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Location-Route Planning for VTOL Airport and UAV Urban Logistics Network – A Case Study of Tianjin

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ABSTRACT

With the potential for fast, contactless and environmentally friendly delivery, unmanned aerial vehicles (UAVs) have gained increasing attention and application due to their cost-effectiveness and convenient and rapid delivery operations. In future cities, a multi-level airport that supports vertical take-off and landing (VTOL) of UAVs and forming a delivery network is necessary to improve delivery efficiency and provide a competitive advantage. This paper proposes a multi-level airport location-routing problem for UAVs that considers UAV flight energy consumption and operational costs. The goal is to minimise the number of locations and minimise delivery path planning while meeting delivery demands within the service range. Based on the traditional distribution centre site-path problem, the UAV distribution network is constructed to solve the problem of airport location and flight path planning, and the two-layer genetic algorithm is used to solve it. Based on this, the validity of the model and algorithm is verified using the urban area of Tianjin as an example. The experimental results show that the constructed model can be used for UAV airport layout planning, which is applicable to large-scale, multi-aircraft-type and multi-level airport layout planning. Data analysis results indicate that when the location layout of the vertical hub airport is on the edge of the VTOL points, both the flight distance and the total cost of the delivery network relatively increase. Increasing the payload capacity will reduce the number of UAV operations, but the total cost shows a decreasing-then-increasing trend. This study can provide a theoretical basis for the selection of airport sites and UAV types in future UAV urban delivery networks.

KEYWORDS

UAV urban logistics; UAV vertical take-off and landing airport; logistics delivery network; location-routing problem; bi-level genetic algorithm.

1. INTRODUCTION

With the widespread adoption of the internet and the booming development of the e-commerce industry, as well as the emergence of new delivery methods, the number of delivered packages has been increasing steadily [1] and UAV-based transportation systems have been introduced.

Recently, UAVs have received considerable attention as an emerging tool for air transportation, offering solutions to ground congestion and carbon emissions [2]. With the advancement of their endurance, automatic navigation systems and payload capabilities, as well as the improvement of related regulations, UAVs are being studied and applied in fields such as emergency rescue [3], medical services [4] and logistics delivery [5, 6]. Companies such as Amazon Prime Air [7], Jing Dong, Antwork Technology and SF Express have already launched pilot operations. With the development of these services, many scholars have conducted research on UAV-related topics.

Although UAVs offer potential advantages, they do have certain technical limitations. On one hand, UAVs have limited battery capacity, which restricts their flight range. On the other hand, UAVs have small sizes and limited payload capacity [8]. The aforementioned disadvantages clearly hinder the possibility of UAVs independently serving customers. In response to the limitations of UAVs, the concept of vertiports and UAV combination delivery models have been proposed. The vertiports are located around the customer base and provide a landing platform and storage facilities for UAVs and goods, thus avoiding the problem of insufficient flight distance for UAVs. At the same time, in order to solve the problems that may arise in the use of drones mentioned above, most current research focuses on the combination of UAVs with trucks [9-11]. However, due to the limited battery capacity of UAVs, trucks provide charging and shifting batteries, resulting in a lower amount of goods carried each time. Given the ground traffic congestion in urban areas, truck transportation is still significantly affected. Consequently, in recent years, some scholars have investigated UAV charging stations [12, 13], which can ensure longer UAV delivery distances and provide temporary storage space for goods.

This paper addresses the problem of UAV vertiport facilities location and flight route planning of UAVs for optimising the cost of the overall delivery network. The above-stated problems are similar to the distribution centre location problem and truck path planning problem in the traditional ground logistics system. A phased approach is adopted to deal with these two problems [14, 15]. The first stage is to solve the location problem, using clustering, spatial geographic analysis or evaluation methods to compare the advantages and disadvantages of indicators, and then select the central point. In the second stage, the path planning problem is solved. When dealing with the UAV delivery path [16, 17], the impact of UAV flight height, no-fly zone and flight duration on the flight path will be considered. However, this phased method is a local optimal solution, which does not reach the optimal of the whole distribution system. This study will establish a set of UAV delivery networks and consider the location and flight path of UAV distribution centres from the perspective of multi-level, multi-model and low energy consumption. However, since these decisions are interdependent, this staged decision-making method may not optimise the overall delivery cost.

