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End-of-line delivery vehicle routing optimization based on large-scale neighbourhood search algorithms considering customer-consumer delivery location preferences

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ABSTRACT

Logistics is an important guarantee for economic and social development. Among the various aspects of logistics, the urban logistics end distribution link, which involves the direct connection between distribution personnel and customers, has a direct impact on customers' sense of experience and satisfaction with logistics services. At present, there are unscientific and unreasonable selection methods for logistics end distribution paths, often based on the subjective experience of distribution personnel, which often results in a mismatch between distribution paths and distribution needs, affecting market demand while further increasing the distribution costs of enterprises. Therefore, based on the characteristics of customer-consumers, this paper considers that consumers can select multiple receiving addresses, and each address has a corresponding time window limit. This paper finds that it needs to spend a lot of costs for the enterprise to improve the service level of distribution, and the enterprise can save the cost from time window, as well as obtain the better distribution time by using alternative addresses through the verification and analysis of an example. Based on the above analysis, this paper proposes the urban logistics terminal distribution path optimization path based on large-scale neighbourhood search algorithm, which can promote the further matching between logistics distribution enterprises and customer needs, so as to improve the probability of consumers receiving goods in time as well as reduce the cost of enterprises.

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1. Introduction

With the development of e-commerce and the residents' travel behaviour always change, consumers often encounter the problem of receiving express delivery effectively at the end of the delivery. For customers, each day's life trajectory is distributed in different areas, there are living areas, work areas, entertainment areas, etc. Each area is often distributed in different places, and the life trajectory and time have a close relationship. For office workers, during the working day, the 9 to 5 hours are at the company, while the time spent at home is usually in the evening. The mismatch between courier services and customers' usage needs and living habits can result in lower service satisfaction. If the delivery address is filled in as the place of residence, there may be a situation where the customer is at work and signs for the delivery in person, which may end up being collected by the doorman or placed at an inconvenient pick-up point, easily resulting in lost items. If the delivery address is the workplace, there may be a meeting or business trip where the courier cannot be signed for in person. This puts the flexibility of the "last

mile" delivery location to the test. The current courier delivery model can only choose one address for a customer's delivery, which can easily cause a mismatch between the delivery location and the customer's location of activity, which can also cause the consumer to not receive the goods in a timely manner, and the courier company's delivery failure will also increase the cost of delivery.

The changing nature of consumers' activity locations over time has led to new consumer expectations for services with diverse delivery locations. If consumers can provide multiple delivery locations in a single delivery service, the delivery company can flexibly deliver according to the consumer's delivery location, which not only increases the probability of timely receipt of goods by the consumer, but also avoids the cost of secondary delivery.

This paper considers the vehicle path problem with alternative addresses, which is an extension of the vehicle path problem with time windows. In this case, each customer may provide more than one delivery address in a delivery, each delivery address has priority, and each delivery address has its own time window. A large-scale neighbourhood search algorithm is also designed to solve the problem. The analysis of consumers who do not follow the first address for delivery reveals the following characteristics of these consumers: the time window does not match other consumers in that neighbourhood of the path; the preferred address is far from the delivery area of the path, while the alternative address is closer to the delivery area; and consumers who choose the alternative address tend to be at the beginning or the end of the path. The relationship between a company's distribution costs and service level was also analysed and it was found that the service level required the highest costs when the service level was in the medium to high range.

2. Literature review

The vehicle path problem was originally proposed by Dantzig and Ramser [1] equal to 1959 and applied to logistics and distribution activities. The vehicle path problem refers to the method of seeking the goods from the distribution centre to the customer under the constraints of multiple factors, such as the number of goods, the number of distribution vehicles, the address of the distribution centre and the address of the passenger and cargo receipt, etc. Through analysis and planning of reasonable distribution routes, the whole distribution process can achieve the least distribution time, the shortest distance and the lowest distribution cost. With the continuous expansion and deepening of theories in the field of logistics, the optimization of vehicle paths for end-of-line distribution has gradually become a key and hot issue of concern in the logistics industry in recent years, causing scholars to explore and research continuously. The article summarizes and analyses the vehicle path problem of end-delivery from three perspectives: path optimization considering self-pickup service, path optimization considering consumer preference, and path optimization considering differentiated service.

2.1 Vehicle route optimisation considering self-pick-up services

Self-pick-up service is an important part of terminal distribution, and with the diversification of consumer demand for self-pick-up, it has become increasingly important to improve the level of service, so it is imperative to continuously optimise the vehicle path of self-pick-up service. In the process of optimising the delivery route, the main considerations are the radiation range of the pick-up site, the service capacity of the site, the layout of the site, consumer satisfaction, the operating cost of the site and the price of the pick-up service.

In recent years, scholars at home and abroad have carried out diverse and extensive in-depth studies on the optimization of self-pickup services. Current and Schilling [2] pointed out that the pickup site must be within the service area of the delivery vehicle, and used the travel merchant problem to analyse and interpret the self-pickup behaviour of consumers. Li and Mao [3, 4] pointed out that no matter what form of self-pickup points such as Jingdong self-pickup cabinets, Feng Chao express cabinets, CaiBird post stations, etc., they all face the problem of optimizing the path for reasonable self-pickup services, and then the authors used indicators such as construction cost, customer satisfaction, and service capability to evaluate the service capability of

