Academic Journal of Emerging Technologies
ISSN Print: 3104-4417
ISSN Online: 3104-4425
CD ISSN: 3104-4433
https://doi.org/10.63313/AJET.9014

# Research on Route Optimization of Fresh Food Distribution to Residential Areas in Emergency Scenarios

**Chu Xiao**
School of Modern Post, Chongqing University of Posts and Telecommunications, Chongqing, 400065, China
Email: 2420832586@qq.com

**How to cite this paper:** Xiao, C. (2025). Research on Route Optimization of Fresh Food Distribution to Residential Areas in Emergency Scenarios. Academic Journal of Emerging Technologies, 1(2), 86–99. ISSN Print: 3104-4417; ISSN Online: 3104-4425.
https://doi.org/10.63313/AJET.9014
**Published: 2025-10-28**

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## Abstract

When cities are hit by sudden public safety incidents such as natural disasters, toxic gas leaks, extreme air pollution and epidemics, the daily supply of fresh food for residents cannot be guaranteed. This paper constructs a multi-center demand-splittable model for residents' material distribution in emergency scenarios, aiming to solve the problem of distributing materials from urban emergency warehouses to residential areas in controlled zones. The comprehensive objectives of this model are to minimize the total distribution time and make full use of the service capabilities of each distribution center. Through case analysis, an improved genetic algorithm is used to solve the proposed model. The results show that the distribution scheme can comprehensively utilize the service capabilities of various distribution centers, ensure the efficient delivery of fresh food, and thus has practical significance.

## Keywords

Emergency Scenarios; Fresh Food Distribution; Route Optimization; Multi-Center; Demand Splittability

## 1. Introduction

With the acceleration of urbanization, when cities are hit by sudden public safety incidents such as natural disasters, toxic gas leaks, extreme air pollution, and epidemics, emergency control measures must be implemented in risk-affected areas to ensure residents' lives and safety. Consequently, the problem of distributing basic daily necessities and fresh food to residents restricted from going out during the control period arises.

Currently, some scholars have conducted research on the guarantee of fresh food supplies for residents in emergency scenarios. Zhang[1] designed an unmanned aerial vehicle with automatic delivery function to complete the last-mile contactless distribution within residential areas. Huang et al.[2] constructed a mixed-integer programming model for fresh food e-commerce logistics distribution by considering factors such as distribution priority and disinfection time, aiming to solve the problem of pseudo-shortage of materials in areas with high epidemic incidence. He et al.[3] built a vehicle routing optimization model for fresh food e-commerce based on the group purchasing characteristics of home-based consumers in residential areas under the epidemic context, with the goal of completing the surge in demand orders using the minimum number of vehicles. Li et al.[4] established a retail logistics model by considering the order release time to shorten the distribution completion time and transportation costs. Zhang et al.[5] constructed a vehicle-UAV distribution model targeting the minimization of total cost, which includes transportation cost, fixed operation cost of distribution stations, and temperature control cost of refrigerated vehicles, and solved it using an improved K-means three-dimensional clustering algorithm.

Regarding the design and solution of multi-center and demand-splittable models, scholars have proposed different approaches. Xu et al.[6] comprehensively considered factors such as multi-depot, multi-vehicle type, multi-commodity, unbalanced supply and demand among customers, and arbitrary splitting of pickup and delivery demands, established a mixed-integer optimization model, and designed a two-stage heuristic solution algorithm. Liang et al.[7] constructed a comprehensive clustering algorithm and applied the spatiotemporal clustering results to the route solution. Fan et al.[8] designed an ant colony algorithm to solve the optimization model that minimizes the sum of vehicle transportation cost, dispatch cost, time penalty cost, and fresh food loss cost. Xiong et al.[9] designed a three-stage tabu search algorithm based on a bi-level programming model to solve the vehicle routing problem with splittable demands. Li et al.[10] proposed an improved pyramid evolution strategy to solve the vehicle routing problem with splittable demands.

