Terminal Collaborative Path Optimization of Multi-Distribution Subjects for Electric Unmanned Vehicles

Zifu Fan[1,a,*], Zhiqiao Sun[2,b,*]

[a]E-mail address:1600249722@qq.com, [b]E-mail address:1015695228@qq.com.

[1]Chongqing University of Posts and Telecommunications, Chongwen Road, Chongqing, China.
[2]Corresponding author. Chongqing University of Posts and Telecommunications, Chongwen Road, Chongqing, China.

Abstract: Because the planning and design of urban logistics systems do not incorporate terminal logistics distribution into unified solutions, less consideration is given to the collaborative distribution environment of multiple distribution subjects. This oversight results in low overall efficiency and service quality of logistics distribution. Simultaneously, considering the impact of reducing energy consumption and episodic sites on logistics distribution, electric unmanned vehicles with high efficiency, low cost, and noncontact features have become the main vehicle of terminal logistics distribution. Therefore, this paper considers urban terminal distribution, constructs a multiagent collaborative distribution model with electric unmanned vehicles as the carrier, and designs an improved Tabu Search algorithm to solve the model. In simulation, our optimization model can fully realize the advantages of energy savings, emission reduction and cost reduction of electric unmanned vehicles compared to operation using the traditional single distribution and single source vehicle distribution models. The solution provided here can also reduce the promotion of terminal distribution in logistics activities and promote the green, low carbon and sustainable development in cities.

Keywords: Electric Unmanned Vehicle Logistics; Multiple distribution subjects; Collaborative distribution; Terminal delivery; Path optimization

1. Introduction

End-of-line delivery is a logistics distribution process designed to deliver goods to the terminal (i.e., customer). It is also known as "last mile delivery". The time and cost of end-of-line delivery account for more than 30% of the entire logistics process[1]. This occurs because of its small single batch size, multiple delivery categories, and multiple access nodes[2]. Due to the complexity of the system and other characteristics, the existing urban logistics system has not included end-to-end distribution in unified planning, resulting in a single distribution entity and duplicate distribution paths, reducing the overall efficiency of logistics activities. Simultaneously, most urban logistics transportation vehicles use gasoline and are thus highly dependent on fossil fuels, severely affecting green, low-carbon, and sustainable development of logistics distribution systems. Therefore, it is necessary to coordinate multiple distribution entities and carry out joint distribution path optimization, reduce losses in the process of end-to-end logistics distribution. Moreover, it is necessary to actively promote the distribution of electric unmanned vehicles, reduce the dependence on

IEDM 2024, February 23-25, Kuala Lumpur, Malaysia

DOI 10.4108/eai.23-2-2024.2345955

fossil fuels for urban terminal distribution, reduce energy loss during the distribution process, and cause environmental pollution in the city.

Collaborative distribution refers to the process of collaborative distribution among multiple distribution entities to improve distribution efficiency and reduce the duplication of distribution paths. For example, there are several different distribution enterprises in the same city or region, and each enterprise can use distribution centers, equipment and facilities to implement joint distribution for different customers. We have also used large-scale neighborhood search algorithms to solve the problem. Ke Jianchao[3] designed a hybrid heuristic algorithm consisting of K-means clustering algorithm and improved NSGA-II algorithm to optimize the MOCVRPTWA model, which can reduce costs and ensure customer satisfaction in logistics network design when the expected time window is not satisfied in multi-party collaborative delivery mode. The third is the research on the practical demand for innovative collaborative delivery models among multiple entities. Yang Mengke[4] and Li Naiwen[5] then established a collaborative distribution model with multiple distribution entities, despite only solving batch distribution was for demand points within a limited area, the superiority of the collaborative distribution model was proved.

