Research on Cargo Volume Forecasting and Vehicle Scheduling Based on LSTM-Linear Regression and Integer Programming

Wei Huang[1,a,*], Ruipeng Dong[2,b], Hongyu Liao[1,c]

[1]Chongqing University of Posts and Telecommunications, Chongqing, China

[2]Wuhan University of Technology, Wuhan, China

[a]857367517@qq.com, [b]1612862531@qq.com, [c]2112940497@qq.com

*Corresponding author

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Abstract: This paper aims to improve transportation efficiency and control costs by integrating LSTM, linear regression and integer programming to predict the volume of goods and dispatch vehicles in short-distance logistics transportation. First, the LSTM model optimized by Bayesian optimization is used to predict the daily volume of goods on each route, and then the prediction results are refined to 10-minute granularity through linear regression. In terms of scheduling strategy, the transportation task is divided into two stages: Stage 1 handles the whole volume of goods, and uses the greedy algorithm to prioritize the dispatch of owned vehicles to reduce costs; Stage 2 uses integer programming to generate a tail cargo point-to-point solution with the goal of minimizing total cost and maximizing the turnover rate of owned vehicles and the vehicle full load rate. In order to further improve efficiency, containerization operations are introduced to shorten the loading and unloading time to 10 minutes. Although the loading volume is reduced to 800 units, the model optimizes the turnover efficiency in stages by preferentially allocating containers to owned vehicles that can be dispatched again. Stage 1 calculates the vehicle return time after the container is used, and stage 2 uses the owned vehicles that return early to reduce the demand for external vehicles and outputs the decision on whether the vehicle uses the container. After introducing a random disturbance of about 5%, the results show that the turnover rate of owned vehicles remains stable, the vehicle loading balance fluctuates slightly, and the total cost is more sensitive to the prediction deviation, indicating that the model has a certain degree of robustness in terms of efficiency and load, but relies on prediction accuracy in cost control.

1. Introduction

Short-distance transportation, as the "last mile" of logistics, connects distribution centers to end consumers and directly impacts customer satisfaction. Efficient short-haul delivery ensures timely services like same-day or next-day delivery, boosts customer trust, and supports business growth. It also bridges long-distance transport modes and enhances the overall logistics efficiency. Moreover, it facilitates regional goods circulation, drives retail development, and allows delivery personnel to collect valuable customer feedback.

Accurate cargo volume forecasting and smart vehicle scheduling are crucial to its effectiveness. Forecasting helps allocate resources and plan routes, while real-time vehicle dispatching optimizes capacity use, reduces delays and costs, and enables personalized services. Together, they ensure timely delivery, lower operational risks, and maximize the value of short-distance transportation in the logistics chain.

In the field of logistics and transportation, cargo volume forecasting and scheduling optimization have become important research directions for improving transportation efficiency and reducing operating costs. Chou et al. [1] used fuzzy regression methods to predict air cargo volume in the early stage, providing ideas for modeling transportation demand under uncertain environments.

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With the development of intelligent algorithms, Gurnak et al. [2] proposed intelligent management of logistics supply chains based on transportation volume forecasting, emphasizing the key role of forecasting in the optimization of the entire chain. In recent years, deep learning methods have gradually been introduced into cargo volume forecasting tasks. Luo et al. [3] combined ARIMA with LSTM to construct a hybrid forecasting model to improve the accuracy of cargo volume forecasting and adapt to the nonlinear and time-series characteristics of logistics data. At the same time, Haonan [4] and Chencheng [5] also explored the integration of neural networks and integer programming, using BP neural networks and multi-objective programming (MOP) models to solve comprehensive problems such as freight forecasting and personnel scheduling. Based on previous work, this paper comprehensively applies LSTM, linear regression and integer programming algorithms, and introduces Bayesian optimization to further improve the prediction accuracy. While ensuring the internal vehicle turnover rate and vehicle loading balance, it optimizes the total cost control strategy, showing stronger practicality and robustness, and expanding the depth and breadth of the application of intelligent scheduling models in the field of logistics.

