientific Research Fund Grant Project (1204-13).

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Problem with Time Windows (DDVRPTW).

Regarding the research on DDVRP without time window constraint, LI[4] et al. adopted the way of dividing the working hours of distribution centers into several time slices for the DDVRP with continuous updating of customer information, and proposed a periodic customer real-time reset strategy based on delayed service, and proposed a hybrid variable neighborhood artificial bee colony algorithm. Jingling ZHANG[5] et al. 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, and 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[6] et al. not only studied the dynamic changes of customer demand, but also considered the impact of vehicle speed change on the whole distribution process, combined the idea of pre-optimization and dynamic adjustment, built a multi-vehicle DDVRP model, and proposed an improved adaptive genetic algorithm to solve it.

For the DDVRPTW, scholars have designed various models and proposed a variety of solution methods, which are mainly classified into exact algorithms and heuristic algorithms[7]. Among them, the exact algorithm can obtain the optimal solution in the initial state, but as time goes on, the customer needs are constantly updated, and the algorithm has a certain degree of limitations in the dynamic adjustment stage, which cannot guarantee to find a stable and better solution, and when the customer size increases, the exact algorithm needs a long solution time, which cannot meet the instantaneous requirement of the algorithm for DDVRPTW. Therefore, most of the research on this kind of problems adopt heuristic algorithms. Feng Wang[8] et al. established a multi- objective optimization model of DDVRPTW, proposed EL-DMOEA algorithm, and used population-based prediction strategy, migration strategy and stochastic strategy to improve the performance of the algorithm. Nan[9] et al. studied the DDVRPTW under the mixed distribution mode of fuel and electric vehicles, constructed a two-stage solution model with the objective of minimizing the distribution cost, and designed an improved adaptive large-scale neighborhood search algorithm. ZHANG[10] et al. established a DDVRP model with soft time windows constraint, and adopted a two-stage solution strategy, using an improved genetic algorithm in the initial stage and a simulated annealing algorithm in the dynamic adjustment stage. Yang[11] et al. studied the DDVRP with soft time windows, established the corresponding mathematical model, designed an improved RTR algorithm in the initial planning stage, and proposed a plug-in real-time route planning algorithm in the real-time optimization stage. Schyns[12] constructed a corresponding mathematical model considering various dynamic factors such as customer demand change, new customer demand, customer cancellation of service, and service time window change and so on. Xiaofen Lu[13] et al. used a competitive co-evolutionary algorithm to solve the DDVRP. In addition, there are many intelligent optimization algorithms for solving dynamic vehicle routing problems, such as improved artificial ant colony algorithm[14], adaptive large neighborhood search algorithm[15], hybrid particle swarm algorithm[16], etc.

By combing the above references, it is found that there are few researches on the DDVRPTW, and the solution algorithm that it is easy to fall into the local optimum and the calculation time is long. To address the above shortcomings, this paper takes DDVRPTW as the research object, establishes the mathematical model with the objective of minimizing the total distribution distance according to the characteristics of the model, designs the Improved Genetic Algorithm (IGA) to obtain the pre-optimized distribution route; according to the changes of customer demand, adopts the periodic optimization strategy and the neighborhood search operator to adjust the configuration quantity and distribution route of vehicles, so as to provide a theoretical basis for suppliers to obtain a reasonable and effective distribution plan.

1 Model Formulation

1.1 Problem Description

DDVRPTW is based on the traditional VRP and considers the impact of the dynamic changes of customer demand information on the distribution route planning during 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 to 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 will be new customer needs, customer cancellations of service and changes in the customer's delivery address. Under the premise of meeting the needs of existing customers, the distribution scheme will be dynamically adjusted according to the real-time customer information with the goal of minimizing the total distribution cost. The assumptions of DDVRPTW model 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) 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 can not be split. each customer is only visited once.

