


## Article

# Vehicle Dispatch and Route Optimization Algorithm for Demand-Responsive Transit

Deyong Guan <sup>1</sup>, Xiaofang Wu <sup>2</sup>, Ke Wang <sup>1,\*</sup>  and Jie Zhao <sup>2</sup><sup>1</sup> College of Transportation, Shandong University of Science and Technology, Qingdao 266000, China<sup>2</sup> Qingdao Tongdao Planning and Design Institute Co., Ltd., Qingdao 266000, China

\* Correspondence: ucwangke@gmail.com

**Abstract:** Giving priority to the development of public transit is an important way to achieve efficient, convenient, safe, comfortable, economic, reliable, green and low-carbon sustainable development. In view of the highly dispersed and regular passenger flow, demand responsive transit is an important complementary means for traditional public transport to improve passenger satisfaction. However, high operating costs and low load factor will have a bad impact on the operation of public transport and reduce passenger satisfaction. In this work, firstly, by analyzing the demand frequency of historical travel stations, the stations with high demand are extracted by time periods as high probability travel points; On this basis, a dynamic vehicle dispatching optimization model is established, and the static vehicle dispatching is carried out with the goal of minimizing the running mileage of the bus system; Finally, based on the initial static route and the later real-time travel demand, the accurate dynamic planning algorithm is used to optimize the dynamic route with the goal of minimizing the change of the system mileage, so as to achieve timely response to the demand. The results show that the two-phase scheduling optimization model based on the station extraction strategy can provide a reasonable real-time vehicle scheduling and route optimization scheme, improve the utilization rate of vehicles and the passenger load factor, and provide a theoretical basis and application guidance for actual vehicle scheduling.



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**Keywords:** urban traffic; route optimization; LNS-genetic algorithm; demand-responsive transit; vehicle dispatch

## 1. Introduction

With China's rapid development of urbanization and frequent changes in residents' travel demand, it is difficult for traditional public transport to adapt quickly [1]. Some bus lines are too long with many stations, and the number of passengers at some stations along the line is uneven. As a result, the resources of the public transport system are not fully utilized, and the development of new transport modes is becoming increasingly urgent. Urban residents mainly travel short and medium distances, taxis have high flexibility but their carrying capacity is small, and the subway has a large carrying capacity but is not flexible enough. However, the urban public transport system has the advantage of wide coverage, a large carrying capacity, and high flexibility [2]. Therefore, it is necessary to combine the existing public transport system of the city to realize the flexible setting of stations and driving routes for vehicles according to the needs of passengers to make them more flexible.

Demand-responsive transport is flexible public transport that provides special travel services for passengers with similar travel needs (starting and ending stations, travel time, etc.) according to the requests sent by passengers [3]. Its specific characteristics are still "public transportation". It uses fixed stations and completely unfixed lines to provide citizens in the area with a new type of "public" travel service that can call or book in real time. The system aggregates and matches in real time to generate

dynamic lines in real time. Its new service characteristics between private cars and traditional public transport can meet the diversified travel requirements of passengers, especially the high-quality travel requirements, and change the travel mode of some private cars to public transport. Shenzhen, Beijing, Xi'an, and other cities have begun to implement this transit mode; the number of registered users has increased continuously, which has been recognized by the market. However, considering the problems of operating costs and profits, the ticket price of demand-responsive public transport is generally slightly higher than that of conventional public transport, and the vehicle operation time is generally in the morning peak and evening peak hours. The people served are those who make reservations in advance or go to work, so the applicable range of passengers is small [4]. Poor punctuality and high operating costs keep emerging. In urban areas with incomplete road networks and small populations, difficulties include lines being ignored, low occupancy rates, and insufficient passengers signing up for lines. Therefore, it is of great significance to deeply study the dispatching and optimization of demand-responsive transit and improve the service level of demand-responsive transit.

Flusberg [5] was the first to explore the public transport service mode, propose a flexible public transport mode, and carry out the actual operation. Later, some scholars studied this public transport service mode [6–12]. Through comparison and simulation experiments, they found that demand-responsive and traditional public transport have advantages under different levels of passenger demand. Nourbakhsh et al. [13] studied the departure interval and line setting in a rectangular area with low-density demand. Jiang et al. [14–16] focused on the dispatching and route optimization of the demand-responsive public transport of the feeder type. Ma et al. [17] established a model with passenger travel cost, took the operating income and cost as optimization objectives, and designed a genetic algorithm to analyze the customized vehicle route scheme. Boyer et al. [18] mainly considered flexible public transit management, analyzed the human factors related to demand-responsive transit dispatching, and discussed the various impacts of drivers' rest time, continuous working time, and overtime on dispatching. Nam et al. [19] studied the vehicle dispatching model with the objective of minimizing the environmental cost of fuel consumption and carbon emissions from the perspective of environmental protection. Bellini [20] established a DRT vehicle dispatching model. Schilde [21] studied the impact on DRT service levels under different speeds.

In the 1990s, Malucelli et al. [22] established a public transport dispatching model with maximum revenue for MAST (Mobility Allowance Shuttle Transit) under different operating environments. To effectively solve the problems related to demand-responsive public transportation, Pan et al. [23] established a bi-level planning model that can optimize the vehicle operation lines and vehicle service scope. Huang et al. [24] proposed a dynamic insertion method to deal with the model of the dynamic phase, which integrated the dynamic decision-making process of operators and passengers and solved the passenger travel demand in low-demand areas. Huang [25] studied a demand-responsive transit (DRT) service to meet the flexibility and convenience requirements of passengers. Nickkar [26] explored whether demand-responsive feeder transport can be optimized by picking up and sending passengers through door-to-door services or temporary stops and developed a model using meta-heuristic methods. Aalfa et al. [27] adopted the method of combining 3-Opt and annealing algorithms to solve the large-scale search problem in the VRP solution process, but it is very difficult to solve accurately, which is almost impossible under the current conditions. In the vehicle routing optimization problem, Wang et al. [28] designed a dual genetic algorithm and conducted an experimental comparison and analysis of demand-responsive vehicle dispatching optimization under the simultaneous pickup/drop-off mode. Compared with the separate pickup/drop off mode, the simultaneous pickup/drop off mode has specific and better seat utilization and cost-saving advantages. Lyu [29] built an

optimization model aimed at maximizing the revenue of operators and designed a heuristic algorithm based on the travel choice behavior of passengers. An [30] put forward the interval uncertainty stochastic theory to optimize the public transit network. Nassir [31] optimized the customized transit network through the impedance access theory. Kerkma [32] put forward the optimization theory of public transport networks combining multi-dimensional space.

