International Journal of Global Economics and Management
ISSN: 3005-9690 (Print), ISSN: 3005-8090 (Online) | Volume 7, Number 3, Year 2025
DOI: https://doi.org/10.62051/ijgem.v7n3.18
Journal homepage: https://ijgem.org

Research on the Application of Vehicle Routing Problem in Company M Based on AMPL

Jie Zhao *

School of Economics and Management, Southwest Petroleum University, Chengdu 610000, China
*Corresponding Author: 1404352985@qq.com

ABSTRACT

This paper first reviews the current research status of the Vehicle Routing Problem (VRP), and analyzes the achievements of domestic and foreign scholars in VRP variants and the application of intelligent algorithms. Then, it describes in detail the distribution problem of Company M and establishes a mathematical model, which is solved by AMPL software. The research results show that the optimized distribution plan significantly improves the vehicle loading rate, reduces the number of distribution vehicles and the total driving distance, thereby greatly reducing the distribution cost. Specifically, before optimization, three vehicles were needed to complete the distribution task, with a total driving distance of 73.17 kilometers and a total distribution cost of 621.31 yuan; after optimization, only two vehicles are needed, the total driving distance is reduced to 55.56 kilometers, and the total distribution cost is reduced to 419.16 yuan, a cost reduction of 32%. This study verifies the effectiveness of AMPL software in vehicle routing optimization, providing a practical and feasible distribution optimization plan for Company M, significantly improving the efficiency of logistics distribution and reducing operating costs. Future research can further expand the data scale and consider more complex factors in actual scenarios to enhance the applicability and optimization effect of the model.

KEYWORDS

Vehicle Routing Problem (VRP); Capacitated Vehicle Routing Problem (CVRP); AMPL; Distribution Optimization; Logistics Management

1. INTRODUCTION

With the vigorous development of the baking food industry, the global logistics and supply chain network is rapidly expanding and becoming more complex, opening up broader market opportunities for enterprises. However, in the current context, especially since the outbreak of the COVID-19 pandemic, chain catering enterprises inevitably face increasing transportation demands and operational pressures. Enterprises not only have to deal with the uncertainties brought by the pandemic to the market but also confront the challenge of rising logistics costs. Under such circumstances, an increasing number of chain enterprises have begun to recognize the importance of logistics and started to optimize and enhance the efficiency of logistics management. Therefore, in the face of the growing transportation demands in the baking industry, how to effectively plan the distribution routes of products has become a crucial issue. In-depth research on the vehicle routing problem and the formulation of reasonable and effective transportation plans can avoid cost waste and inefficient transportation, thereby bringing more economic benefits to enterprises. This paper takes the logistics transportation of fresh products as the research object and optimizes the logistics distribution routes by constructing the Dynamic Vehicle Routing Problem with Time Windows

(DVRPTW), reducing distribution costs, saving distribution time, and ensuring the completion of fresh cold chain logistics distribution within the customer-satisfying time window.

The Vehicle Routing Problem (VRP) is a classic combinatorial optimization problem. Since it was first proposed by Dantzig and Ramser in 1959, it has been an important research field in logistics distribution and emergency management. It involves how to plan the distribution routes of a group of vehicles to meet the demands of all customers while minimizing costs (such as the shortest distance and the least time consumption) [1]. Due to its complexity, it becomes very difficult to find the optimal solution when the problem scale increases. Over the past decades, the VRP has developed into many variants and new practical problems and complex methods have been proposed to solve VRP, such as the Vehicle Routing Problem with Time Windows (VRPTW), the Multi Distribution Center Vehicle Routing Problem (MDCVRP), the Vehicle Routing Problem Based on Multi Objective Optimization (VRPMO), the Dynamic Vehicle Routing Problem (DVRP), and the Large Scale Vehicle Routing Problem (LSVRP), etc. [2], all of which have made significant progress.