The VRP problem has been derived from pure electric unmanned vehicles, which are used as logistics transportation vehicles for delivering goods. In logistics, this formulation is called the pure electric logistics vehicle routing problem. Ye C[6] divided EVRP models into four types: EVRP considering load and battery life constraints, EVRP with a time window and considering charging strategies, the study of vehicle routing problems for hybrid fleets, and EVRP combined with charging/swapping station location. In recent years, research on this type of problem has mainly included innovation in path planning under different constraint conditions. Abhinav Gupta[7] considered VRP along with additional constraints of capacity and time-windows (CVRPTW), he aimed to provide a fast and approximately optimal solutions to large-scale CVRPTW problems, and presented a deep Q-network with encoder-decoder based reinforcement learning approach to solve CVRPTW. Messaoud E[8] solved the Electric Vehicle Routing Problem with Stochastic Travel Times (EVRPSTT) by proposing a Chance Constrained Programming (CCP) Model, as well as a new scheme based on an Improved Large Neighborhood Search (ILS) algorithm and a Monte Carlo Sampling (MCS) procedure.Jie Wanchen[9] and Zhen Cao[10] have also established a multi vehicle electric vehicle path planning problem model in our research on the charging and power consumption of electric vehicle batteries. S Fujimura[11] proposed an attention-based end-to-end DRL model to solve VRP which embeds edge information between nodes for rich graph representation learning.The third type of research on pure electric logistics vehicle routing is to start exploring VRP problems by combining external complex conditions. Wang Yong[12]After designing a 3D-K-means spatiotemporal clustering algorithm that takes into account customer geographic location and demand time windows, a multiobjective particle swarm optimization (MOPSO) hybrid algorithm based on Clarke Wright (CW) conservation algorithm (CW-MOPSO) is proposed. Pasha J[13] designed a customized multi-objective mixed meta heuristic solving algorithm that directly considers the specific properties of the problem.

In summary, end-of-line delivery is a crucial aspect of the entire logistics activity, and the quality of its service will determine customer satisfaction with the entire delivery process. However, currently, most research on end-of-line delivery issues is focused on single distribution centers, and the delivery path is a closed loop. Few studies have involved the collaborative allocation of vehicles by multiple delivery entities before delivery, and most of the research models on electric unmanned vehicles only consider factors such as range constraints, load constraints, or time window constraints that affect the vehicles themselves, without considering the actual application conditions of vehicle-to-vehicle collaborative allocation. Based on the above background, this paper constructs an EVRPDD (Electric Vehicle Routing Problem with Dynamic Demands) model for multiagent collaborative distribution needs and constructs target models for allocation and distribution stages. An improved Tabu Search algorithm with good local search ability was designed to solve the model[14]. Tabu Search algorithm is one of the most general theory and mature algorithms in artificial intelligence algorithms, which conforms to four criteria for good heuristics: accuracy, rapidity, simplicity, and adaptability[15]. Therefore, this work has certain significance for comprehensively improving efficiency in "last mile" delivery.

2. Model establishment

2.1 Problem Description

Here, the problem of collaborative distribution among end-of-life distribution entities is divided into two stages. The process of adjusting the ownership of goods between distribution entities is denoted the allocation process, and the process of end-of-life distribution by distribution entities is denoted the distribution process. Using electric unmanned vehicles as vehicles, the delivery path is semiopen, signifying that the unmanned vehicles in the delivery stage can return to any nearby delivery entity for the optimization of the entire end-to-end pickup and distribution path. The objective is to minimize the sum of shipping costs, charging costs, and mileage costs while considering both the deployment and distribution stages. The optimization objective is to minimize the cost of picking up accessories from the entire terminal and reduce the cost of end-to-end distribution in the entire logistics process. There are multiple different distribution entities in the same area, each with warehousing functions. Before starting the distribution task, each distribution entity contains a certain number of unmanned delivery vehicles. The demand for each delivery service and the location of the end demand point are known. After the delivery task is completed, the unmanned delivery vehicle returns to a nearby distribution center. During the delivery process, if the battery of the unmanned vehicle is insufficient to complete the remaining mileage, then it can go to the charging station to replenish the battery, fully charge it, and then continue to deliver to the next customer node.

Certain assumptions are made regarding the above issues, as follows:

1. During the delivery and allocation phase, vehicles may not return to the original center

2. Assuming that the remaining battery charge is directly proportional to the range that can be driven

3. Each end demand point has only one logistics vehicle for service.

4. When the delivery vehicle departs from the distribution center, its load capacity does not exceed its upper limit.

5. Each distribution entity simultaneously serves as a distribution center that is responsible for loading and unloading goods from transport vehicles. Initially, each distribution center has 5 unmanned distribution vehicles, with a maximum capacity of 10 distribution vehicles.