(4) The vehicle must not arrive at the customer's designated location earlier or later than the specified service time window;

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

1.2 Symbols

In order to facilitate the construction of the DDVRPTW mathematical model, it is necessary to list the corresponding symbols:

N : Known customer collections and distribution center;

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

N_0 : The distribution center;

K : The vehicle collection, $K = \{1, 2, 3, ..., m\}$;

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 that the 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 is a 0-1 variable, $x_{ij}^k = 1$ if the vehicle k passes the road between customer i and customer j, otherwise $x_{ij}^k = 0$;

y_i^k is a 0-1 variable, $y_i^k = 1$ if the vehicle k services for customer i, otherwise $y_i^k = 0$.

1.3 Mathematical model

We adopt the strategy of "pre-optimization and real-time optimization" to solve the DDVRPTW, as shown in Figure 1. In the pre-optimization stage, the improved genetic algorithm is used to generate a pre-optimized distribution plan; in the real-time optimization stage, the periodic optimization strategy combines various neighborhood search operators to adjust the delivery route in time.

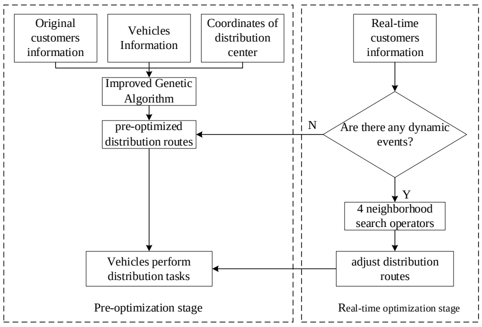

Fig.1 Pre-optimization and Real-time optimization strategy

The constructed DDVRPTW mathematical model is

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

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

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

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

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

Equation (1) indicates that the goal of the model is to minimize the total distance; Equation (2) shows that the total load on each route cannot exceed the rated load of the vehicle; Equation (3) represents that each customer is served by one vehicle only once; Equation (4) indicates that the vehicle starts and ends at the distribution center; Equation (5) indicates the time window constraint to satisfy the customer.

1.4 Dynamicity analysis of DDVRPTW

The dynamic nature of DDVRPTW is mainly reflected in the dynamic changes of customer demand information. After the completion of pre-optimization, the distribution center issues the task dispatching instruction and the vehicles start the distribution service, the dynamic customer demands appear. How to reasonably and effectively balance the demands of original customers and new customers, and plan a distribution scheme to meet the demands of all customers with the objective of minimizing the distribution distance while meeting the above constraints is the problem to be solved in this paper.

With the dynamic change of customer demands, based on the idea of periodic optimization, the working time of the distribution center is divided into several time slices with equal period, and the sub-problem in each time slice can be regarded as a static vehicle routing problem[17]. The optimization plan is transmitted and adjusted between successive time slices, and finally a complete distribution plan is formed. Suppose 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, set $t=(T+1)/2$, and the duration of each time slice is $(t+1)/n$. After the end of the current time slice, the dynamic request will readjust the distribution route by combining the current planned route scheme and the information of unserviced customers.

2 Algorithm design for DDVRPTW

2.1 Pre-optimization algorithm design

We design an intelligent optimization algorithm IGA (Improved Genetic Algorithm) that incorporates Large-scale Neighborhood Search (LNS) to improve the local search ability of Genetic Algorithm (GA), while introducing multiple removal operators and a repair operator to reconstruct the solution and improve the quality of the solution.

2.1.1 Encoding method and generation of initial population

The encoding method of the IGA adopts integer encoding. Randomly generate m chromosomes of length N, each number represents a customer number in the chromosome. 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 to generate the initial population. Assuming that there are 12 customers to be served, the decoding process of chromosome is shown in Figure 2. According to the order of customers, the customer demand is accumulated from the first customer 8 of chromosome. Assuming that the vehicle load constraint cannot be met at customer 9, record it, insert number 0 (distribution center) in front of customer 9, and rearrange the vehicle at the recorded customer, Repeat the above process until the customer assignment in the chromosome is completed. Finally, insert the number 0 at the head and tail of the chromosome, and the decoding operation is completed. 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, route 4: 0-10-0.