To sum up, the existing studies on responding to passenger demand are often determined by experience, which is subjective and lacks quantitative research. Some studies assume that the system only operates a single vehicle, passengers at the same station have the same travel demand, and that there is unlimited vehicle capacity. These research scenarios are too idealistic, and China's actual road network has not been considered, ignoring the personalized time-window requirements for passengers. Therefore, this paper proposes a high-probability station extraction strategy by analyzing the spatial and temporal distribution of passenger demand and the origin and destination (OD), according to the historical ride request frequency of the station and extracted high-probability demand stations. Under the constraints of vehicle capacity and passenger demand time, a two-phase demand-responsive transit dispatching and routing optimization model was established. Finally, a static vehicle dispatching decision scheme was generated that can cover all high-probability stations, continuously adjust the route scheme through dynamic route optimization, and finally generate a dynamic optimized route that can respond to passenger travel in real time. This research could improve the decision-making efficiency of vehicle dispatching and the utilization rate of buses. It is of great significance to advocate public transport priority and green low-carbon travel.

## 2. Model Construction

### 2.1. Description of the Problem

This paper abstracts the service mode of the demand response transit as a shortest-route planning problem, in which the vehicle starts from a fixed depot, passes through each demand station with time constraints in turn, updates the vehicle dispatching scheme at intervals during operation, and finally returns to the depot. According to the actual data in the area, we define the stations with a boarding frequency of more than 60 times as high-probability boarding stations, and stations with a drop-off frequency of more than 60 times as high-probability alighting stations.

### 2.2. Problem Assumptions

To facilitate modeling, the following assumptions were made:

- (1) Each station can have at most one request, and if a station has multiple requests at the same time, it is split into multiple stations with the same geographic location in the model.
- (2) The start and end of each vehicle task occur at the distribution center.
- (3) The distance between any station is the shortest distance.
- (4) Default passengers are waiting at the station.
- (5) The moment each vehicle arrives at the station is the moment when service begins.
- (6) Regardless of road congestion, vehicles travel at the same average speed.

### 2.3. Vehicle Static Dispatching Model

The main constraints of the model are the passengers' travel time and vehicle capacity. The mathematical model is solved with reference to the number of people served and the service time requirements of each station. In the model, we define 0 as the depot.  $a_{lij}$  as a 0–1 decision variable, namely 1 if vehicle  $l$  goes from  $i$  to  $j$ .  $a_{lij}$  means the visit sequence of vehicles to stations.

The objective function is:

$$\min_{a_{lij}} D = \sum_{l \in L} \sum_{i,j \in N} d_{ij} \cdot a_{lij} \quad (1)$$

where  $D$  is the total operating mileage.  $d_{ij}$  is the shortest distance between stations.  $i, j$  are the demand stations.  $N$  is the collection of demand stations. Equation (1) means that the total operating mileage is the smallest.

The constraints are:

$$\begin{cases} \sum_{i \in N} \sum_{j \in N} d_{ij} \cdot a_{lij} \leq d_{\max}, & \forall l \in L \\ \sum_{l \in L} \sum_{j \in N} a_{lij} \geq 1, & \forall i \in N \\ \sum_{i \in N^*} a_{lij} = \sum_{k \in N^*} a_{ljk}, & \forall l \in L, j \in N^* \end{cases} \quad (2)$$

where  $a_{lij}, a_{ljk}$  are the 0–1 decision variable.  $d_{\max}$  is the maximum distance that one vehicle can drive in the initial route.  $N^*$  is the collection of depot and demand stations and  $N^* = N \cup \{0\}$ .  $L$  is the collection of all vehicles. Equation (2) means in the initial route one vehicle's driving distance cannot exceed  $d_{\max}$ . All the demand stations must be covered by vehicles. The number of vehicles entering and leaving the same station is equal.

$$\begin{cases} \sum_{j \in N} a_{l0j} = 1, & \forall l \in L \\ \sum_{i \in N} a_{li0} = 1, & \forall l \in L \end{cases} \quad (3)$$

where  $a_{l0j}, a_{li0}$  are the 0–1 decision variable. Equation (3) means the vehicle departs from the depot and eventually returns to the depot.

$$\sum_{i \in N^*} \sum_{j \in N^*} a_{lij} \leq m + 1, \forall l \in L \quad (4)$$

$$a_{lij} \in \{0, 1\}, \forall l \in L; i, j \in N^* \quad (5)$$

where  $m$  is the maximum number of stations that each vehicle can visit in the initial route. Equation (4) means that in the initial route, the number of stations visited by vehicle cannot exceed  $m$ . Equation (5) means they are the 0–1 decision variable.

#### 2.4. Vehicle Dynamic Route Optimization Model

In the vehicle dynamic route optimization phase, each vehicle can respond to real-time ride requests from the surrounding area. We take minimizing mileage variation as the goal, the order that the station is visited and the time of arrival and departure at each station as a decision variable. Established a model to solve the problem. We define  $x_{ij}$  as the 0–1 decision variable, namely 1 if the vehicle goes from  $i$  to  $j$ .  $x_{ij}$  means the station visit order that the vehicle needs to adjust in this phase.

