Optimization Scheduling Algorithm of Logistics Distribution Vehicles Based on Internet of Vehicles Platform

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Abstract. In the phase of logistics distribution vehicle scheduling, the distribution time and travel distance of vehicles are relatively long due to the influence of the real-time change attribute characteristics of the actual traffic environment state. Therefore, this paper proposes an optimization scheduling algorithm for logistics distribution vehicles based on the Internet of Vehicles platform. The Internet of Vehicles platform including acquisition layer, transmission layer, data layer and application layer is constructed to achieve the acquisition and analysis of real-time information of the actual traffic environment status. In the logistics distribution vehicle scheduling phase, the objective function of comprehensively arranging the number of vehicles, the total distance traveled by the distribution vehicles and the time window constraint punishment is constructed. After the objective function is input into the Internet of Vehicles platform, the greedy algorithm strategy is used to achieve the optimal scheduling of vehicles. In the test results, the design algorithm achieves the goal of shortening the vehicle delivery time and driving distance without considering the results under traffic conditions and the scheduling effect under dynamic conditions. To sum up, the optimization scheduling algorithm of logistics distribution vehicles based on the Vehicle-to-everything platform can help optimize the travel distance and distribution time of vehicles, and improve the efficiency and accuracy of logistics distribution.

Keywords: Internet of Vehicles Platform · Logistics Distribution Vehicles · Optimal Scheduling · Number of Vehicles · Total Distance Traveled · Constraint Punishment

1 Introduction

At present, the advantage of logistics development is the increasing scale of the logistics industry, in which the proportion of the logistics industry in the gross domestic product is increasing, And drive the increasing number of logistics employees [1]; The logistics service capability has been significantly improved, and has been developing towards professional and social services: the technical conditions have been significantly improved [2], the establishment of information systems, cloud computing, Internet of Things and

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other information technologies have been preliminarily applied; The infrastructure network is gradually improved, including railway transportation, port transportation, airport transportation, etc.; The logistics development environment has been continuously optimized, and it is proposed to vigorously develop the modern logistics industry [3]. At present, the main task is to improve the professional and social service level of logistics, develop third-party logistics, adopt modern management concepts, and improve logistics service capabilities; Strengthen the construction of logistics informatization [4], apply advanced information technology as soon as possible, establish logistics information system, and promote the development of logistics information sharing platform [5]. Establish an Internet of Vehicles platform to collect logistics resources, store and process logistics data, realize logistics information sharing [6], save resources and improve logistics service capability. The Internet of Vehicles platform is based on cloud computing and relies on the efficient processing capability provided by cloud computing technology to realize the virtual integration of physical resources. Through network technology, massive logistics information will be integrated as an information sharing platform for enterprises to use, and the resource pool formed by virtualization of basic resources will be uniformly scheduled and managed. The platform is used to operate logistics resources and customer resources, and it is processed through cloud computing technology to provide an optimized route for logistics distribution, improve the logistics transportation process, improve the transportation efficiency, reduce the cost of logistics enterprises, and improve the utilization rate of resources, which is of great significance to the development of the logistics industry [7]. An important prerequisite for the stable development of the modern logistics industry is to reduce the logistics transportation cost, and the key to solving the transportation cost problem of the logistics industry is to optimize the logistics system [8]. The key step of logistics system optimization is the reasonable scheduling of logistics distribution vehicles. By optimizing the scheduling of distribution vehicles, enterprises can reduce transportation costs, improve customer service levels and economic benefits, and thus obtain more profits. The logistics vehicle optimal scheduling problem is also known as the vehicle routing problem (VRP) [9]. This problem was first proposed by Dantzig and Ramser scholars in 1959. It focuses on providing goods distribution services to some customers with different quantities of goods demand by using a fleet (several vehicles) from the distribution center. Arrange an appropriate driving route for this fleet, comply with certain constraints, and complete distribution to meet customer needs, The arranged driving routes reach the goals such as the shortest total driving distance, the lowest total transportation cost or the shortest total service time [10]. Therefore, it can be described as that distribution vehicles start from one (or more) distribution centers and pass through several distribution points (randomly distributed) in a certain order under various constraints, so as to ensure that each distribution point is served by distribution vehicles and only one vehicle serves.