To summarize, existing research on fresh food routing optimization in emergency scenarios mainly focuses on order distribution routes within the last mile or e-commerce distribution scope, lacking overall distribution schemes for the entire urban area. In the design and solution of multi-center and demand-splittable models, the factor of distribution center load balance has not been directly incorporated into the model, and the number of demand splits is limited. However, in the early stage of an emergency scenario, the imbalance between supply and demand can easily lead to a severe shortage of materials for a large number of residents; the elderly and children also have difficulty purchasing materials through e-commerce channels, and a single residential area may require multiple vehicles for distribution.

In this study, multiple large-scale agricultural and sideline product centers in the urban area are selected as distribution centers, and residential areas are treated as individual distribution customers to investigate the fresh food distribution problem in the urban area. In the early stage of an emergency scenario, the government coordinates the material transportation capacity of large-scale agricultural markets to provide basic fresh food packages for various residential areas in the urban area. This practice is of great practical significance for ensuring residents' normal lives, stabilizing the supply-demand relationship and commodity prices, and it also provides a new idea for solving the route optimization problem of fresh food distribution to residential areas in emergency scenarios.

## 2. Model Construction and Algorithm Design

### 2.1. Model Construction

#### 2.1.1. Problem Description

In emergency scenarios, to ensure residents' daily necessities, sufficient supplies must be delivered to each residential community on schedule. Upon receiving household demand data from each residential area, relevant authorities coordinate the scale and transport capacity of multiple large-scale agricultural markets near the urban area. They then schedule vehicle routes to deliver standardized supply packages to each residential area, where volunteers subsequently distribute the supplies to individual households. The distribution network is illustrated in Figure 1, with solid lines representing delivery routes for scattered demand and dashed lines indicating distribution centers serving whole-number demand from residential areas. To minimize disruption to urban residents' lives during emergencies, delivery timelines must be strictly managed to ensure every household receives daily necessities as early as possible. Given the widespread impact on fresh produce markets during crises, coupled with shortages of personnel and available vehicles, vehicle delivery plans require optimization. This aims to balance the limited capacity across distribution centers while completing deliveries as quickly as feasible. After completing a delivery run, each vehicle returns to its original dispatch center to await the next assignment. Scattered neighborhood requests may be split no more than once to enhance vehicle utilization and load capacity. Multiple centers may serve the same neighborhood multiple times. When solving the delivery plan, both total delivery time and dispatch center load balancing metrics are considered comprehensively. This achieves the goal of rapidly completing delivery tasks through the balanced utilization of each center's shipping and delivery capabilities.

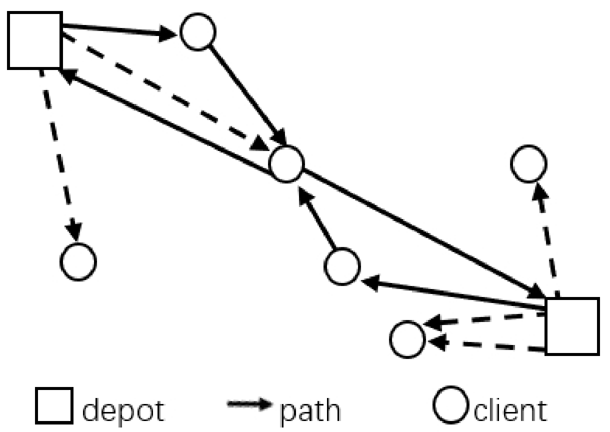


**Figure 1.** Diagram of the distribution network

To address the issue of limited transportation capacity at distribution centers during emergency scenarios, resulting in residents struggling to receive fresh supplies promptly, this paper makes the following fundamental assumptions:

(1) Multiple distribution centers exist, with vehicles of the same model departing from these centers, visiting customer locations, and ultimately returning to their originating distribution center;

(2) Each trip duration includes queueing time, loading time, customer visit time, unloading time, and travel time. Queueing time at the distribution center is fixed, while loading time is proportional to cargo weight. Customer visits require fixed parking time plus unloading time proportional to the weight unloaded at each location. Loading and unloading speeds are constant, and vehicles travel at uniform speed.