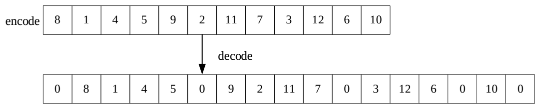

Fig.2 Chromosome encoding and decoding process

2.1.2 Selection and crossover

In this paper, the selection is based on the minimum objective function value of equation 1; the selection operation adopts 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 the OX crossover method. First, determine the parent generation A and the parent generation B; then select two crossover points in a random way, the area between the two crossover points is the crossover segment, and the crossover segment of the parent B placed in front of parent A. Similarly, the crossover fragment of parent A is placed in front of parent B. The genetic positions in parent A and B that are duplicated in the inserted crossover fragment are marked separately, and finally the genetic positions marked in both parents are deleted to create two new offspring individuals. The procedure of the crossover operation is shown in Figure 3.

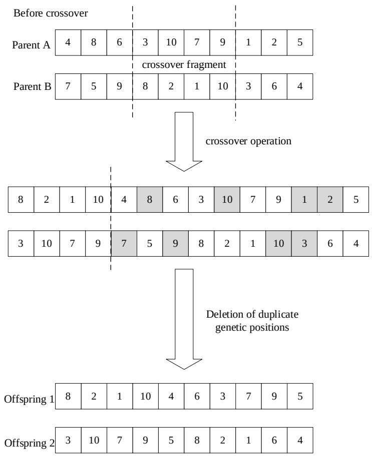

Fig.3 Crossover operation

2.1.3 Improved mutation operation

In order to enhance the local exploitation ability of genetic algorithms, large-scale neighborhood search operators are introduced in the mutation operation. The large-scale neighborhood search algorithm is mainly used to adjust the solution in the neighborhood of the feasible solution by the “destroy” and “repair” methods to obtain a high-quality solution[18]. The “destroy” and “repair” operations are implemented by the removal and insertion operators, respectively, as follows: first, remove some customer nodes from the current solution using the removal operators, and then reinsert the removed nodes 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 paper.

① Random removal operator

The removal operator randomly removes m customers through equal probability in each route, where m is a random positive integer, the value range is 1, 2, …, m_{max}, where m_{max} is the maximum value that m can get, and the selection probability of each value is $1 / m_{max}$.

② Similarity removal operator

Firstly, the operator randomly selects a customer i and removes it from the existing distribution scheme, then calculates the similarity measure $R(i,j)$ between other customers and customer i in the scheme, and finally removes the customer with the smallest $R(i,j)$ (the customer with the largest similarity). Repeat the above operations until m customers are removed. The calculation formula is

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

where N is the set of all customers requiring services; D_{ij} represents the distance between customers i and 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 difference between the demand of customer i and j; The distance between customers, the difference of the earliest service time between customers and the difference of customer demands will affect the measurement of similarity. In order to normalize the measurement, parameters γ_1 , γ_2 and γ_3 are introduced to represent the weight of each influencing factor respectively.

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: first, define the cost of customer i: $w_i(i,s)=f(s)-f_{-i}(s)$, each customer is arranged in descending order according to the value of $w(i,s)$, and finally select m customers with higher cost to remove. Where s represents a current solution; $f_{-i}(s)$ represents the cost after removing customer i from s.

(2) Repair operator

In this paper, the greedy insertion operator is used as the repair operator, so that the generated neighborhood solutions are satisfying the constraints and the better solution can be obtained to a large extent. This method minimizes increase in total cost by reinserting the removed customers into the optimal position in the route. The specific operations are as follows: Assume that the set of removed customers is O, select a customer i randomly from the set O, traverse each route, find all the insertion positions that satisfy the customer service time window constraint and vehicle load constraint, calculate the distance increment of customer i at each insertion position as in equation (7), find the best insertion location (the position with the smallest distance increment value) and add customer i to it, and calculate the equation as follows.

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

Equation (7) represents the distance increment between the customer j and j+1 inserted by customer i into route p.

If the insertable position that meets both the time windows constraint and the vehicle load constraint cannot be found by traversing all routes, a new route is constructed and the customers to be inserted are added to it, and the above steps are repeated until all the customers in the set O are reinserted into the route.