The objective function is:

$$\min_{x_{ij}} \Delta d = \sum_{l \in L} \sum_{i,j \in N^*} d_{ij} \cdot x_{ij} \quad (6)$$

where  $\Delta d$  is the change of the total mileage.  $d_{ij}$  is the shortest distance between stations.  $x_{ij}$  is the 0–1 decision variable. Equation (6) indicates that the total mileage change is minimum.

The constraints are:

$$\sum_{j \in N^*} x_{jk} = 1, \quad \forall k \in N^{(m)} \quad (7)$$

$$\sum_{j \in N^*} x_{jg} \leq 1, \quad \forall g \in N^{(s)} \quad (8)$$

$$\sum_{j \in N^*} x_{jr} = \sum_{h \in N^*} x_{rh}, \quad \forall r \in N \quad (9)$$

where  $N^{(m)}$  is the collection of must visit stations.  $N^{(s)}$  is the collection of stations the vehicle can choose to visit.  $g, h, j, k, r$  are the stations, and  $x_{jk}, x_{jg}, x_{jr}, x_{rh}$  are the 0–1 decision variable. Equation (7) means that the vehicle must visit station  $k$ . Equation (8) means that the vehicle can choose to visit station  $g$ . Equation (9) means that the vehicle must leave after visiting the middle station  $r$ .

$$\sum x_{ij} = \sum x_{kj^*}, \quad \forall i, j, k \in N^* \quad (10)$$

$$t_j + 2t^{(s)} + T_{jj^*} \leq t_{j^*}, \quad \forall j \in N \quad (11)$$

where  $j^*$  is the corresponding alighting station of ' $j$ '.  $t_j$  is the time point that the vehicle enters the station  $j$ .  $t^{(s)}$  is vehicle start/stop time.  $x_{ij}, x_{kj^*}$  are the 0–1 decision variable.  $T_{jj^*}$  is the travel time from station  $j$  to station  $j^*$ . and  $t_{j^*}$  is the time point of the vehicle entering the station  $j^*$ . Equation (10) means that if the vehicle visits the boarding station  $j$ , it must visit its corresponding alighting station  $j^*$ . Equation (11) means that the vehicle must first visit the boarding station before it can access its alighting station.

$$q_0^{(j)} \leq Q, \quad \forall j \in N \quad (12)$$

$$\begin{cases} \sum_{k \in N} x_{0k} = 1 \\ \sum_{j \in N} x_{j0} = 1 \end{cases} \quad (13)$$

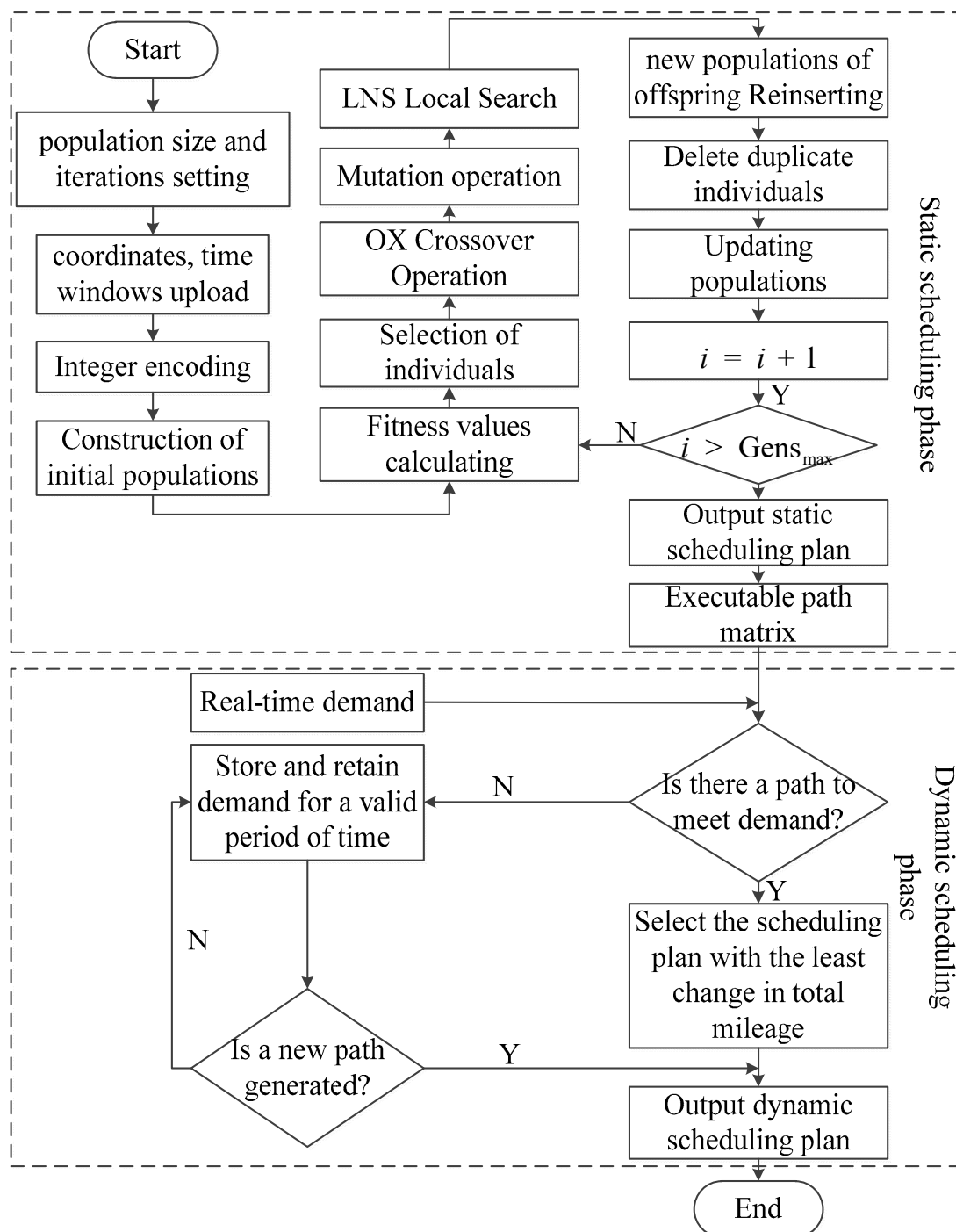
$$x_{ij} \in \{0, 1\}, \quad \forall i, j \in N^* \quad (14)$$

where  $q_0^{(j)}$  is the number of passengers on board before the vehicle arrives at the station  $j$ .  $Q$  is the capacity of each vehicle. Equation (12) means that the total number of passengers on board does not exceed  $Q$ . Equation (13) means that the vehicle departs from the depot and eventually returns to the depot. Equation (14) means they are the 0–1 decision variable.