(3) Distribution center and customer locations are known, and each customer's demand is known;

(4) Each customer demand is divisible. If a customer point's demand exceeds vehicle capacity, integer multiples of the vehicle capacity (n times) are transported by n separate vehicles. Scattered demand portions smaller than vehicle capacity may be served by different centers and different vehicles, but such scattered demand may be visited by delivery vehicles no more than twice;

(5) Each vehicle's load must not exceed its maximum carrying capacity;

(6) The total delivery time and total delivery weight capacity of each distribution center are proportional to the center's scale.

### 2.1.2. Notation and Variable Explanation

The following definitions are provided for the sets, parameters, and decision variables involved in the model:

1. Sets

$A_d$: Set of distribution centers, where $A_d$= {1，2…，n}；

$S_c$: Set of demand points (residential areas), where $S_c$= {n+1，n+2,…，n+m}；

V: Combined set of distribution centers and demand points, where V=$S_c \cup A_d$;

$K_1$: Set of vehicle schedules for full-vehicle demand;

$K_2$: Set of vehicle schedules for split-vehicle demand;

K: Total set of vehicle schedules, where K= {k|k=1, 2…, K} and K=$K_1 \cup K_2$;

2. Parameters

$C_{ij}$: Distance between vertex i and vertex j, where i, j∈V;

Q: Maximum load capacity of a single vehicle;

$E_c$: Total demand of demand point c, where c∈ $S_c$;

$M_c$: Integer part of $E_c$/Q, representing the number of full-load vehicle schedules required independently for demand point c;

$D_c$: Remainder part of $E_c$/Q, representing the scattered demand of demand point c that requires consolidated delivery (if $D_c$=0, no consolidated delivery is needed);

$x^k$: Number of demand points visited by vehicle schedule k;

$w^k$: Actual load weight of vehicle schedule k;

$w_c^k$: Weight of goods delivered to demand point c by vehicle schedule k;

$F_d$: Scale of distribution center d; total scale of all distribution centers: F=$\sum_{d \in A_d} F_d$;

$I_d$: Number of vehicle schedules allocated to distribution center d; total number of vehicle schedules across all distribution centers: I=$\sum_{d \in A_d} I_d$;

$W_d$: Total actual load weight of vehicle schedules $I_d$ allocated to distribution center d; total actual load weight across all distribution centers: W=$\sum_{d \in A_d} W_d$

$T_d$: Total travel time of vehicle schedules $I_d$ allocated to distribution center d; total travel time across all distribution centers: T=$\sum_{d \in A_d} T_d$;

TA0: Queuing time of a vehicle schedule at a distribution center;

TA1: Loading time of a vehicle schedule at a distribution center;

TB0: Total parking and start-up time of a vehicle schedule during the entire trip; t: Parking and start-up time per demand point visited;

TB1: Unloading time of a vehicle schedule at demand points;

TC Travel time of a vehicle schedule on roads;

v1: Loading speed at distribution centers;

v2: Unloading speed at demand points;

v: Driving speed of vehicles on roads;

$\alpha$: Penalty cost coefficient for weight imbalance;

$\beta$: Penalty cost coefficient for time imbalance.

3. Decision Variables

$x_{ij}^k$: Binary variable for the demand portion of demand points. It equals 1 if vehicle schedule k travels directly from vertex i to vertex j, and 0 otherwise;

$y_c^k$: Binary variable for the scattered demand portion of demand point c. It equals 1 if the scattered demand of demand point c is served by vehicle schedule k, and 0 otherwise.

### 2.1.3. Vehicle Schedule Time Cost

The total travel time of a single vehicle schedule consists of five components: queuing time at the distribution center (TA0), loading time at the distribution center (TA1), total parking and start-up time during the trip (TB0), unloading time at demand points (TB1), and road travel time (TC).