Combined with the above discussion, this paper proposes a logistics distribution vehicle optimal scheduling algorithm based on the Internet of Vehicles platform. By utilizing the collection, transmission, data, and application layers of the Internet of Things platform, real-time information on traffic environment status is obtained and analyzed to address the impact of actual traffic environment changes on vehicle delivery time and driving distance. This algorithm constructs an objective function that comprehensively considers the number of vehicles, total distance traveled, and time window constraints in the vehicle scheduling stage, and utilizes a greedy algorithm strategy to achieve optimal vehicle scheduling.

2 Optimization Algorithm Design of Logistics Distribution Vehicles

2.1 Structural Design of Internet of Vehicles Platform

At present, the demand for logistics is increasing day by day, and the cooperation between logistics enterprises is very little [11]. The reuse of human, material, financial and other resources is increasingly high, resulting in waste of resources. The government urgently hopes to promote the development of public logistics information service platform, encourage cooperation between enterprises, and achieve logistics information sharing. In the face of huge logistics resource storage and calculation, it is necessary to establish a uniformly managed Internet of Vehicles platform, which can gather logistics resources together, make more reasonable use of them, promote the better development of the logistics industry, and provide better services for other related industries, which has important social significance [12].

The Internet of Vehicles platform built in this paper is a public information platform. It collects information related to logistics activities for various industries, and improves the efficiency of logistics resource utilization through business processing, saves unnecessary resource reuse, saves logistics costs to a large extent, and promotes the development of logistics economy [13]. The logistics public information platform needs to have huge logistics information storage capacity and business logic processing capacity. It provides a perfect technical solution for the establishment of the platform by taking advantage of the characteristics of cloud computing, such as workflow standardization and intelligent decision-making [14]. The construction of the Internet of Vehicles platform requires computer network communication technology and database management technology to realize logistics information [15].

Share technology, equipment and other resources to achieve resource integration, including cloud computing, Internet of Things, GPS and other resources.

Advanced technology, automatic collection and storage of logistics information, through the application of computer information technology.

The function of the cloud platform is more powerful, and the logistics system is more perfect. The logistics distribution vehicle scheduling system based on the cloud platform studied in this paper uses the Internet of Things technology to collect logistics data, The collected data is stored and processed. The overall structure of the system can be divided into acquisition layer, transmission layer, data layer, application layer, etc. Four module representation.

Acquisition layer: mainly completes the conversion of data from the physical world to the information world. Logistics distribution vehicle scheduling system.

The data to be collected include cargo information, customer information, cargo logistics information, vehicle information, order information and other relevant information Interest.

Transport layer: to complete the transmission of logistics data, the main technical means are: broadband connection, WIFI, 5G mobile.

Communication technology, Internet of Things, etc., as shown in Fig. 1.Its purpose is to connect the acquisition layer and the data layer, and finally collect the data of the physical world to the cloud computing platform through the transport layer.

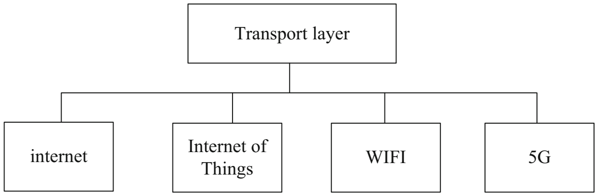


Fig. 1. Transport Layer Structure Diagram

Data layer: mainly used for the storage of logistics data, receiving data from the acquisition layer and storing it on the Internet of Vehicles platform.

According to the requirements of the application layer, the stored data is transferred to the application layer. Logistics data can be stored in SQLServer.

MySQL, Oracle and other databases, and SQLServer 2008 database is used for storage.

Application layer: also known as platform display layer, it is designed according to user requirements, and generally includes some information systems, including cargo information management system, vehicle information management system, logistics scheduling system, etc., as shown in Fig. 2. According to the query data specified by the user, query in the database through the service program, and feed back the results to the main user interface for presentation to the user.

