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Research on Vehicle Distribution Route Optimization Considering Carbon Emissions

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Abstract. The distribution of low carbon logistics is very important to the current environmental issues given the background of the market economy's and logistics industry's rapid development, the growing scale of distribution, the low efficiency of distribution costs, and the influence of carbon emission pollution. In order to reduce the overall cost of distribution, this work develops a general function model of vehicle carbon emissions and solves it using the neighborhood search algorithm. An example demonstrates the model's viability. The findings of the study demonstrate that the distribution model increases distribution effectiveness while safeguarding the environment, and it can also reduce costs, offering direction and a point of reference for the use of low-carbon logistics distribution.

Keywords: carbon emission · neighborhood search algorithm · path optimization

1 Introduction

With the changing times of society, express delivery has gradually become a part of people's lives. The logistics industry is also rising rapidly. As people's demand for express delivery increases, the amount of staff delivery also increases, and the number of delivery vehicles also increases, leading to an increase in carbon emissions in the logistics field. Logistics enterprises pursue delivery time and efficiency while also implementing the concept of environmental protection into their services, so how to achieve low-carbon delivery and sustainable development is a point to be considered in the logistics industry.

The optimization of the path of the vehicle's travel, which is the vehicle path problem, or VRP, was first proposed by Dantzi and Ramserp [1]. Solomom et al. [2] first introduced the concept of a time window, i.e., (Time Windows VRP) TWVRP. Jabali et al. [3] proposed a model for the VRP problem with a soft time window. Yajun Qiu et al. [4] considered the factor of carbon emission, established a multi-objective vehicle routing problem model combining transportation cost and carbon emission, and optimized the design of the vehicle routing problem based on an improved genetic algorithm, which was further validated by example analysis. Rao Weizhen et al. [5] constructed an urban logistics distribution model with the optimization goal of minimizing the total energy consumption of distribution vehicles by fully considering the factors of driving distance,

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load weight, vehicle speed, and road slope. Li Jin et al. [6] established a multi-model routing optimization model based on the low-carbon routing problem with a fixed number of vehicles, considering the speed and capacity of vehicles, and verified the effectiveness and feasibility of their algorithm using benchmark test examples. Zhao Yanwei et al. [7] established a calculation method for carbon emissions considering vehicle loading models and distances for the characteristics of modern logistics, modeled the low-carbon routing problem with multiple vehicles taking delivery at the same time, and solved it using a quantum evolutionary algorithm. Tang Jinhuan et al. [8] established a nonlinear mixed integer programming model for the path problem considering travel time and carbon emissions by combining the speed variation factors under time-varying networks, and solved it by using an improved multi-objective particle swarm optimization algorithm. Kang et al. [9] considered carbon emission factors and converted them into carbon emission costs in the study of vehicle routing optimization with fuzzy prescribed time windows. Li et al. [10] established two mathematical models by considering the vehicle routing problem of carbon emissions and solved them by the simulated annealing method. The results show that the distribution distance is an important factor affecting carbon emissions, and carbon emissions can be reduced by optimizing the distribution order. Chen et al. [11] proposed a multi-compartment vehicle routing problem considering carbon emissions with time windows and solved the MCVRPTW problem by a variable neighborhood search (VNS) method with local search and jitter operation as the main framework.

Starting from the above problems, this paper optimizes the vehicle routing under consideration of carbon emissions, establishes a mathematical model with the goal of minimizing the cost, and uses the large neighborhood search algorithm to solve the problem. The solution to this problem can reduce the carbon emission pollution in the distribution process and provide a reference value for low-carbon vehicle distribution.

2 Mathematical Model

2.1 Problem Description

Distribution service means that the distribution center takes into account the customer's demand, known customer point coordinates, and other variables, adopts a scientific method to plan the distribution route reasonably with the goal of minimizing the total cost of distribution, and all the distribution vehicles start from the distribution center and deliver the items to the customer point in accordance with the customer's demand in quality and quantity, on time and efficiently, and finally all return to the distribution center. To ensure the completeness of the model construction in this paper, the following prerequisite assumptions are given:

(1) The locations of distribution centers and customer points are known, as is the demand, and all customers must be served;
(2) The maximum payload of the vehicles is known, and they are homogeneous;
(3) There is no time window requirement at each customer point;
(4) The vehicle maintains a steady speed regardless of the effect of road conditions;
(5) The vehicle does not produce carbon emissions while serving customers;

Table 1. Model Symbol Definition

d_{ij}	Driving distance from customer point i to j	k	Number of vehicles driven
v_{ij}	Truck speed from customer point i to j	s	Unit carbon emission cost
q_i	Demand of customer point i	r	Rental cost per vehicle
K	Distribution vehicle set	C	All customer point sets

2.2 Parameter Description

The model parameters are set as in Table 1.