The total time cost of vehicle schedules refers to the total duration required for both full-vehicle demand schedules (K1) and split-vehicle demand schedules (K2) from the start of queuing at the distribution center to their return to the distribution center. This cost is mathematically expressed as Equation (1):

$$C1 = \sum_{k\in K_1}[TA0 + t + Q(\frac{1}{v1}+\frac{1}{v2}) + \sum_{i\in V}\sum_{j\in V} C_{ij}\, x_{ij}^k/v] + \sum_{k\in K_2}[TA0 + tx^k + w^k(\frac{1}{v1}+\frac{1}{v2}) + \sum_{i\in V}\sum_{j\in V} C_{ij}\, x_{ij}^k/v] \quad (1)$$

### 2.1.4. Penalty Cost for Unbalanced Load of Distribution Centers

The total actual load capacity of vehicle schedules allocated to each distribution center unit is unbalanced, with penalty costs calculated as per Equation (2).

$$C2 = \sum_{d\in A_d}(\alpha F_d|\frac{W_d}{F_d}/\frac{W}{F}-1|) \quad (2)$$

The total actual delivery time of vehicle schedules allocated to each distribution center unit is unbalanced, with penalty costs calculated as per Equation (3).

$$C3 = \sum_{d\in A_d}(\beta F_d|\frac{T_d}{F_d}/\frac{T}{F}-1|) \quad (3)$$

The following model is established for the problem studied in this paper:

$$\min C = C1 + C2 + C3 \quad (4)$$

Subject to the following constraints:

$$1 \le \sum_{i\in V}\sum_{k\in K_2} x_{ij}^k \le 2, \forall(j \in S_c \cap D_i > 0), i \ne j \quad (5)$$

$$\sum_{k\in K} y_i^k \ge 1, \forall(i \in S_c \cap D_i > 0) \quad (6)$$

$$\sum_{j\in S_c} x_{dj}^k = \sum_{i\in S_c} x_{id}^k = 1, \forall k \in K, d \in A_d \quad (7)$$

$$w^k \le Q, \forall k \in K \quad (8)$$

$$\sum_{i\in S_c, j\in S_c} x_{ij}^k = x^k - 1. \forall k \in K \quad (9)$$

$$\sum_{i\in A_d}\sum_{k\in K_1} x_{ic}^k = M_c, \forall c \in S_c \quad (10)$$

$$\sum_{i \in A_d} \sum_{j \in A_d} x_{ij}^k = 0, \forall k \in K \tag{11}$$

$$\sum_{k \in K_2} w_c^k = D_c \tag{12}$$

$$w_c^k > 0 \tag{13}$$

Equation (4) denotes the minimization of three cost components: the total distribution time cost for the split-vehicle demand and integer demand portions, as well as the load imbalance costs associated with the total actual load weight and total distribution time across all distribution centers. Equation (5) specifies that a customer with a non-zero consolidated delivery demand can be split for delivery at most once. Equation (6) ensures that each customer with a non-zero consolidated delivery demand is served by at least one vehicle schedule. Equation (7) requires that a vehicle departing from distribution center d must return to the same distribution center d after completing its delivery route. Equation (8) stipulates that the total demand of customers served by a single vehicle schedule shall not exceed the maximum load capacity of the vehicle. Equation (9) is designed to eliminate sub-tours in the consolidated demand portion of customer delivery routes—this constraint prevents vehicles from forming independent partial routes that do not connect back to the origin distribution center, ensuring the integrity of the entire delivery route. Equation (10) states that the integer demand portion of customer c requires a total of $M_c$ full-load vehicle schedules from all distribution centers for service. Equation (11) indicates that there is no direct route connection between different distribution centers, meaning vehicles do not travel between distribution centers during the delivery process. Equation (12) ensures that the sum of split weights for the split-vehicle delivery portion of a customer equals the remainder demand $D_c$. Equation (13) specifies that the delivery weight of a vehicle schedule when serving a customer must be greater than 0—this avoids the situation where a vehicle is assigned to a customer but delivers no goods, ensuring the rationality of vehicle schedule allocation.

## 2.2. Algorithm Design

The algorithm studied in this paper for optimizing delivery routes of fresh food supplies to residential communities during emergency scenarios primarily divides the problem-solving process into the following steps:

(1) Initial Population Generation: 50% generated by heuristic algorithms, 50% randomly generated (all valid solutions);

(2) Iterative Process: Each generation undergoes selection, crossover, mutation, and fitness calculation to update the population;

(3) Termination Condition: Iteration stops after 1000 iterations or when the optimal fitness remains unchanged for 50 consecutive iterations.