2.2 Real-time optimization algorithm design

2.2.1 Initial solution construction

In the pre-optimization stage, we use IGA to generate a pre-optimized distribution plan based on the known customer information and related parameters. At this time, the plan is complete, and dispatching instructions can be issued to enable each vehicle to start the distribution task. At the end of the time slice, the distribution path needs to be adjusted instantly with dynamic customer information. First, the sub-paths in the planned distribution path are filtered and tracked, and the served customers and the next customers who are close to the service start time are set as unchangeable customers, and then the remaining paths in the sub-paths are operated. For customers with canceled service, they are directly deleted from the route; For customers with changed delivery address, they are deleted from the route and considered as new demand customers. The adjustment of the distribution route is mainly for the customers with new demands. The new customers are inserted into the route by the greedy insertion method (the same idea as the repair operator in Section 2.1.3).

When all the new customers are added to the path, the construction of the initial solution is completed.

2.2.2 Optimization stage

By constructing the initial solution, the distribution scheme is feasible, but not necessarily optimal. Four neighborhood search operators are used for fast local optimization of feasible solutions.

(1) 2-opt operator in path. Randomly select two customer points on the same path and flip the two customer points and the points between them, as shown in Figure 4.

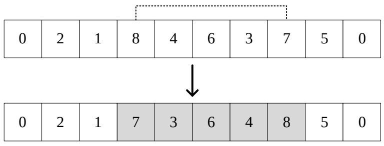

Fig.4 2-opt operator in path

(2) Point insertion operator between paths. Select a random customer point respectively in two different paths, and add one customer point to the position behind the other customer point, as shown in Figure 5.

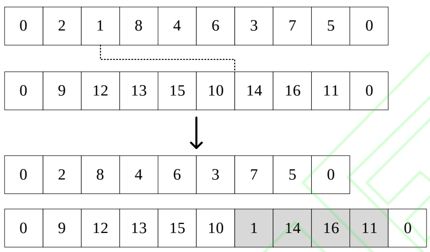

Fig.5 Point insertion operator between paths

(3) Points exchange operator between paths. Select a random customer point respectively in two different paths and exchange the positions of the two customer points, as shown in Figure 6.

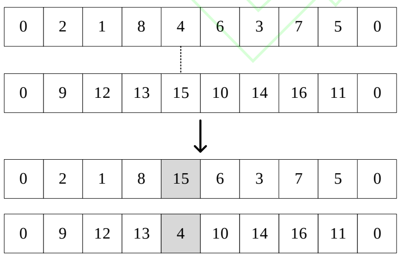

Fig.6 Points exchange operator between paths

(4) Fragments exchange operator between paths. Randomly select the customer segments in two different paths and change the positions of the two customer segments, as shown in Figure 7.

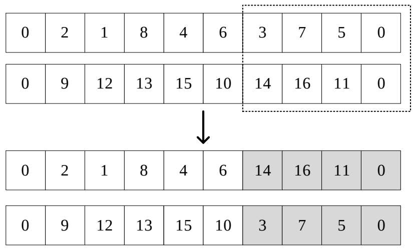

Fig.7 Fragments exchange operator between paths

3 Experiment and analysis

The experiment uses MATLAB (R2016a) to run on a computer with Intel (R) Core (TM) i5-7300HQ CPU@2.50 GHZ.

In order to verify the effectiveness of the proposed algorithm, two experiments with different customer scales are designed. In the IGA, the population size is set to 100, the maximum number of iterations is 100, the crossover probability is 0.9, and the mutation probability is 0.05.

3.1 Small-scale experiment

The coordinates of the distribution center are (0,0), the working time window of the distribution center is [7,18], the deadline for receiving customer change demand is 13, the time window of the real-time optimization stage is [7,13], the initial customer demand information is referred to literature [10], there are 24 initial customers, the load capacity of the vehicle is 60, and the average driving speed of the vehicle is set to 40 km/h. This experiment has 29 customers, which is a small-scale experiment.

The IGA proposed in this paper is used to obtain the distribution scheme of the pre-optimization stage, as shown in Table 1, and the distribution route is shown in Figure 8.