For the calculation of CO2 emissions, this paper refers to the relevant formula of the European Commission [12] as follows:

$$E = a_0 + a_1 v + a_2 v^2 + a_3 v^3 + a_4/v + a_5/v^2 + a_6/v^3 \tag{1}$$

In the formula, E represents the carbon emissions generated by the vehicle when driving at v unit (g/km), where the coefficients of each item $a_0, a_1, a_2, a_3, a_4, a_5, a_6$ are determined according to the attributes of the vehicle. This paper coefficient setting reference [12] related research. The coefficients are set to 110,0,0,0.000375,8702,0,0, and then the carbon emission formula is expressed as follows:

$$E = 110 + 0.000375v^3 + 8702/v \tag{2}$$

2.3 Model Construction

According to the problem description, a logistics distribution model is established as shown below:

$$\min Z = s \sum_{(i,j)\forall A} \sum_{k \in K} E_{ij} + \sum_{k \in K} rk \tag{3}$$

$$\sum_{j \in C} y_{ijk} \leq 1, \forall (i,j) \in A, k \in K \tag{4}$$

$$\sum_{\mathrm{i} \in C} y_{ijk} - \sum_{i \in C} y_{\mathrm{ji}k} = 0, \forall j \in C, \forall k \in K \tag{5}$$

$$\sum_{j \in C} f_{ji} - \sum_{j \in C} f_{ij} = q_i, \forall i \in C \tag{6}$$

$$\sum_{\mathrm{i} \in C} y_{ijk} - \sum_{\mathrm{i} \in C} y_{jik} = 0 \quad \forall j \in C, \forall k \in K \tag{7}$$

$$\sum_{k \in K} X_{ik} = 1, \forall i \in C \tag{8}$$

$$x_{ij} = \{0, 1\} \tag{9}$$

$$X_{ik} = \{0, 1\} \tag{10}$$

$$y_{ijk} = \{0, 1\} \tag{11}$$

The objective functional equation indicates the use of the least cost to deliver items to customers in a timely manner. Constraint (3) indicates minimizing the total cost, including carbon emission costs and rental costs; constraint (4) indicates that each vehicle makes only one delivery; constraint (5) indicates the conservation of flow; constraint (6) indicates that each customer is served; constraint (7) indicates that the vehicle leaves after serving the customer; constraint (8) indicates that each customer point is served only once; constraints (9) to (11) indicate the variable type and range.

3 Algorithm Design

Because the vehicle distribution problem is an NP-hard problem, the general exact algorithm can only solve small-scale problems, so this paper adopts the large neighborhood search algorithm to optimize the design of its paths. The algorithm introduces the concept of matching degree to make the range of each search iteration wider and find the suitable path with a higher probability, which increases the efficiency of the search; when calculating the best position of a node inserted into a certain path, the time difference insertion method is introduced to improve the speed of checking constraints such as the time window and cargo capacity.

3.1 Construction of Initial Solution

In this paper, we use the parallel insertion method to construct the initial solution. First, m paths containing only the starting and ending points of vehicles are generated, and then the remaining demand with the least cost is inserted into the best position in the path until all demands are inserted or no demands are inserted.

3.2 Demand Removal

Common requirements removal include three ways, each removing n requirements from the current solution.

1) Random removal: a completely random selection of the part to be removed is used to increase the diversity of the LNS search;
2) Highest-cost removal of requirements: remove the unreasonable or poorly performing parts of the path to get a larger improvement space, which may make it easier to get the optimal solution.
3) Shaw removal: selective removal based on the similarity between all requirements, which makes it easier to obtain feasible solutions;

Ropke [13] has tested and compared these three methods of removal, and their efficiency in generating quality solutions can be evaluated. The test results show that ways (1) and (3) have similar results, while way (2) is less effective, in large part because it is not stochastic, resulting in the generation of a small neighborhood space, while its presence in diversity should be prioritized in the process of demand removal. Because the effects of ways (1) and (3) are similar, but way (1) is simpler and faster to compute, this paper adopts way (1), which randomly removes n demands from each path with equal probability.

3.3 Demand Redistribution

In the process of re-constructing the paths, unselected requirements are assigned to each path to be inserted. In this paper, a random allocation method is used to ensure a wider range of searches, and a matching evaluation mechanism is designed to improve the probability of searches in order to find a more matching path.

3.4 Best Insertion Position

The removed demand is compared and analyzed with the target value after inserting it back, and if the target value is small, then it can be reinserted into the customer point and a new distribution solution can be obtained.