2.2 Mathematical models

According to the problem description, the entire distribution process is divided into two stages (distribution and allocation), which are modelled tseparately.

$$MinC_0 = C_1 + C_2 + C_3 \tag{1}$$

$$C_1 = f_1 \sum_{k\in K}\sum_{i\in M'}\sum_{j\in N_m^{m'}} x_{ijk} + u_1 \sum_{k\in K}\sum_{i\in M'\cup N_m^{m'}}\sum_{j\in N_m^{m'}} x_{ijk} d_{ij} \tag{2}$$

$$C_3 = u_3 \sum_{j\in F} y_{jk} \tag{3}$$

$$\sum_{i\in M'\cup N_m^{m'}} x_{ijk}=1 \quad \forall j \in N_m^{m'} \quad \forall k \in K \tag{4}$$

$$\sum_{\forall i\in M'\cup N_m^{m'}} x_{ijk}= \sum_{\forall p\in M'\cup N_m^{m'}} x_{jpk} \quad \forall j \in N_m^{m'} \quad \forall k \in K \tag{5}$$

$$x_{m'jk} = 1 \quad \forall j \in N_m^{m'} \cup m'' \quad \forall k \in K \tag{6}$$

$$x_{im''k} = 1 \quad \forall j \in N_m^{m'} \cup m' \quad \forall k \in K \tag{7}$$

$$D_{jk} = [D_{ik}(1-y_{ik}) + y_{ik} D_{\max} - D_{ij}] x_{ijk}$$
$$\forall j \in \sum_{m\in M} N_m \cup F \cup M'' \quad \forall i \in \sum_{m\in M} N_m \cup F \cup M' \quad \forall k \in K \tag{8}$$

$$D_{jk} \geq 0 \quad \forall j \in \sum_{m\in M} N_m \cup F \cup M'' \quad \forall k \in K \tag{9}$$

$$D_{m'k} = D\max \quad \forall k \in K \tag{10}$$

$$\sum_{i\in M'\cup N_m^{m'}}\sum_{j\in N_m^{m'}} x_{ijk} q_j \leq W_{\max} \quad \forall k \in K \tag{11}$$

$$y_{jk} \leq z_j \quad \forall j \in \sum_{m\in M} N_m \cup F \cup M'' \quad \forall k \in K \tag{12}$$

$$x_{ijk}=\{0,1\} \quad \forall j \in N_m^{m'} \cup m'' \quad i \in M' \cup N_m^{m'} \quad \forall k \in K \tag{13}$$

$$y_{jk} = \{0,1\} \quad \forall j \in \sum_{m\in M} N_m \cup F \cup M'' \quad \forall k \in K \tag{14}$$

(1) Delivery stage model:

Equation (1) represents the total cost consists of distribution cost, allocation cost, and charging cost; Equation (2) indicates that the delivery cost is determined by the number of dispatched vehicles and the total mileage traveled; Equation (3) represents the charging cost; Equation (4) ensures that vehicles are available for service at each demand point; Equation (5) represents the conservation of traffic at the service point, ensuring that the vehicle leaves after delivery; Equations (6) and (7) ensure that the vehicle departs from the distribution center and ultimately returns to the distribution center; Equations (8) and (9) represent mileage constraints to ensure that the remaining range of the electric unmanned vehicle at any node is not zero, and the vehicle always follows the shortest path; Equation (10) indicates that when departing from the distribution center, the power of the distribution vehicle is full; Equation (11) indicates that the loading capacity of the delivery vehicle at any node does not exceed the vehicle capacity; Equation (12) indicates that the transport vehicle is only fully charged at a fixed charging station; Equation (13)1 variable, represented as the initial route; Equation (14)1 variable, represented as the initial charging plan

(2) Allocation stage model:

$$C_2 = f_2 \sum_{k' \in K'} \sum_{i \in M'} \sum_{j \in N_m^{m'}} x_{ijk'} + u_2 \sum_{k' \in K'} \sum_{i \in M' \cup N_m^{m'}} \sum_{j \in N_m^{m'}} x_{ijk'} d_{ij} \tag{15}$$

$$\sum_{i \in M' \cup N_m^{m'}} x_{ijk'} = 1 \quad \forall j \in N_m^{m'} \quad \forall k' \in K' \tag{16}$$

$$\sum_{\forall i \in M' \cup N_m^{m'}} x_{ijk'} = \sum_{\forall p \in M' \cup N_m^{m'}} x_{jpk'} \quad \forall j \in N_m^{m'} \quad \forall k' \in K' \tag{17}$$

$$x_{m'jk'} = 1 \quad \forall j \in N_m^{m'} \cup m'' \quad \forall k' \in K' \tag{18}$$

$$x_{im''k'} = 1 \quad \forall j \in N_m^{m'} \cup m' \quad \forall k' \in K' \tag{19}$$

$$\sum_{i \in M' \cup N_m^{m'}} \sum_{j \in N_m^{m'}} x_{ijk'} q_j \le W'_{\max} \quad \forall k' \in K' \tag{20}$$

$$x_{ijk'} = \{0,1\} \quad \forall j \in N_m^{m'} \cup m'' \quad i \in M' \cup N_m^{m'} \quad \forall k' \in K' \tag{21}$$