2. Model building and solving

2.1. Daily cargo volume prediction model based on LSTM

The total cargo volume of each route is visualized, and the total cargo volume from 0:00 to 23:50 every day from December 1, 2024 to December 15, 2024 is selected as the daily cargo volume. The changes in daily cargo volume of some routes are shown in Figure 1.

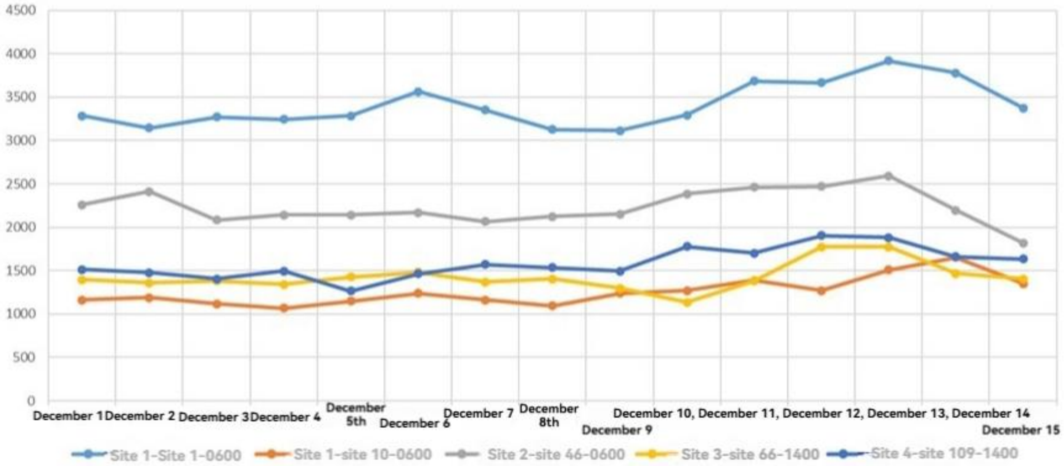

Figure 1 Changes in daily cargo volume on some routes.

According to Figure 1, the daily cargo volume of each route changes generally smoothly. It can be roughly considered that special time points such as "Double 12" and weekends have no effect on the daily cargo volume, so no data outlier processing is performed.

The total cargo volume of each time period is visualized, and the cargo volume in every ten minutes from 0:00 to 23:00 is summed up. Finally, the cargo volume change of each time period is shown in Figure 2.

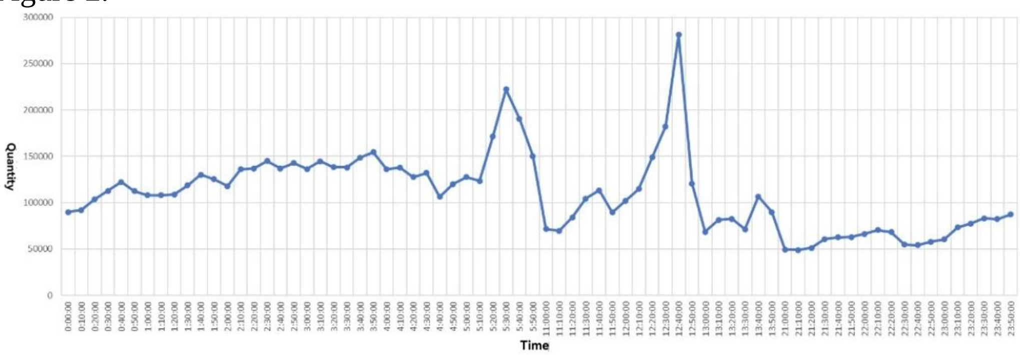

Figure 2 Changes in cargo volume over time

From the analysis of Figure 2, we can see that there are two peak intervals for cargo generation in a day, namely: 5:00~5:50 and 12:00~13:00. 21:00~24:00 is the time period with the lowest cargo generation in a day, and the cargo generation is about 25% of the peak generation. The cargo generation in other time periods is similar, about 50% of the peak generation.