Table 1 Pre-optimized distribution scheme

Vehicle	distribution route	Transport distance/km	Total distance /km
Vehicle 1	1-20-21-22-19-18	44.04	135.25
Vehicle 2	4-10-11-12-13-14-15-16	47.72	
Vehicle 3	5-9-7-8-6-17	21.10	
Vehicle 4	3-2-23-24	22.39	

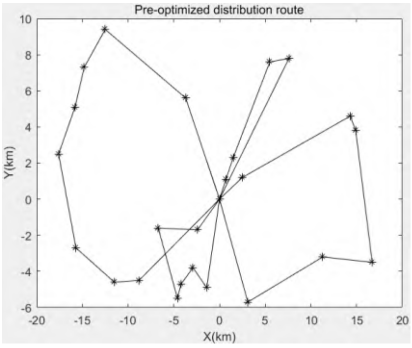

Fig.8 Pre-optimized distribution route

When the vehicle is fully loaded and starts delivery service from the distribution center, the dynamic service is also opened, receiving new customer demand and original customer change information, and entering the real-time optimization stage. The periodic optimization time interval is 1h, and there are 6 time slices, namely: [7,8], [8,9], [9,10], [10,11], [11,12], [12,13]. The dynamic customer demand information received by the vehicle during the distribution process is shown in Table 2 and Table 3.

Table 2 Change information of original customers

Number	Variation type	New delivery address	Present moment
24	Change delivery address	(3,8.2)	9:35
19	Change delivery address	(-4.6,10)	11:24
17	Cancel service	-	11:33

Table 3 New customer demands information

Number	coordinate	Demand	Service time window	Length of service time	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	Vehicle location	Remaining load
Vehicle 1	On the road from customer 1 to customer 20	49
Vehicle 2	Serving customer 10	50
Vehicle 3	Serving customer 5	60
Vehicle 4	Has not departed from the 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 Figure 9.

Table 5 9:00 optimized distribution scheme

Vehicle	Delivery route	Transport distance/km	Total distance /km
Vehicle 1	1-20-21-22-19-18	44.04	
Vehicle 2	4-10-11-12-13-14-15-16	47.72	135.88
Vehicle 3	5-9-7-8-6-17	21.10	
Vehicle 4	3-2-23-24-25	23.02	

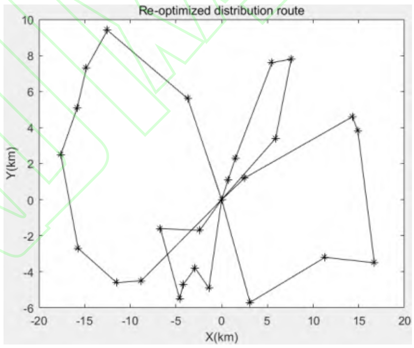

Fig.9 9:00 optimized distribution route

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

Table 6 10:00 optimized distribution scheme

Vehicle	Distribution route	Transport distance/km	Total distance /km
Vehicle 1	1-20-21-22-19-27-18	44.72	
Vehicle 2	4-10-11-12-13-14-15-16	47.72	153.62
Vehicle 3	5-9-7-8-6-17	21.10	
Vehicle 4	3-26-2-24-23-25	40.07	

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 adds customers 28 and 29. At 12:00, readjust the distribution route, the final distribution scheme is shown in Table 7, and the distribution route is shown in Figure 11.

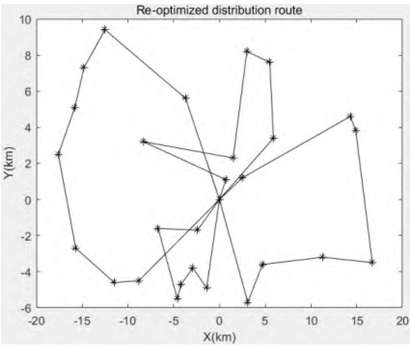

Fig.10 10:00 optimized distribution route

Table 7 12:00 optimized distribution scheme

Vehicle	Distribution route	Transport distance/km	Total distance /km
Vehicle 1	1-20-21-22-18-27-28-6	66.35	
Vehicle 2	4-10-11-12-13-14-15-16	47.72	193.07
Vehicle 3	5-9-7-8-29-19	38.93	
Vehicle 4	3-26-2-24-23-25	40.07	