### 3. Algorithm Design

#### 3.1. Two-Phase Dispatching Optimizes Model Algorithm Flow

The algorithm consists of two phases: static vehicle dispatching and dynamic route optimization. The static dispatching is a linear integer programming model; this paper uses a genetic algorithm based on LNS Strategy to solve the static vehicle dispatching problem and uses destructive and repair operators to improve the solution quality; the main framework is like that of traditional genetic algorithms. Dynamic route optimization adopts a precise planning algorithm to insert the obtained dynamic requirements into the initial route and continuously update the route. Figure 1 is a two-phase dispatching optimization process.

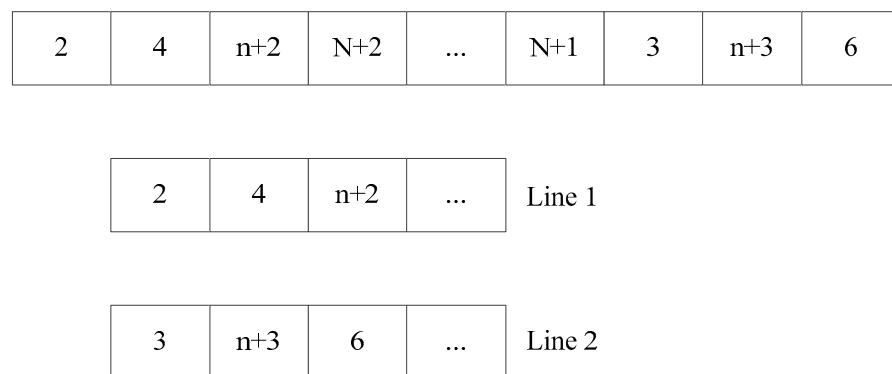


**Figure 1.** Process of two-phase dispatching optimization.

### 3.2. Algorithm Description

#### (1) Coding

The initial route of demand-responsive transits is arranged in a certain order by multiple stations,  $1, 2, \dots, n$  indicates a high probability of boarding at a station in the service area, and its corresponding drop-off station is numbered with  $n + 1, n + 2, \dots, 2n$ . The chromosome is encoded as an integer; when the number of stations is  $N$ , the maximum number of vehicles used is  $L$ , the length of the chromosome is  $(N + L - 1)$ , and  $N + 1, N + 2, \dots, N + l - 1$  divides the number of stations into three segments.  $L$  running routes are generated, as shown in Figure 2.



**Figure 2.** Schematic diagram of vehicle line code.

## (2) Initial populations

The quality of the initial population will affect the search efficiency of the genetic algorithm; to improve the quality of chromosomes in the initial population and ensure population diversity, the following methods are used to generate chromosomes in the initial population:

STEP1: Randomly disrupt the order of OD pairs for high-probability travel.

STEP2: A pair of high-probability travel OD  $n_1^{(+)}n_1^{(-)} \in N\{1, \dots, n\}$  are randomly selected from all passengers to form the first pair of stations for the first vehicle.

STEP3: Select the next pair of high-probability OD, insert them into the stopover route of the  $l(l = 1, 2, \dots, l_1)$  vehicle, abide by the principle of the minimum amount of change in the running distance after insertion, then determine whether the vehicle capacity constraint is met, and if the passengers' travel time windows constraint is satisfied, adjust the initial route of the vehicle; otherwise, insert the high-probability station pair into the stopover route of the next vehicle. Repeat the above process until the best insertion location that satisfies the constraint is found.

STEP4: Select the remaining high-probability travel OD pairs in turn and repeat STEP3 until all high-probability travel pairs are inserted into the vehicle's initial route.

## (3) Adaptation function

To ensure that each delivery route can meet the vehicle capacity and passengers' travel time-window constraints, using the penalty function  $f(l)$  to solve it, we set the violation capacity constraint weight  $\alpha$  as 10, and the violation time window constraint weight  $\beta$  as 100. Because the objective function should be minimized, the adaptability function is set to the reciprocal of the penalty function, that is,  $1/f(l)$ . The penalty function equation is:

$$f(l) = D(l) + \alpha q(l) + \beta w(l) \quad (15)$$

where  $f(l)$  is the penalty function,  $D(l)$  is the total operating mileage of the vehicle  $l$ ,  $q(l)$  is the capacity constraint value violated by vehicle  $l$ ,  $w(l)$  is the sum of passengers who violate the time constraint of vehicle  $l$ , and the fitness function is the reciprocal of the penalty function.

## (4) LNS local search operation

The local search uses the destruction operator to remove a number of passengers from the current solution through the similarity equation and then uses the repair operator to reinsert the removed passengers back into the position that causes the least increase in vehicle distance while satisfying the vehicle capacity constraint and the passenger time constraint.