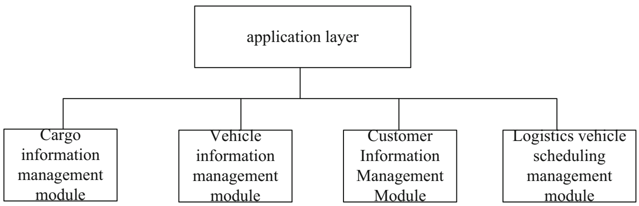


Fig. 2. Application Layer Settings

Under the above architecture design, the acquisition layer obtains corresponding data through sensors or other service platforms, and calls the interface in the data layer for data transmission. In the transmission process, the data can be transferred by registering the service with the data layer and completing the registration after obtaining the corresponding permissions. The data application is the opposite of the collection process. You need to build a computing instance first. After the instance is initialized, you can obtain the corresponding data from the cloud storage platform according to the application needs. You can directly analyze the obtained data, or create a database as needed to complete the data application.

In this way, the construction of the Internet of Vehicles platform is realized, and the acquisition of traffic vehicle information and the analysis of traffic operation status are realized, providing a reliable data basis for the subsequent logistics distribution vehicle scheduling.

2.2 Logistics Distribution Vehicle Scheduling Based on the Internet of Vehicles Platform

When carrying out logistics distribution tasks, the objective demand of customers is received. This paper introduces the time window mechanism, and on this basis, the distribution vehicle scheduling problem is split.

$$\sum_{j=1}^{N} x_{ijk} = \sum_{j=1}^{N} x_{ijk} \leq 1, i = 0, k \in \{1, 2, ..., K\} \tag{1}$$

$$\sum_{i=0}^{K} d_i \sum_{j=1}^{N} x_{ijk} =\leq q_k, k \in \{1, 2, ..., K\} \tag{2}$$

$$\sum_{i=0}^{K} \sum_{j=1}^{N} x_{ijk}(t_{ij} + s_i + w_i) \leq ET_0 \tag{3}$$

$$\sum_{i=0}^{K} \sum_{j=1}^{N} x_{ijk}(t_{ij} + s_i + w_i + t_i) = t_j, j \in \{1, 2, ..., N\} \tag{4}$$

$$ST_i \leq w_i + t_i \leq ET_i \tag{5}$$

Among them, t_i It means that the delivery vehicle drives to the customer i Time of, w_i It means that the delivery vehicle stops at the customer i Time of, K Indicates the total number of vehicles owned by the distribution center, N Indicates the total number of customers served by the distribution center, t_{ij} Represent customer i To customers j Vehicle travel time, d_i Represent customer i Demand, q_k Indicates the delivery vehicle k Maximum load of ST_i, ET_i Represent customer i's receiving time range, ST_i Is a customer i The earliest receiving time, ET_i Represent customer i Latest receiving time, s_i It means that the delivery vehicle is delivered to the customer i Time taken for unloading and delivery.

$$x_{ijk} = \begin{cases} 1 \\ 0 \end{cases} \tag{6}$$

where, when the vehicle k By customer i Drive to customer j When, then x_{ijk} value is 1, otherwise it is 0.

In the above formula, (1) represents the constraint condition of each vehicle starting from the distribution center and returning to the distribution center finally; (2) It means that the total volume or weight of goods to be delivered to customers for the loading of distribution vehicles cannot exceed the maximum loading capacity of distribution vehicles; (3) Is the constraint of the maximum travel time of distribution vehicles; (4) Indicates that the delivery vehicle has arrived at the customer j Time at is equal to the delivery vehicle arriving at the customer i Time at t_i, in the customer i Waiting time at w_i, in the customer i The sum of the service time, (5) represents the constraint of the customer's time window, and the delivery vehicle arrives at the customer i The time of plus the waiting time is within the customer's time window.

On this basis, this paper sets the weight value w_1, w_2, w_3 The objective function of this paper is composed of the total number of vehicles, the total distance traveled by vehicles and the penalty value, as shown in Formula (2–10).

$$\min(w_1 \sum_{i=0}^{K} \sum_{j=1}^{N} x_{ijk} + w_2 \sum_{i=0}^{K} \sum_{k=0}^{N} \sum_{j=1}^{N} c_{ij} x_{ijk} + w_3 p(t_i)) \tag{7}$$

Among them, c_{ij} Represent customer i To customers j Of vehicle travel, w_1 To arrange the weight of the total number of vehicles, w_2 Is the weight of the total distance traveled by distribution vehicles, w_3 It is the weight of punishment due to time window constraints, $p(t_i)$ represents the objective function of starting the number of vehicles, and the final optimization goal is to arrange the number of vehicles, the total distance of distribution vehicles, and the punishment due to time window constraints. The sum of the three weights is the smallest.