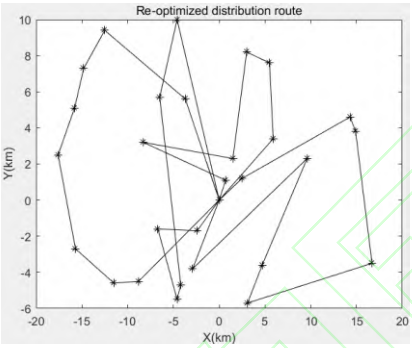

Fig.11 12:00 optimized distribution route

3.2 Large-scale experiment

The coordinates of the distribution center are (40,50), and there are 100 initial customers to be served. The information of these 100 customers comes from the C101 example in the classical Solomon dataset, which has a specific time window for the customers. In order to test the performance of the algorithm more scientifically, the original time window was not adjusted, but the working time window of the distribution center [0,21] was too long. Two drivers take turns to serve customers. The continuous service time of customers is a random number between 10 and 30, the vehicle load is 200, and the average speed is 40 km/h. The time interval for periodic optimization is 1h, and the deadline for receiving customer change requests is 11, so [0,11] is the real-time optimization stage. The vehicle departs from the distribution center with full load, and serves each customer in turn according to the pre-optimized distribution scheme shown in Table 8, and the distribution route is shown in Figure 12.

Table 8 Pre-optimized distribution scheme

Vehicle	Distribution route	Transport distance/km	Total distance /km
Vehicle 1	20-24-25-27-29-30-28-26-23-22-21	50.80	
Vehicle 2	90-87-86-83-82-84-85-88-89-91	76.07	
Vehicle 3	5-3-7-8-10-11-9-6-4-2-1-75	59.62	
Vehicle 4	81-78-76-71-70-73-77-79-80	127.30	
Vehicle 5	98-96-95-94-92-93-97-100-99	95.94	
Vehicle 6	32-33-31-35-37-38-39-36-34	97.23	828.94
Vehicle 7	67-65-63-62-74-72-61-64-68-66-69	59.40	
Vehicle 8	13-17-18-19-15-16-14-12	95.88	
Vehicle 9	57-55-54-53-56-58-60-59	101.88	
Vehicle 10	43-42-41-40-44-46-45-48-51-50-52-49-47	64.81	

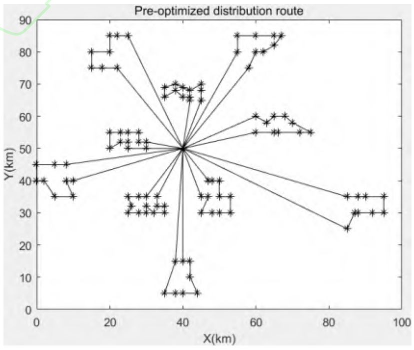

Fig.12 Pre-optimized distribution route

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

Table 9 Change information of original customers

Number	Variation type	New delivery 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

Number	Coordinate	Demand	Service time window	Length of service time	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 2 new customers, customer 6 cancels the service, and customer 14 changes the delivery address. Re-plan the distribution route at 8:00, the distribution scheme is shown in Table 11, and the re-optimized distribution route is shown in Figure 13.

Table 11　8:00 optimized distribution scheme

Vehicle	Distribution route	Transport distance/km	Total distance /km
Vehicle 1	20-24-25-27-29-30-28-26-23-22-21	50.80	
Vehicle 2	90-87-86-83-82-84-85-88-89-91-101	118.50	
Vehicle 3	5-3-7-8-10-11-9-4-2-1-75	59.61	
Vehicle 4	81-78-76-71-70-73-77-79-102-80	136.79	
Vehicle 5	98-96-95-94-92-93-97-100-99	95.94	
Vehicle 6	32-33-31-35-37-38-39-36-34	97.23	931.38
Vehicle 7	67-65-63-62-74-72-61-64-68-66-69	59.40	
Vehicle 8	13-17-18-19-15-16-12	95.88	
Vehicle 9	57-55-54-53-56-58-60-59	101.88	
Vehicle 10	43-42-41-40-44-46-45-14-48-51-50-52-49-47	115.33	