self-pickup points, and also established a combined integer planning model with the lowest logistics service cost as the goal. Zhou *et al*. [5, 6] proposed the current path optimization problem faced by self-pickup services, i.e., consumers are widely and densely distributed, and it is impossible to accurately calculate the distribution path of goods, and took the customer points within the streets of Yudong in Banan District of Chongqing as the research object, argued the relationship between the location of self-pickup points and path optimization, and built a path optimization model for self-pickup distribution. Koç *et al*. [7] and Hua *et al*. [8] pointed out that the location of logistics distribution centres is an important task in the overall network optimisation of logistics systems, and a scientific centre location can assist in improving the relevant effects of path optimisation. To solve the location problem of distribution centres, Hua *et al*. [8] proposed an adaptive particle swarm optimisation algorithm with non-linear inertia weights and time-varying acceleration coefficients. Sankaran *et al*. [9] sorted out the problem of siting two groups of high-capacity facility locations and proposed a method for optimizing the siting of self-pickup sites by aggregating consumer pickup point information. Wang *et al*. [10] pointed out that there is a certain correlation between the price of self-service and brand image, and constructed a correlation function between the reachable distance of self-pickup path, the price of self-pickup service and the brand of self-pickup service. Guo *et al*. [11] conducted a study on vehicle route optimization and service strategies based on consumers' pickup radius, and pointed out that self-pickup considering consumers' pickup radius can effectively reduce the number of delivery vehicles and personnel, which can achieve the purpose of reducing the operation cost of end-distribution.

2.2 Vehicle path optimisation considering consumer preferences and behavior

In end-of-line delivery, consumers will consider various factors such as delivery method, delivery time and delivery price, and their preferences and behaviour towards different choices will also have an impact on vehicle route optimisation. In terms of delivery methods, 2.1 summarises the vehicle path optimisation considering self-pick-up services; meanwhile, domestic and international scholars have conducted in-depth and extensive research on vehicle path optimisation for home delivery, which is summarised in this summary. In terms of path optimisation for end-delivery home delivery services, Khouadjia [12] *et al*., and Okulewicz and Mańdziuk [13] argue that in the end-delivery process, once a delivery person has accepted the instruction to deliver to a consumer, he or she cannot change the new delivery target until the current delivery task is completed before the next task can be carried out; based on this premise, Okulewicz and Mańdziuk [13] used a meta-heuristic to optimise the paths associated with the receipt of delivery instructions to vehicle assignment. Abdallah *et al*. [14] considered the end-of-pipe delivery problem as dynamic vehicle path optimisation and suggested that, for more efficient delivery of continuous goods, delivery personnel should go to a nearby planning delivery node at the completion of the delivery task and wait at the node for new delivery instructions and vehicle scheduling solutions. Keçeci *et al*. [15] pointed out the path optimisation for home delivery as variational path optimisation with pickup and delivery functions, and proposed a hybrid meta-heuristic based on simulated annealing algorithm and local search algorithm of SA-LS with minimum delivery cost as the objective. Silvestrin and Ritt [16] analysed the scenario of multi-carriage vehicles, where several different qualities or types of products that must be kept or handled separately and use a forbidden search algorithm to solve the problem. Soto *et al*. [17] solve the multi-warehouse open vehicle routing problem, which is a generalised case of capacity vehicle path optimisation; in this scenario, vehicles perform delivery services from different warehouses, visit consumers and complete the delivery of goods, without the goods deliverer then having to return to the end of the route at the warehouse.

Consumers' preferences for delivery time and delivery price also affect the path optimisation of delivery vehicles. Most of the current research on delivery time focuses on time window theory, while most of the research on delivery price focuses on delivery pricing theory. In terms of end distribution time, Taş *et al*. [18] studied the vehicle path problem with time window and random travel time, combined the relationship between transportation cost and service cost, i.e., the total vehicle travel distance and cargo arrival time, and proposed a path optimisation model

based on this. Zhu *et al*. [19] considered the constrained situation of time window and built a path optimisation model for multi-vehicle logistics distribution under different environments with the objective of lowest total delivery cost and shortest delivery time. Gutierrez *et al*. [20] set the vehicle travel time and service time as random variables and solved the vehicle path optimisation problem under the premise that each consumer is served. Guedes and Borenstein [21] borrowed the processing method of space-time grid for distribution path optimisation and analysed the multi-warehouse vehicle type scheduling problem. Veenstra *et al*. [22] studied the problem of goods distribution and delivery based on the time window. Kim *et al*. [23] combined the uncertainties of delivery time, delivery demand, and real-time traffic conditions to build a logistics and delivery model for path optimisation. In terms of end-delivery prices, Tounsi *et al*. [24] develop a new heuristic algorithm for the delivery service pricing problem, where the delivery service and path optimization are carried out by the delivery side according to the price of the service chosen by the consumer. Hayel *et al*. [25] point out that consumer behaviour, especially the choice of a reasonable price, affects the path optimisation of end-delivery, and the authors later use a game theoretical. The topic was studied from a game theoretical perspective; Yang *et al*. [26] considered the different delivery costs of consumers for different delivery time slots, thus building a route optimization model with real-time pricing.

End-delivery is the last link in the transportation of goods, and the consumer as the participant in the final link can have a profound impact on route optimisation, regardless of the behaviour, in addition to the factors summarised above. For example, Ren *et al*. [27] argue that consumer preference behaviour can have an impact on end delivery and that customers may hold different attitudes towards different types of goods, while the authors later build a 4PL path optimisation model to conduct relevant research, proving the scientific validity of their view. Therefore, paying attention to consumer preferences and their behaviours has a positive significance and important role in the route optimisation of end-delivery, and can effectively improve the service efficiency of end-delivery.

2.3 Vehicle route optimization considering differentiated service provision

In the process of end-delivery, in addition to the service demand for ordinary delivery, increasingly diverse and differentiated services have emerged [28, 29], with the existence of cold chain logistics end-delivery, takeaway delivery, same-city delivery and end-delivery services in emergency scenarios (such as the delivery of emergency materials after a disaster). In addition, some end-delivery services are subject to certain additional top-up fees to ensure efficient delivery of goods.