Equation (15) represents that the allocation cost is composed of the fixed departure cost of the allocated vehicles and the operating cost of the allocated vehicles; Equations (16) and (17) indicate that all goods have been detected, and each item of goods has only one vehicle serving it; Equations (18) and (19) ensure that each allocation vehicle departs from the distribution center and returns to the distribution center; Equation (20) indicates that the delivery vehicle ensure its loading capacity does not exceed the vehicle's capacity at any node; Equation (21) is a binary variable that represents the validity of a given virtual freight transportation route

(3) Variable and parameter definitions

C_0 Total cost C_1 Delivery cost C_2: Allocation cost C_3 Charging cost

u_1 Distribution center delivery unit distance cost (yuan/km)

u_2 Unit distance cost of allocation between distribution centers (yuan/km)

u_3 Single charging cost (yuan/time)

f_1 Single dispatch cost of delivery vehicles in the distribution center (yuan)

f_2 Single dispatch cost of vehicles allocated by the distribution center (yuan)

M The collection of distribution centers where the end demand point begins to belong

M' Collection of distribution centers assigned to end demand points (starting point)

M'' Collection of distribution centers (endpoints) assigned to end demand points

F Charging Station Collection

N_m Collection of end demand points belonging to distribution center m

$N_m^{m'}$ The collection of end demand points belonging to distribution center m but assigned to distribution center m '

K Collection of vehicles during the delivery phase

K' Collection of vehicles in the deployment phase

d_{ij} Distance traveled between point i and point j

q_j Weight of goods at demand point j

$W_{\max}$ Loading capacity of delivery vehicles

$W'_{\max}$: Adjusting the loading capacity of vehicles

x_{ijk} 1 decision variable, when the vehicle travels from point i to point j, it is 1; otherwise, it is 0

y_{jk} 1 decision variable, 1 when vehicle k is charged at point j, otherwise 0

$d_{mm'}$ The distance between distribution centers m and m '

3. Algorithm Design

3.1 Attribution allocation

(1) Generate the initial solution

Because the final result and solving speed of taboo search algorithms largely depend on the quality of the initial solution, a heuristic rule is used to generate the initial solution for the cost stage based on the ratio of the demand at the end demand point and the distribution distance from the distribution center. Thus, the demand points closer to the distribution center and with larger distribution volumes are served earlier.

(2) Taboo search algorithm logic

Define two operations: "move" and "exchange". Use A and B to refer to two distribution entities. Move refers to changing one or more distribution points belonging to distribution entity A to distribution entity B for distribution. Exchange refers to the exchange of one or more distribution points belonging to distribution entities A and B.

3.2 Distribution Path Planning

(1) Encoding

The transportation vehicle used in this study is an electric unmanned vehicle, which needs to consider not only the problem of distribution points but also the problem of charging stations when the remaining mileage of the electric vehicle is insufficient due to distance constraints. Therefore, the problem needs to be able to show the order of vehicle visits to the stations, which can be encoded in natural number order.

(2) Decoding

Decoding is the reverse of encoding. The end effector used in this article is an unmanned delivery vehicle, so the above encoding needs to determine the remaining mileage on the subpath. If the remaining mileage is not enough to reach the nearest charging station from the next node, then proceed to the nearest charging station to the current node for charging.

(3) Neighborhood movement

Combining the current solutions to generate neighborhoods, these movement methods can be divided into two categories: inter path operations and intrapath operations. These operations are detailed in Table 1.