Schermer et al. [3] proposed a VNS-Tabu hybrid search algorithm to solve the vehicle routing problem for drones and air routes (VRPD) to minimize the total time consumption by integrating drones into the last-mile delivery. Vidal et al. [4] summarized the existing and emerging variants of vehicle distribution problems and argued that research should not only focus on cost optimization but also include other related performance indicators and objectives, such as reliability, service quality, and environmental impact, and require integration with other tactical decisions as well as more precise and applicable models. Mandi et al. [5] proposed a neural network model for learning hidden preferences in the vehicle routing problem. This model learns implicit preferences from past solutions and incorporates these learned preferences into the optimization process, allowing for the consideration of additional features and automatic parameter estimation. Tang Huiling et al. [6] studied the vehicle routing problem with carbon emission constraints and proposed a multi-objective nonlinear programming model, which was solved using an improved ant colony system algorithm. This algorithm reduces the probability of getting stuck in local optima through a chaotic perturbation mechanism, enhancing the algorithm's adaptability and search efficiency. Zhou Xiancheng et al. [7] proposed a model for the multi-depot green vehicle routing problem, considering the impact of time-varying speeds and real-time loads on vehicle fuel consumption and carbon emissions. They designed an improved ant colony algorithm to reduce the total cost of logistics distribution and vehicle fuel consumption and carbon emissions, promoting energy conservation and emission reduction in logistics distribution enterprises. Liu Zhishuo et al. [8] proposed using the adaptive large neighborhood search algorithm (ALNS) to solve the cold chain electric vehicle routing problem with soft time windows (CEVRPTW) and established a linear programming model. They proved the effectiveness of the ALNS algorithm. Zhao Xiong et al. [9] pointed out that by combining mean shift clustering and the large neighborhood search algorithm, the heterogeneous vehicle routing problem (HVRP) can be effectively solved, while improving vehicle utilization and the convergence speed of the algorithm.

In summary, for the research on the vehicle routing problem, foreign scholars have focused on developing various variants of VRP, exploring new real-world problems and complex methods to solve VRP, including VRP with time windows, multi-depot VRP, multi-objective optimization VRP, dynamic VRP, and large-scale VRP, etc. They have achieved significant breakthroughs in multiple fields such as drone delivery, smart logistics, and deep reinforcement learning. Domestic scholars have concentrated on applying intelligent algorithms to practical VRP problems and proposing vehicle routing models that better fit domestic conditions, such as VRP with carbon emission constraints, multi-depot green VRP, and CEVRPTW with soft time windows. It can be seen that there is still a need for solutions to more challenging, dynamic, and complex real-world problems in VRP research, which requires in-depth analysis. Therefore, this study starts from the complexity and dynamic changes of real logistics operations and conducts in-depth research on the effectiveness of intelligent algorithms in practical applications. It can optimize the efficiency and cost of logistics distribution within a certain range, thus making VRP have certain practical significance in modern logistics and emergency management fields.

2. PROBLEM DESCRIPTION AND MODEL ESTABLISHMENT

2.1. Problem Description

This paper studies the vehicle routing problem with capacity limitations, aiming to optimize the delivery route scheme of baked goods for MD Company's various stores in Nanning City. In this issue, the models and loading capacities of all vehicles are the same, and only a single delivery task is performed, without considering practical factors such as the time window and different vehicle models. The objective of optimization is to build a mathematical model based on the known distance and use the AMPL software to find the best distribution route plan: starting from the distribution factory to each store, covering 12 stores during the process, and not exceeding the loading capacity of the vehicle. Furthermore, the distances between the distribution factory and each store are known. The ultimate optimization goal is to minimize the total distance of the distribution route while maximizing the vehicle loading rate, thereby reducing transportation costs. To ensure the feasibility of the model, the following assumptions are made for the model:

(1) The distance and demand of each store point are predetermined and determined, and the demand of each store point will not exceed the maximum carrying capacity of any vehicle. All the deliveries are of a single product.

(2) There is only one distribution factory. All distribution vehicles depart from this factory and must return to the distribution factory after completing the distribution.

(3) Each store point can only be delivered by one delivery vehicle, and each delivery route must not be repeated under any circumstances, that is, the number of times each route is passed cannot exceed once.

(4) The result of the route solved can only be that each delivery vehicle has exactly one loop. It is not allowed for one vehicle to have multiple sub-loops. That is to say, the solution obtained must ensure that each delivery vehicle has only one complete loop and eliminate the possibility that any vehicle has multiple separate loops.