4 Example Analysis

Since there is no applicable example for this kind of problem, this paper uses the data in the Solomon dataset to generate the example, and adds the delivery data by randomly generating the original demand data in the example as the pickup data of each node. There are three types of cases: R-series (randomly distributed customer points), C-series (aggregated distributed customer points), and RC-series (mixed distributed customer points), and the case data in this paper is obtained by selecting any one of these three sets of test data and modifying them according to the problem characteristics. Table 2 is the test example data used in this paper. The vehicle speed and maximum load capacity are set to 50 km/h and 200kg in this paper.

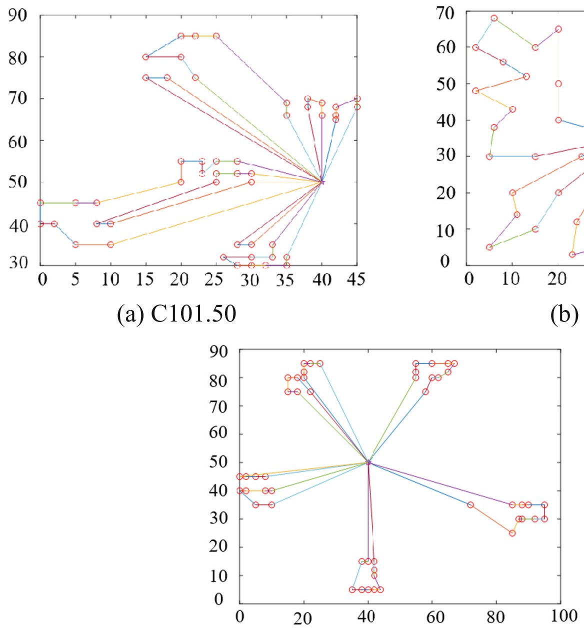
4.1 Test Analysis of 50 Customer Points

The large neighborhood search algorithm is used to analyze the 50 customer points in Table 2, the logistics network with a distribution center is constructed, and then the optimal path scheme for the three data sets is solved, as shown in Fig. 1.

It can be seen from Fig. 1 that different types of data have different optimal distribution paths. These three types of data use 8 vehicles, 6 vehicles, and 7 vehicles, respectively. Table 3 shows the results obtained by the large neighborhood search algorithm.

Table 2. Test Data Examples of Different Sizes

Data Scale	Data Type	Total number of all nodes	Number of distribution centers
50	C101	51	1
	R101	51	1
	RC101	51	1
100	C101	101	1
	R101	101	1
	RC101	101	1



(a) C101.50 (b) R101.50

(c) RC101.50

Fig. 1. The algorithm optimal path diagram under three types of data distribution of scale 50

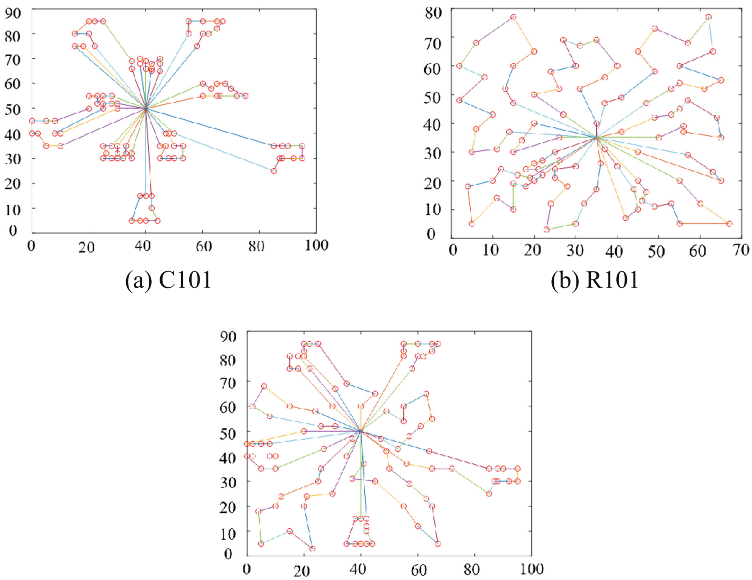
Table 3. Distribution distance (km) and distribution cost (RMB) of each type of data

Data type	Distribution distance	Carbon emissions cost	Total cost
C101.50	517.8761	3427459.39	3429059.39
R101.50	602.746	3989153.85	3990353.85
RC101.50	658.9669	4361240.63	4362640.63

4.2 Test Analysis of 100 Customer Points

The large neighborhood search algorithm is used to analyze the 100 customer points in Table 2, the logistics network with a distribution center is constructed, and then the optimal path scheme for the three data sets is solved, as shown in Fig. 2.

It can be seen from Fig. 2 that these three types of data use 13 vehicles, 11 vehicles, and 11 vehicles, respectively. From the running time of the algorithm results, rc101 takes the least time in the solution process. For different types of 100 customer points, the large neighborhood algorithm can solve the proposed problem well, and the algorithm's iteration effect is stable. Table 4 shows the results obtained by running the large neighborhood search algorithm.