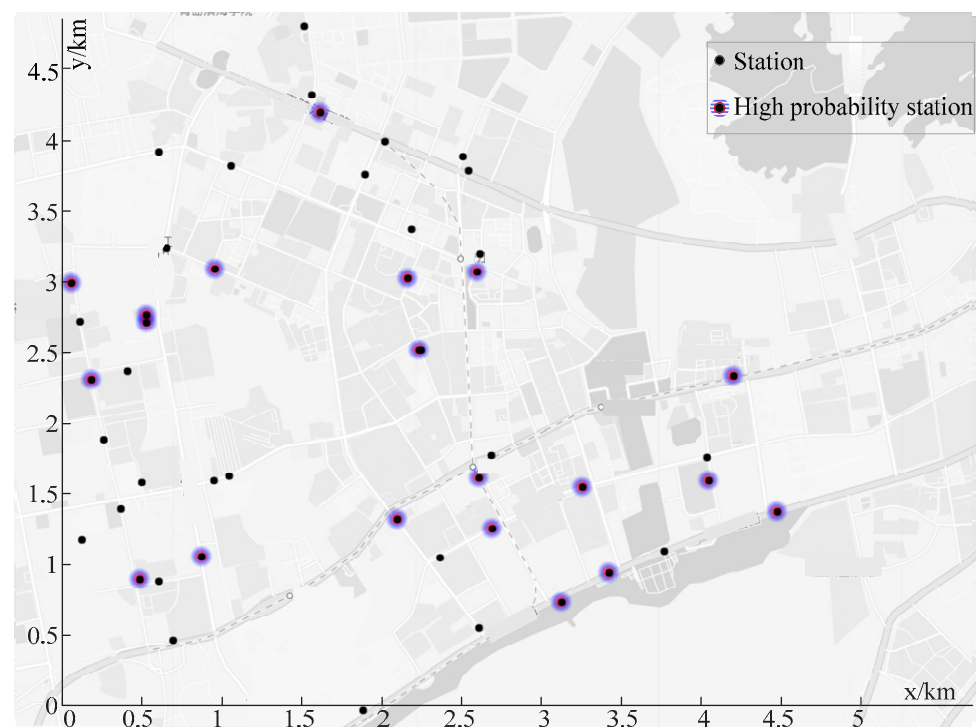


## 4. Case Study

### 4.1. Algorithm Description

There is demand responsive transit operating in a certain area, based on the demand response transit data of this area, we conducted a presentation of a case of vehicle scheduling and route optimization.

We used MATLAB to program and test 11,909 demand data of the region in September. First, by analyzing the temporal and spatial rules of residents' travel by public transport in the region, 232 pieces of data were extracted, which are the valid travel data of passengers at 8:00 a.m. on the 28th day of September. Then, we analyzed the origin and destination rules of travel included in the data and obtained 48 demand stations. Finally, by measuring the shortest route distance between every two stations, we obtained the distance matrix of all the stations. The distribution of stations in the study area is shown in Figure 3. In the programming model, we set the depot station as coordinate station 1 and passenger boarding and alighting stations as coordinate stations 1–48. The maximum passenger capacity of the vehicle was set to 28, the average formal speed of the vehicle was 25 km/h, the boarding and alighting time of passengers was 1 s/capita, the initial maximum distance of one vehicle was 20 km, and the operating cost of the vehicle was 18 RMB/km. The penalty coefficient for vehicle violation of onboard capacity is 10, and the penalty coefficient for violation of passengers' required time windows is 100.



**Figure 3.** Station distribution of the study area.

### 4.2. Validity Experiments

To verify the effectiveness of the algorithm, static vehicle dispatching is performed for the demand, setting the initial population size to 100, crossover probability  $pc = 0.9$ , variation probability  $pm = 0.05$ , and maximum number of iterations to 200. Figure 4 shows that the optimal solution is obtained and enters the convergence state when the number of iterations is about 100.

The results of the three tests are shown in Table 1, and the deviation of the results is 3.1%, which is within the acceptable range; the experimental results show that the stability of the algorithm for problem-solving is good.



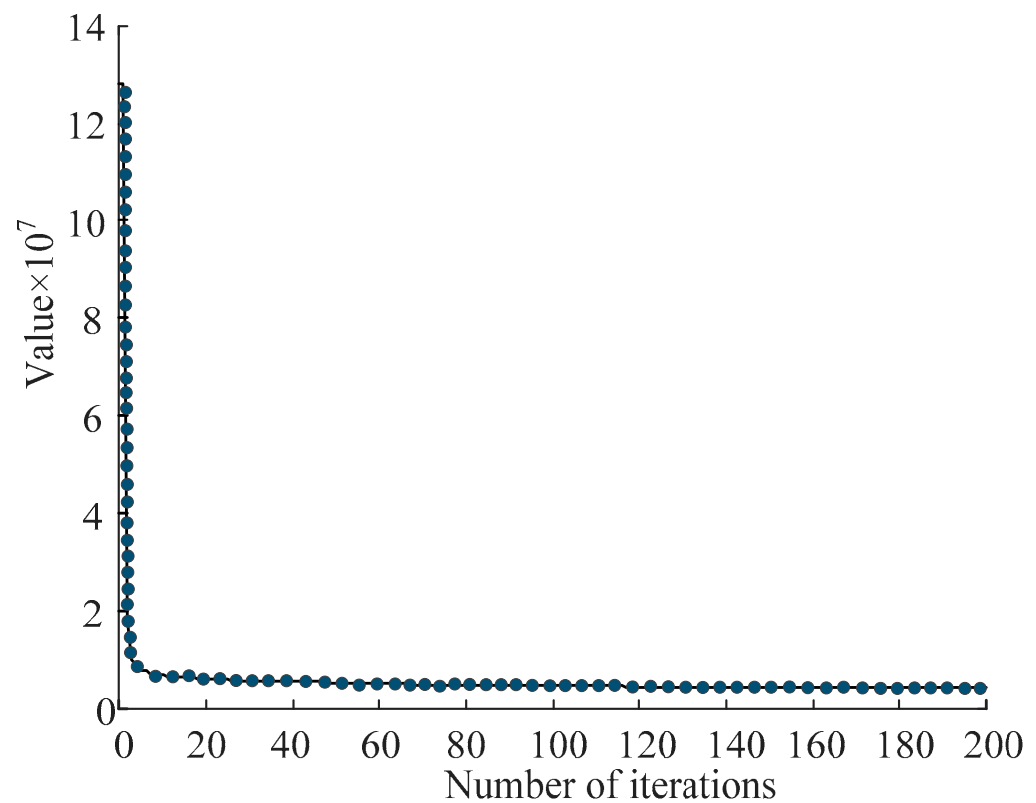


Figure 4. The best solutions found by GA in successive iterations.