2.2. Model Establishment

(1) First, declare that i represents the starting point, j represents the destination station, k represents the vehicle, and S represents the total number of nodes (1, 2, ...) S), V represents the total number of vehicles (1, 2, ...) V);

(2) Then define C_k as the capacity of vehicle k and D_i as the demand of node i;

(3) in order to facilitate, said statement said A will access point, (1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13) set of all I and j point connection;

(4) Given that the distance between each point is (i, j, distance), expressed as D_{ij}, and then according to the 0-1 type integer programming, let:

$$x_{ijk} = \begin{cases} 0 & \text{Vehicle k does not pass through the path from i to j} \\ 1 & \text{Vehicle k travels along the path from i to j} \end{cases}$$

In this way, the objective function can be obtained, representing the minimization of the driving distance of the store points that meet all the demands within the area:

$$min \sum_{ij \in A} \sum_{k \in V} D_{ij} \bullet X_{ijk}$$

By definition, to ensure that the model can operate correctly, the following restrictive conditions also need to be set:

(1) Restriction one: Every vehicle must depart from the factory:

$$\sum_{(1,j) \in A, j \neq 1} X_{1jk} = 1 \ , \quad \forall k \in \{1..V\}$$

(2) Restriction two: Each vehicle must eventually be returned to the factory:

$$\sum_{(i,1) \in A, i \neq 1} X_{i1k} = 1 \ , \quad \forall k \in \{1..V\}$$

(3) Restriction three: Each store point can only be visited once:

$$\sum_{(i,j) \in A} \sum_{k \in \mathrm{V}} X_{ijk} = 1 \ , \quad \forall i \in \{2..S\}$$

(4) Restriction condition four: Each node's inbound = outbound:

$$\sum_{(i,J) \in A} X_{ijk} = \sum_{(J,i) \in A} X_{jik} \ , \quad \forall i \in \{1..S\} \ , \quad \forall k \in \{1..V\}$$

(5) Restriction five: The total demand carried by each vehicle shall not exceed the vehicle's carrying capacity:

$$\sum_{(i,j) \in A} R_i \bullet X_{ijk} \leq Q_k \ , \quad \forall k \in \{1..V\}$$

(6) Restriction condition 6: To ensure the generation of a complete loop, the Miller-Tucker-Zemlin (MTZ) constraint is used:

$$u_i - u_j + 1 - S \bullet \left(1 - X_{ijk}\right) \leq 0 \ , \quad \forall k \in \{1..V\} \ , \quad \forall i \in \{2..S\} \ , \quad \forall j \in \{2..S\} \ , \quad i \neq j$$

2.3. AMPL Model File

Create an AMPL model file, name it CVRP, and set the file suffix as mod. According to the previously set model, first define a set S and a set V, which are respectively used to represent all nodes and all available delivery vehicles. Next, set the parameter demand to specify the demand of each node i, the parameter capacity to represent the maximum load capacity of each vehicle k, and the parameter distance to represent the distance between node i and j. This parameter will be indexed by ARCS. Introduce a binary variable X to identify whether the road is passed by delivery vehicles, and use the binary attribute to indicate that it is a binary variable. In addition, set the variable "Load" to represent the load of the vehicle when it reaches node i. With the addition of restrictive conditions, the model file of AMPL can be obtained in this way. The details are shown in Figure 1 on the following page.

```
param S;
param V;
set ARCS:= {i in 1..S, j in 1..S: i<>j};
param demand{1..S} >=0;
param capacity{1..V};
param distance{ARCS} >=0;
var X{ARCS , 1..V}binary;
var Load {2..S} >=1, <= S-1;
minimize Total_distance: sum {(i,j) in ARCS, k in 1..V} distance[i,j] * X[i,j,k];
subject to limit1{k in 1..V}: sum{(1,j) in ARCS} X[1,j,k] =1;
subject to limit2{k in 1..V}: sum{(i,1) in ARCS} X[i,1,k] = 1;
subject to limit3{i in 2..S}: sum{(i,j) in ARCS, k in 1..V} X[i,j,k] = 1;
subject to limit4{i in 1..S, k in 1..V}:
sum{(i,j) in ARCS} X[i,j,k] = sum{(j,i) in ARCS} X[j,i,k];
subject to limit5{k in 1..V}:
sum{(i,j) in ARCS} demand[i]*X[i,j,k] <= capacity[k];
subject to limit6_MTZ{k in 1..V,i in 2..S, j in 2..S: i<>j}:
Load[i] - Load[j] +1 - S*(1-X[i,j,k]) <=0;
```

Figure 1. AMPL model file

2.4. AMPL Data File

After the model file is established, an AMPL data file needs to be created, named CVRP, with the file suffix dat.