On this basis, input the objective function into the Internet of Vehicles platform built in Sect. 1.1. First, initialize the basic data, including the set population size, cross mutation probability, evolution algebra, maximum vehicle load, maximum vehicle travel distance, customer coordinates, customer demand, distance between customers, and other information. Initializing the vehicle information is to define a two-dimensional array vehicle [K, 3] with multiple rows and three columns. The row number represents the serial number of the vehicle. The first column represents the maximum loading capacity of the vehicle, the second column represents the maximum driving distance of the vehicle, and the third column represents the driving speed of the vehicle. Initializing customer demand information is to read the coordinates and demand information of customer points; Use a pair of one-dimensional arrays x [] and y [] to save the X axis coordinates and Y axis coordinates of each customer point, use the one-dimensional array guestDemand [] to save the demand of each customer point, use the distance formula between two points to calculate the distance between the distribution center and customers, and between customers, and save it in the two-dimensional array guest distance [,] for subsequent calculation, Use the paintPoint () method to draw the customer points on the graphical interface, and use the paintLine () method to draw the lines between customer points to visually display the line information.

Secondly, initGroup is the initial population. The general genetic algorithm obtains the initial population by randomization. The resulting population is not highly adaptive due to the randomness of individuals, and has a certain impact on the convergence speed and solution quality of the algorithm. In this paper, according to the characteristics of greedy algorithm that can quickly solve the local optimal solution, individuals with high fitness can be obtained by initializing the population. Adding greedy algorithm strategy can improve the fitness of the initial population to a certain extent, and accelerate the convergence speed of the algorithm. The specific implementation process of population initialization is to initialize with an empty two-dimensional array old Group. The number of rows represents the number of chromosomes, and the columns represent the gene fragments of chromosomes, that is, the customer's order. For each chromosome, first assign a random number to the first gene, which is a natural number from 1 to the length L of the chromosome. Then compare the next gene with the previous genes. If not, assign the random number to the current gene to ensure that the gene is not duplicate with the previous genes. The population size is controlled by the parameter scale, and scale chromosomes are generated continuously.

Finally, greedy algorithm strategy is used to realize the optimal scheduling of vehicles. Start with the customer represented by the gene generated in the random method and find the customer closest to the initial customer i As the next object of vehicle distribution, the customer i Mark as traversed, and then traverse the remaining customers that have not been traversed to find the customers that are far away i Recent Customers j, the customer j Mark as traversed, and then j As the starting customer, then find the distance customer j For the nearest customer, follow this rule to find the next customer until all customers have been traversed, and then get the full order of customers, that is, the order of vehicle delivery.

Therefore, the optimal scheduling of logistics distribution vehicles is realized.

3 Test Experiment Analysis

3.1 Test Environment Parameter Setting

(1) Time-varying road network constraint

The capacity of urban road vehicles is limited, especially the number of road lanes planned and constructed in the early stage is small, which is easy to cause congestion. The degree of traffic congestion will directly affect the speed of vehicles, and the degree of traffic congestion can be evaluated in more detail and reasonably with other easily measured or predicted traffic flow parameters, which can link other traffic flow parameters with the speed, providing a reasonable basis for the calculation of vehicle travel time. According to the relevant urban traffic management regulations, the road traffic congestion can be divided into the following four types, as shown in Table 1.

Table 1. Relationship between road traffic congestion and vehicle speed

degree of crowding	Speed (km/h)
open	≥30.0
Mild crowding	20.0–30.0
Crowding	10.0–20.0
Severe crowding	<10.0

In addition, the driving speed of vehicles under the time-varying network is closely related to the road type, as well as the city size and time period. For this reason, this paper has carried out a detailed study on the relationship between the expressway and national and provincial highways in different time periods and the vehicle speed.

Analysis, and set the division criteria as shown in Tables 2 and 3.

