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Research on Dynamic Path Planning for Urban Ground-Air Collaborative Delivery in Intelligent Networked Environments

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Abstract: With the rapid implementation of intelligent networking and low-altitude logistics technology, ground-air collaborative distribution has become a new technological path to solve the bottleneck of end-of-pipe logistics distribution in urban and rural areas, thanks to its advantages of flexibility, efficiency, three-dimensional coverage, and dynamic adaptation. In response to the strong timeliness of delivering characteristic agricultural products in rural areas of Dalian, as well as the pain points of traditional vehicle delivery services such as large radius, high empty driving rate, and shortage of transportation capacity during peak hours, this paper takes rural logistics in Dalian as the research object, introduces the "vehicle drone" ground-air collaborative delivery mode, and conducts dynamic path planning optimization research in rural scenarios. Based on the spatial distribution characteristics of rural distribution customers, the DBSCAN clustering algorithm is used to aggregate and divide the demand nodes for village level distribution, and accurately locate the vehicle parking points based on the centroid of each clustering cluster. Simultaneously building a collaborative delivery scheduling model, solving and validating the model through improved ant colony algorithm. The research results indicate that DBSCAN clustering can effectively integrate village-level distribution nodes, significantly reducing the frequency of vehicle stops and detours. Compared to traditional bicycle delivery models, the two collaborative modes of "vehicle-drone" parallel delivery and portable delivery can effectively reduce comprehensive delivery costs and improve the operational efficiency of end-of-pipe delivery.

Keywords: Low altitude economy; Ground-air collaborative distribution; DBSCAN clustering

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1. Introduction

As a national strategic emerging industry, the low altitude economy continues to release policy dividends, providing institutional support for the large-scale implementation of unmanned aerial vehicle logistics and distribution, and also providing a new technological path to solve the "last mile" distribution dilemma at the end. In 2024, the low altitude economy was first included in the Government Work Report, marking the industry's acceleration from top-level policy planning to practical application scenarios. In the context of the booming development of the low altitude economy, unmanned aerial vehicle logistics and distribution have outstanding advantages such as not being constrained by ground road conditions, strong maneuverability, and controllable operating costs. They can effectively cover remote areas that are difficult for traditional ground distribution to reach, and provide feasible solutions for the pain points of end-of-pipe distribution in rural areas of China with many points, wide coverage, small quantities, and complex road conditions.

2. Analysis of collaborative delivery mode

The ground-air collaborative distribution mode refers to the combination of the long-distance and heavy-load transportation advantages of ground vehicles with the short-distance and high-mobility terminal distribution advantages of drones, and through reasonable task allocation and path coordination, achieves the complementary advantages of the two transportation resources. According to whether there is a physical carrying relationship between the vehicle and the drone, this mode can be divided into two types: parallel delivery and portable delivery.

2.1. Classification of ground-air collaborative delivery

Due to the hardware constraints of maximum range and rated load capacity, relying solely on drones to independently complete end-of-pipe delivery operations is difficult to fully adapt to the logistics business needs in real-world scenarios. To compensate for the inherent shortcomings of drones in terms of load capacity and endurance, many scholars have proposed an innovative operation mode of vehicle-drone collaborative distribution.

The existing vehicle-drone collaborative delivery can be classified into four typical operating modes, namely vehicle-drone parallel delivery mode, drone-assisted vehicle delivery mode, vehicle-assisted drone delivery mode, and vehicle-drone portable delivery mode. The vehicle drone parallel delivery mode and the vehicle drone portable delivery mode are more in line with the actual situation of rural logistics in Dalian, and are analyzed separately.

2.1.1. Parallel delivery mode

Parallel delivery mode refers to the situation where both delivery vehicles and drones originate from township-level distribution centers, independently carrying out delivery operations without any constraints on each other. Among them, delivery vehicles complete the mainline transportation task along the regional main road and unload goods to various village-level transfer stations in sequence; Drones rely on township-level distribution centers or nearby take-off and landing points to undertake the final delivery work for scattered customers in the surrounding area. After completing delivery tasks, they autonomously return to the take-off and landing points.