Based on the sorted data, input the data part, assign values to the corresponding parameters and sets (S represents the number of points, V represents the number of delivery vehicles, demand represents the demand value of each store, capacity represents the load capacity of each vehicle, and cost represents the distance values between the factory and each store, as well as between stores), and complete the entire coding design process. The details are as shown in Figure 2 below.

```
param S:= 13 ;
param V:= 2 ;
param demand:=
1 0
2 156.25
3 212.5
4 112.5
5 168.25
6 193.75
7 168.25
8 75
9 75
10 75
11 199.5
12 112.5
13 250   ;
param capacity:= 1 1000 2 1000 ;
param distance:
    1       2       3       4       5       6       7       8       9       10      11      12      13:=
1   .       3.43    6.19    9.63    10.78   11.36   12.07   11.19   14.1    12.25   9.42    3.82    2.37
2   3.43    .       2.8     6.47    7.82    8.51    9.32    8.44    11.4    8.93    6.2     1.22    5.36
3   6.19    2.8     .       4.76    6.38    7.19    8.1     7.28    10.12   6.67    3.5     3.14    7.88
4   9.63    6.47    4.76    .       1.67    2.51    3.45    2.74    5.39    2.86    5.71    5.81    11.79
5   10.78   7.82    6.38    1.67    .       0.84    1.78    1.15    3.75    2.98    7.3     7       13.03
6   11.36   8.51    7.19    2.51    0.84    .       0.94    0.52    2.95    3.41    8.13    7.64    13.65
7   12.07   9.32    8.1     3.45    1.78    0.94    .       0.89    2.08    4.03    9.05    8.4     14.38
8   11.19   8.44    7.28    2.74    1.15    0.52    0.89    .       2.96    3.92    8.43    7.51    13.49
9   14.1    11.4    10.12   5.39    3.75    2.95    2.08    2.96    .       5.12    10.76   10.46   16.43
10  12.25   8.93    6.67    2.86    2.98    3.41    4.03    3.92    5.12    .       6.04    8.46    14.29
11  9.42    6.2     3.5     5.71    7.3     8.13    9.05    8.43    10.76   6.04    .       6.64    10.74
12  3.82    1.22    3.14    5.81    7       7.64    8.4     7.51    10.46   8.46    6.64    .       6.02
13  2.37    5.36    7.88    11.79   13.03   13.65   14.38   13.49   16.43   14.29   10.74   6.02    .     ;
```

Figure 2. AMPL data file

2.5. Result Analysis

After completing the writing of the model file and data file, enter the code (model CVRP.mod;) in the execution box of AMPL data CVRP.dat; option solver cplex; solve; display X;) The result can then be obtained, as shown in Figure 3 below.

```
AMPL
ampl: model CVRP.mod;data CVRP.dat;option solver cplex;solve;display X;
CPLEX 22.1.1.0: optimal integer solution; objective 55.56
3687375 MIP simplex iterations
338419 branch-and-bound nodes
X [*,*,1]
:    1   2   3   4   5   6   7   8   9  10  11  12  13    :=
1    .   0   0   0   1   0   0   0   0   0   0   0   0
2    0   .   0   0   0   0   0   0   0   0   0   0   0
3    0   0   .   0   0   0   0   0   0   0   0   0   0
4    0   0   0   .   0   0   0   0   0   0   0   1   0
5    0   0   0   0   .   1   0   0   0   0   0   0   0
6    0   0   0   0   0   .   0   1   0   0   0   0   0
7    0   0   0   0   0   0   .   0   1   0   0   0   0
8    0   0   0   0   0   0   1   .   0   0   0   0   0
9    0   0   0   0   0   0   0   0   .   1   0   0   0
10   0   0   0   1   0   0   0   0   0   .   0   0   0
11   0   0   0   0   0   0   0   0   0   0   .   0   0
12   1   0   0   0   0   0   0   0   0   0   0   .   0
13   0   0   0   0   0   0   0   0   0   0   0   0   .

 [*,*,2]
:    1   2   3   4   5   6   7   8   9  10  11  12  13    :=
1    .   0   0   0   0   0   0   0   0   0   0   0   1
2    1   .   0   0   0   0   0   0   0   0   0   0   0
3    0   1   .   0   0   0   0   0   0   0   0   0   0
4    0   0   0   .   0   0   0   0   0   0   0   0   0
5    0   0   0   0   .   0   0   0   0   0   0   0   0
6    0   0   0   0   0   .   0   0   0   0   0   0   0
7    0   0   0   0   0   0   .   0   0   0   0   0   0
8    0   0   0   0   0   0   0   .   0   0   0   0   0
9    0   0   0   0   0   0   0   0   .   0   0   0   0
10   0   0   0   0   0   0   0   0   0   .   0   0   0
11   0   0   1   0   0   0   0   0   0   0   .   0   0
12   0   0   0   0   0   0   0   0   0   0   0   .   0
13   0   0   0   0   0   0   0   0   0   0   1   0   .
;
```

Figure 3. Solution results of AMPL

As can be seen from the figure, the AMPL software uses the CPLEX solver. Through 3,687,375 iterations and 338,419 branches and bound nodes, it finally solved the target at 55.56, that is, the target value result of minimizing the total delivery mileage is 55.56 kilometers. A total of 2 distribution routes were calculated, corresponding to the driving routes of the two vehicles respectively: Route 1: 1→5→6→8→7→9→10→4→12→1; Route 2: 1 →2→3→11→13→1.