Table 1 Neighborhood movement method

category	type	Specific operations	Before moving	After moving
Between paths (two randomly selected nodes are not in the same path, (Delivery by different vehicles) (Bold display in distribution center)	Front insertion	Insert delivery point i in front of delivery point j	*1* 234 *11* 567 *1…1*	*1* 24 *11* 5367*1*…1
	Backward insertion	Insert delivery point i after delivery point j	*1* 234 *11* 567 *1…1*	*1* 24 *11* 5637 *1…1*
	exchange	Swap delivery points i and j	*1* 234 *11* 567 *1…1*	*1* 264 *11* 537 *1…1*
	Reverse order	Flip (including delivery point i and delivery point j)	*1* 234 *11* 567 *1…1*	*1* 765 *11* 234 *1…1*
	Change distribution center	Swap the returned distribution centers to other optional distribution centers	*1* 234 *11* 567 *1…1*	*1* 234*21* 567 *1…1*
Within the path (two randomly selected nodes in the same path)	Front insertion	Insert delivery point i in front of delivery point j	*1* 234567 *1…1*	*1* 245367 *1…1*
	Backward insertion	Insert delivery point i after delivery point j	*1* 234567 *1…1*	*1* 245637 *1…1*

(Bold display in distribution center)	exchange	Swap delivery points i and j	*1* 2<u>3</u>45<u>6</u>7 *1…1*	*1* 2<u>6</u>45<u>3</u>7 *1…1*
	Reverse order	Flip (including delivery point i and delivery point j)	*1* 2<u>3</u>45<u>6</u>7 *1…1*	*1* 7<u>6</u>54<u>3</u>2 *1…1*

(4) Determination of candidate set

Select a certain number of feasible solutions from the neighborhood as the candidate set.

(5) Evaluation of solutions

The process of evaluating of the solution includes updating the current solution, finding the optimal solution from the neighborhood of the current operation, and moving the iteration toward a more optimal solution. The evaluation standard applied in this stage is the lowest total delivery cost, which includes the sum of the driving cost, departure cost, and charging cost.

(6) Taboo rules

The taboo length is a fixed constant that determines how many iterations the taboo object will not appear repeatedly. The taboo object is the route scheme corresponding to the optimal solution of nontaboo objects in the candidate set in each iteration.

(7) Stop criteria

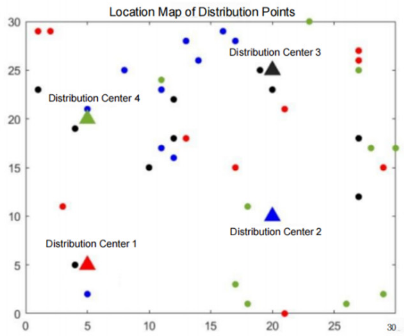
An upper limit on the number of iterations is assigned a fixed value.

4. Case simulations

4.1 Example Overview

There are four express delivery companies in a certain area, with coordinates [5,5], [20,10], [20,25], [5,20]. In one day, all four express delivery companies have 10 delivery tasks in the morning, and these delivery points are distributed within the urban area of 30 km x 30 km. The algorithm assumes that the distance between delivery points is the Euclidean distance, and delivery vehicles deliver at an average speed. The coordinates of the delivery points are as follows: The distribution centers to which each distribution point belongs and the distribution quality of each distribution point are shown in the table below. Currently, the four delivery companies adopt a joint distribution mode. Each delivery company has 5 delivery unmanned vehicles and 1 distribution vehicle at the station before the start of the task today. The delivery unmanned vehicle has a transportation fee of 50 yuan/vehicle, a maximum driving distance of 60 km, a driving cost of 1 yuan/kilometer, a maximum load capacity of 100 kg, and an average driving speed of 30 km/h. The transportation cost for the allocated vehicle is 100 yuan/vehicle, with a maximum driving distance of 200 km, a driving cost of 2 yuan/kilometer, a maximum load capacity of 200 kg, and an average driving speed of 40 km/h.

The coordinates of the distribution center and distribution points are shown in Figure 1.



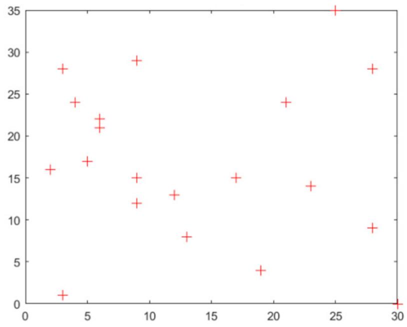


Figure 1 Distribution Point Coordinate Map **Figure 2** Coordinate diagram of charging station