The LSTM model can handle the long-term dependency problem in time series. It can learn the complex time patterns in the data and effectively capture the possible long-term dependency relationship of cargo volume data. This paper selects the LSTM model to predict the future daily cargo volume.

The LSTM model is essentially an improvement on the traditional RNN. Its structure can improve the problems of excessive weight influence and gradient disappearance during RNN training, and has better processing capabilities for long time series. Compared with RNN, LSTM adds three gates, namely input gate, forget gate, and output gate, and each is connected to a multiplication element. By setting the weights at the edge where the memory unit of the neural network is connected to other parts, the input, output and state of the cell unit of the information flow are controlled. The LSTM unit can store useful data for a long time and capture long-term dependencies better than the traditional RNN. Its structure diagram is shown in Figure 3.

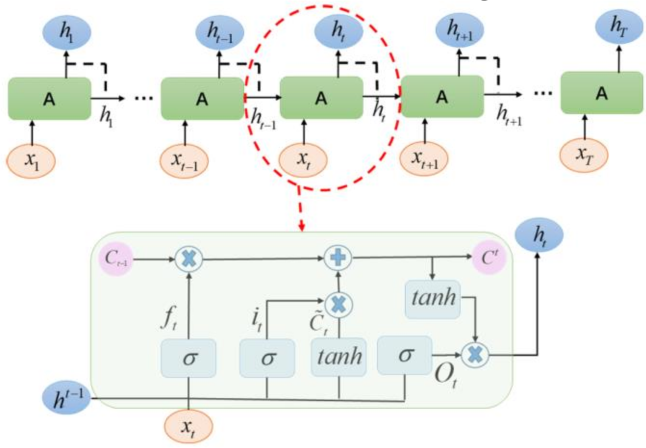

Figure 3 LSTM Schematic.

LSTM is suitable for processing cargo volume data with time series characteristics. The forget gate determines the information to be discarded from the current state input and uses the activation function to selectively forget the information, as shown in the following formula:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{1}$$

The input gate mainly determines which information is taken and updates the information, as shown in the following formula:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{2}$$

$$C_t = tanh\left(W_c \cdot [h_{t-1}, x_t] + b_c\right) \tag{3}$$

Update the cell state, add the information passing through the forget gate and the new information passing through the input gate to get the new state, as shown in the following formula:

$$C_t^{'} = C_{t-1}^{'} \cdot f_t + C_t \cdot i_t \tag{4}$$

Output gate, Sigmoid determines the output part, and then multiplies it with the updated cell state to get the final output, as shown in the following formula:

$$O_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{5}$$

$$h_t = O_t \cdot \tanh(C_t^{'}) \tag{6}$$

$$y_t = f(W_p \cdot h_t + b_p) \tag{7}$$

According to the prediction model established above, the data grouped by route and date are imported into the model for training, and the LSTM network is subjected to Bayesian optimization, mainly optimizing the number of network layers and neurons. Finally, the cargo volume on December 16 is predicted, and the prediction results of some routes are shown in Figure 4.