In the analysis of the distribution case of MD Company, it is learned that before scientific planning, the use of vehicle resources and distribution routes were decisions with personal experience. The driving mileage, distribution route plan and loading rate are shown in Table 1 as follows:

Table 1. Loading Table of Route Schemes before Optimization

Route	Driving route (x)	Load capacity (kg)	Loading rate
1	1→12→2→13→1	530.75	53.08%
2	1→8→7→9→6→5→4→1	792.75	79.28%
3	1→3→11→10	487	48.7%

The CVRP model for the distribution route problem of MD Company was established using AMPL. The results of the optimized driving mileage, distribution route planning and loading rate are shown in Table 2 as follows:

Table 2. Loading Table of the Optimized Route Scheme

Route	Driving route (x)	Load capacity (kg)	Loading rate
1	1→5→6→8→7→9→10→4→12→1	980.25	98.03%
2	1→2→3→11→13→1	830.25	83.03%

In the vehicle distribution optimization case of MD Company, the original distribution route was optimized by using the AMPL software through precise algorithms. Through analysis, it can be known that the distribution plan before optimization was completed by 3 vehicles for the distribution task, while after optimization, only 2 vehicles are needed to complete the same task. Before optimization, the loading rates of the three routes were 53.08%, 79.28%, and 48.7% respectively. After optimization, the loading rates of the two routes have significantly increased. The loading rate of the first route has risen to 98.03%, and that of the second route has increased to 83.03%. The increase in loading rate means that each delivery can make more full use of the vehicle's carrying capacity. By reducing empty runs, it can lower delivery costs and simultaneously enhance the economic benefits of logistics and distribution.

It is known through the optimization of AMPL software that the total driving distance of the route has changed significantly before and after the optimization. According to the data shown in Table 3 and Table 4, the driving distances of the original three routes were 12.77 kilometers, 29.25 kilometers and 31.15 kilometers respectively, with a total driving distance of 73.17 kilometers. However, the driving distances of the two optimized routes are 32.72 kilometers and 22.84 kilometers respectively. The total mileage driven has decreased to 55.56 kilometers. This indicates that after adjusting the distribution routes through the optimization algorithm, the distribution efficiency of MD Company has been significantly improved. The driving distance has been reduced by approximately 24%, directly reducing fuel consumption and vehicle wear and tear, and enhancing operational efficiency.

Table 3. Distance table of the route Scheme before Optimization

Route	Driving route (x)	Driving distance (km)	Total mileage
1	1→12→2→13→1	12.77	73.17
2	1→8→7→9→6→5→4→1	29.25	
3	1→3→11→10	31.15	

Table 4. Distance Table of the Optimized Route Scheme

Route	Driving route (x)	Driving distance (km)	Total mileage
1	1→5→6→8→7→9→10→4→12→1	980.25	55.56
2	1→2→3→11→13→1	30.25	

Comparative analysis of Distribution Cost Optimization Before and after:

According to the comparison before and after optimization in Table 5, it can be known that before the optimization, MD Company used 3 vehicles for distribution, traveling a total of 73.17 kilometers, with a total distribution cost of 621.31 yuan. However, after optimizing the distribution routes and loading rates, only 2 vehicles were used for distribution, traveling a total of 55.56 kilometers. The total distribution cost has decreased to 419.16 yuan. The reduction in cost is mainly attributed to the decrease in the number of vehicles in use, the shortening of driving distance and the increase in loading rate. The effect of a 32% cost reduction highlights the significant value of optimization algorithms in logistics management.