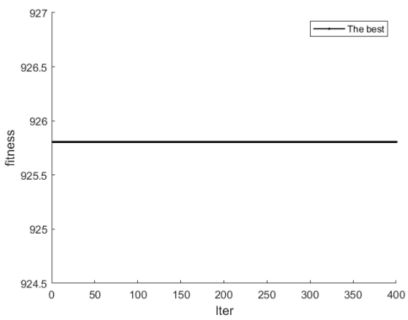
There are a total of 20 charging stations within the urban area, as shown in Figure 2. The charging time for unmanned vehicles is 30 minutes each time, and the charging cost is 15 yuan/time. The coordinates of the charging stations are shown in the Appendix. To prevent vehicles from being too concentrated at a certain distribution station, a virtual parking system is established, with a maximum of 10 unmanned vehicles distributed in each distribution center. The average waiting time for delivered goods to arrive at the distribution point is 5 minutes.

4.2 Comparative analysis

(1) The situation of traditional single mileage vehicle delivery

To verify the effectiveness of the algorithm, the case where the traditional single mileage delivery vehicle is used by the delivery subject for separate delivery is first analyzed. This delivery vehicle has a load capacity of 100 kg, a travel cost of 1 yuan/kilometer, a maximum travel distance of 80 km, and a fixed departure cost of 50 yuan. The mileage saving method is used for optimization, and 400 iterations are executed.

A total of four delivery routes were generated, with a total delivery cost of 925.5 yuan. The iterative optimization situation is shown in Figure 3, and the single mileage vehicle delivery route is shown in Figure 4.



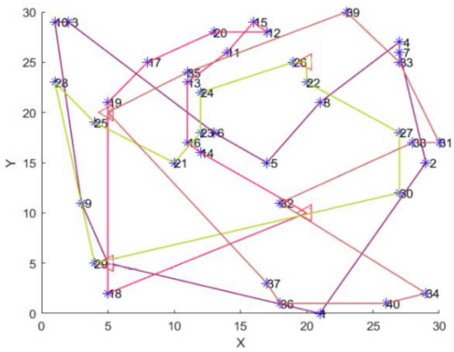


Figure 3 Iterative Optimization Diagram **Figure 4** Single Mileage Vehicle Roadmap

(2) The situation of using rechargeable electric vehicles for delivery

This section investigates the use of rechargeable electric vehicles without coordinated distribution among delivery entities. The delivery vehicle has a capacity of 100 kg, a travel cost of 1 yuan/kilometer, a fixed travel cost of 50 yuan, a maximum travel distance of 100 kilometers, and an average speed of 30 km/h. There are 20 charging stations, with a charging time of 30 minutes and a charging cost of 15 yuan/time. The taboo search algorithm is used for optimization, based on 100 neighborhood searches and a maximum of 100 iterations. The taboo length is 80.

The results show that four distribution centers independently used rechargeable electric vehicles for distribution, and a total of six electric vehicles were each dispatched for distribution and charged once, yielding a total distribution cost of 764 yuan. The iterative optimization situation is shown in Figure 5, and the roadmap is shown in Figure 6.

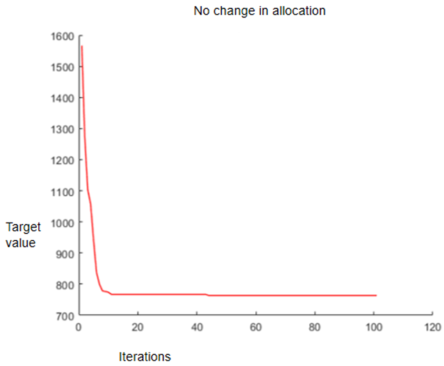


Figure 5 Non collaborative optimization iteration diagram

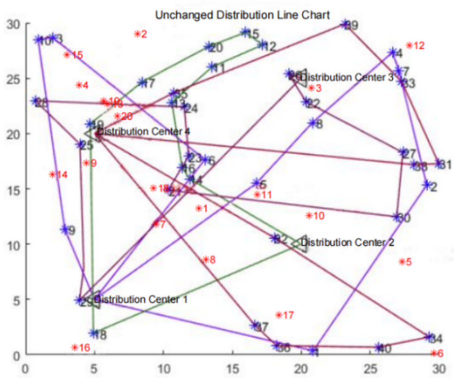


Figure 6 Collaborative Roadmap
*Charging station

(3) The situation of using electric unmanned vehicles for collaborative delivery

The distribution mode Includes a delivery cost for unmanned vehicles of 50 yuan/vehicle, with a maximum driving distance of 60 km, a driving cost of 1 yuan/kilometer, a maximum load capacity of 100 kg, and an average driving speed of 30 km/h. The transportation cost for the deployment vehicle is 100 yuan/vehicle, with a maximum travel distance of 200 km, a travel cost of 2 yuan/kilometer, a maximum load capacity of 200 kg, and an average travel speed of 40 km/h. In this stage, an improved taboo search algorithm is used to optimize the delivery and deployment stages, with a neighborhood search frequency of 100 times, a maximum number of iterations of 1000 times, and a taboo search length of 80.