The delivery target of cold chain logistics is usually frozen food, so the delivery service has to be completed within the period of food refrigeration to avoid food spoilage. As cold chain logistics plays an indispensable role in people's lives, research on cold chain logistics has been a hot topic for experts and scholars at home and abroad. Among them, in the end distribution of cold chain logistics, Deng *et al*. [30] and others believe that the end distribution process of cold chain logistics needs to increase the consideration of factors such as the degree of goods loss and goods refrigeration market, and through the introduction of the concepts of penalty cost, goods loss cost, refrigeration cost, out-of-stock cost, transportation cost and fixed cost, the path optimization of the end distribution of cold chain logistics is carried out. Zhang *et al*. [31] and others constructed a path optimisation model for cold chain logistics vehicles using a soft time window model and solved the optimal solution using an improved genetic algorithm. Ren *et al*. [32] studied a distribution scenario with multiple distribution centres sharing resources under the premise of ensuring on-time food delivery and established a vehicle path optimisation model for delivery at the lowest delivery cost of fresh food.

Food delivery service is a special kind of end delivery driving, the start and end point of food delivery are in the same city, and the delivery distance is significantly shortened compared to other methods. In addition, as consumers have the actual demand for fast meals, there are higher requirements for their takeaway delivery speed. Wang *et al*. [33] argued that merchants would have certain time requirements for delivery services to improve consumers' satisfaction with takeaway delivery, while the authors later used the relevant random travel time based on

the purpose of improving consumer satisfaction Chen and Shi [34] considered factors such as consumer time satisfaction and optimised the traditional pick-up and delivery vehicle path model. Liu [35] introduced the k-means concept to build a dynamic demand-based path optimisation model for the complexity of the takeaway model. Similar to takeaway delivery, same-city delivery also belongs to same-city proximity delivery, and now also belongs to the category of end-of-line delivery, and the route optimization approach is also very similar to that of takeaway delivery. Tounsi *et al*. [24] developed a new heuristic algorithm for the delivery service pricing problem, in which the delivery service is developed by the delivery provider according to the price level of the service chosen by the consumer Hayel *et al*. [25] show that consumers' behaviour, especially their choice of reasonable price, affects the route optimisation of end-delivery, and then use a game-theoretic perspective to study this topic. Yang *et al*. [26] build a route optimisation model with real-time pricing by considering the different delivery costs of consumers at different delivery timeslots.

Scholars have widely applied large-scale neighbourhood search algorithm in the research of terminal distribution vehicle routing to solve the vehicle routing problem, such as the routing problem with delivery options, the terminal distribution routing problem using UAVs, the routing optimization of multiple warehouses and vehicles, and the vehicle routing optimization problem with time windows [7, 36-38]. The studies summarised above are all about the distribution of goods in safe and stable scenarios, but there are also demands for the distribution of goods in various unexpected scenarios caused by accidents, and emergency scenarios, such as the emergency distribution of materials after a disaster, play an even more vital and irreplaceable role. The scenarios analysed above do not cover all the differentiated logistics distribution [39]. Different distribution modes of different nature are applicable to different consumer needs or distribution occasions, all of which play a unique role in people's production life and are indispensable in the logistics service industry.

3. Model building and algorithm design

3.1 Model building

A distribution station in the city is responsible for supply, and goods are transported from the distribution station to each consumer point by multiple vehicles within the time required by the consumer, and then the delivery vehicles return to the distribution station. Each customer-consumer may provide more than one delivery address in a single delivery, and each delivery address has priority, and each delivery address has its own time window. The vehicle can select any one of these locations for delivery. As shown in Fig. 1, the blue triangle in the diagram represents the distribution center from which the vehicle departs from the delivery station and delivers to each consumer point. The same-coloured dots represent the delivery locations set by the consumer. The vehicle simply serves one of these and eventually returns to the distribution station.

The precise algorithm is still more suitable for small-scale distribution scenarios. Although the algorithm can calculate the optimal route of vehicles, it considers fewer constraints and has a slow speed in large-scale and complex scenarios Genetic algorithm (GA) is an algorithm for searching the optimal solution, which is proposed by simulating the genetic principle and evolutionary process of biology. It has certain advantages in solving complex combinatorial problems and has been widely studied and applied by many industries. Therefore, the application scope of the precise algorithm in the end distribution route optimization is less than that of the meta heuristic algorithm and the adaptive large-scale neighbourhood search algorithm. The neighbourhood search algorithm searches for the "neighbourhood" solution of the current solution through countless iterations and obtains a better solution through comparative analysis. The larger the neighbourhood, the better the solution. At present, the application of neighbourhood search algorithm has been extended to the field of vehicle routing optimization in terminal distribution. Each customer i has a demand q_i and each customer has a preferred delivery location. As a result, customers have different satisfaction levels for each address and the overall delivery of the vehicle needs to meet the overall satisfaction level constraint.

The earliest and latest time windows $[e_{i^a}, l_{i^b}]$ are different for different delivery locations i^a for each customer i. The vehicle may arrive earlier than the earliest time window of the customer, but needs to wait until the earliest time window to be served, being subject to a waiting cost, and is subject to a delayed service penalty if it arrives later than the latest time window. The vehicle arrives at customer point i^a with a service time of s_{i^a} and leaves immediately after servicing that point. There is no limit to the number of vehicles k available for use at the depot, but each vehicle incurs an operating cost θ_k. The vehicles are homogeneous. The model notation is illustrated as follows:

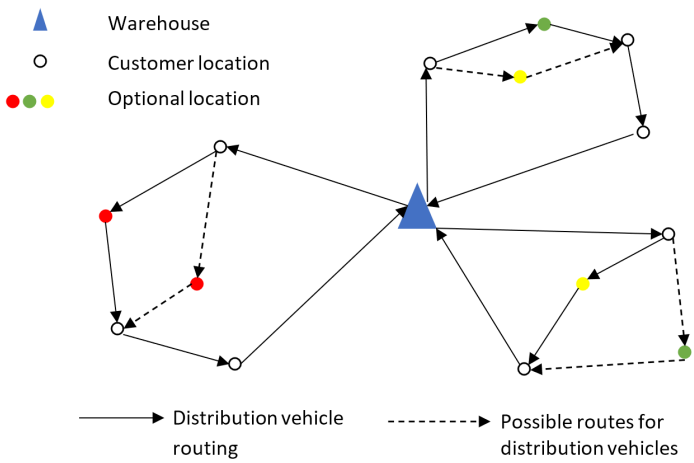

Fig. 1 Distribution vehicle route planning diagram

0	Warehouse
C	Collection of customers, $C = \{1,2,\dots,m\}$
N	Collection of customers and warehouses, $N = \{0,1,2,\dots,m\}$
K	Vehicle collection, $K = \{1,2,\dots,k\}$
L_i	Collection of optional distribution locations for L_i customer i
$d_{i^a j^b}$	Arc the distance between (i^a, j^b), i.e. the distance from ath optional distribution location of customer i to b-th optional distribution location of customer j
$c_{i^a j^b}$	Arc running cost between (i^a, j^b)
q_j	Customer j demand
e_{i^a}, l_{i^a}	Time window for customer i's a-th optional delivery location
ε_{j^b}	Customer satisfaction when vehicle delivers customer j's b-th delivery location
r_{i^a}	The time to start serving customer i's a-th optional delivery location
s_{i^a}	Service time of customer i's a-th optional delivery location
t_{j^b}	Minimum waiting time or minimum delayed service time for customer i's a-th optional delivery location
P	Unit waiting costs or delayed service penalty costs for P vehicles
θ_k	Operating costs of θ_k vehicles
Q_k	Capacity limits for $\theta_k$vehicles
D_k	Distance limit for vehicles
v_k	Average speed of the vehicle
S	Overall customer satisfaction required by warehouse S
M	A sufficiently large positive number
u_{i^l}	Auxiliary decision variables
$x^k_{i^a j^b}$	Is 1 if vehicle k passes through arc(i^a, j^b); otherwise it is 0
$y^k_{j^b}$	Is 1 if customer j's bth optional delivery location is served by vehicle k; 0 otherwise z_k
z_k	Vehicle k is used or not

Based on the above scenario description and assumptions, the model for this path planning problem is shown below.

Objective function:

$$min\, c \sum_{k\in K}\sum_{i\in N}\sum_{a\in L_i}\sum_{j\in N}\sum_{b\in L_j} x_{i^a j^b}^k d_{i^a j^b} + \sum_{k\in K} z_k\theta_k + \sum_{j\in N}\sum_{b\in L_j} Pt_{j^b} \tag{1}$$

Binding conditions：

$$\sum_{i\in N}\sum_{a\in L_i} x_{i^a j^b}^k = y_{j^b}^k,\ \ \forall k\in K, j\in N_c, b\in L_j \tag{2}$$

$$\sum_{k\in K}\sum_{b\in L_j} y_{j^b}^k = 1,\ \ \forall j\in C \tag{3}$$

$$\sum_{k\in K}\sum_{j\in N}\sum_{a\in L_i}\sum_{b\in L_j} x_{i^a j^b}^k = 1, \qquad \forall i\in C \tag{4}$$

$$\sum_{i\in C}\sum_{a\in L_i} x_{0i^a}^k = \sum_{i\in C}\sum_{a\in L_i} x_{i^a 0}^k,\ \ \forall k\in K \tag{5}$$

$$u_{i^a} - u_{j^b} + |N| x_{i^a j^b}^k \le |N| - 1,\ \ \forall i,j\in C, i\ne j, a\in L_i, b\in L_j, k\in K \tag{6}$$

$$r_{i^a} + s_{i^a} + \frac{d_{i^a j^b}}{v} \le M\left(1 - x_{i^a j^b}^k\right) + r_{j^b}\ \ \forall\, i,j\in N, k\in K \tag{7}$$

$$y_{i^a}^k e_{i^a} \le r_{i^a}\quad \forall i\in C, k\in K, a\in L_i \tag{8}$$

$$t_{j^b} \ge max\left[y_{j^b}^k e_{j^b} - \left(r_{i^a} + s_{i^a} + \frac{d_{i^a j^b}}{v}\right), 0, y_{j^b}^k\left(r_{j^b} + s_{j^b}\right) - l_{j^b}\right], \tag{9}$$

$$\forall i,j\in C, i\ne j, a\in L_i, b\in L_j, k\in K$$

$$\sum_{k\in K}\sum_{b\in L_j} y_{j^b}^k q_j \le Q_k, \qquad \forall\, k\in K \tag{10}$$

$$\sum_{i\in N}\sum_{a\in L_i}\sum_{j\in N}\sum_{b\in L_j} x_{i^a j^b}^k d_{i^a j^b} \le D_k, \forall\, k\in K \tag{11}$$

$$\sum_{k\in K}\sum_{j\in C}\sum_{b\in L_j} y_{j^b}^k\, \varepsilon_{j^b} \ge S(|N| - 1) \tag{12}$$

$$z_k \ge y_{j^b}^k,\ \ \forall i\in C, b\in L_j, k\in K \tag{13}$$

$$x_{i^a j^b}^k \in \{0,1\},\quad \forall i,j\in N, a\in L_i, b\in L_j, k\in K \tag{14}$$

$$y_{j^b}^k \in \{0,1\},\ \ \forall j\in C, b\in L_j, k\in K \tag{15}$$

$$u_{i^a}, u_{j^b} > 0,\ \ \forall i,j\in N, a\in L_i, b\in L_j \tag{16}$$

Eq. (1) is the objective function with two components: distribution cost and vehicle operating cost. Constraints Eqs. 2 to 4 indicate that all of each customer can only be delivered by one vehicle. Constraint Eq. 5 indicates that the vehicle departs from and returns to the warehouse. Constraint Eq. 6 is a Miller-Tucker-Zemlin constraint that prevents the creation of subloops so that each vehicle's delivery route forms a loop, where u_{i^l}, u_{j^e} are auxiliary variables. Constraint Eq. 7 represents the relationship between the starting service moments of two adjacent customer points visited by the vehicle. Constraint Eq. 8 represents the service time of the delivery vehicle cannot be earlier than the time requested by the customer. Constraint Eq. 9 represents the minimum waiting time or delayed service time for each customer point. Constraint Eq. 10 represents the vehicle capacity constraint, each vehicle cannot exceed its maximum load capacity.