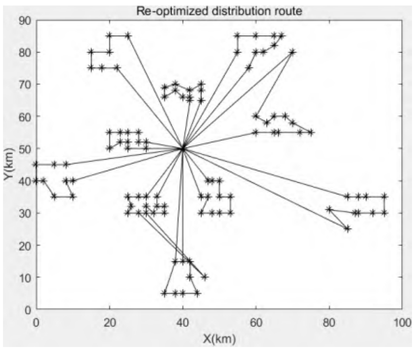

Fig.13　8:00 optimized distribution route

It can be seen from Table 9 and Table 10 that in the time slice [9,10], there are 5 new customers, customer 47 cancels the service, and customer 21 changes the delivery address. Re-plan the distribution route at 10:00, the distribution scheme is shown in Table 12, the distribution route is shown in Figure 14, and the total distance is 1066.05.

Table 12　10:00 optimized distribution scheme

Vehicle	Distribution route	Transport distance/km	Total distance /km
Vehicle 1	20-24-25-27-29-30-28-26-23-22-105-107	134.19	
Vehicle 2	90-87-86-83-82-84-85-88-89-91-101	118.50	
Vehicle 3	5-3-7-8-10-11-9-4-2-1-75	59.62	
Vehicle 4	81-78-76-71-70-73-77 -79-102-80-104-106-69	162.05	
Vehicle 5	98-96-95-94-92-93-97-100-99	95.94	
Vehicle 6	32-33-31-35-37-38-39-36-34	97.23	1066.05
Vehicle 7	67-65-63-62-74-72-61-64-68-66	58.14	
Vehicle 8	13-17-18-19-15-16-12-21	106.10	
Vehicle 9	57-55-54-53-56-58-60-59	101.88	
Vehicle 10	43-42-41-40-44-46-45-14-48-51-103-50-52-49	132.40	

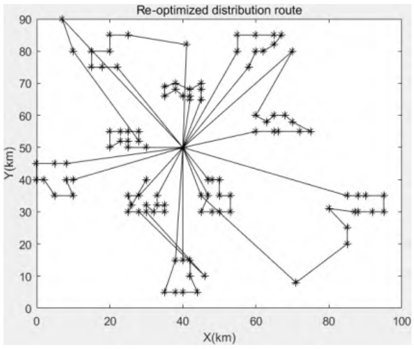

Fig.14　10:00 optimized distribution route

4　Conclusions

In actual logistics distribution, the problem of dynamic changes in customer demand is very common. In order to reduce the distribution cost, seeking better optimization strategies and algorithms with stronger solving performance becomes the most important way. For the DDVRPTW, this paper studies the situation with three dynamic elements, including new customers, original customers canceling services, and changes in the original customer's delivery address. At the same time, considering the customer's service time window, a mathematical model with the optimization goal of minimizing the total distribution cost is established. In the pre-optimization stage, the initial distribution scheme is planned by using the IGA proposed in this paper; In the real-time optimization stage, the distribution scheme is quickly adjusted by combining the periodic optimization strategy with the neighborhood search method. Finally, the experiments with two different scale examples show that the algorithm can respond to the dynamic demand information of customers quickly, and provide reasonable and effective decision support for logistics enterprises. DVRP has a wide range of applications, including freight, passenger transport, express delivery services, production scheduling, equipment maintenance services and other fields. In response to the national call for "low-carbon travel and green environmental protection", the main work in the future is to design a model with the goal of minimizing carbon emission and an algorithm with better optimization effect by considering factors such as carbon emissions and customer satisfaction on the basis of this paper.

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基于时间窗和动态需求的车辆路径优化算法

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摘　要：为了满足供应商在货物进行配送过程中，出现新增客户需求、客户取消需求和客户改变收货地址三种信息更新的情况，以最小化车辆行驶距离为目标，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。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性能，并引入多种操作算子扩大邻域解的搜索空间；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 4 种邻域搜索算子快速进行路径调整。设计了两种不同规模的算例分别进行实验，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，及时调整配送路线，能够为供应商解决动态需求下的车辆路径问题提供理论指导。

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 window and dynamic demand. Journal of Measurement Science and Instrumentation, 2024, 15: 1-12.