# Design of Intelligent Dispatching System for Logistics Distribution Vehicles Based on Transfer Learning

Li Yu(✉) and Yuanyuan Guan

College of Finance and Economics, Chongqing Chemical Industry Vocational College, Chongqing 400000, China

**Abstract.** The traditional logistics vehicle scheduling system can only perform scheduling based on static information, which makes it difficult to change the scheduling decision according to the actual situation, resulting in a high logistics distribution cost and poor timeliness of Veneto. In response to the above problems, this research designs an intelligent dispatching system for logistics distribution vehicles based on migration learning. The hardware part of the system is composed of three modules: GPS satellite positioning module, GPRS wireless communication module and ARM central control module, and then uses migration learning theory to locate the vehicle position. Realize the dispatch of delivery vehicles by establishing a dynamic dispatch model. Through comparative experiments with traditional dispatching systems, it is verified that the system in this paper can effectively reduce the cost of logistics and improve the timeliness of distribution, and has certain practical value.

**Keywords:** Migration learning · Logistics distribution · Intelligent vehicle scheduling · Vehicle positioning

## 1 Introduction

With the rapid development of the transportation industry and e-commerce, the development of the logistics and distribution industry tends to be informative, and industry competition is becoming increasingly fierce. The logistics industry is the product of the social and economic development to a certain level. It integrates the warehousing industry, transportation industry and other complex service industries, and is the main component of the national economy. With the improvement of social material living standards, customers have increasingly higher requirements for the timeliness of logistics and distribution. The logistics industry is becoming more and more important in the market economy. To develop the modern logistics industry in a long-term and stable manner, it is necessary to effectively solve the transportation cost problem and optimize the logistics system [1].

Vehicle scheduling problem is the key to optimize the logistics system. In recent years, the vehicle scheduling problem has become a hot topic, which involves many


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uncertain factors. In the past, a large number of vehicle scheduling studies are based on static assumptions, that is, all tasks or requirements are known before scheduling decision and route planning. Once the scheduling decision is implemented, all situations will not change. This assumption has become increasingly unrealistic in today's rapid development of e-commerce and logistics. However, there are still few research results for more models and algorithms that are in line with the actual situation, such as vehicle routing problem with multiple time Windows, vehicle routing problem with consideration of road traffic conditions at different time periods, and vehicle routing problem with both requirements of cargo collection and delivery [2]. Therefore, related scholars have also begun to pay attention to the new research direction of dynamic vehicle scheduling.

The core idea of transfer learning is to store and use the knowledge gained in the process of learning tasks in the original field, and apply it to the learning tasks in the new target field, so as to improve the performance effect of the target task [3]. Therefore, according to the above analysis, aiming at the problems of traditional logistics vehicle scheduling system, this paper designs an intelligent vehicle scheduling system based on transfer learning.

## 2 System Hardware Part Design

The hardware part of the system designed in this paper is mainly to collect the real-time location data of vehicles, so as to adjust the movement path of logistics vehicles in time.

The on-board unit is the hardware part of the whole system, mainly composed of three modules: GPS satellite positioning module, GPRS wireless communication module and ARM9 STM32F101 central control module.

1) GPS satellite positioning module. It is composed of data processing part and antenna, which can receive and analyze GPS satellite message, calculate the longitude and latitude of GPS antenna, carrier movement speed, driving direction and GPS standard time, which are read by the control module and sent back to the server through GPRS module. GPRS technology has the characteristics of real-time, and the maximum transmission rate can reach 171.2 kbit/s [4, 5]. In this paper, the mg323 GSM M2M industrial GPRS communication unit of Huawei Company is selected to realize the transmission of logistics positioning information. Mg323 has four communication bands, supports 8-wire serial port, and the sensitivity of data transmission and reception is less than - 107 dBm. When mg323 carries out GPRS communication, the maximum downlink transmission rate is 85.6 kbps, the maximum uplink transmission rate is 42.8 kbps, and the data transmission protocol is embedded TCP/IP protocol.
2) GPRS wireless communication module. After the connection with the GPRS network is completed, the data exchange between the on-board unit and the server can be realized, the GPS positioning data of the on-board unit and the status information collected by related sensors are packaged and sent to the server, while monitoring and responding to the remote control sent by the monitoring center to the server And scheduling instructions.
   The working status of asynchronous transceiver interface of GPRS communication unit is described in Table 1.