Constraint Eq. 11 represents the vehicle travel distance constraint, the constraint Eq. 11 represents the vehicle distance constraint that each vehicle cannot travel more than its maximum distance. Constraint Eq. 12 represents the overall satisfaction rate of the delivery to be higher than the required satisfaction rate. Constraint Eq. 13 determines whether the vehicle is used or not. Constraints Eqs. 14 to 16 are the decision variables definition fields.

3.2 Algorithm design

Initial setting

Since the objective function is profit maximisation, we need to start with the objective function. Eq.17 is the corresponding function expression.

$$T = O(S^0) \times P_{init} \tag{17}$$

Neighbourhood structure

Since the delivery method of customers who have ticked the value-added service will no longer change, we add new removal and insertion policies to the original removal and insertion policies to improve the feasibility of the path. For ease of description, we will refer to consumers who have ticked the value-added service as value consumers. The basic idea behind these two strategies is that the higher the proportion of value consumers included in a path, the lower the number of solutions generated by adjusting the customer delivery method for that path, and the less favourable it is to generate feasible solutions in the early stages of the algorithm. Therefore, our two strategies operate mainly on such paths to ensure the convergence speed of the algorithm.

Path removal strategy

Step1: Count the proportion of each path in a solution S that contains consumers of value, and then arrange them in descending order.
Step2: Remove the paths until the number of removed is n_r.

Distribution location factor insertion strategy

The distribution location factor insertion strategy is based on the distribution location to determine whether consumer points are allowed to be inserted.
Step1: Calculate the distribution location association of the arc with the consumer point to be inserted.

Since the arc (i, j) is assumed to be an arc on the P path, K is the target insertion point and $E_i \leq E_k \leq E_j$. The association between the arc (i, j) and the consumer point K distribution location is calculated as

$$\sigma_{ik} = \begin{cases} max\{L_i - E_k, 0\} & E_i \leq E_k \\ min\{L_i, L_k\} - E_i & E_k < E_i \leq L_k \\ max\{L_k - E_i, 0\} & E_i > L_k \end{cases} \tag{18}$$

$$\sigma_{kj} = \begin{cases} max\{L_k - E_j, 0\} & E_k \leq E_j \\ min\{L_k, L_j\} - E_k & E_j < E_k \leq L_j \\ max\{L_j - E_k, 0\} & E_k > L_j \end{cases} \tag{19}$$

$$\sigma_{ij} = \sigma_{ik} + \sigma_{kj} \tag{20}$$

Step2: Insert the consumer point K into the arc (i, j) with the highest correlation to the distribution location.

The delivery location correlation here is different from the previous chapter, mainly because later in the algorithm, due to the presence of value consumers, basic constraints such as vehicle capacity are easy to satisfy, but satisfying the delivery location constraint is more difficult and incurs a larger penalty cost that needs to be specifically addressed for the delivery location. In contrast, the increased cost of considering arcs (i, j) to insert consumer points K does not require much consideration. Therefore, we need to recalculate the correlation.

4. Example analysis: Results and discussion

4.1 Calculation example using

In this paper, five neighbourhoods near Beixiaoguan Street in Haidian District, Beijing are used as the basis for the calculation of the example analysis. Steel Research Community, Jiaoda Jiayuan, Mingguang Village neighbourhood, Tianzhao Home and Changhewan neighbourhood are selected as the community delivery area, and the number of delivery customers in each neighbourhood is 89, 87, 99, 85 and 75 respectively. To simplify the analysis and to better present the results, the delivery points of consumers in each neighbourhood are simplified to 5 (see Fig. 2). Based on the research of the actual courier company, the distribution centre was selected in this paper at the ground floor of the Yihai Business Hotel, No. 33 College South Road, Haidian District.

Fig. 2 Community distribution district selection

4.2 Optimal route and delivery method

First path analysis

The primary delivery area for Path 1 is in the Mingguang Village neighbourhood. The numbering of those consumers who are not at their preferred delivery address is as follows in Table 1.

The time windows for these consumers' preferred addresses are in the afternoon, and if delivery is made to the preferred address, there is a long wait time. To save time window waiting time costs, the delivery person should deliver to these consumers' second or third addresses (Table 2). In addition, this consumer's alternative address is also closer to the Mingguang Village neighbourhood, and delivering these consumers together with the Mingguang Village neighbourhood could reduce costs (see Fig. 3).

Table 1 Table of path results

Serial No.	Path
1	[0,200,367,399,293,403,424,427,309,142,246,304,225,349,82,402,385,8,129,44,141,283,429,325,338,71,87,114,120,149,289,131,324,308,110,166,102,162,206,207,209,247,279,316,331,397,400,421,428,431,328,9,255,124,136,178,321,226,21,83,224,152,30,0]
2	[0,258,274,359,391,194,327,416,299,377,99,395,145,157,244,61,89,37,176,184,195,48,20,201,222,251,317,330,271,323,128,96,430,273,352,197,307,411,92,150,305,27,42,74,57,298,75,93,112,155,223,172,272,280,379,387,393,396,10,77,239,84,58,122,0]
3	[0,132,35,50,115,436,337,390,264,350,346,168,270,230,2,426,62,368,404,40,189,343,205,334,383,250,101,358,23,39,290,372,432,281,417,98,180,183,243,186,314,144,1,277,109,116,103,164,284,419,153,364,67,49,407,127,4,143,192,126,287,0]
4	[0,265,326,237,345,348,433,41,175,312,319,306,167,181,216,435,214,282,382,68,80,117,208,66,295,365,212,3,170,320,14,229,165,146,19,63,130,335,344,418,204,18,218,11,28,160,177,187,231,275,398,107,233,422,356,106,234,81,51,0]
5	[0,73,333,156,260,388,232,256,384,140,125,238,423,235,353,425,378,413,303,286,374,373,242,7,249,31,252,104,147,16,105,78,43,64,297,69,95,301,190,60,196,203,245,254,217,360,278,336,339,340,351,406,357,434,76,354,161,253,262,0]
6	[0,313,137,219,148,113,261,292,266,25,276,329,53,72,210,386,401,26,90,311,392,310,332,36,47,52,355,97,65,86,94,179,408,322,376,100,185,34,410,227,381,108,22,6,236,118,220,409,79,135,241,291,13,55,29,294,375,173,0]
7	[0,17,268,347,199,341,369,202,415,88,134,5,56,121,380,389,45,139,318,366,257,123,420,414,302,159,191,394,12,54,151,171,174,32,405,363,24,211,163,91,138,296,111,361,248,371,267,38,300,33,133,198,85,269,59,70,188,193,221,240,263,412,362,119,342,315,0]
8	[0,15,35,132,213,169,50,115,436,259,288,370,154,182,215,285,46,158,228,0]