In future UAV city logistics, multi-level delivery networks are becoming more prevalent, and this study has the following main contributions. (1) Develop a mathematical programming model for optimising the key decisions mentioned above, taking into account various operational costs incurred during UAV deliveries, such as the cost of purchasing or leasing UAVs due to capacity limitations, energy costs arising from multiple flight stages, and maintenance and battery replacement costs during UAV operation. (2) Construct a UAV logistics distribution network consisting of three levels of airport facilities, where the operation process is divided into two stages of transportation: vertihubs to vertiport, and vertiports to vertistops. (3) Propose a bi-level optimisation heuristic algorithm to obtain a high-quality solution and achieve the optimal overall network distribution cost.

The subsequent sections are organised as follows: Section 2 presents a detailed review of related literature, Section 3 describes the problem studied in this article and Section 4 introduces a bi-level mathematical programming model and proposes a bi-level genetic algorithm for solving it. Section 5 uses the main urban area of Tianjin City as the research scenario and discusses the calculation results and numerical analysis. Finally, Section 6 presents conclusions and directions for future research.

2. LITERATURE REVIEW

With the growth of the UAV delivery industry, one crucial factor in planning UAV operations is the limited flying range of battery-powered or fuel-powered UAVs. Currently, various strategies have been proposed to compensate for the shortcomings of UAVs. One method is to combine UAVs with trucks, leveraging the advantages of trucks to offset the disadvantages of UAVs. For instance, a delivery mode can be established where the truck serves as the launch platform and the UAV serves as the transport vehicle for the last-mile delivery [10, 18, 19]. Another method is to use UAVs exclusively for transportation, but reliance on battery charging and charging stations or docking points is necessary [20, 21, 22].

The deployment of such charging facilities is similar to that of electric vehicle (EV) charging facilities, which have been extensively studied [23, 24]. EV charging facilities often require a large facility space to accommodate the larger size of the vehicles. Additionally, the deployment of EV charging facilities relies on the road transport network. Furthermore, the driving distance after an EV is fully charged will be several times that of a UAV, and changes in EV charging facilities' location could potentially affect the UAV's flight path. Therefore, the deployment of UAV charging stations differs from that of EV charging facilities, and a new model needs to be established to optimise the location of UAV charging stations. Considering that UAVs will be involved in urban delivery systems in the future, this paper introduces the concept of UAV airports. These airports can not only meet the charging needs of UAVs but also provide warehousing and distribution functions for logistics activities. Therefore, finding the facility location of UAV airports and planning the delivery routes of UAVs is the focus of this study.

The location problem of UAV airport and the routing problem of UAV delivery is similar to the location and route problem of traditional distribution centres and truck cooperation. Balakrishnan et al. [25] first studied the LRP problem, which typically involves a single objective function, one demand per customer, no intermediate stops, known potential facility locations and a static planning situation. Due to the interdependence between facility location and routing decisions, the LRP problem has been a focus of research for several decades. Therefore, various variants of the standard LRP problem have emerged, such as multi- or N-echelon vehicle routing problems and LRPs (NE-VRPs/LRPs), multi-objective variants and pickup and delivery LRP problems. According to Michael's survey, the multi-echelon LRP problem remains the most important LRP variant problem in recent years [26], and its research can be traced back to Gonzalez Feliu, Perboli and others [27-29]. The study of this problem has gradually been applied to postal parcel delivery, e-commerce, multimodal transportation and international consumer goods distribution networks [30], which highlights the importance of multi-echelon LRP in urban logistics planning and explains the necessity of introducing multi-echelon airport facilities in this paper. Perboli et al. [29] proposed a mixed-integer programming (MIP) formulation based on arc variables for two-echelon LRPs, which includes a level-0 facility and a level-1 facility of capacity limit. The facility has no fixed cost but has a variable facility cost that depends on the load of facility transfers. Crainic et al. [31] studied a heuristic algorithm for a two-phased LRP with a level-0 facility and limited vehicles. Since the LRP problem is widely used in the logistics field, Chen et al. [32] constructed a cold chain logistics location model that considers carbon emission costs from a low-carbon environmental perspective and solved it using an improved genetic algorithm in the fresh cold chain. In emergency logistics, Wu et al. [33] established an optimal disaster prevention and reduction model considering factors such as human input, producer contribution, capital and effective government expenditure. For urban logistics, a multi-centre location-routing problem under capacity, maximum cost and time window constraints was considered, and the problem was transformed into an assignment problem using the branch and bound method [34]. Çağrı Koç et al. [35] constructed a location-routing model that accounts for vehicle fixed costs, warehouse costs and delivery path costs, and proposed a hybrid evolutionary search algorithm that combines several heuristic methods to solve the problem. In urban logistics distribution, researchers mainly consider the fixed costs of vehicles or warehouses and the operating costs generated in the delivery path. Therefore, building on previous research, this article considers the operating costs of UAVs in the delivery process, such as depreciation, battery loss and energy consumption, to establish a UAV urban logistics location-routing model.