### 2.2.1. Design of Two-Layer Encoding and Decoding

Encoding Rules

A two-layer integer encoding method (including a center assignment layer and a route sequence layer) is adopted to accommodate multi-center scenarios and capacity constraints.

1. Center Assignment Layer

The length of this layer is equal to the total number of delivery points. Here, each delivery point is defined as follows: Each full-vehicle demand of a residential area is treated as an independent delivery point; Each split-vehicle demand of a residential area is also treated as an independent delivery point. The value of each gene in this layer ranges from 1 to n (where n denotes the number of distribution centers), representing the distribution center to which the corresponding residential area belongs. For instance, the encoding sequence [1, 1, 2, 3] indicates that the first two delivery points (linked to two residential areas) are assigned to distribution center 1, the third to distribution center 2, and the fourth to distribution center 3.

2. Route Sequence Layer

This layer is a permutation of all delivery points, with each gene representing the serial number of a delivery point. Its structure follows a specific order: The front segment contains delivery points corresponding to full-vehicle demand; The rear segment contains delivery points corresponding to the split-vehicle demand of residential areas.

Decoding Rules

The decoding process is executed in the following steps to generate feasible vehicle schedules.

1.Determine Delivery Points Covered by Each Center

First, read the center assignment layer to clarify which delivery points fall under the coverage of each distribution center. This step establishes the initial service scope for each center.

2. Split Vehicle Delivery Sequences by Route Order

Based on the route sequence layer, split the delivery sequence of each distribution center into two parts and assign vehicle schedules accordingly:

For the front segment, each delivery point is assigned to a separate vehicle schedule because the demand of each delivery point matches the maximum load capacity of a vehicle;

For the rear segment, create an empty vehicle schedule and sequentially insert delivery points into it. When the total demand of the inserted delivery points exceeds the vehicle's capacity limit, split the overloaded portion of the last inserted delivery point and finalize this as a feasible vehicle schedule. Recreate an empty vehicle schedule and repeat the above insertion and splitting process until all delivery points in the rear segment are assigned to vehicle schedules.

### 2.2.2. Construction of Fitness Function

Since each chromosome corresponds to a path scheme, this paper sets the fitness function as the inverse of the objective function to evaluate individuals.

### 2.2.3. Design of Genetic Operators

To balance the exploration and exploitation capabilities of the algorithm, three core genetic operators (selection, crossover, and mutation) are designed as follows, tailored to the two-layer encoding structure.

1. Selection Operator

A combination of roulette wheel selection and elite preservation strategy is adopted.

Roulette wheel selection: The retention probability of each individual is proportional to its fitness value. This ensures that individuals with higher fitness have a greater chance of being retained, while also maintaining population diversity by allowing individuals with lower fitness to be selected occasionally.

Elite preservation strategy: The top 10% of individuals with the highest fitness from the previous generation are directly retained to the next generation. This avoids the loss of high-quality genes caused by random selection and accelerates the algorithm's convergence toward optimal solutions.

2. Crossover Operator

Crossover operations are designed separately for the two encoding layers to preserve the rationality of the solution structure.

For the center assignment layer: Single-point crossover is implemented. Taking two parent individuals as examples—Parent 1: [1, 2, 2, 3] and Parent 2: [1, 3, 3, 4]—a random crossover point is selected. After crossover, two offspring are generated, such as Offspring 1: [1, 2, 3, 4] and Offspring 2: [1, 3, 2, 3].

For the route sequence layer: Partial matching crossover is applied only to the segment corresponding to split-vehicle demand delivery points. The crossover operation is restricted to exchanging route sequences within the same distribution center.

3. Mutation Operator

An adaptive mutation strategy is adopted, where the mutation probability is initially high and gradually decreases with the number of iterations. This balances the algorithm's early-stage exploration (to avoid local optima) and late-stage exploitation (to refine optimal solutions). Specific mutation operations for each layer are as follows.

For the center assignment layer: Randomly select several delivery points and change their corresponding distribution center.

For the route sequence layer: Target the segment of split-vehicle demand delivery points and perform either of two operations: Swap the positions of two randomly selected delivery points in the sequence; Reverse the order of a randomly selected continuous sub-sequence of delivery points.