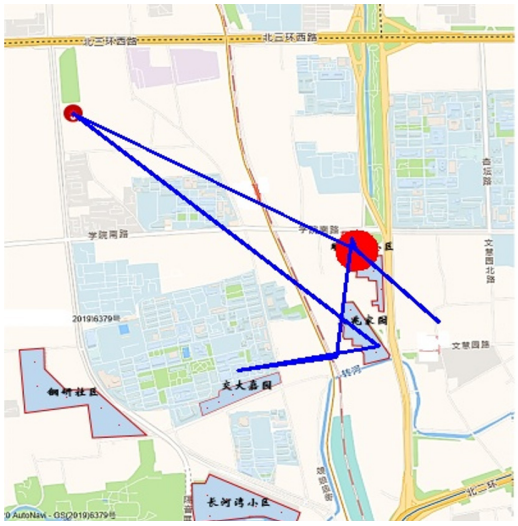

Fig. 3 Distribution of consumers for path 1 and the optimal path

Table 2 Consumers in path 1 who were not delivered to their preferred address

No.	Address serial number
200	2
367	3
399	2
225	2

Fig. 4 Distribution of consumers for path 2 and the optimal path

The main delivery areas for Path 2 are in the Mingguang Village neighbourhood and the Tianzhao Home (see Fig. 4). The consumers who are not preferred delivery addresses are numbered 416 and 239, both of which are second addresses. By analysing the characteristics of the consumers, it can be found that the preferred address of consumer 416 is in Mingguang Village Sub-district, but the time window of the preferred address is after 3pm, while the consumers in Mingguang Village Sub-district all made their deliveries before 1pm, so to deliver consumer 416, they need to drive from Tianzhao Home to Mingguang Village Sub-district and back to Tianzhao Home after 3pm. However, the time window for the second address of consumer 416 is in the morning and is between Mingguangcun Subdistrict and Tianzhao Home, so it is a better choice to deliver according to the second address.239 The time window for the preferred address of con-

sumer 239 is in the afternoon, but the preferred address is in Steel Research Community, which is farther away from Tianzhao Home and Mingguangcun Subdistrict, and the second address is closer to Tianzhao Home, and the time window of the second address also better match, so delivery at the second address is more appropriate.

The main delivery area for Path 3 is also in the Mingguang Village neighbourhood and Tianzhao Home, but there are also a small number of consumers in the Jiaoda Jiayuan and Steel Research neighbourhoods (see Fig. 5). The consumers who are not the preferred delivery address are numbered 132 and 35, both of which are second addresses. By analysing the characteristics of the consumers, we can find that the preferred address of consumer 132 is in Jiaoda Jiayuan, but the time window of the preferred address is 8:00-12:00, while the consumers in Jiaoda Jiayuan in route 3 all deliver after 8:00 pm, so it is not suitable for delivery with other consumers in Jiaoda Jiayuan. In this case, it is more appropriate to choose the second address of consumer 132 and deliver in the morning.35 The preferred address of consumer 35 is in Changhewan district, but there are no other consumers in Changhewan district in route 3, and the second address of this consumer is closer to Tianzhao Home and Mingguang Village district, so delivery can be made through the second address.

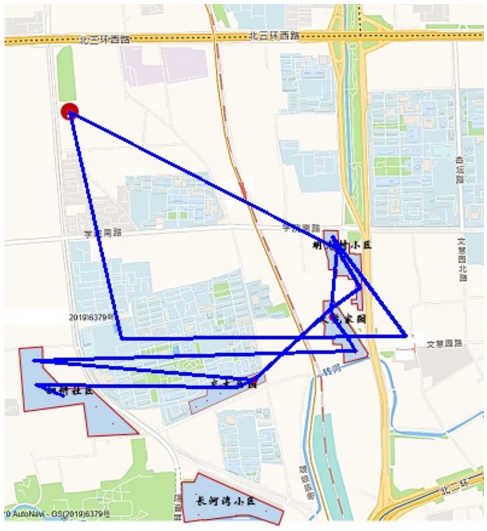

Fig. 5 Distribution of consumers for path 3 and the optimal path

The main delivery areas for Path 4 are in Jiaoda Jia Yuan and the Steel Research community. The consumers who are not preferred delivery addresses are numbered 265 and 41, both of which are second addresses (see Fig. 6). By analysing the characteristics of the consumers, it can be found that the preferred addresses of both 265 and 41 consumers are in Jiaoda Garden. However, the time window for consumer 265's preferred address was after 1pm, which did not lend itself to delivery in the morning with other consumers in Jiaoda Jiaoyuan, so delivery to the second address was chosen. In fact, Consumer 265's second address was closer to the Tianzhao Home and Mingguang Village neighbourhoods, so why was it not delivered in a path where the main delivery area was these two neighbourhoods? The reason is that although the distance is close, the time window for 265's second address is after 10am, whereas the initial delivery time in the other paths is often before 10am, so the time windows do not match. Consumer 41, although both the time window and address match those in the Long River Bay subdivision in path 4, is preferable to its second address for delivery due to the high number of consumers in the Long River Bay subdivision and the fact that they are mainly concentrated in the afternoon and do not have the spare time to make additional deliveries to 41.