Table 5. Costs Before and after Optimization

Result comparison	Use the vehicle	Total mileage	depreciation cost (yuan)	distribution cost (yuan)
Before optimization	3	73.17	48.9	621.31
After optimization	2	55.56	32.6	419.16

Based on the above results:

Overall, this method brings significant advantages to the vehicle distribution efficiency, cost control and resource utilization of MD Company. Through algorithm optimization, MD Company has achieved significant improvements in three aspects: vehicle loading rate, driving distance and distribution cost. Firstly, in terms of vehicle loading, the carrying capacity of vehicles has been utilized more fully, reducing the phenomenon of empty running during the distribution process. This, in turn, has indirectly and effectively lowered the distribution cost and enhanced the economic benefits of logistics distribution. Secondly, in terms of mileage, it directly reduces fuel consumption and vehicle wear, significantly improves operational efficiency, and saves distribution costs for the company's direct connection. Finally, in terms of total distribution costs, such a reduction not only increases the profit margin but also enhances the company's competitive edge in the market. The reduction in the number of delivery vehicles, the shortening of driving mileage and the increase in loading rate have jointly contributed to a significant reduction in costs. In conclusion, this optimization has enhanced the loading efficiency of vehicles, reduced unnecessary operating costs, and also improved service quality, providing strong support for the company to gain an edge in the fierce market competition.

3. CONCLUSIONS

This paper takes the vehicle distribution route optimization problem of MD Company as the starting point and explores the vehicle routing problem (VRP) in operations research, especially the vehicle routing problem with capacity limitations (CVRP). From theory to practice, this paper not only thoroughly examines the necessity of vehicle distribution optimization, but also adopts the advanced integer programming method and realizes the solution of the optimization model through the AMPL software. The beginning of the research was a comprehensive understanding of MD Company and its current logistics distribution situation. Through data collection and market analysis, the company's distribution model was accurately depicted, and its main problems were identified, such as low vehicle loading utilization rate, unreasonable distribution route planning and high distribution cost. Subsequently, by constructing a mathematical model, converting it into executable code, and conducting tests with actual data, the validity of the model was verified. The results show that the optimized vehicle distribution scheme has achieved remarkable results in increasing the loading rate, reducing the driving distance and lowering the distribution cost, thereby confirming the application value of the proposed method in the field of logistics management. Before the optimization, the distribution plan of MD Company was completed by 3 vehicles, but after the optimization, only 2 vehicles are needed. The re-planning of the distribution routes and the improvement of vehicle loading efficiency have reduced the total distribution cost by 32%. This not only reflects the effectiveness of the algorithm, but also provides a valuable reference for production-oriented chain industries that are sensitive to operating costs.

The model and algorithm proposed in this paper still have many deficiencies. In the subsequent research, it is necessary to supplement and expand the data, collect and organize the data of actual scenarios, carry out case studies, and further optimize and streamline the algorithm.

ACKNOWLEDGMENTS

The author would like to express sincere appreciation to colleagues at Southwest Petroleum University for their valuable insights and support.

REFERENCES

[1] DANTZIG G B, RAMSER J H. The truck dispatching problem[J]. Management Science, 1959, 6(1):80-91.

[2] Jiang Huawei, Guo Tao, Yang Zhen. Research Progress on Vehicle Routing Problems [J]. Acta Electronica Sinica, 2022, 50(2): 480-492

[3] Schermer D, Moeini M, Wendt O. A hybrid VNS/Tabu search algorithm for solving the vehiclerouting problem with drones and en route operations[J]. Computers & Operations Research, 2019, 109: 134- 158

[4] Vidal T, Laporte G, Matl P. A concise guide to existing and emerging vehicle routing problem variants[J]. European Journal of Operational Research, 2020, 286(2): 401-416.

[5] Mandi J, Canoy R, Bucarey V, et al. Data driven vrp: A neural network model to learn hidden preferences for vrp[J]. arXiv preprint arXiv:2108.04578, 2021

[6] Tang Huiling, Tang Hengshu, Zhu Xingliang. Research on Low-Carbon Vehicle Routing Problem Based on Improved Ant Colony Algorithm [J]. Chinese Journal of Management Science, 2021, 29(07): 118-127.

[7] Zhou Xiancheng, Lu Yang, He Caihong, et al. Green vehicle routing model and Optimization Algorithm for Multi-depot considering time-varying Speed [J]. Control and Decision, 2022, 37 (02): 473-482.

[8] Liu Zhishuo, Li Qiuyu, Dong Ziqi, et al. Research on the Routing Problem of Cold Chain Electric Vehicles with Soft Time Windows [J]. Journal of Beijing Jiaotong University, 2022, 46(03): 57-66.

[9] Zhao Xiong, Li Lin. Solving Heterogeneous VRP Problem Based on Clustering-based LNS algorithm [J]. Computer Technology and Development, 2023, 33(09): 98-04.