3) ARM central control module. The control center of the entire vehicle terminal, on the one hand, completes the extraction, packaging and packaging of GPS satellite positioning data, time synchronization data, and vehicle status data; on the other hand, it controls the communication response, voice call, and data transmission and reception of the GPRS module and the monitoring center. At the same time, it responds to various alarm requests of the on-board unit and executes various instructions of the monitoring center, so that the driver can implement corresponding control of the vehicle in time according to the requirements of the dispatch center and perform vehicle-related scheduling tasks [6].

**Table 1.** Description of the working status of the asynchronous transceiver interface

| Pin | Signal | Describe | Characteristic | Direction |
|---|---|---|---|---|
| 29 | UART1_RD | Data sender | DTE receive serial number | DCE—DTE |
| 33 | UART1_TD | Data receiver | DTE send serial number | DTE—DCE |
| 38 | UART1_RING | Ringing indication | Notify DTE of remote call | DCE—DTE |
| 32 | UART1_DTR | Terminal ready | DTE ready | DTE—DCE |
| 34 | UART1_RTS | Request to send | Inform DCE to request sending | DTE—DCE |
| 36 | UART1_SDR | Data device ready | DCE ready | DCE—DTE |
| 28 | UART1_CTS | Clear send | DCE has switched to receive mode | DCE—DTE |
| 24 | UART1_DCD | Carrier detection | Data link connected | DCE—DTE |

ARM processor controls GPRS module to access mobile GPRS network, and then connects to computer monitoring center through Internet to realize wireless data transmission; GPS module transmits received data to main control chip through serial port for preprocessing; flash memory is used to store debugged application program and embedded uClinux operating system.

On the basis of the above-mentioned system hardware part, the software part of the intelligent dispatching system of logistics distribution vehicles is designed by using the principle of migration learning to complete the system design process and realize the system preset function.

## 3 System Software Design

### 3.1 Distribution Vehicle Location Based on Migration Learning

The basis of real-time and accurate scheduling of logistics distribution vehicle intelligent scheduling system is to track the real-time position of the vehicle to be dispatched. Therefore, in addition to using the data transmitted back from the vehicle hardware module, in order to avoid the impact of signal interference on the positioning accuracy, it is also necessary to use the migration learning theory to locate the vehicle license plate, so as to assist the scheduling system.

This article uses transfer learning theory to improve the SSD positioning algorithm. SSD does not need to generate candidate regions during the detection process, so the detection speed has been greatly improved. The SSD algorithm uses the feature maps of different convolutional layers to achieve target detection of different sizes [7]. SSD uses VGG-16 as the basic component of the network to improve and optimize. Using the transfer learning theory, the last two full connection layers of VGG-16 network structure are replaced by the convolution layer. Meanwhile, four convolution layers are added to construct the complete SSD network structure. The feature pyramid of SSD network structure is realized by using the feature graph of six different convolutional layers.

For each feature map, two different $3 \times 3$ convolution kernels are used to output the confidence level and regression coordinates. Among them, each default box generates 21 categories of confidence and 4 coordinate values $(x, y, w, h)$. The core idea of the SSD network is to use feature maps of different sizes for convolution calculations to detect target objects of different sizes. Each default box needs to predict the scores of the categories and 4 offsets. Assuming that each feature map cell generates $k$ default box, then for a $m \times n$ size feature map, $m \times n$ feature graph units and $k \times m \times n \times (c + 4)$ output will be generated. Where $k \times m \times n \times c$ is the confidence level of each default box, that is, the probability of the category; $k \times m \times n \times 4$ is the coordinates of each default box after regression. In the training process of transfer learning, a complete picture should be sent to the network and each feature map should be obtained. Then, the default box actually selected should be matched with the real label. If the match is successful, it means that the actual default box contains the desired target, and the default box is positive sample. If the match fails, the default box is negative sample.