(a) C101 (b) R101

(c) RC101

Fig. 2. The algorithm optimal path diagram under three types of data distribution of scale 100

Table 4. Distribution distance (km) and distribution cost (RMB) of each type of data

Data type	Distribution distance	Carbon emissions cost	Total cost
C101	982.9566	6505501.66	6508101.66
R101	964.383	6382576.01	6384776.01
Rc101	1099.2535	7275189.44	7277389.44

Table 5. The 50 Customer Point Comparison Table

	C101.50	R101.50	RC101.50
Consider carbon emission target values	3429059.39	3990353.85	4362640.63
No consideration of carbon emission target values	3387580.12	3884537.49	4287126.44

Table 6. The 100 Customer Point Comparison Table

	C101	R101	RC101
Consider carbon emission target values	6508101.66	6384776.01	7277389.44
No consideration of carbon emission target values	6454302.71	6291372.33	7169258.61

4.3 Analysis of Carbon Emission Factors

The model constructed in this paper takes the carbon emission cost into account in the objective function model, and the following is a comparative analysis of the two cases. A comparative analysis of 50 customer points is shown in Table 5, and the comparative analysis of 100 customer points is shown in Table 6. The results show that the operation cost when carbon emission costs are considered is higher than when they are not considered, but in the actual distribution of logistics, if the carbon emission factor is ignored, it will lead to an increase in the number of vehicles used, which is not conducive to the impact on environmental benefits; if the carbon emission factor is considered, it will limit the use of traditional vehicles.

5 Conclusions

In this paper, considering the rental cost and carbon emission cost of distribution vehicles, a mathematical model of vehicle distribution path optimization considering time window and carbon emission is established with the goal of minimizing the total cost of distribution, and a large neighborhood search algorithm is used to solve the constructed model. The model and algorithm in this paper are simulated and tested using the Solomon data set as an example. Compared with the vehicle distribution path scheme without considering carbon emissions, not only can a reasonable vehicle distribution path scheme be obtained, but this scheme can also significantly reduce the carbon emission cost and obtain greater environmental benefits without significantly increasing the cost. This has a positive role in promoting the implementation of low-carbon logistics in China's logistics enterprises. Therefore, the model and solution algorithm established in this paper are applicable and effective for low-carbon vehicle distribution path planning with time windows and provide strong support for the development of low-carbon logistics.

References

1. Dantzig G B, Ramser J H. The truck dispatching problem [J]. Management Science, 1959, 6(1):80–91.
2. Solomon M, Desrosiers J. Time Window constraint routing and scheduling problems [J]. Transportation Science, 1988, 22(1):1–13.
3. Jabali O, Leus R, Van Woensel T, et al. Self-imposed time windows in vehicle routing problems [J]. O R Spectrum, 2015, 37(2):331–352.
4. Qiu Yajun, Song national defense. Research on vehicle routing problem considering carbon emissions [J]. Logistics, 2012, 31(13):227–229 + 258.
5. Rao Weizhen, Jin Chun, Meng Qiunan. Urban low-carbon logistics distribution problem model and solution strategy [C]//Chinese Society of Systems Engineering, 2012:13.
6. Li Jin, Fu Peihua. Multi-vehicle low-carbon routing problem with fixed number of vehicles and its algorithm [J]. Computer Integrated Manufacturing System, 2013, 19(06):1351–1362.
7. Zhao Yanwei, Li Wen, Zhang Jingling, etc. Research on the low-carbon path of simultaneous pickup and delivery of multiple models [J]. Journal of Zhejiang University of Technology, 2015, 43(01):18–23.
8. Tang Jinhuan, Ji Shoufeng, Shen Guicai. Vehicle routing optimization considering carbon emissions under time-varying networks [J]. System Engineering, 2015, 33(09):37–44.
9. Kang Kai, Han Jie, Ma Yanfang. Research on fuzzy timed vehicle routing problem based on carbon emissions [J]. Industrial Engineering and Management, 2017, 22(04):17–22.
10. Li Y, Tan W R, Sha R L. The empirical study on the optimal distribution route of minimum carbon footprint of the retail industry [J]. Journal of Cleaner Production, 2016, 112:4237–4264.
11. Chen J M, Dan B, Shi J. A variable neighborhood search approach for the multi-compartment vehicle routing problem with time windows considering carbon emission [J]. Journal of Cleaner Production, 2020, 277:123932.
12. Ji Shoufeng, Tang Jinhuan. Low-carbon logistics [J]. Beijing: China Fortune Publishing House, 2015:140–141.
13. Ropke S, Pisinger D. An adaptive large neighborhood search heuristic for the pickup and delivery problem with time windows [J]. Transportation Science, 2006, 40(4): 455–472.

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