The parallel delivery mode is suitable for delivery scenarios where customer space distribution is scattered, drone range can cover multiple terminal customers within the area, and the opportunity cost for vehicles waiting to return is high. Based on the actual situation of rural logistics in Dalian, farmers in the northern mountainous areas of Zhuanghe and the eastern hills of Wafangdian are scattered and have complex road conditions, resulting in high operating costs and low feasibility of door-to-door delivery by delivery vehicles. Adopting a parallel delivery mode, relying on nearby stationed points to release drones to complete scattered delivery at the end, can effectively avoid the shortcomings of ground distribution and significantly improve the delivery efficiency and economy of remote rural end logistics.

2.1.2. Portable delivery mode

The portable delivery mode adopts the operation form of "vehicle-mounted machine following and dynamic collaboration." The delivery vehicle is equipped with a drone to travel along the preset delivery path, and the drone is released at key stopping points to independently complete the end delivery task in the surrounding area. After completing the drone operation, it can return to the original vehicle or go to the next node to merge with the delivery vehicle, and the delivery vehicle can synchronously go to the next stopping point to carry out the operation.

The portable delivery mode is suitable for logistics scenarios where customers are clustered and distributed, and the order size in a single area is moderate. The core advantage is that during the unmanned aerial vehicle terminal operation, the delivery vehicles can synchronously complete tasks such as unloading goods and collecting agricultural products, without idle waiting time. The overall operational efficiency and resource utilization rate are significantly improved. Based on the actual scenario of rural logistics in Dalian, this model can accurately match the distribution needs of farmers living in the surrounding areas of established villages and village-level agricultural product centralized purchase points, adapt to the characteristics of rural agglomeration orders, and effectively improve the overall economy and synergy of regional logistics distribution.

2.2. Collaborative delivery operation process

The core difference between the two modes lies in the degree of coupling between the vehicle and the drone. Parallel mode has a high degree of decoupling and flexible scheduling, but it requires higher autonomous flight capability and endurance for unmanned aerial vehicles. The coupling of the carrying mode is tight, requiring higher coordination between vehicle paths and drone routes, but the effective service radius of drones can be greatly expanded by the movement of vehicles. In practical operation, the two modes are not mutually exclusive, but can be mixed according to the spatial distribution density and timeliness requirements of customers. Overall, remote areas with highly dispersed customers and beyond the single endurance radius of drones are suitable for adopting a portable mode; the parallel mode is suitable for areas with relatively concentrated customers located around the town center. The operational process of the collaborative delivery mode is shown in **Figure 1**.