Simulation results generated a total of 5 delivery paths, with a total delivery cost of 630 yuan. The iterative optimization situation is shown in Figure 7, and the roadmap is shown in Figure 8.

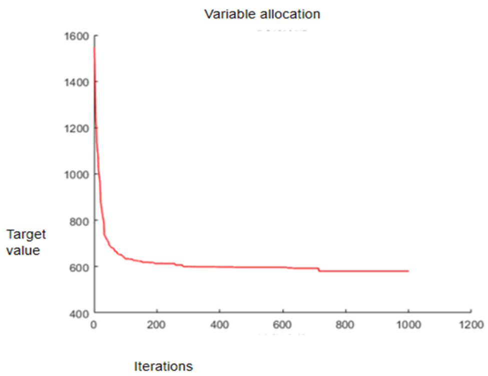


Figure 7 Collaborative Iteration Optimization Diagram

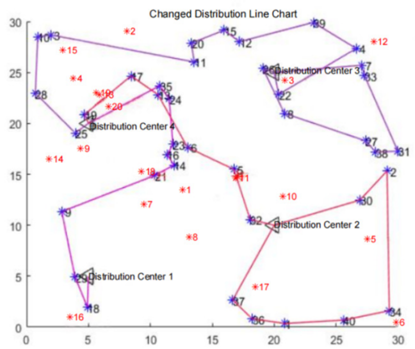


Figure 8 Collaborative Path Diagram
*Charging station

Table 2 Each delivery vehicle path

	Access sequence
Car1	3→26→8→43→16→19→24→15→7→14→32→29→4
Car2	2→41→40→5→44→38→6→34→2
Car3	3→11→37→35→42→31→12→30→3

Car4	4→39→28→27→20→18→25→13→33→22→1
Car5	2→36→9→10→17→21→23→4

According to Table 2, a total of 5 unmanned vehicles were dispatched from the 4 distribution centers for distribution operations.

Table3 Allocation Route Table

Starting point for deployment	Number of tasks	Loading and unloading volume (1 for loading and 2 for unloading)	volume of goods loaded and unloaded
4	0	0	0
4	8	1	49
4	9	1	40
1	3	1	9
1	2	1	49
1	1	1	36
3	9	2	40
3	6	1	9
3	2	2	49
2	5	1	26
2	6	2	9
2	1	2	36
2	4	1	41
2	8	2	49
3	7	1	35
3	4	2	41
4	3	2	9
4	5	2	26
4	7	2	35
4	0	0	0

From Table 3, it can be seen that the deployment of vehicles.

In this example, to verify the effectiveness of the algorithm, vehicles with the same load and mileage constraints were used in both the collaborative and non collaborative modes. The corresponding results are shown in Table 4. The collaborative delivery mode reduced driving costs by 55.3%, and the optimization amplitude of the total cost was 15.8%.

Table 4 Optimization Results Analysis Table

	Driving cost	Dispatching cost	Charging cost	Allocation of driving costs	Allocation of dispatch costs	Total cost
Center1	133	100	0	0	0	233
Center2	77	50	0	0	0	127
Center3	98	50	30	0	0	178
Center4	125	100	0			
Total cost before collaboration	434	300	30	0	0	764
Total cost after collaboration	194	250	30	86	100	660

Optimization amplitude	55.3%	16.6%				15.8%

Through case analysis and comparison with other literature, the experimental results show that the multiagent end-to-end collaborative delivery model established by myself can effectively reduce delivery costs compared to traditional delivery models, fully demonstrating the superiority and practicality of the collaborative delivery model proposed in this paper. Simultaneously, this model and report also provide practical concepts for logistics enterprises to optimize the "last mile" delivery path and reduce the proportion of end-to-end logistics costs