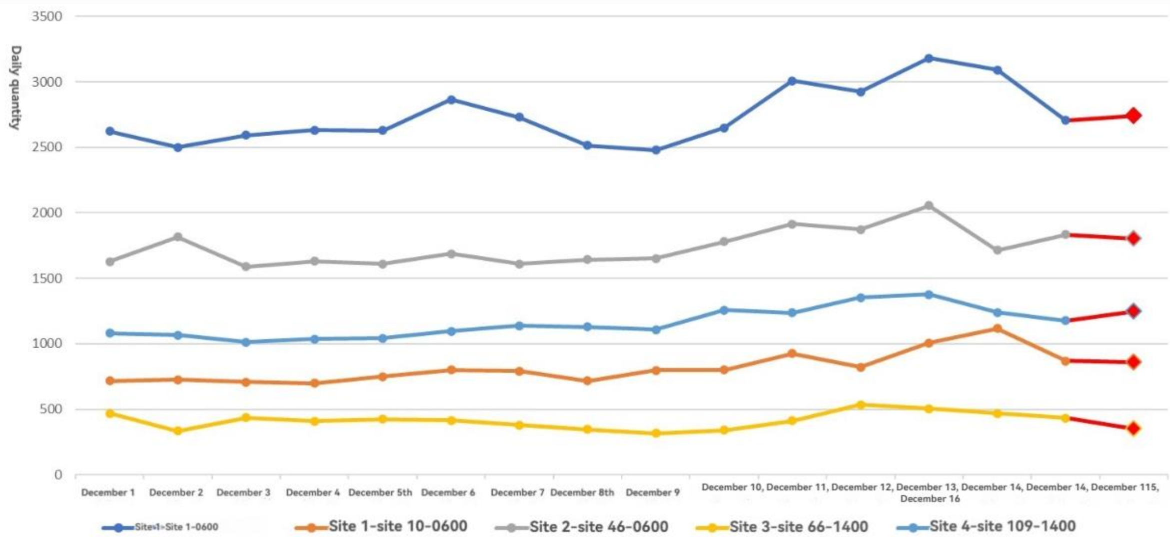

Figure 4 Cargo volume forecast for some routes on December 16

By observing Figure 4, we can see that the data is generally flat without major fluctuations, which is consistent with the law shown in Figure 1, indicating that the predicted results are highly reliable. The prediction results of some lines are shown in Table 1.

Table 1 Daily cargo volume forecast results for some routes

Line Coding	Date	Volume
Site 3 - Station 83-0600	2024/12/16	4141
Site 3 - Station 83-1400	2024/12/16	771

2.2. 10-minute granularity cargo volume prediction model based on linear regression

By observing the data, it is found that the difference in cargo volume of each route in the same time period on different dates is small, and there is a relatively obvious linear correlation, so linear regression is selected to predict the cargo volume of each route at a 10-minute granularity.

The principle of linear regression is simple and the calculation is efficient. It only needs to fit the linear equation through the least squares method, without complex iteration or parameter tuning. It is suitable for rapid deployment and real-time prediction, and the model is highly interpretable and the physical meaning of the model parameters is clear. The model structure is as follows:

$$y_t = \alpha + \beta t + \epsilon_t \tag{8}$$

y_t: predicted value of cargo volume at time t, α: intercept, β: trend slope, t: time variable (10 minutes), ϵ_t: random error term (obeys normal distribution).

Fitting process: Minimize the sum of squared errors by the least squares method to solve the parameters α and β

$$\beta = \frac{\sum_{i=1}^{n}(t_i - \bar{t})(y_i - \bar{y})}{\sum_{i=1}^{n}(t_i - t)^2} \tag{9}$$

$$\alpha = \bar{y} - \beta \bar{t} \tag{10}$$

n is the number of historical data points, $\bar{t}$ and $\bar{y}$ are the means of time and volume.

The 10-minute granularity cargo volume forecast results for some routes are shown in Table 2.

Table 2 10-minute granularity cargo volume forecast results for some routes

Line Coding	Date	Minutes start	Volume
Site 3 - Station 83-0600	2024/12/15	21:00:00	51
Site 3 - Station 83-0600	2024/12/15	21:10:00	136
Site 3 - Station 83-0600	2024/12/15	21:20:00	51
…	…	…	…
Site 3 - Station 83-1400	2024/12/16	13:30:00	12
Site 3 - Station 83-1400	2024/12/16	13:40:00	64
Site 3 - Station 83-1400	2024/12/16	13:50:00	34

2.3. Integer Programming Based on Tail Goods

Taking the route of site 1-0600 as the research object, the accumulated cargo volume in each time period (10-minute granularity) is counted. The departure times indicate the number of trips that depart once the cargo volume reaches 1000, and the final tail cargo indicates the residual cargo volume of the route when approaching the deadline. It can be seen that in the later time periods, the cargo volume quickly exceeds 1000. When the cargo volume accumulates to 1000, it is necessary to dispatch vehicles immediately to send the cargo, and return the internal vehicles as quickly as possible for the second transportation to improve the utilization rate of internal vehicles. In addition, the cargo must be sent before the node time. In the later time periods, the work intensity will be high due to the large amount of accumulated cargo, so it is more appropriate to send the cargo immediately after the cargo volume reaches 1000.