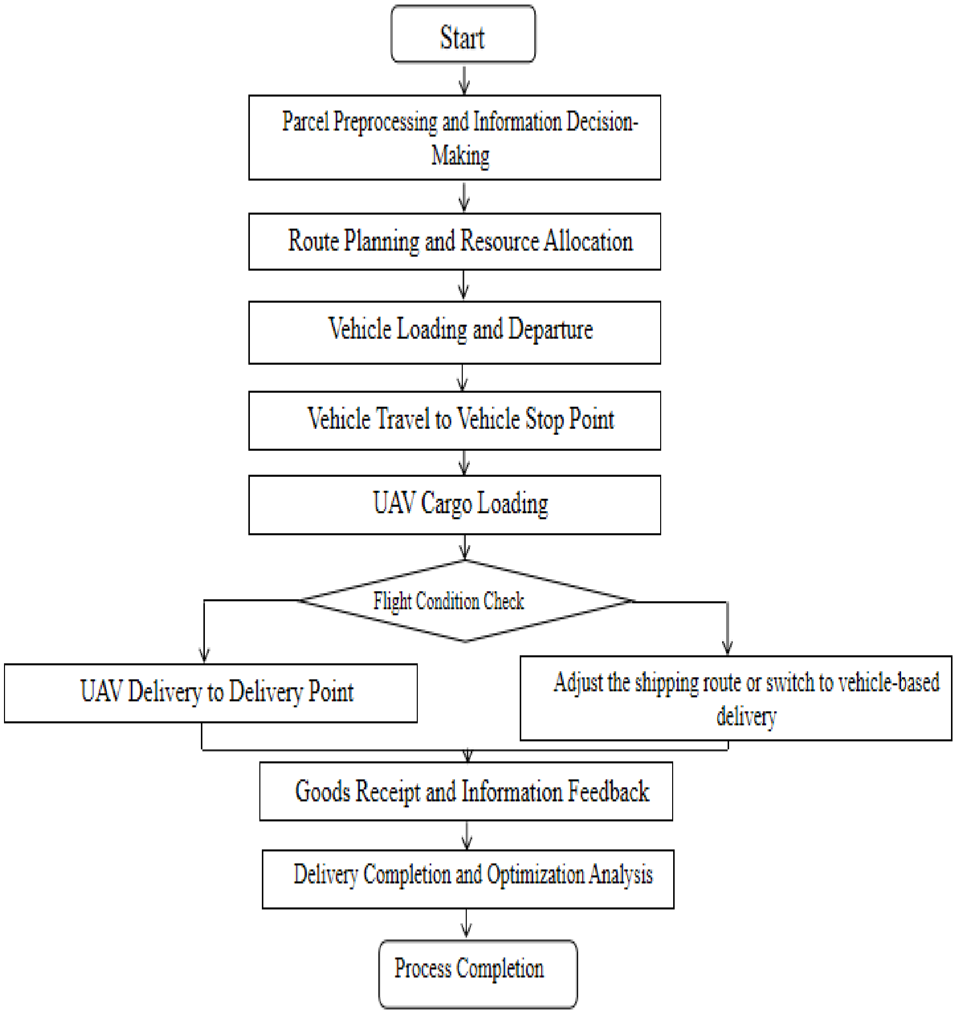

Figure 1. Operation process of collaborative delivery mode as shown in the figure

3. Construction of collaborative delivery network based on DBSCAN clustering

3.1. Reconstruction of distribution network hierarchical structure

3.1.1. Functional positioning of third level nodes

Taking Dalian as an example, the logistics distribution network presents a clear three-level structure in physical space. The first level is the township-level distribution center, located at the township government headquarters, responsible for the centralized sorting, temporary storage, and transit functions of regional parcels, as well as serving as a drone dispatch management center and vehicle departure station. The second level is the village-level distribution transfer station, which is a comprehensive service station for postal and logistics in established villages, responsible for temporary storage, self-pickup services, and collection of agricultural products for express delivery. The third level is rural residential customer points, which are demand points that need to receive express delivery or consignment.

3.1.2. Characteristics of collaborative delivery path

The inherent logic of reconstructing the path is that vehicles do not need to traverse all village level stations, only select a portion of the stopping points to complete centralized unloading, and then use drones to distribute the stopping points to the end of the surrounding customers; As a collaborative node for vehicle parking and drone takeoff and landing, the number of resident points is much smaller than the total number of village level stations. Simultaneously, simplifying the model has multiple characteristics. On the one hand, it can compress the scale of nodes to be visited in vehicle path planning, reducing the dimensionality of hundreds of village level stations to a minimum of a few resident points, significantly reducing costs; On the other hand, it can achieve decoupling between vehicle paths and drone delivery paths, breaking them down into two types of paths: distribution center dwell point and dwell point customer. This provides conditions for the implementation of phased optimization strategies and can effectively avoid subjective arbitrariness caused by manual point selection [1].

3.2. Distribution node clustering based on DBSCAN

3.2.1. Customer node clustering rules

Density-Based Spatial Clustering of Applications with Noise (DBSCAN) [2] is a spatial clustering method with noise based on data density. The idea of this algorithm is that, in space, if a point's neighborhood contains a sufficient number of points, then that point is considered a core point, and the core point and its density-reachable points form a cluster; Points that do not belong to any cluster are marked as noise.