Table 1. Optimization results.

No.	Minimum Cost	Run Time/s	Distance/km	Number Passengers Violating Constraints	Number of Passenger Requests
1	$4.2426 \times 10^6$	5306.9	277.74	153	230
2	$4.5694 \times 10^6$	7130.4	303.63	157	230
3	$4.2908 \times 10^6$	7136.2	339.63	177	230
Average	$4.3676 \times 10^6$	6524.5	307.00	163	230

#### 4.3. Analysis of the Effectiveness of High-Probability Station Extraction Strategy

From the 48 demand stations, 20 high-probability demand stations are selected according to the demand frequency, and the vehicle is statically dispatched for the high-probability demand stations in the region. The latitude and longitude information of each demand station are shown in Table 2.

Table 2. Number and location of high-probability travel stations.

Station No.	Station Name	Station Latitude/Longitude	Station No.	Station Name	Station Latitude/Longitude
1	Daigezhuang SQ	120.15, 35.96	11	Jindao HY	120.15, 35.96
2	Guangsha HY	120.17, 35.97	12	Weiye huayuan DM	120.18, 35.96
3	Chengfa DS ZX	120.16, 35.96	13	Shangliuhui	120.19, 35.94
4	Liangbuan	120.16, 35.94	14	Chengshichuanmei	120.20, 35.95
5	Jiangshanruicheng	120.16, 35.94	15	Xihaianqiche DZ	120.18, 35.95
6	Guanting SC	120.18, 35.96	16	Jinggangshanlu DTZY	120.18, 35.95
7	Matouxixiancun	120.20, 35.95	17	Chengfadasha	120.16, 35.96
8	Dingjiahe	120.20, 35.95	18	Zhongyedongfang DS	120.19, 35.95
9	Qiantangjiang LX	120.15, 35.96	19	Jinggangshanlu DTZ	120.19, 35.95
10	Fengaigouwu GC	120.18, 35.96	20	Yunhe GC	120.18, 35.94

Setting the number of iterations to 200 and the population size to 100, we compare Figures 5 and 6. It shows that the total cost of using the strategy is smaller and can satisfy most of the demands with fewer vehicles.

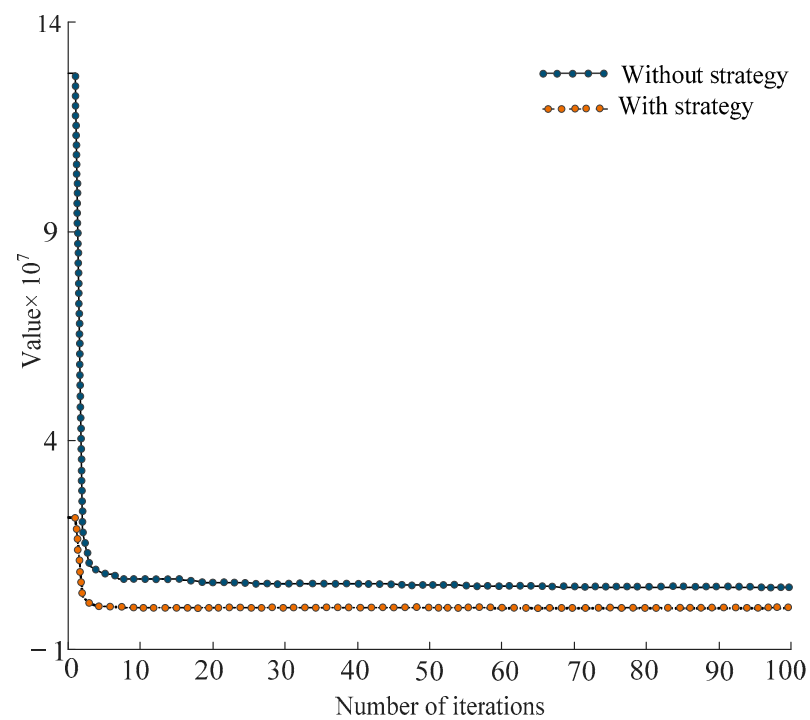


Figure 5. The best solutions of GA with or without strategies in successive iterations.

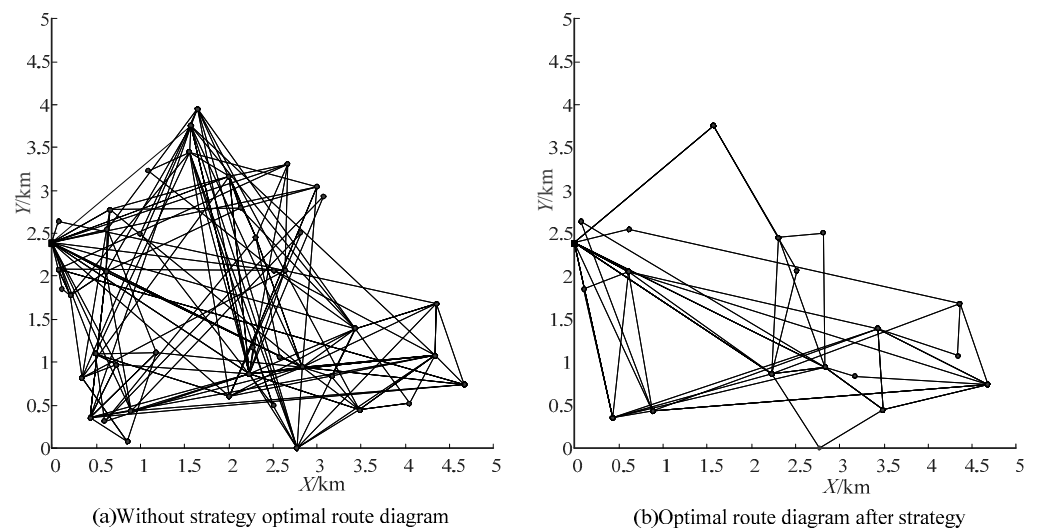


Figure 6. Optimal route with or without strategies.