In the first part of the first phase of the work, the first task is to determine the number of external vehicles required. According to the data, the total number of internal vehicles is fixed, so it is necessary to calculate the number of external vehicles that need to be deployed in the dispatching method of dispatching vehicles when the cargo volume reaches 1000.

First, set the total number of vehicles as a variable parameter, the lower limit is the number of internal vehicles (internal vehicles can be transported at least once), the upper limit is set to a sufficiently large value, and then gradually increase the number of vehicles. When the number of vehicles is small, there may be a backlog of goods, and the backlog of goods will continue until the departure deadline.

If the maximum remaining cargo volume of a station at the deadline is greater than or equal to 1000, it means that the current number of vehicles is insufficient to meet the transportation demand of dispatching vehicles when the number of vehicles reaches 1000. Only when a certain total number of vehicles makes the backlog of cargo on all routes at the deadline just not exceed 1000, this number of vehicles is the minimum number of vehicles required in the first stage. Taking site 1-0600 as an example, the minimum number of vehicles is calculated to be 75 (three vehicles can be loaded for the second time) and the minimum number of transportation times is 78, of which the number of internal vehicles is 29.

In the process of solving the minimum number of vehicles, the number of departure and return vehicles at each time point with an interval of 10 minutes can also be determined. However, the previous part only finds the minimum number of vehicles. Next, it is necessary to further clarify whether to choose internal vehicles or external vehicles to deliver the goods to the designated station at different times. This is a typical vehicle assignment problem. If a comprehensive optimization solution is performed, a large number of combinations will be generated. For example, if 10 vehicles are involved in two cargo deliveries, each time we need to consider a series of complex issues such as which vehicle returns, whether the returning vehicle is an internal vehicle, and which station the vehicle will go to next. In order to simplify the problem, the greedy algorithm is used to handle it. The core goal of the greedy algorithm is to minimize the total transportation cost by reasonably allocating internal and external vehicles. The variables that need to be decided include: given the total number of vehicles, the departure time points, and the number of return vehicles, determine the attributes of each vehicle at different time points (whether it is an internal vehicle or an external vehicle), as well as the departure time and return time of each internal vehicle, and whether there is a second departure.

From the data, we can see that the cost of internal vehicles is lower than that of external vehicles in any case. In order to reduce costs and increase the turnover rate of internal vehicles, when a decision can be made each time, if there is an idle internal vehicle, the internal vehicle will be given priority; if there is no idle internal vehicle, the external vehicle will be sent. Finally, we can get the arrangement of sending vehicles when the cargo volume is full of 1,000.

At the last minute, close to 9 o'clock, the tail goods were processed and all internal vehicles had been dispatched. Currently, the only vehicles left at station 1 were external vehicles. Therefore, with the goal of minimizing the cost, integer programming can be performed for external vehicles.

There are 36 sites to be visited. Although the number of external vehicles is theoretically unlimited, we can assume that there are 36 external vehicles. However, when planning the route to connect the various sites, some external vehicles do not need to participate in this task and will not go to any site throughout the journey.

Assume that the decision variable is a 36×36 matrix. In this matrix, each row corresponds to a car, and each column corresponds to a station. This is a 0-1 matrix. When the value of a certain position in the matrix is 1, it means that the car corresponding to the position will drive to its corresponding station; when the value of a certain position is 0, it means that the car corresponding to the position will not go to its corresponding station. The matrix table is shown in Table 3.