In rural logistics distribution scenarios, there is an uneven distribution of customers, which gather along roads, valleys, and residential areas. DBSCAN can naturally identify these clustering patterns, grouping spatially adjacent customers into the same distribution cluster while treating truly isolated customers as noise separately. This is highly consistent with the actual needs of centralized distribution, decentralized areas, and flexible processing in rural distribution areas.

3.2.2. Customer node clustering steps

Firstly, select a core object as the center point and use density-based clustering to expand to surrounding nodes. The expanded cluster can be composed of one or more core objects. If there is only one core object in the clustering cluster, then all other non-core objects are in the neighborhood of this core object. If in the neighborhood of the core object, the set of all objects forms a parameter (ε ,MinPts) that can describe the clustering density of the core object's neighborhood distribution. Among them, represents the threshold size of the neighborhood distance of the core object. (MinPts) represents the number of non-core objects with a neighborhood distance of. When isolated data points that are not in the cluster are found, they are considered outliers. The advantage of the DBSCAN algorithm is that it can automatically identify the number of clusters and has no requirements for the shape and size of clusters.

The specific calculation steps of the DBSCAN algorithm are as follows:

Step 1: Let the sample dataset be T , $T=\{t_u,t_{u+1},...,t_{u+12}\}$, $u=[1,2,...,13]$, where the neighborhood ε of the sample t_u includes t_u at least (MinPts) samples, and the t_u becomes the core point. That is , the expression for the domain ε is , which k is a constant. For non core point samples t_b , if they are within the neighborhood of any core point, they are considered boundary points. Any point outside the core area t_u is called a noise point.

Step 2: Calculate the radius distance between the core object and each sample. Through sensitivity testing, it was found that when the sample radius (eps) is equal to 0.09, it meets the constraint of a minimum sample size of 1.

In the DBSCAN algorithm, the concept of proximity is generally used as the clustering criterion, and its calculation formula is as follows:

$$s(t_u)=\begin{cases}1-\dfrac{a(t_u)}{b(t_u)}, a(t_u)<b(t_u)\\ 0, a(t_u)=b(t_u)\\ \dfrac{b(t_u)}{a(t_u)}-1, a(t_u)>b(t_u)\end{cases}$$

$a(t_u)$ indicates that the smaller the average distance between the sample and other samples, the more likely the sample is to be clustered into that cluster, and this point belongs to the core point; $b(t_u)$ indicates the minimum distance from the sample to the other samples. $s(t_u)$ represents the clustering result, if there is only one core point in the clustering cluster, the contour coefficient is defined as 0.

Step 3: Find the set of reachable samples within the core object domain, forming a cluster.

Step 4: Continue repeating the steps of Step 3 and indiscriminately search for the sample set reachable by the core object.

Step 5: Obtain all clustering clusters. Use Python software to program until all core object clusters are computed.

3.2.3. Key parameter setting

Two key parameters in clustering algorithms are neighborhood radius ε and minimum number of points (MinPts). The value of ε determines the scale of spatial aggregation, which is determined by referring to the effective flight radius of the drone. For rural areas in Dalian, the lower value of 3 kilometers is taken for the Wafangdian South and Pulandian areas with higher customer density, and the higher value of 5 kilometers is taken for the Zhuanghe North mountainous area with lower customer density. The value of MinPts determines the minimum customer size required to form a cluster. In the delivery scenario, a value that is too small can lead to too many clusters and too dense dwell points; If it is too large, it will misjudge the customer group that should have formed an independent distribution cluster as noise.

3.2.4. Cluster result analysis

To meet the logistics and distribution needs of various regions, clustering is performed based on the population density statistical yearbook data of rural areas in Dalian City and the relative positions of regional divisions, as shown in **Table 1**. After clustering, each cluster generates a candidate location for a resident point. There are currently 303 administrative village sites in Dalian, which are expected to be integrated into 80 clusters after clustering; that is, 80 delivery vehicle stations. Compared to the original, the reduction in the number of vehicle stops means that the vehicles are more concentrated on the main roads and the detour mileage is significantly reduced.