SSD network uses feature maps of different layers to detect objects of different sizes. Feature maps of different layers generate default boxes with different scales to cover objects of different shapes and sizes. SSD defines the scale formula of default box as follows [8]:

$$s_k = s_{\min} + \frac{s_{\max} - s_{\min}}{m - 1}(k - 1), k \in [1, m] \tag{1}$$

Among them, $m$ represents the number of feature maps, $s_{\min}$ represents the scale size of the lowest level feature map, and its value is 0.2 by default, and $s_{\max}$ represents the scale size of the highest level feature map, and its value is 0.9 by default. SSD also defines 5 different default frame aspect ratios, as shown in the following formula, the aspect ratio is represented by $a_r$:

$$a_r = \left\{1, 2, 3, \frac{1}{2}, \frac{1}{3}\right\} \tag{2}$$

Thus, the width $w_k^a$ and height $h_k^a$ of each default box can be calculated as follows:

$$\begin{cases} w_k^a = s_k \cdot a_r \\ h_k^a = \dfrac{s_k}{\sqrt{a_r}} \end{cases} \tag{3}$$

After the default frame size is determined, the SSD algorithm is optimized and improved using migration learning technology. In the training process, the loss is composed of two parts: positioning loss and confidence loss. As shown in the following formula [9]:

$$L(x, c, l, g) = \frac{1}{N}\left[L_{conf}(x, c) + \alpha L_{loc}(x, l, g)\right] \tag{4}$$

Where $x$ is the Jaccard coefficient matching the $i$ selection default box with the $j$ real label box of category $p$. $c$ represents the confidence level, $l$ represents the prediction box, $g$ represents the real label box, $N$ represents the number of matches between the real label box and the actual selected default box, $L_{conf}$ represents the confidence loss, and $L_{loc}$ represents the positioning loss.

By reducing the loss function, the network is trained to obtain the optimal parameters. After using the algorithm to determine the parameters to locate the logistics distribution license plate, a dynamic scheduling model is constructed to realize the scheduling of vehicles.

### 3.2 Realize the Dynamic Scheduling of Distribution Vehicles

The dynamic vehicle scheduling problem is evolved from the static vehicle scheduling problem, and its main feature is the uncertainty of logistics information. According to the relevant literature on the dynamic vehicle scheduling problem, it can be described as: before optimizing the execution of scheduling, collecting information related to distribution, including customer demand information, cargo distribution information, and dispatching vehicle information, etc., this information is called Is the delivery information. In the process of performing optimal scheduling, the collected distribution information may change over time, and the changed information needs to be optimized and adjusted, instead of using the previous distribution route.

The optimization objective of dynamic vehicle scheduling problem is to minimize the transportation cost or distribution cost. The constraints include the maximum vehicle load constraint, the distribution time constraint and various specified conditions. A customer can only have one vehicle to distribute, and the distribution vehicle starts from the distribution center and must return to the distribution center. The dynamic vehicle scheduling can be regarded as a static vehicle scheduling problem at each time. By calculating the optimal distribution cost at each time, the optimal total distribution cost can be obtained.

The mathematical model of dynamic vehicle scheduling of the entire system is established through the above constraints, and the following variables are defined: $t$ represents the time of the entire distribution network; $o$ represents the distribution center; $P$ represents the key point.

In order to make the driving route arrangement flexible, the number of vehicles required to complete the delivery task at time $t$ can be estimated in advance. The process is as follows:

$$M = \left\lfloor \frac{\sum\limits_{i \in W_u(t)} q_i}{Q} \right\rfloor + 1 \tag{5}$$

Among them, $M$ is the total number of distribution vehicles that complete all the distribution requirements at time $t$; [] is the downward rounding of the values in brackets, that is, the integer part; $i$ is the $i$ customer, $W_u(t)$ is the dynamic customer and static customer set of unfinished distribution service at time $t$; $q_i$ is the cargo demand of the $i$ customer at time $t$; $Q$ is the maximum load capacity of the distribution vehicle [10].