Table 3 Decision variable table

	Site 1	Site 2	…	Site 36
Vehicle 1	$X_{1,1}$	$X_{1,2}$	…	$X_{1,36}$
Vehicle 2	$X_{2,1}$	$X_{2,2}$	…	$X_{2,36}$
…	…	…	…	…
Vehicle 36	$X_{36,1}$	$X_{36,2}$	…	$X_{36,36}$

(1) Since the number of all the remaining goods is less than 1,000, they must be transported by one vehicle. In addition, in order to reduce the complexity of transportation and avoid excessive connection points that increase costs, we let the vehicles at one station be transported by one vehicle,so the sum of the decision variables in each column of the matrix must be 1. That is:

$$\sum_{i=1}^{36} X_{i,j} = 1 \cdots (j = 1, 2 ... 36 \cdot) \tag{11}$$

(2) There is another scenario for transportation demand: for some adjacent routes, if the quantity of goods is small, or the remaining quantity of goods after the whole vehicle is shipped is not enough to fill a whole vehicle, the quantity of goods on multiple routes will be integrated and shipped by one vehicle. This scenario is called "connecting points". Usually, the number of routes involved in "connecting points" is not allowed to exceed 3. In other words, a vehicle will only pass through 3 stations at most, which is reflected in the previously assumed matrix, that is, the sum of all components in each row of the matrix is less than or equal to 3. That is:

$$\sum_{j=1}^{36} X_{i,j} \le 3 \cdots (i = 1, 2 \ldots 36) \tag{12}$$

(3) Because we judge that the total number of remaining goods is less than 1,000, there is no need to split these goods, so the number of goods loaded on each vehicle should be equal to the sum of the number of goods to be delivered to each station. Let's make a mark, and record the number of goods that need to be delivered from site 1 to each station at 6 o'clock as $S_1, S_2, \ldots, S_{36}$ respectively, then:

$$\sum_{j=1}^{36} S_j \cdot X_{i,j} \le 1000 \cdots (i = 1, 2 \ldots 36) \tag{13}$$

(4) Some stations can be connected in series. In this case, we need to determine whether each station can be connected in series. Suppose there are two stations p and q. If they can be connected in series, this means that in the corresponding decision matrix, the variable $X_{i,p}$ representing the first car going to station p and the variable $X_{i,p}$ representing the first car going to station q can both take the value of 1. Conversely, if these two stations cannot be connected in series, then at most only one of the two variables $X_{i,p}$ and $X_{i,p}$ can take the value of 1. Based on the above situation, we get:

$$X_{i,p} + X_{i,q} \le 1 \cdots (i, p, q = 1, 2 \ldots 36 \text{ and } p \ne q) \tag{14}$$

(5) The decision variable is an integer between 0 and 1.

$$X_{i,j} \in [0,1] \text{ and } X_{i,j} \in Z \tag{15}$$

(6) The quantity of goods is non-negative.

$$S_j \ge 0, \forall j \tag{16}$$

Considering the actual situation, it is believed that the transportation method with the lowest cost is the best. Therefore, the cost factor is first considered as the key object. In the current situation, all external vehicles are used, so there are cost prices for external vehicles to transport from site 1 to each site, which are recorded as C_1、C_2,...,C_{36} respectively. Since it involves the "link point" transportation mode, assuming that the goods are delivered to sites 1 and 2, the cost of going to site 1 is m yuan (according to experience, it is the minimum cost to go to site 1), and the cost of going to site 2 is n yuan (according to experience, it is the minimum cost to go to site 2). If you finally go to site 2, and going to site 1 is on the way, the cost is n yuan. If it is not on the way, it is (m+k) yuan, k is the cost from site 1 to each site, but (m+k)>n, so it is more accurate to take the maximum cost, so in fact the cost of the i-th vehicle should be:

$$Max\{C_1 X_{i,1}, C_2 X_{i,2}, ..., C_{36} X_{i,36}\} \tag{17}$$

It is not possible to take the maximum value and then process it in the objective function. Take the negative sign to convert it into the minimum value form. Finally, the lowest total cost can be expressed as:

$$-Min\left\{-C_1 X_{i,1}, -C_2 X_{i,2}, ..., -C_{36} X_{i,36}\right\} \tag{18}$$