Table 1. Population distribution in rural areas of Dalian City

Region	Administrative land area (km²)	Number of households	Population	Population density (persons/km²)
Lüshunkou District	512.15	89,468	221,463	432
Jinzhou District	1,352.54	296,776	787,211	582
Pulandian District	2,769.90	281,651	816,323	295
Wafangdian City	3,576.40	343,201	988,501	276
Zhuanghe City	3,655.70	279,857	888,519	243
Changhai County	156.89	25,473	71,226	454

Based on the daily average express delivery volume balance calculation, if 8–10 delivery vehicles provide services to 80 stopping points, each vehicle will visit 6–8 stopping points per day, with a single trip distance of about 120–160 kilometers, and complete the delivery task within 7–8 hours. Compared to traditional modes, the utilization rate of vehicles has significantly increased, and the labor and time costs of loading and unloading have decreased synchronously.

4. Optimization model and algorithm validation for collaborative delivery path scheduling

4.1. Problem description and model assumptions

4.1.1. Problem description

This study focuses on a single distribution center with a sufficient number of delivery vehicles and drones to meet the demand. Based on the clustering results and customer differentiation needs, customer nodes can be served separately by vehicles and drones, as well as collaboratively delivered. In the collaborative delivery process, ground vehicles have dual functions of customer order fulfillment and mobile warehousing. Drones use parked ground vehicles as takeoff and landing platforms to complete customer point delivery operations from the vehicle docking node. After completing the delivery task, they return to the vehicle's location and wait for the next stage of scheduling instructions to meet customer needs.

4.1.2. Model assumptions

The optimization model for ground-air collaborative delivery path scheduling constructed in this article classifies deliveries based on the actual weight of packages required by customers. In the first category, when the weight of the delivery task exceeds the load threshold of the drone, the delivery vehicle directly delivers the package. The second type of nodes that meet the requirements of drone delivery are directly delivered by drones, with vehicles waiting at nearby delivery or parking points. After the drone delivery is completed, the next level of delivery tasks are carried out, or vehicles are loaded back to the distribution center. After clustering processing, the candidate parking points for vehicles are strictly constrained within the set of customer nodes, enabling delivery resources to accurately target actual service objects, avoiding unnecessary parking behaviors, and reducing the ineffective consumption of transportation resources [3,4].

The assumptions related to the model are as follows:

(1) The geographical location and order demand of the distribution center and all customer nodes are known conditions, and the distribution center has no pending delivery demand.

(2) A single delivery vehicle can carry multiple drones for collaborative delivery operations.

(3) The delivery vehicles are of the same specifications and equipment, and the performance parameters of each drone are consistent.
(4) Customer node order requirements cannot be split and must be delivered in one go.
(5) Each customer node only allows one-time delivery services to be completed by a single vehicle or drone.
(6) Both vehicles and drones are subject to maximum load capacity and maximum flight/travel distance constraints.
(7) A single drone can serve one or more customer nodes in a single mission. After the operation is completed, it returns to the vehicle parking point to complete battery replacement and cargo replenishment.
(8) The takeoff and landing position of the drone remains at the same vehicle parking point; After completing all customer delivery tasks within the clustering group, all drones will return to their vehicles and be transferred to the next docking node.
(9) The vehicle travels and the drone flies at a constant speed.
(10) The vehicle is equipped with sufficient backup batteries to meet the battery replacement needs of drone operations.
(11) The delivery distance between vehicles and drones is calculated using Euclidean distance, and the generation of sub-loops is prohibited in path planning.