## 3. Case Study and Analysis

To validate the algorithm's effectiveness, model verification was conducted using data from Shanghai's Putuo District. In emergency scenarios, the government allocates supply packages to residential communities, which are then delivered to individual households by community volunteers. This study selected five agricultural markets of varying scales in the vicinity of Shanghai's Putuo District as distribution centers. Python was employed to crawl data on household numbers, geographical coordinates, and other details for all residential communities within Putuo District. Following data screening, 1,562 communities were retained as delivery points for the supply packages. The rated total service time and delivery weight capacity of each agricultural market center are proportional to its scale. Relevant data for these centres is presented in Table 1.

**Table 1.** Information of distribution centers

| Distribution Center | Longitude | Latitude | Scale Factor |
|---|---|---|---|
| Center0 | 121.408979 | 31.292237 | 2 |
| Center1 | 121.351631 | 31.285540 | 2 |
| Center2 | 121.381744 | 31.252335 | 1 |
| Center3 | 121.372313 | 31.213827 | 1 |
| Center4 | 121.448029 | 31.270932 | 1 |

Assuming each household of three requires 10 kilograms of fresh produce daily and each lorry has a payload capacity of 8 tonnes, the demand for each residential area is calculated accordingly. Distribution point information is detailed in Table 2. Among the 1,560 demand points, scattered demand necessitates shared-load deliveries, while 700 demand points require at least one full-load delivery per trip. Using Python, a distance matrix between distribution centers and demand points is generated based on their latitude and longitude coordinates. When calculating the travel time of each vehicle schedule, the following parameters are set:

The queuing time of the vehicle schedule at the distribution center is 2 minutes, with a loading speed of 600 kilograms per minute;

For each residential area visited, the vehicle’s parking and start-up time is 2 minutes, and the unloading speed is 300 kilograms per minute;

The uniform driving speed within the urban area is 600 meters per minute.

**Table 2.** Resident information

| Delivery Point | Longitude | Latitude | Number of Households | Demand | full-vehicle demand | scattered demand |
|---|---|---|---|---|---|---|
| Delivery point0 | 121.446551 | 31.243052 | 397 | 3970 | 0 | 3970 |
| Delivery point1 | 121.363361 | 31.261614 | 1430 | 14300 | 1 | 6300 |
| Delivery point2 | 121.409684 | 31.245867 | 762 | 7620 | 0 | 7620 |
| ... | ... | ... | ... | ... | ... | ... |
| Delivery point1559 | 121.429719 | 31.237090 | 1390 | 13900 | 1 | 5900 |
| Delivery point 1560 | 121.401850 | 31.234722 | 3888 | 38880 | 4 | 6880 |
| Delivery point 1561 | 121.442034 | 31.253524 | 4522 | 45220 | 5 | 5220 |

The probability density distribution of residential area demand is shown in Figure 2, where the horizontal axis represents the demand of residential areas and the vertical axis represents the probability density of demand. The mean value of the demand distribution is obviously right-skewed, indicating that there are a large number of residential areas with demand exceeding the vehicle load capacity.

In this study, the demand of each residential area is divided into two parts: full-vehicle demand and split-vehicle demand. Within the designed model, only the assignment of full-vehicle demand to appropriate distribution centers needs to be considered. This approach not only simplifies the calculation process of the algorithm but also improves both the efficiency of the algorithm and the quality of the optimization results, as it focuses on the core demand segment that has a more significant impact on the overall distribution schedule.