In summary, the car platooning model based on integer programming is:

$$-Min\{-C_1 X_{i,1}, -C_2 X_{i,2}, ..., -C_{36} X_{i,36}\}$$
$$s \cdot t \begin{cases} \sum_{i=1}^{36} X_{i,j} = 1 \quad (j = 1, 2 ... 36) \\ \sum_{j=1}^{36} X_{i,j} \le 3 \cdots (i = 1, 2 ... 36) \\ \sum_{j=1}^{36} S_j \cdot X_{i,j} \le 1000 \cdots (i = 1, 2 ... 36) \\ X_{i,p} + X_{i,q} \le 1 \cdots (i, p, q = 1, 2 ... 36 \ and \ p \ne q) \\ X_{i,j} \in [0,1] \ and \ X_{i,j} \in Z \\ S_j \ge 0, \forall j \end{cases} \tag{19}$$

According to the above model, the model is programmed and solved, and then the final result is obtained by summarizing the results of the cargo volume of 1000 or more. The scheduling results of some routes are shown in Table 4.

Table 4 Partial line dispatch results

Line Coding	Date	Estimated delivery time	Shipping vehicle
Site 3 - Station 83 - 0600	2024/12/16	00:30:00	5
Site 3 - Station 83 - 0600	2024/12/16	03:00:00	68
Site 3 - Station 83 - 0600	2024/12/16	05:50:00	99
Site 3 - Site 60 - Site 83 - 0600	2024/12/16	06:00:00	118
Site 3 - Site 70 - Site 83 - 1400	2024/12/16	14:00:00	48

2.4. Optimizing vehicle turnover rate by phased decision considering standard containers

2.4.1. Phase I analysis

There is currently a standard container that significantly reduces the loading and unloading time of vehicles using this container to 10 minutes, and the vehicle load will be reduced from 1,000 to 800. For this container, this article will adjust it according to the vehicle dispatch situation mentioned above.

First, analyze which vehicles can use this container and divide the vehicles into the following situations:

1) Internal vehicles that are dispatched just at the latest departure time and cannot be dispatched again.

2) Internal vehicles that are dispatched fully before the latest departure time and can return for a second load.

3) Internal vehicles that are dispatched fully before the latest departure time but cannot return for a second load under normal circumstances.

4) Internal vehicles that cannot return for a second load under normal circumstances and using this container before the latest departure time.

5) External vehicles.

In the above five situations, since there is no limit on the number of external vehicles and the cost is high, all external vehicles do not use this container. For the internal vehicles belonging to Case 1 and Case 4, using the container will not only fail to increase the number of loading times, but will also reduce the loading volume, so it is not suitable to use the container. At the same time, the internal vehicles belonging to Case 2 are also not suitable to use the container because they can return to load for the second time under normal circumstances, and using the container will reduce the loading volume. Therefore, based on the above description, the internal vehicles that are suitable for using the container are only those belonging to Case 2.

In order to explain the situation in detail, this article takes the vehicles at each station in the time period of site 1 - 0600 as an example. Based on the above, all vehicles suitable for installing the container can be obtained, as shown in Table 5:

Table 5 The time before and after the container vehicle is installed and returned

Internal car destination	Dispatch time	Return time	Return time after adding container
1	35	57	50
21	35	59	52
17	36	61	54
2	37	58	51
4	37	58	51
5	39	56	49
20	39	56	49
16	40	61	54
30	40	58	51
32	40	61	54
15	41	60	53
7	42	61	54
25	42	56	49
34	43	58	51

Since these vehicles are all internal vehicles and their return time is close to the last departure time, considering that the follow-up goods can hardly fill the vehicles even at the last departure time, the remaining goods can be transported by external vehicles. All internal vehicles in the table will be retained for continued use in the second phase of planning.

2.4.2. Phase II analysis

The decision variables are changed to the first 14 cars being internal cars and the last 14 cars being external cars. The rest remain unchanged, and the same decision conditions as in 2.3 above are used.