To establish $t$ mathematical model of the dynamic vehicle scheduling problem at time A, first define two decision variables $x_{ijk}$ and $y_{ki}$. When the value of $x_{ijk}$ is 1, it means that the vehicle $k$ is driving from point $i$ to point $j$; otherwise, the value of $x_{ijk}$ is 0. When the value of $y_{ki}$ is 1, it means that the delivery task of point $i$ is completed by vehicle $k$; otherwise, the value is 0.

Then the objective function of the model is as follows:

$$MinZ = F + \sum_{i,j \in W_{upo}(t)} \sum_{k=1}^{M} c_{ij} x_{ijk} \tag{6}$$

Among them, $Z$ represents the objective function of the model; $F$ is the fixed cost of distribution vehicles; $i$ and $j$ are the $i$ customer and the $j$ customer respectively; $W_{upo}(t)$ is the collection of dynamic customers, all key customer points, static customers who have not completed the distribution service and distribution center at $t$ time; $k$ is the $k$ vehicle; $c_{ij}$ is the transportation cost from customer point $i$ to $j$.

Constraints of logistics distribution:

$$\begin{aligned} & \sum_{i \in W_u(t)} q_i y_{ki} \le Q - Q_{jk}(t) \\ & j \in W_{uo}(t), k = 1, 2, \cdots, M \end{aligned} \tag{7}$$

Equation (7) means that the sum of the cargo volume carried by vehicle $k$ is not greater than the maximum load capacity of the vehicle; where $W_u(t)$ represents the set of dynamic customers who put forward new demands at time $t$ and static customers who have not completed the delivery service; $W_{uo}(t)$ represents the distribution center and time $t$ A collection of dynamic customers who propose new requirements and all static customers who have not completed the delivery service; $Q_{jk}(t)$ represents the cumulative weight of the goods after the delivery vehicle departs from customer $i$ at time $t$ ($Q_{0k}(t) = 0$, represents the cumulative weight of the delivery vehicle from the distribution center 0).

After the above model is established, the genetic algorithm is used to solve the model, and the vehicle scheduling scheme is obtained. All the customer points are numbered according to the number a, and these customer points are grouped into chromosomes by natural number coding according to the constraint conditions of the problem. Each gene in the chromosome represents $(1, 2, \cdots, K)$ customer. Since the distribution vehicles need to return to the distribution center after completing the distribution service, the representative distribution center is inserted into these chromosomes to distinguish each sub path.

This paper uses the nearest neighbor search method to create a better initial population of individuals. First, randomly select a customer point as the starting node for the search, find the closest customer node as the suffix node, and then find the closest node to the suffix node as the suffix node, until the demand for these nodes meets the vehicle capacity limit, then a line is formed Sub-path, find the next sub-path in this way, until all customer points are allocated. Then calculate the fitness value of each individual for comparison, select the individual with the largest fitness function value to enter the next-generation mutation, and calculate the population fitness. Select individuals who meet the constraints of the model for mutation processing. Repeat the above steps until the individual fitness function does not change, stop the calculation. The current calculation result is the optimal dispatching plan for the delivery vehicle.

Through the above research on the hardware and software parts of the system, the design of intelligent vehicle scheduling system for logistics distribution based on transfer learning is completed.

## 4 Test Experiment

In order to test the effectiveness of the intelligent scheduling system for logistics distribution vehicles based on transfer learning designed in this study, the following experiments were designed on the Matlab platform.

### 4.1 Experiment Design

Contrastive experiments were introduced in this study. Among them, the experimental group is the intelligent logistics distribution vehicle scheduling system based on transfer learning designed in this paper, and the contrast group is the traditional logistics distribution scheduling system. In order to comprehensively verify the performance of the two groups of logistics distribution scheduling systems, the comparative experimental indicators of this experiment are: the cost of logistics distribution under different systems scheduling and the total distance of distribution routes.