Table 3 analyses the average total cost of operating vehicles, which, with and without this strategy, is  $1.04 \times 10^4$  RMB and  $4.38 \times 10^6$  RMB, respectively, and the results show that the high-probability station extraction strategy has a significant impact on route optimization and passengers' travel time-saving.

Table 3. Comparison of high-probability station strategies.

No.	With Strategy			No Strategy		
	Minimum Total Cost/RMB	Full Load Rate	Passenger Response Rates	Minimum Total Cost/RMB	Full Load Rate	Passenger Response Rates
1	$6.71 \times 10^3$	26.6%	35.6%	$4.24 \times 10^6$	25.0%	33.3%
2	$1.22 \times 10^4$	27.9%	37.4%	$4.60 \times 10^6$	10.7%	14.3%
3	$1.23 \times 10^4$	27.9%	37.4%	$4.29 \times 10^6$	17.2%	23.0%
Average	$1.04 \times 10^4$	27.6%	36.8%	$4.38 \times 10^6$	17.6%	23.5%

The average waiting time is the average value of the difference between the request time of all passengers and the arrival time of the requested vehicle at the station, and the expression is:

$$\bar{T} = \frac{\sum_{q=1}^Q |t_{qd} - t_{qr}|}{Q} \quad (16)$$

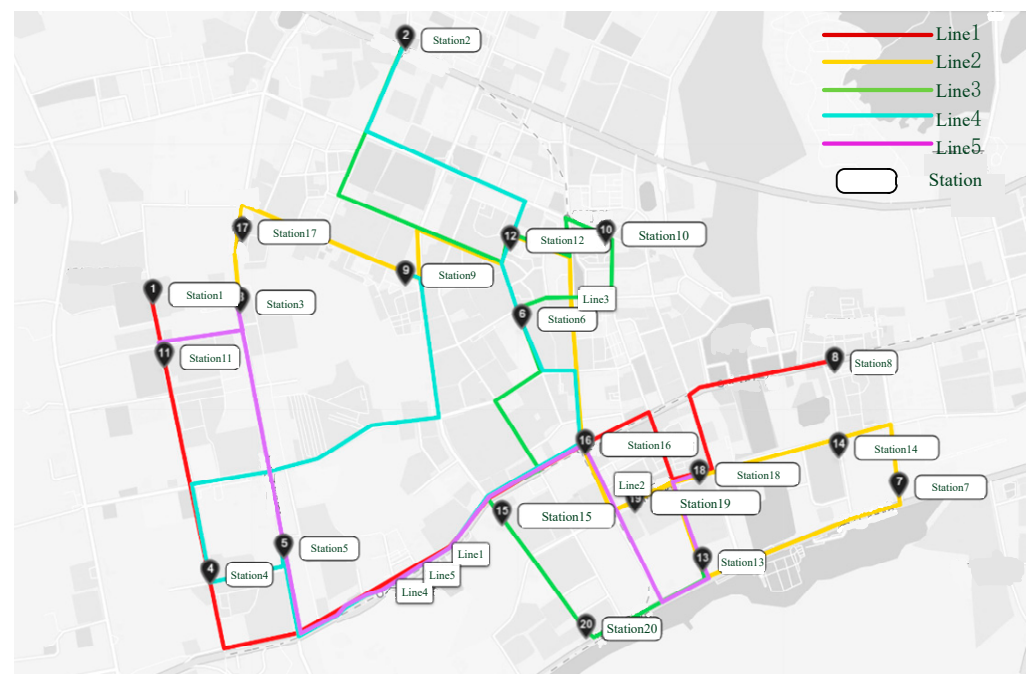
where  $\bar{T}$  is the average vehicle waiting time,  $Q$  is the total number of passengers,  $q$  is the per passenger,  $t_{qd}$  is the time when passenger  $q$  sends a request, and  $t_{qr}$  is the time when the vehicle comes for passenger  $q$  arrives at the station.

Five selected lines from the dispatching results and their static dispatching schemes are shown in Table 4. The average passenger waiting time is 5.4 min. By analyzing the historical operation information of these five lines in the district test data, we find that the average passenger waiting time is 6.23 min, which is the average waiting time of traditional bus passengers. This demonstrates that the average passenger waiting time was reduced by 13.4%.

**Table 4.** Static phase dispatching options.

Line	The Travel Route of Static Dispatching	Vehicle Mileage/km	Line Operating Costs/RMB	Average Passenger Waiting Time/min	Full Load Rate/%
1	8, 18, 16, 15, 4, 1	6.28	113.04	5.4	17.9
2	19, 7, 14, 12, 17, 3	6.62	119.16		25
3	2, 12, 10, 6, 15, 20, 13	5.64	101.52		17.9
4	9, 4, 5, 15, 16, 6, 12, 2	7.9	142.20		50
5	11, 3, 5, 15, 16, 13, 18, 8	6.95	125.10		57

A visualization of the results of this static dispatching is shown in Figure 7. After the static dispatching is completed, the generated routes are stored in the executable dispatching plan matrix, which provides the invocation policy for dynamic optimization.



**Figure 7.** Vehicle dispatching and route result in static dispatching phase.

#### 4.4. Dynamic Route Optimization Analysis

The 49 random travel demands generated from 8:05:00 to 8:20:00 in the vehicle operation are counted in three time periods, inserting their ODs into the executable

dispatching plan matrix and using the exact dynamic planning algorithm for the first round of dynamic optimization.