4.2. Construction of Collaborative Delivery Scheduling Model

4.2.1. Objective Function Construction

4.2.1. Objective Function Construction

The model aims to optimize the delivery routes in rural areas of Dalian city, ultimately achieving the minimum total delivery cost. Therefore, considering the fixed costs, distribution costs, and depreciation costs of vehicles and drones, the following objective function is established [5]. Among them, c_1 is the fixed cost of vehicles, c_2 is the fixed cost of drones; c_v is the delivery cost per unit distance for vehicles; c_u is the unit distance delivery cost for drones.

$$\min Z=c_1 v+c_2 u+c_v\sum_{i\in N}\sum_{j\in N}\sum_{v\in N}T_{ij}^{v}d_{ij}+c_u\sum_{i\in N_u}\sum_{j\in N_u}\sum_{k\in K}\sum_{u\in U}X_{ij}^{uk}l_{ij}$$

4.2.2. Constraints

(1) After completing all demand point tasks from the distribution center, the vehicle needs to return to the distribution center. Among them, N is the set of all nodes, where both the starting and ending points are distribution centers, and V is the set of vehicles.

$$\sum_{j\in N}T_{1j}^{v}=\sum_{i\in N}T_{i,n+1}^{v},\ \forall v\epsilon V$$

(2) For any customer in the third-level node, it is sufficient to be delivered by drone or vehicle only once to meet the demand, and there is no situation where a single customer node is served multiple times. Among them, N_c is a collection of customer demand points; K: Collection of drone voyages

$$\sum_{v\epsilon V}\sum_{i\epsilon N_c}T_{ij}^{v}+\sum_{u\epsilon U}\sum_{i\epsilon N_c}X_{ij}^{uk}=1,\quad \forall j\epsilon N_c\quad \forall k\epsilon K$$

(3) Due to the use of two collaborative delivery modes for delivery, the takeoff and landing points of drones before and after completing delivery tasks should be consistent with the relative position of the vehicles parked, and at least one drone should own and complete the delivery task during the delivery process. Among them, N_k is the collection of vehicle parking points; U is a collection of unmanned aerial vehicles; V is a collection of vehicles.

$$\sum_{j\epsilon N} H_j \preceq \sum_{i\epsilon N}\sum_{j\epsilon N} T_{ij}^{v}, \quad \forall v\epsilon V$$

$$H_i \preceq \sum_{u\epsilon U}\sum_{j\epsilon N_u} X_{ij}^{uk}, \quad \forall i\epsilon N_k \quad \forall k\epsilon K$$

$$\sum_{i\epsilon N} X_{ij}^{uk} = 1, \ \forall u\epsilon U, \quad \forall k\epsilon K$$

(4) The maximum flight distance for drones to complete delivery tasks cannot exceed the maximum flight radius. Among them, R is the maximum flight radius; l_{ij} is the flight distance of the drone from node i to node j.

$$S_{ij} l_{ij} < R, j\epsilon R$$

(5) Due to the timeliness of delivery, drones and vehicles need to leave the delivery node immediately after completing the delivery task. Prolonged stay is considered an abnormal situation. N_u is a collection of vehicle parking points.

$$\sum_{p\epsilon U_u} X_{ij}^{uk} = \sum_{j\epsilon U_u} X_{pj}^{uk}, \quad \forall j\epsilon N_u \quad \forall u\epsilon U \quad k\epsilon K$$

$$\sum_{i\epsilon N_v} T_{ij}^{v} = \sum_{p\epsilon N_v} T_{jp}^{v}, \quad \forall j\epsilon N_v \quad \forall v\epsilon V$$

(6) After completing a single delivery task, the drone needs to return to the delivery vehicle and return to the distribution center together. If it is lost or not returned together, it will be considered an abnormal situation.

$$F_i + F_j + X_{pj}^{uk} \preceq 2, j\epsilon N, \forall u\epsilon U, \ k\epsilon K$$

(7) The maximum load capacity of a drone for a single delivery task cannot exceed its rated load value. Among them, Q represents all demand points and $\ddot{o}_2$ is the rated load capacity of the drone.

$$\sum_{i\epsilon N_k}\sum_{j\epsilon N_u} X_{ij}^{uk} q_j \preceq \varphi_2$$

(8) The maximum load capacity of the delivery vehicle for the delivery task cannot exceed its rated load value. Among them, φ_1 is the rated load capacity of the vehicle.