This article has two types of vehicles, internal vehicles and external vehicles, so when calculating the cost, we should distinguish between the two situations and calculate the specific vehicle. According to the above content, we still record the transportation cost of external vehicles as $C_1, C_2, \dots, C_{36}$. Since there is transportation of internal vehicles, we can record the transportation cost of internal vehicles as $C_1, C_2, \dots, C_{36}$,. Due to the existence of the string point situation, we still take the method of taking the maximum cost, so the actual cost of the j-th vehicle should be:

$$Max\{C_1' X_{i,1}, C_2' X_{i,2}, \dots, C_{36}' X_{i,36}\} \cdots (i = 1, 2 \dots 14) \tag{20}$$

$$Max\{C_1 X_{i,1}, C_2 X_{i,2}, \dots, C_{36} X_{i,36}\} \cdots (i = 15, 16 \dots 36) \tag{21}$$

It is not possible to take the maximum value and then process it in the objective function. Take the negative sign to convert it into the minimum value form. Finally, the lowest total cost can be expressed as:

$$-Min\{C_1' X_{i,1}, C_2' X_{i,2}, \dots, C_{36}' X_{i,36}\} - Min\{C_1 X_{i,1}, C_2 X_{i,2}, \dots, C_{36} X_{i,36}\} \tag{22}$$

The car platooning model based on integer programming is:

$$-Min\{C_1' X_{i,1}, C_2' X_{i,2}, \dots, C_{36}' X_{i,36}\} - Min\{C_1 X_{i,1}, C_2 X_{i,2}, \dots, C_{36} X_{i,36}\}$$

$$s.t \begin{cases} \sum_{i=1}^{36} X_{i,j} = 1 \quad (j = 1, 2, \cdots, 36) \\ \sum_{i=1}^{36} X_{i,j} \le 3 \quad (i = 1, 2, \cdots, 36) \\ \sum_{i=1}^{36} S_j \cdot X_{i,j} \le 1000 \quad (i = 1, 2, \cdots, 36) \\ X_{i,p} + X_{i,q} \le 1 \quad (i, p, q = 1, 2, \cdots, 36) \\ X_{i,j} \in [0,1] \ and \ X_{i,j} \in Z \\ S_j \ge 0, \forall j \end{cases} \tag{23}$$

According to the above, based on the objective functions of the two stages, the results are obtained by programming and solving. Finally, the overall objective functions of the two stages are as follows: cost 1 (ownership vehicle turnover rate) is 1.4483, cost 2 (vehicles are all packaged) is 1010.2784, and cost 3 (total cost) is 16522. The results of some route scheduling are shown in Table 6:

Table 6 Partial line dispatch results

Line Coding	Date	Estimated delivery time	Whether to use container	Delivery vehicle
Site 3 - Station 83 - 0600	2024/12/16	00:20:00	No	29
Site 3 - Station 83 - 0600	2024/12/16	03:10:00	No	70
Site 3 - Station 83 - 0600	2024/12/16	05:50:00	No	99
Site 3 - Station 83 - 0600	2024/12/16	06:00:00	No	104
Site 3 - Station 83 - 1400	2024/12/16	14:00:00	No	24

3. Conclusion

In summary, the logistics short-distance transportation optimization model based on LSTM, linear regression and integer programming proposed in this paper shows strong practicality and robustness in cargo volume forecasting and vehicle scheduling. By introducing Bayesian optimization to improve the prediction accuracy and refine it to high time resolution, the model can effectively support the formulation of scheduling strategies. The actual simulation results show that when the model faces cargo volume forecast deviation, the internal vehicle turnover rate and the average package volume of vehicles show good stability, reflecting the reliability of vehicle resource utilization efficiency and loading balance; but in terms of total cost, it is more sensitive to forecast deviation, suggesting that attention should be paid to the improvement of forecast accuracy in future applications. Overall, the model has clear logic, reasonable structure, good computing efficiency and certain anti-interference ability, and has high promotion value. It is not only suitable for urban logistics and e-commerce distribution, but can also be expanded to multiple resource scheduling fields such as public transportation and industrial manufacturing. After further development, it is expected to become an intelligent decision support tool for multiple industries.

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