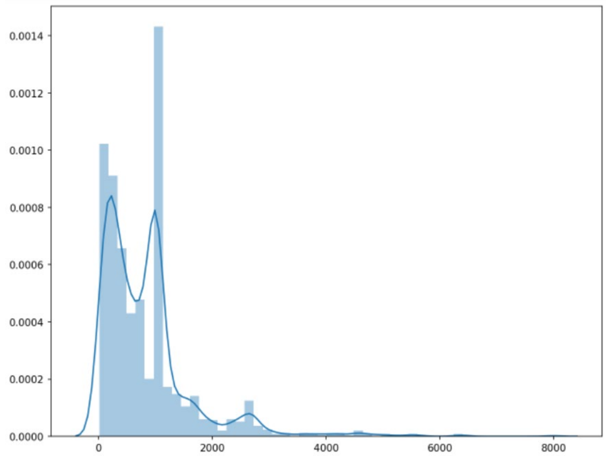


**Figure 2.** Diagram of demand probability density distribution

The geographical distribution of centers and residential areas' demand is shown in Figure 3, where the five triangles represent distribution centers and the black dots denote residential areas. The area of each dot is proportional to the demand size. The geographical distribution of demand exhibits significant disparities. If the objective function solely minimizes distance or time, distribution centers in densely populated areas would shoulder excessive delivery tasks, while those in remote locations would see their service capacity underutilized. By incorporating penalties for weight and time imbalances per unit capacity of distribution centers into the model, both the prolonged queue times in high-demand zones and the idle capacity of remote distribution centers are effectively mitigated.

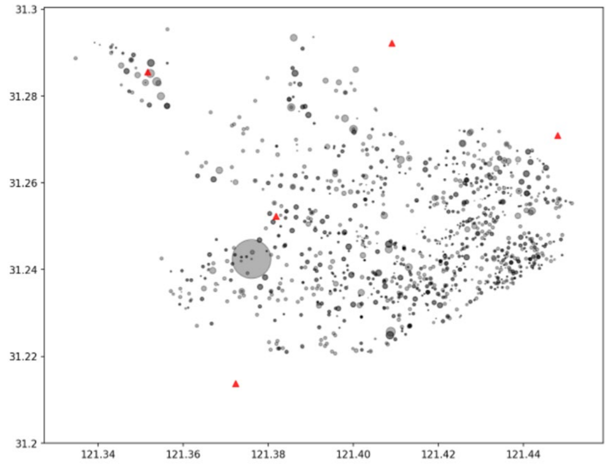


**Figure 3.** Diagram of centres and total demand distribution

When solving the problem, a heuristic algorithm is first employed to generate a TSP path for scattered demands, as shown in Figure 4. Subsequently, the.TSP path is partitioned by the algorithm to yield split-vehicle routes. Full-vehicle routes and split-vehicle routes are then assigned to respective distribution centers, yielding an initial population where 50% of routes are generated by the heuristic algorithm. Enhancing the quality of the genetic algorithm's initial population reduces search time and improves the quality of the final solution.

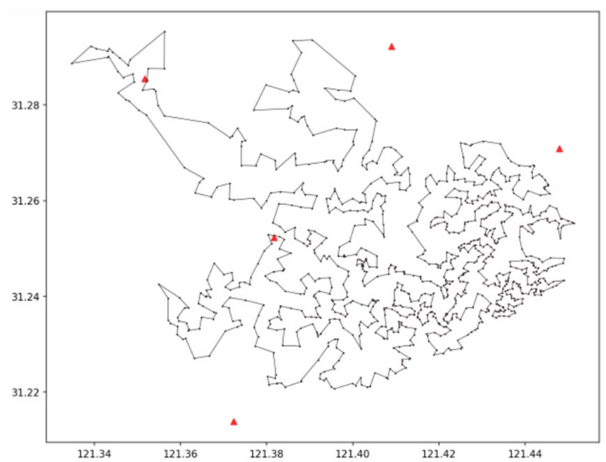


**Figure 4.** Diagram of scattered demand delivery sequence

Using Python to compute the case study, the delivery plan minimizing the objective function was obtained through iterative genetic algorithm solutions. The optimized delivery plan utilized a total of 1,822 vehicle schedules, comprising 1,226 full-vehicle schedules and 596 split-vehicle schedules. The allocation of vehicle schedules to distribution centers is presented in Table 3. The weight coefficient (denoted as ad) for distribution center d is defined as ad=$(W_d/F_d)/(W/F)$; The time coefficient (denoted as bd) for distribution center d is defined as bd=$(T_d/F_d)/(T/F)$.

ad, bd are both relatively close to 1. When total costs are minimized, the delivery plan achieves balanced vehicle allocation, effectively addressing the issues of prolonged queue times in high-demand areas and idle capacity at remote distribution centers.