$$\sum_{i\epsilon N_c} q_i N_v + \sum_{i\epsilon N_c} q_i N_u \preceq \varphi_1$$

(9) There are no duplicate delivery routes between delivery vehicles and drones in the collaborative delivery path.

$$v_i - v_j + nT_{ij}^{v} \preceq n-1, \forall i,j\epsilon N, \ v\epsilon V, i \neq j$$

$$u_i - u_j + nX_{ij}^{uk} \preceq n-1, \forall i,j\epsilon N, \ u\epsilon U, k\epsilon K, i \neq j$$

(10) Explanation of Decision Variables

T_{ij}^{v}: 0-1 variable, with a value of 1 indicating that vehicle v travels from node i to node j, otherwise it is 0;

X_{ij}^{uk}: 0–1 variable, with a value of 1 indicating that the drone u has traveled from node i to node j for the kth time and is 1, otherwise it is 0;

S_{ij}: 0–1 variable, a value of 1 indicates that customer node i is assigned to vehicle parking point j, otherwise it is 0;

H_i: 0–1 variable, with a value of 1 indicating that node j is the drone takeoff point, otherwise it is 0.

4.3. Two-stage ant colony algorithm solution

The two-stage algorithm forms an optimized chain that connects the allocation of dwell points and customers, as well as the order of vehicle access. The first stage is to carry out spatial decoupling optimization. Divide the customer point delivery mode based on the weight of the order package and the drone load threshold, and divide the demand nodes into vehicle service nodes and drone service nodes. Using the DBSCAN clustering algorithm, combined with drone endurance constraints, cluster the drone delivery points into the smallest and non-overlapping clusters within the delivery area, and determine the corresponding vehicle parking nodes for each cluster. The results of the first stage directly determine the amount of cargo that needs to be unloaded at each stopping point, which in turn affects the optimization of the vehicle path in the second stage. The second stage is to carry out path scheduling. Construct a mixed integer programming model with the goal of minimizing the total delivery cost, and use an improved genetic algorithm to achieve global optimization of the vehicle trunk path; Consider each vehicle docking point as a virtual distribution center, solve the flight path for unmanned aerial vehicles to access the corresponding demand nodes at each docking point, and ultimately achieve collaborative distribution optimization between vehicles and unmanned aerial vehicles. The algorithm flow is shown in **Figure 2**.