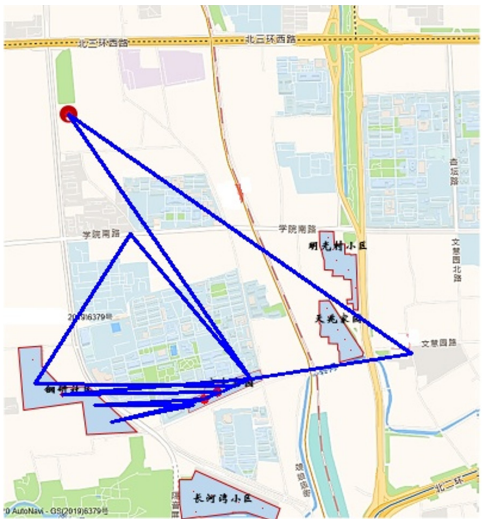

Fig. 6 Distribution of consumers for path 4 and the optimal path

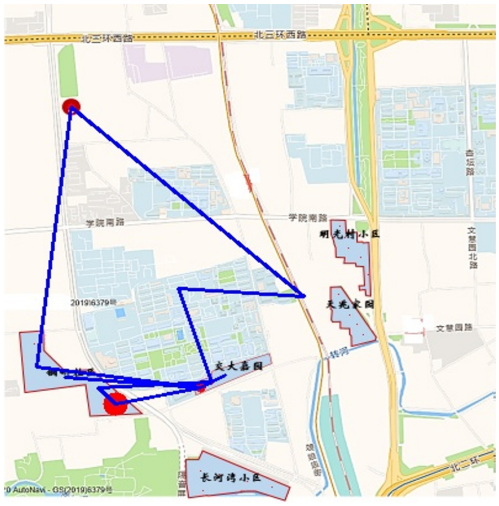

Fig. 7 Distribution of consumers for path 5 and the optimal path

The primary delivery area for Path 5 is in Jiaoda Jia Yuan and the Steel Research community. The consumers who are not preferred delivery addresses are numbered 333 and 353, both of which are second addresses (see Fig. 7). 333 and 353 consumers' preferred addresses are both in the main delivery area of Path 5, but why are they not delivered at their preferred addresses? Analysis of the consumers' characteristics reveals that the time window for consumer 333's preferred address is after 12pm, while other consumers in the Steel Research community where consumer 333 is located concentrate their deliveries in the morning, so they can be delivered at the second address in the morning through the time window. The main reason for Consumer 353 to deliver with a second address is also due to the more suitable time window for 353 and the proximity of the second addresses of 333 and 353 to the Steel Research Community and Jiaoda Jiayuan.

The main delivery areas for path 6 are in Jiaoda Jiayuan, the Steel Research community and the Changhewan neighbourhood (see Fig. 8). The number of the consumer who is not the preferred delivery address is 137, the second address. 137 The preferred address is Jiaoda Jiayuan and the time window is after 4pm, but the time window for all other consumers in Path 6 is before 4pm, so in order not to have to make additional deliveries separately, the closer second address can be chosen for delivery.