Table 2. Relationship between Expressway and Speed in Different Time Periods

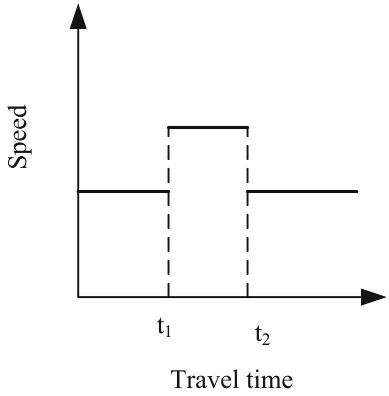
time interval	Corresponding period	Corresponding speed (km/h)
0:00–10:00	Low peak period	110
10:00–16:30	Peak period	80
16:30–24:00	Low peak period	110

Table 3. Relationship between Provincial Highway and Speed in Different Time Periods

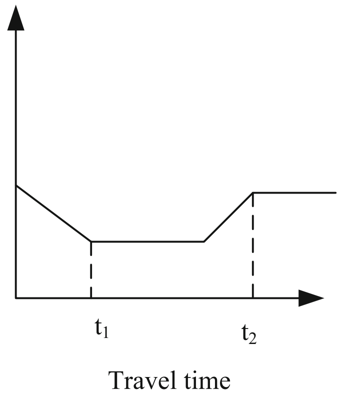
time interval	Corresponding period	Corresponding speed (km/h)
0:00–7:00	Low peak period	60
7:00–9:30	fastigium	30
9:30–17:00	Peak period	50
17:00–18:00	fastigium	30
18:00–24:00	Peak period	60

In order to make the travel time of vehicles uniform and uninterrupted, the existing travel speed model is referred. The speed step distribution and travel time function are shown in Fig. 3 below.

It can be seen from Fig. 3 that the model meets the “first in, first out” criterion, the travel time can be described by speed, and the travel time is calculated by the ratio of link length and travel speed. In real life, although the traffic data system collects information all the time, the real-time traffic data we can know is generally updated according to a certain interval of time, such as 3min and 5min.Therefore, the data obtained in this paper can only be the data after 5 min.



(a) Expressway running speed and running time function



(b) Travel speed and travel time function of provincial highway

Fig. 3. Function Diagram of Travel Speed and Travel Time

(2) Actual traffic conditions.

In the face of complex urban traffic conditions, the efficiency of urban logistics distribution service will be very passive affected by it. Understanding the traffic changes in different time periods and avoiding congested roads will help the road passing rate of vehicles in transit and reduce the driving time. Therefore, this paper will collect the travel speed distribution of a certain urban road during the impasse period through relevant software. Although it is difficult to obtain specific travel directions for individual vehicles, each city basically has its own inherent general travel rules for the entire urban group. Fig. 4 below shows the trend chart of the average speed of urban roads and road congestion index in a city on a day (not a weekend holiday).

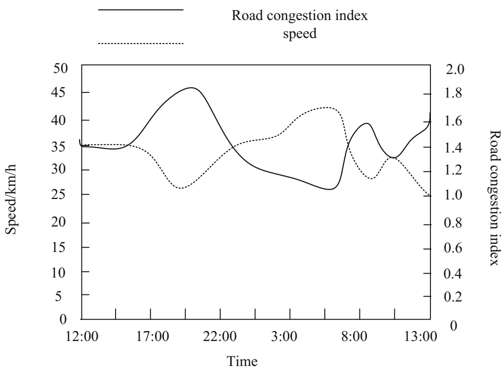


Fig. 4. Trend Chart of Average Speed and Congestion Index of Urban Roads

The road congestion index can be considered as the ratio of the actual travel time to the travel time when the road is clear. In Fig. 4, we can roughly see the peak, flat peak and valley peak periods of urban roads.

The average running speed of vehicles divided into sections is 31.2 km/h. According to Fig. 4, the time period from 7:00 to 9:00 and from 17:00 to 19:30 can be divided into peak periods, with the average speed set as 25 km/h, and the time period from 9:00 to 17:00 belongs to the flat peak period, with the average speed set as 40 km/h. The divided time period and speed are applied to the example in the next section.

3.2 Test Plan

This section will quote the data of the logistics distribution center of A logistics distribution center in a city under the actual road traffic for the experiment. The specific experimental data are shown in Table 4 below.