The average vehicle travel time is the average of all passengers' time on board, including the stopping time, and the expression is:

$$T = \frac{\sum_{q=1}^Q |t_{qs} - t_{qd}|}{Q} \quad (17)$$

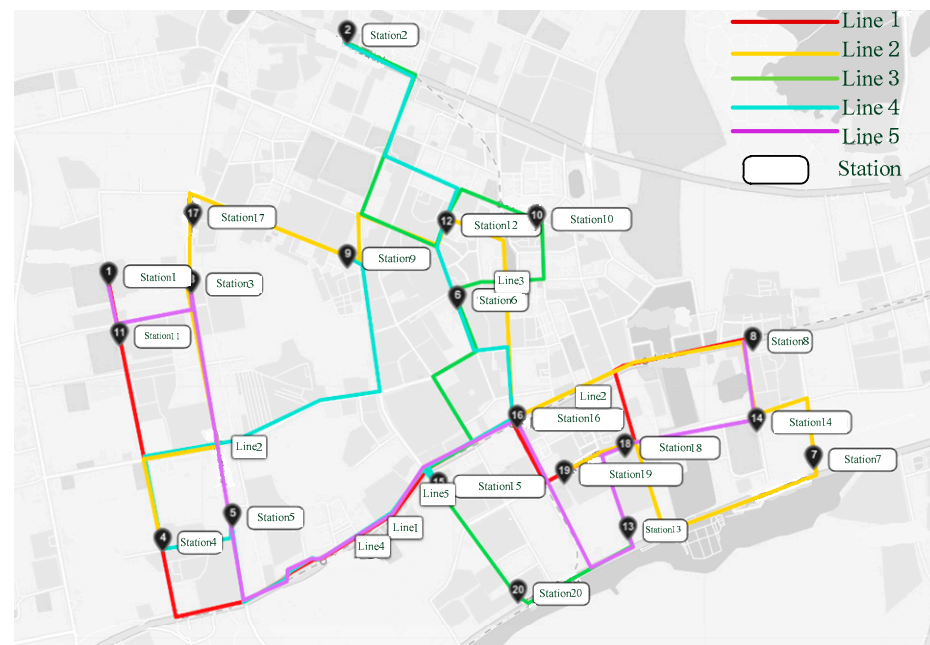
where  $T$  is the average travel time of passengers,  $Q$  is the total number of passengers,  $q$  is each passenger,  $t_{qs}$  is the time of boarding for passenger  $q$ , and  $t_{qd}$  is the time of alighting for passenger  $q$ .

Analyzing the historical operation data of these five routes in the area, the average travel time of passengers was 23 min, which is the average travel time of traditional bus passengers. The second phase of the optimized decision scheme is shown in Table 5, and line 2 responded to the real-time demand of 12 passengers, carrying 19 passengers. The number of unresponsive passengers is 1, corresponding to the vehicle operating routes from 19, 7, 14, 12, 17, and 3 to 19, 7, 14, 12, 17, 3, and 4. The average travel time for those passengers who were responded to was 20.6 min, and the average passenger travel time was reduced by 2.4%.

**Table 5.** Dynamic phase dispatching schemes.

Line	Passenger Travel Demand	The Optimized Route after Dynamic Dispatching	Optimized Operating Mileage/km	Response to Dynamic Demand	Average Travel Time/min
1	-	8, 18, 16, 15, 4, 1	6.28	0	20.6
2	(7, 17) (14, 4)	19, 7, 14, 12, 17, 3, 4	11.13	12	
3	(6, 20) (6, 13)	2, 12, 10, 6, 15, 20, 13	7.43	7	
4	-	9, 4, 5, 15, 16, 6, 12, 2	9.32	0	
5	(1, 14) (3, 13) (3, 18)	1, 11, 3, 5, 15, 16, 13, 18, 8, 14	9.27	6	

A visualization of the results of the dynamic phase dispatch, as shown in Figure 8.



**Figure 8.** Vehicle dispatching and route result in dynamic dispatching phase.

As shown in Table 6, the route optimization model has a high response rate to passenger demand, a 17.92% increase in vehicle full load rate, a reasonable change in operating cost, and a cost reduction of RMB 1.08 per passenger, which reduces the company's operating costs and improves the passenger satisfaction, yielding better results.

**Table 6.** Analysis of two-phase dispatching results.

Dispatching Phase	Vehicle Operating Costs/RMB	Average Full Load Rate	Demand Response Rate	Total Running Mileage/km	Cost per Capita/RMB
Static	601.02	33.58%	100%	33.39	12.02
Dynamic	781.74	51.50%	72%	43.43	10.94
Change	180.72	17.92%	−28%	10.04	−1.08

## 5. Conclusions

To study the operational decisions of dynamic demand response transits, a two-phase optimization model was established, including static vehicle dispatching and dynamic route optimization. Using the vehicle route planning method of the genetic algorithm, a dynamic optimization model of an accurate dynamic programming algorithm is designed for the optimization route, combined with the existing initial operation route, timely response to real-time requests, and true realization of the important feature of demand response.

Aiming at the dynamic transit being highly discrete and with random passenger demand, the high-probability station extraction strategy is proposed, and the dynamic demand response transit service and operation strategy is optimized. In total, 11,909 real data in September in the dynamic transit operation area of a certain district were selected, and 232 valid data at a certain time were extracted according to the actual operation situation; it was found through programming numerical experiments that the genetic algorithm had a small deviation from the solution result of the route and good stability. After extracting the high-probability stations, the operating costs and passenger experience have been significantly optimized; the two-phase dispatching optimization model can maximize the use of vehicle resources, further save operating costs, have feasibility and high use value, and provide application guidance for vehicle dispatching and route optimization.

Due to the small operation data of the study area, small number of passenger flow requests, and number of isolated requests generated, the model focuses on considering the passenger experience, so the full load rate and response rate of the system are not high enough. We will continue to conduct in-depth research on how to select the operating area in the future to make the two achieve their optimal values. Another research direction is the integrated planning of demand responsive transport system and bike-sharing system, one of the fastest growing transportation modes [33], to further improve non-motorized travel efficiency.

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