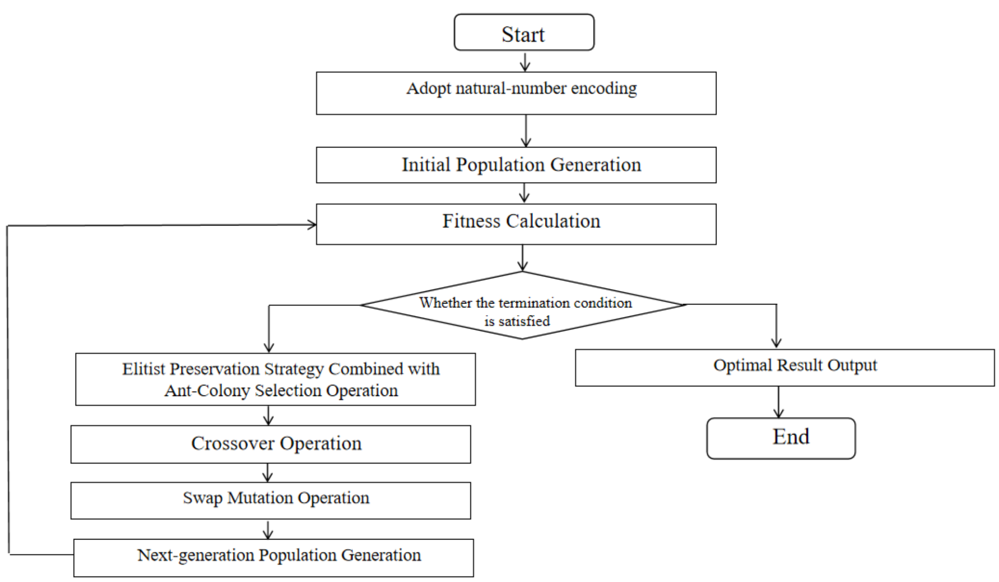

Figure 2. Algorithm flowchart

4.4. Case analysis and effectiveness verification

To verify the effectiveness of the model and algorithm, the rural logistics operation data of Wafangdian City in Dalian was selected as an example. Wafangdian City is the district with the largest volume of express delivery services in Dalian, with a cherry planting area of approximately 300000 acres. For example, one township-level distribution center is set up, and 80 representative customer points are selected from 303 village-level stations based on geographical location and business volume. Through DBSCAN clustering (ε=4km, MinPts=4), 20 resident points are generated. The maximum number of iterations for ant colony algorithm is 200, with =1, =2. The initial pheromone concentration is set based on the nearest neighbor solution, and the adaptive volatilization coefficient decreases linearly from 0.3 to 0.1.

Option A: Traditional vehicles are delivered separately. The vehicle directly accesses all 80 customer points and travels in the shortest path order, with ground delivery throughout the entire journey.

Option B: Parallel delivery of vehicles and drones. Using DBSCAN clustering to generate 20 dwell points, vehicles visit the dwell points, drones take off from the dwell points to serve surrounding customers, and vehicles and drones work in parallel.

Option C: Vehicle+drone delivery. Similarly, based on 20 dwell points, but the drone is mounted on the vehicle, and when the vehicle moves between dwell points, the drone is released to serve customers on the way and converges at subsequent dwell points.

To avoid interference from random factors, each scheme operates independently. The experimental environment is an Intel Core i7-12700H processor with 32 GB of memory and is implemented using Python 3.10.

Table 2. Comparison of results of various plans

Indicator	Plan A	Plan B	Plan C
Vehicle mileage (km)	286.4	178.2	192.5
UAV flight mileage (km)	—	156.8	142.3
Vehicle operating cost (Yuan)	859.2	534.6	577.5
UAV operating cost (Yuan)	—	78.4	71.2
Total cost (Yuan)	859.2	613.0	648.7

Data comparison analysis shows that both Plan B and Plan C achieved significant cost savings, but parallel delivery performed better. The reason is that in parallel delivery mode, vehicles do not need to wait for the drone to return, and the vehicle’s travel path is more compact, avoiding the additional mileage caused by the vehicle’s path being constrained by the drone’s takeoff and landing point and forced to detour in the carrying mode.

Sensitivity analysis indicates that customer distribution density is a key factor affecting the relative advantage of collaborative delivery. When the distribution of customer points tends to be dispersed, parallel delivery has a cost advantage; When customer distribution is highly concentrated, it is more valuable in a decentralized scenario. Meanwhile, controlling the operating costs of drones is crucial for the sustainability of the model.

5. Conclusion

The “vehicle drone” ground-to-air collaborative delivery model is highly adapted to urban logistics scenarios, effectively alleviating problems such as urban congestion and low efficiency of decentralized delivery at the end, and has significant advantages over traditional single-vehicle delivery. This article uses the DBSCAN clustering method to reconstruct the distribution node space, distinguishing the differentiated operation mode of parallel distribution in densely populated urban areas and mobile distribution in scattered suburban areas. The two-stage scheduling model and improved ant colony algorithm constructed can adapt to the dynamic path planning needs of urban ground-air cooperation. By relying on the allocation of dwell points and dynamic path optimization, it meets the requirements of drone endurance, airspace constraints, and dynamic changes in road conditions, achieving efficient coordination of ground-air distribution resources. The research can provide technical support and practical reference for optimizing the intelligent low-altitude logistics path in cities. In the future, multi-dimensional dynamic constraint optimization algorithms such as meteorology and low-altitude control can be integrated to further enhance the intelligence and universality of urban ground-air collaborative distribution.

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Disclosure statement

The authors declare no conflict of interest.

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