On this basis, considering that in the actual logistics distribution process, users' requirements for delivery time also have the characteristics of differentiation. For this reason, this paper sets time windows for different users, as shown in Table 5.

Constrain the execution of distribution tasks according to the time shown in Table 4. In the specific distribution process, the number of vehicles that can be scheduled in the corresponding area of the task is 6. Without considering the influence of other factors, the average speed of the vehicle is set to 32 km/h, and the use cost of the vehicle is 60 per vehicle. According to market statistics, the maximum single capacity of ordinary urban freight vehicles is 200 units, the energy consumption for driving is 12 units per hundred kilometers, and the energy cost per kilometer converted from the current oil price is 0.65.The logistics distribution vehicle optimal scheduling method based on genetic algorithm (control group 1) and the logistics distribution vehicle optimal scheduling method based on ant colony algorithm (control group 2) were used as the test control group to compare the distribution effect under different scheduling mechanisms.

Table 4. Test Case Detailed Data Information

Customer number	longitude	latitude	requirement
0	114. 047928	22.53404	0
1	114. 084007	22.533 106	11
2	114. 063476	22. 517449	13
3	114. 048129	22.569696	16
4	114. 117707	22.547856	9
5	114. 078438	22.557769	5
6	114. 126343	22.580903	28
7	114. 002705	22.548985	16
8	114. 150582	22.560752	14
9	114. 123136	22.566035	12
10	114.13405	22.55548	19
11	114. 10387	22. 557838	23
12	114. 089129	22.56301 1	20
13	114.005573	22.535584	8
14	114.093954	22.547285	19
15	114.05208	22. 547539	8
16	114. 033642	22.564374	12
17	114. 073548	22. 567397	8
18	113. 999491	22.542243	12
19	114. 084514	22.541893	16
20	114. 076734	22. 55464	9
21	114. 025829	22.551368	11
22	114. 051737	22. 522581	18
23	114. 070394	22.547521	29
24	114. 110004	22.570306	21
25	114. 115356	22.560368	6

3.3 Test Results and Analysis

(1) Result analysis without considering traffic conditions

Firstly, the distribution results corresponding to different test methods without considering traffic conditions are counted. The distribution duration and total distance of six logistics vehicles are shown in Fig. 5 and Fig. 6 respectively.

Table 5. Delivery Task Time Window Information

Customer number	Delivery Task Time Window
0	8:00–18:00
1	8:30–8:50
2	8:00–8:30
3	9:00–9:20
4	9:35–9:50
5	10:00–10:20
6	10:30–10:55
7	11:15–11:35
8	11:30–11:55
9	12:00–12:20
10	12:15–12:45
11	13:30–14:00
12	8:00–9:20
13	8:30–10:00
14	14:30–14:50
15	14:45–15:15
16	15:20–15:35
17	16:20–16:55
18	12:20–12:50
19	13:10–13:40
20	12:20–12:45
21	10:20–10:50
22	15:00–15:20
23	16:00–16:30
24	11:20–1150
25	10:35–10:55

According to the test results shown in Fig. 5, in the three groups of test results, the distribution duration of logistics vehicles in control group 1 and control group 2 is always higher than that in the test group. From the overall perspective, the distribution duration of six logistics vehicles in control group 1 is 1696.8 min in total, and the distribution duration of six logistics vehicles in control group 2 is 1760.4 min in total, The total delivery time of six logistics vehicles in the test group is only 1623.6 min. Compared with control group 1, the delivery time saved reached 73.2 min, and compared with control group 2, the delivery time saved reached 163.8 min. It can be seen from this that under the optimization scheduling algorithm of logistics distribution vehicles based