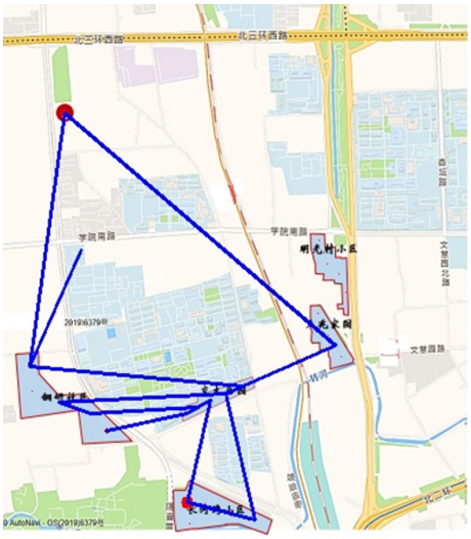

Fig. 8 Distribution of consumers for path 6 and the optimal path

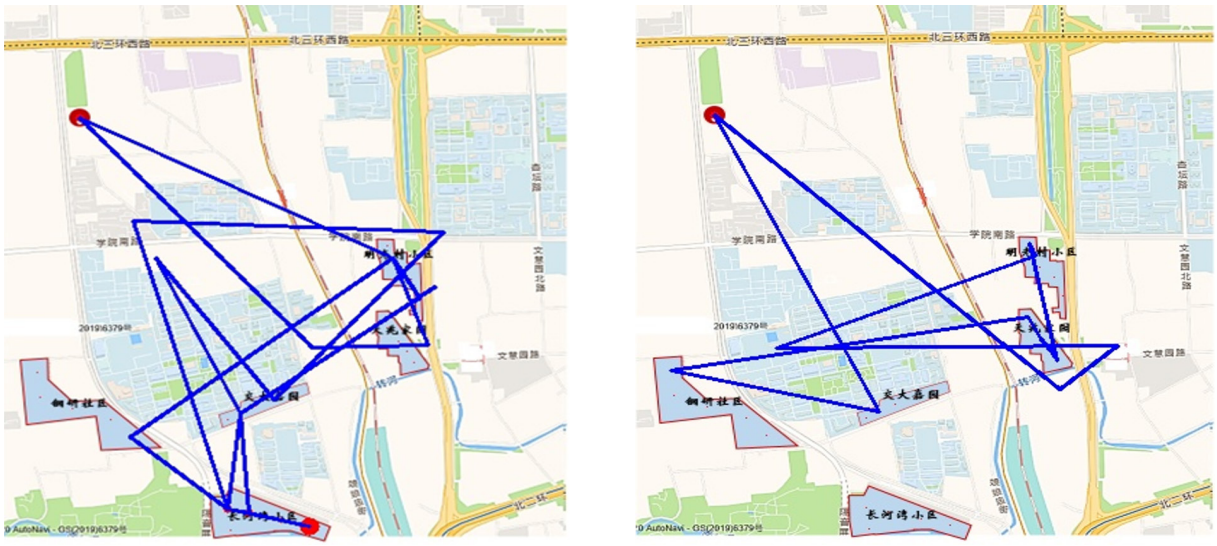

Fig. 9 Distribution of consumers for path 7 and path 8 and optimal path

Path 7 and Path 8 have a wider delivery area coverage, both with more than 4 heel cells (see Fig. 9). There were more of these consumers who were not preferred delivery addresses, with consumer numbers 17, 268, 88, 151, 296, 111, 248, 362, 342, 15, 35, and 132.

An analysis of consumers who are not preferred addresses for delivery reveals the following characteristics of these consumers:

- Time windows that do not match other consumers in that neighbourhood on that path.
- The preferred address is further away from the delivery area of the path, while the alternative address is closer to the delivery area.
- Consumers who choose the alternative address tend to be at the beginning or the end of the path to reduce detours.

4.3 Cost analysis

This paper compares the total cost of the model without alternative addresses with the total cost of the model with alternative addresses. The comparison shows that the total cost of the model with alternative addresses is 283.43 compared to the total cost of the model without alternative addresses of 307.89, a total cost saving of 24.46. By consumers providing alternative addresses, the distribution company saves 24.46. For consumers, total satisfaction decreased as there were

some consumers who did not receive goods from the preferred address. In terms of time window penalty cost, the model saved mainly in terms of time window, which was reduced through alternative addresses and thus better delivery times. Although consumer satisfaction is reduced, consumers are also willing to provide alternative addresses as alternative addresses may allow consumers to get their goods earlier.

4.4 Sensitivity analysis

During the calculations, it was observed that the presence of a service level constraint tends to make the VRPBA algorithm more difficult to solve, so a sensitivity analysis is performed in this section to explore more precisely the effect of different service levels on the total cost, computation time and number of optimal solution instances.

Due to the service level constraint, we make the service level required for the first priority vary between 60 % and 100 % in 4 % steps, i.e. note that a 4 % increase means that 10 additional consumers out of 250 are required whose delivery method must be the first delivery method chosen by the consumer.

The relationship between average path cost and service level is depicted in Fig. 10. As expected, increasing the level of service leads to an increase in total costs. β_1 = 1.0 is approximately 22 % higher than β_1 = 0.6. The impact on total cost and calculation time is analysed according to the VRPBA example. Fig. 9 also shows the average running time and confirms that the problem difficulty decreases when the service level is increased. Furthermore, the service level requires the highest costs, i.e. the absolute slope of the curve, when the service level is at the upper end of the medium range, i.e. when the value of β_1 is between 0.7 and 0.85.

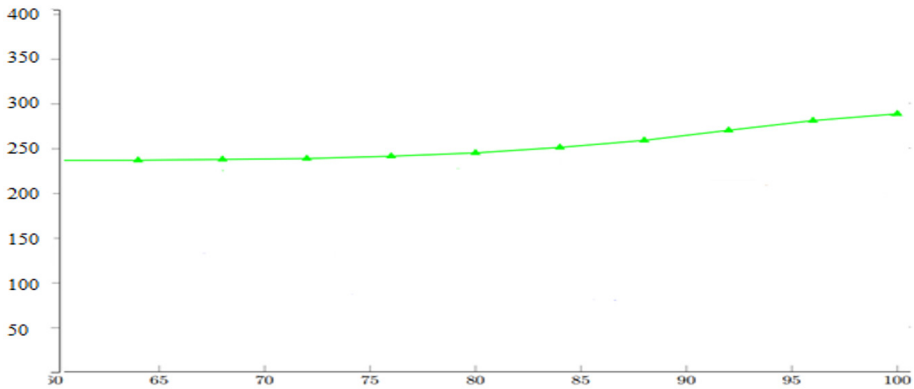

Fig. 10 Relationship between service levels and costs

5. Research conclusions

In this paper, a vehicle path optimisation model based on consumer delivery locations was established to optimise the driving paths and delivery methods of end-of-line delivery vehicles, and the same solution algorithm was designed. Based on the improved algorithm and the construction method of consumer portraits, this paper establishes a solution algorithm based on the data of five real communities and plans the delivery routes and delivery methods. This paper considers the vehicle path problem with alternative addresses, which is an extension of the vehicle path problem with time windows. In this case, each consumer may provide more than one delivery address in a delivery, each delivery address has a priority, and each delivery address has its own time window. The analysis of the arithmetic solution shows that the model saves mainly in terms of time window penalty costs, which are reduced by alternative addresses and thus better delivery times, and therefore time window violation costs. Although consumer satisfaction is reduced, consumers are also willing to provide alternative addresses, as alternative addresses may allow consumers to get their goods earlier.

In addition, this paper considers the vehicle routing problem with multiple delivery addresses, and use large-scale neighbourhood search algorithm to analyse the characteristics of

users who do not deliver according to the first address, and analyse the relationship between the distribution cost and service level of enterprises. The user preference related data in this paper mainly comes from the questionnaire and belongs to static data, which limits the application of the algorithm to a certain extent. Further research can use the machine learning and big data based on historical data is also meaningful. The research focus of this paper only focuses on the logistics terminal distribution path, that is, the link of the urban logistics distribution terminal, and analyses the corresponding path optimization methods. This study does not extend the research to the level of the whole industry chain, especially the logistics distribution within the production system which is an important research point.

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