**Table 3.** Delivery plan

| Distribution Center | Vehicle Schedule Allocation | Scale Factor | Total Load /kg | Total Time /min | $a_d$ | $b_d$ |
|---|---|---|---|---|---|---|
| Center 0 | 1,3,11,12,15,19,22,23… | 2 | 3715020 | 26232 | 0.892358 | 0.937300 |
| Center 1 | 8,10,27,38,39,41,42,45… | 2 | 3056000 | 22331 | 0.734060 | 0.797916 |
| Center 2 | 5,6,7,9,13,14,18,32,35… | 1 | 3040000 | 18135 | 1.460433 | 1.295963 |
| Center 3 | 2,4,16,24,31,33,36,51… | 1 | 2168000 | 14604 | 1.041519 | 1.043675 |
| Center 4 | 17,20,21,30,40,44,46… | 1 | 2592000 | 16651 | 1.245211 | 1.189930 |

## 4. Conclusions

This study focuses on the route optimization of fresh food distribution to residential areas in emergency scenarios. A refined optimization model is constructed by comprehensively considering the total transportation time cost and the unbalanced load cost of distribution centers. Meanwhile, given that there are many residential distribution points with demand exceeding the vehicle load capacity, the route sequence layer is divided into two parts—full - vehicle demand and scattered demand—during the coding process. In the decoding process, it is specified that scattered demand can be further split to improve the vehicle load rate, and an improved genetic algorithm is designed to solve the model.

The results show that the model constructed in this study can effectively address the problems of long queuing times in demand - dense areas and the idle service capacity of remote distribution centers. Additionally, it reduces the total distribution cost. This research can provide a reference for solving the route optimization problem of fresh food distribution to residential areas in emergency scenarios.

## References

[1] Zhang, Y. M. (2023). Design of Delivery UVA for Material Distribution under the Environment of Epidemic Situation. Modern Information Technology, 7(01), 142-144.

[2] Huang, J. D., Zhu, E. G., Huang, X. H., et al. (2022). Virtual Simulation Experiment of Fresh e-Commerce Logistics Distribution During the High Epidemic Period. Research and Exploration in Laboratory, 41(07), 108-114.

[3] He, T., Hou, H. P., & Yang, J. L. (2020). Research on vehicle route optimization of fresh E-commerce enterprises under background of epidemic situation. Journal of Safety Science and Technology, 16(07), 183-188.

[4] Li, W. L., Li, K. P., Tian, Q. N., et al. (2022). The Research on Retail Logistics Distribution Routing Optimization Considering Order Release Dates Epidemic Environment. Chinese Journal of Management Science, 30(09), 195-205.

[5] Zhang, J., & Li, Y. F. (2025). Location-routing Problem of Fresh Product Distribution in Epidemic Environment. Chinese Journal of Management Science, 33(03), 196-208.

[6] Xu, D. Y., Li, K. P., Zheng, P., et al. (2020). The Optimization Research of Multi-Category Unpaired Supply-Demand and Arbitrary Split Pickup and Delivery Vehicle Routing

Problem with Multi-Depot and Multi-Type Trucks. Chinese Journal of Management, 17(07), 1086-1095.

[7] Liang, C., & Zhou, J. X. (2021). Application of Time-Space Clustering in Joint Distribution among Multi Centers Based on GIS. Logistics Sci-Tech, 44(09), 45-47.

[8] Fan, H. M., Yang, X., Li, D., et al. (2019). Half-open multi-depot vehicle routing problem based on joint distribution mode of fresh. Computer Integrated Manufacturing Systems, 25(01), 256-266.

[9] Xiong, H., & Yan, H. L. (2015). A three-phase tabu search heuristic for the split delivery vehicle routing problem. Systems Engineering-Theory & Practice, 35(05), 1230-1235.

[10] Li, H. F., Huang, Z. C., Zhang, Q., et al. (2021). Improved pyramid evolution strategy for solving split vehicle routing problem. Journal of Computer Applications, 41(01), 300-306.