5. Conclusion

The collaborative distribution mode offers certain advantages over a single distribution mode approach in solving terminal distribution problems, reducing costs and increasing efficiency. This paper considers the lowest total transportation cost as the objective function and, upon considering the load and mileage constraints, constructs target models of the deployment and distribution phases in the terminal collaborative distribution process with multiple distribution agents. In the model solution, the initial solution is produced based on the heuristic algorithm. Based on the principle of limited service for points with close proximity and high quality of goods and constrained by vehicle load, an initial allocation plan for ownership is generated. Then, encoding and decoding are performed to obtain an initial solution of the delivery plan, and an improved taboo search algorithm is used for optimization of the solution. Examples from the MDVRP standard case library are used, and mathematical software is developed to test the proposed model. The corresponding simulation results verify the universal applicability and superiority of the innovative delivery model based on this model, which can better plan and more efficiently utilize logistics resources. As a result, the overall efficiency of logistics distribution is improved, and the use of nonrenewable energy is reduced, promoting green, low-carbon, and sustainable development of cities. The establishment of mathematical models is explored, as is the optimization of these models, which are also applicable to the solution of VRP problems

References

[1] Huang Junmei. Exploring the Development of O2O Models in Fruit Communities from the Perspective of Supply Chain [J], Modern Business. 2017,(09):27-28.

[2] Zhang Fen. Discussion on the Quality of Express Delivery Terminal Delivery Service [J]. China Storage and Transportation, 2021, (10); 182-183.

[3] Ke Jianchao, Meng Yanping. Logistics Network Design for Multi party Collaborative Delivery under Time Window Allocation Strategy [J/OL]. Computer Engineering and Applications, 1-15 [2024-03-04].

[4] Yang Mengke, Zhou Xiaoguang Construction of collaborative delivery mode at express terminals in the context of "Internet plus" [J]. Journal of Beijing University of Posts and Telecommunications (Social Science Edition), 2015, 17 (06): 45-50+57.

[5] Li Naiwen, Zhao Yunlong, Li Dan. Research on Simulation Optimization of Express Terminal Logistics Distribution [J]. China Management Informatization, 2016, 19 (18): 75-77.
[6] Ye C, He W, Chen H. Electric vehicle routing models and solution algorithms in logistics distribution: A systematic review[J]. Environmental Science and Pollution Research, 2022, 29(38): 57067-57090.
[7] Gupta A, Ghosh S, Dhara A. Deep reinforcement learning algorithm for fast solutions to vehicle routing problem with time-windows[C]//5th Joint International Conference on Data Science & Management of Data (9th ACM IKDD CODS and 27th COMAD). 2022: 236-240.
[8] Messaoud E. A chance constrained programming model and an improved large neighborhood search algorithm for the electric vehicle routing problem with stochastic travel times[J]. Evolutionary Intelligence, 2023, 16(1): 153-168.
[9] Jie Wanchen, Yang Jun, Yang Chao. Research on Branch Pricing Algorithms for Multi Model Electric Vehicle Routing Problems [J]. Systems Engineering Theory and Practice, 2016, 36 (07): 1795-1805.
[10] Cao Zhen, Han Shuguang. Research on electric unmanned vehicle delivery path planning problem considering charging scheduling [J]. Journal of Zhejiang University of Technology (Natural Science), 2023,49 (06): 784-794.
[11] Fujimura S, Yoshie O, Fellek G, et al. Graph Transformer with Reinforcement Learning for Vehicle Routing Problem[J]. IEEJ Transactions on Electrical and Electronic Engineering, 2023, 18(5):701-713.
[12] Wang Yong, Zhang Jie, Liu Yong, Xu Maozeng. Multi center vehicle path optimization problem for fresh produce based on resource sharing and temperature control [J] Chinese Management Science, 2022, 30 (11): 272-275.
[13] Pasha J, Nwodu A L, Fathollahi-Fard A M, et al. Exact and metaheuristic algorithms for the vehicle routing problem with a factory-in-a-box in multi-objective settings[J]. Advanced Engineering Informatics, 2022, 52: 101623.
[14] Chen J, Gui P, Ding T, et al. Optimization of transportation routing problem for fresh food by improved ant colony algorithm based on tabu search[J]. Sustainability, 2019, 11(23): 6584.
[15] Liu Xia, Qi Huan. Research on Dynamic Vehicle Routing Problem Based on Taboo Search [J]. Journal of Wuhan University of Technology (Transportation Science and Engineering Edition), 2010,34 (02): 293-296.