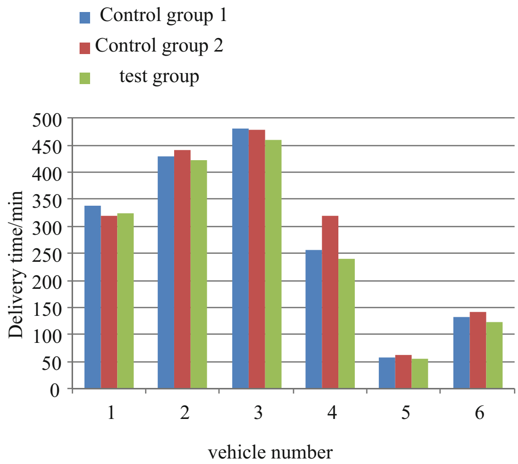


Fig. 5. Comparison Diagram of Vehicle Delivery Duration

on the Internet of Vehicles platform designed in this paper, the time cost of logistics distribution vehicles in the stage of implementing distribution tasks without considering traffic conditions can be effectively reduced. The algorithm in this article constructs an objective function that comprehensively arranges the number of vehicles, the total distance traveled by delivery vehicles, and constrains punishment with time windows. Use greedy algorithm strategy to achieve optimal vehicle scheduling. Therefore, the efficiency of vehicle delivery is good.

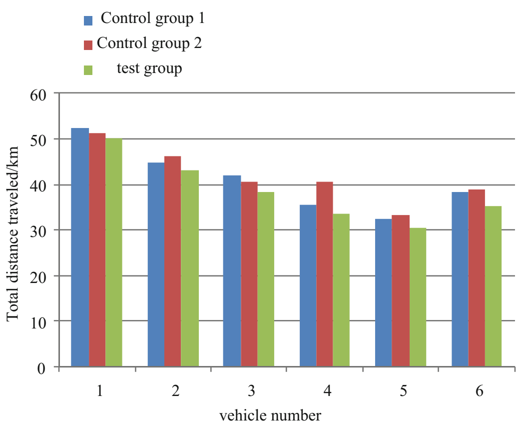


Fig. 6. Comparison Diagram of Vehicle Distribution Distance

Combined with the test results shown in Fig. 6, it can be seen that in the three groups of test results, the driving distance of logistics vehicles in control group 1 and control group 2 is always higher than that of the test group during the delivery task stage. It is also analyzed from the overall perspective, among which, the total distribution driving distance of 6 logistics vehicles in control group 1 is 245.5 km, the total distribution duration of 6 logistics vehicles in control group 2 is 250.8 km, and the total distribution duration of 6 logistics vehicles in test group is only 230.7 km. Compared with control group 1, the distribution distance is shortened by 14.8 km, and compared with control group 2, the distribution distance is shortened by 20.1 km. It can be seen from this that under the optimization scheduling algorithm of logistics distribution vehicles based on the Internet of Vehicles platform designed in this paper, the travel distance of logistics distribution vehicles in the stage of carrying out distribution tasks without considering traffic conditions can be effectively shortened.

(2) Result analysis under dynamic conditions

Urban logistics distribution vehicles are greatly affected by road traffic conditions when providing distribution services. The route scheme of vehicles and the number of service vehicles have been obtained under the initial static conditions without considering the traffic impact. Under dynamic time-varying conditions, the route of vehicles can be adjusted temporarily by predicting the traffic conditions (smooth, ordinary, congested) on the given route. The premise of adjustment is to adjust the service order or choose other road sections at the remaining unserviceable customer points of the current vehicles. Since the traffic data of the government affairs platform is not open, the road information is incomplete when using the program to obtain the historical traffic data on the corresponding road section.

The method of random congestion coefficient is used for auxiliary experiments. Randomly select a certain road section on each path for random congestion number. When the congestion number $r \leq 2$, continue to select the current path to serve the customer point. When $2 \leq r \leq 3.5$, the speed will drop to 3/4 of the original, and when $r \geq 3.5$, adjust the customer service order. On this basis, the distribution results corresponding to different test methods under traffic conditions are counted. The distribution duration and total distance of six logistics vehicles are shown in Fig. 7 and Fig. 8 respectively.