This experiment is carried out in the same logistics distribution, and a certain number of customer points are set. The dispatcher uses the scheduling system of the experimental group and the comparison group respectively to dispatch the logistics distribution vehicles. The test contents of the vehicle driving route scheme formulated by the dispatcher are shown in Table 2.

### 4.2 Experimental Results and Analysis

In the process of the experiment, the realization of the logistics distribution process to determine the cost and its single value, and then the application of different systems after the statistical distribution cost compared with it. The various costs of logistics distribution process and their individual value contents are shown in Table 3.

After applying the experimental group and the comparative group system to logistics vehicle scheduling, the data of logistics distribution cost and total distance of vehicle distribution are shown in Table 4.

According to the analysis of the data in Table 4, the logistics distribution cost and total distribution distance of the experimental group system are lower than those of the control group system. The data in Table 4 shows that there are many distribution paths

**Table 2.** Test cases of developing vehicle distribution scheme

| Numbering | Content | Describe |
|---|---|---|
| 1 | Features | Make a departure plan |
| 2 | Specific description | Generating delivery service sequence of vehicles |
| 3 | Enter | User demand information, vehicle attribute information, traffic status information |
| 4 | Process | Input customer demand information and vehicle resource information |
| 5 | | Enter traffic information |
| 6 | | Optimize the delivery route |
| 7 | Expected results | If the information is not entered and optimized directly, it will prompt “no relevant information has been entered”; if it is entered, it will be prompted that “no relevant information has been entered”<br>Relevant information and route optimization will generate a vehicle delivery service sequence |

**Table 3.** Cost parameters of logistics distribution

| Serial number | Project | Parameter |
|---|---|---|
| 1 | Unit distance freight | 50/km |
| 2 | Unit freight | 100/$m^3$ |
| 3 | Distribution loss | 300/Times |
| 4 | Time costs | 100/h |
| 5 | Distribution staff cost | 200/Person times |
| 6 | Maximum total distribution | 1000 $m^3$ |
| 7 | Number distribution centers | 2–3 |
| 8 | Distribution center operating costs | 1000/day |

that need vehicles to go through repeatedly in the scheduling process of the control group system, which not only increases the total cost of distribution, but also leads to the long distribution distance, which leads to the failure to guarantee the timeliness of distribution.

In summary, it can be seen from the analysis of the above experimental results that the scheduling system based on transfer learning designed in this paper can not only save the logistics distribution cost, but also improve the real-time performance of logistics distribution, with higher practical value.

**Table 4.** Logistics distribution cost and total distance

| Serial number | Experimental group system | | Contrast group system | |
|---|---|---|---|---|
| | Distribution cost/Thousand yuan | Total distance of distribution/Km | Distribution cost/Thousand yuan | Total distance of distribution/Km |
| 1 | 24.91 | 38.65 | 28.63 | 42.92 |
| 2 | 27.27 | 29.78 | 33.62 | 33.08 |
| 3 | 22.36 | 26.43 | 26.57 | 35.68 |
| 4 | 12.24 | 18.91 | 15.65 | 25.47 |
| 5 | 16.95 | 17.66 | 19.28 | 29.53 |
| 6 | 13.85 | 14.27 | 17.31 | 27.62 |
| 7 | 19.46 | 20.06 | 24.08 | 28.09 |
| 8 | 28.76 | 41.59 | 34.53 | 51.00 |

## 5 Conclusion

An important prerequisite for the stable development of the modern logistics industry is to reduce logistics transportation costs, and the key to solving the transportation cost problem in the logistics industry is to optimize the logistics system. The key step in the optimization of the logistics system is the reasonable dispatch of logistics delivery vehicles. By optimizing the dispatch of delivery vehicles, enterprises can reduce transportation costs and improve customer service levels and economic benefits. This paper designs an intelligent dispatching system for logistics distribution vehicles based on transfer learning, and uses transfer learning to effectively improve the reliability and real-time performance of the dispatch system. Through related experiments, it is verified that the system in this paper has practical value.

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