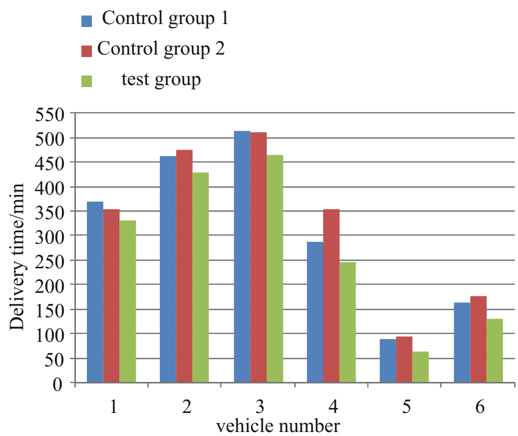


Fig. 7. Comparison Diagram of Vehicle Delivery Duration

Combined with the test results shown in Fig. 7, it can be seen that in the three groups of test results, the logistics vehicle distribution duration of control group 1 and control group 2 is always higher than that of the test group, and the range is significantly expanded compared with the test results without considering traffic conditions. From the overall point of view, the total distribution time of six logistics vehicles in control group 1 was 1884.0min, the total distribution time of six logistics vehicles in control group 2 was 4956.6min, and the total distribution time of six logistics vehicles in test group was only 163.2min. Compared with control group 1, the delivery time saved reached 220.8 min, and compared with control group 2, the delivery time saved reached 302.4 min. Moreover, compared with the test results without considering the traffic conditions, the delivery time of control group 1 increased by 187.2 min, the delivery time of control group 2 increased by 205.2 min, and the delivery time of test group only increased by 39.6 min. It can be seen from this that, considering the traffic conditions, the optimization scheduling algorithm of logistics distribution vehicles based on the Internet of Vehicles platform designed in this paper can also effectively reduce the time cost of logistics distribution vehicles in the stage of implementing distribution tasks.

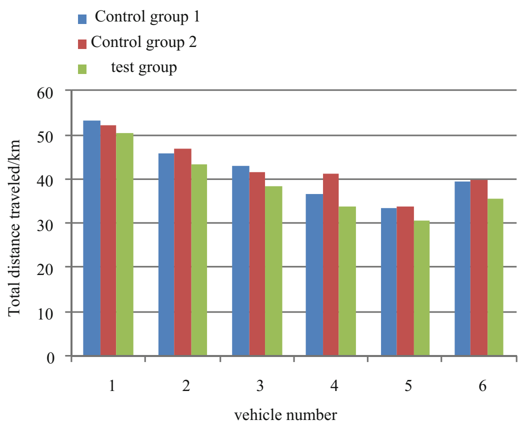


Fig. 8. Comparison Diagram of Vehicle Distribution Distance

According to the test results shown in Fig. 8, in the three groups of test results, the vehicle distribution distance shows the same development trend as the vehicle distribution duration. Among them, the total distance traveled by six logistics vehicles in control group 1 during the delivery task phase is 251.9 km, the total distance traveled by six logistics vehicles in control group 2 during the delivery task phase is 255.3 km, while the total distance traveled by six logistics vehicles in test group during the delivery task phase is only 232.1 km. Compared with control group 1, the distribution distance is shortened by 19.8 km, and compared with control group 2, the distribution distance is shortened by 23.2 km. Moreover, compared with the test results without considering traffic conditions, the distribution distance of control group 1 increased by 6.4 km, the distribution distance of control group 2 increased by 4.5 km, and the distribution distance of test group only increased by 1.4 km. It can be seen from this that, considering the traffic conditions, the optimization scheduling algorithm of logistics distribution vehicles based on the Internet of Vehicles platform designed in this paper can also effectively shorten the travel distance of logistics distribution vehicles in the delivery task phase.

4 Conclusion

Vehicle routing problem has more important practical significance because of the rapid development of logistics transportation in recent years.Many models of vehicle routing problem have been derived from the research process of scholars for many years, among which the algorithm for solving the model is endless.The models of vehicle routing problem include vehicle routing problem with load constraints, vehicle routing problem with time window constraints, dynamic vehicle routing problem, static vehicle routing problem, dynamic vehicle routing problem with time window, random vehicle routing problem, vehicle routing problem with random demands, vehicle routing problem with random customers and demands, etc.This paper proposes the research on the optimization scheduling algorithm of logistics distribution vehicles based on the Internet of Vehicles platform, which greatly improves the utilization rate of logistics distribution vehicles. For the actual logistics distribution work, under the same vehicle configuration conditions, it can effectively improve the efficiency of logistics distribution.With the help of the research and design of the optimization scheduling algorithm for logistics distribution vehicles in this paper, I hope to provide valuable reference for the development of related work.

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