The location-routing problem (LRP) originated from the vehicle routing problem (VRP) and facility location problem (FLP), both of which are NP-hard problems. Therefore, the LRP problem is also an NP-hard problem. Currently, there are four main methods used to solve the LRP model: exact methods, classical heuristics, metaheuristics and simulation. Metaheuristic algorithms have become popular in recent years as they can diversify and centralise the search space by combining different strategies. Currently, metaheuristic methods used to solve the LRP problem include simulated annealing (SA) [36], genetic algorithm (GA) [37], non-dominated sorting genetic algorithm II (NSGA-II) [38], particle swarm optimisation (PSO) [39], tabu search (TS) [40] and large neighbourhood search (LNS) [41]. By comparing the advantages and disadvantages of these algorithms, this paper selects genetic algorithms as the method to solve the model.

In the context of UAV urban logistics, considering the complex urban environment in which UAVs fly and the safety of people and goods, it is necessary to consider UAV energy consumption. Currently, research on UAV energy consumption can be classified into the following categories. (1) UAV energy consumption depends on the flight distance, and as long as the delivery distance does not exceed the distance limit, the UAV can complete the delivery. (2) UAV energy consumption depends on the duration of the flight. (3) UAV energy consumption is represented by a linear model consisting of multiple parameters, but the factor that has the greatest impact on energy consumption is package weight [42]. (4) UAV energy consumption is represented by a non-linear model consisting of multiple adjustable parameters, such as air density, total propeller area, blade count and body resistance [43-45, 11]. To better simulate the flight status of UAVs, this paper uses a non-linear model to calculate flight energy consumption.

The review of the research on unmanned aerial vehicle (UAV) freight delivery paths indicates that the majority of literature focuses on mathematical models, algorithm design and path-solving methods in this field. Mathematical models generally consider objectives such as cost minimisation, path shortening and minimising the number of UAV fleets, while taking into account factors such as time windows, delivery priorities, UAV speed, weight, payload and battery weight. However, in the construction of UAV energy consumption models, there is limited consideration for the complex environmental factors of UAV urban delivery, such as no-fly zones, restricted areas, tall buildings, natural obstacles and artificial obstacles. Nevertheless, there are also studies that investigate the avoidance of obstacles in urban environments. Some literature combines wind fields with urban obstacles [46] and considers the influence of wind on UAV energy in optimising delivery paths, while also considering factors such as avoiding city structures and obstacles [47]. These studies utilise the Dijkstra algorithm to find paths on weighted graphs with specified weights, resulting in optimal energy paths and shortest detour paths. Regarding the issue of UAV path planning for urban logistics in specific areas, Zhang Honghai [48, 49] and Xu Weiwei [50] have adopted grid-based environmental modelling. These models comprehensively consider factors such as UAV performance, task nature and urban environment, aiming to minimise flight distance, altitude variation and hazard level as objective functions, thus constructing multi-constrained path planning models for logistics UAVs.

In summary, our paper is different from previous studies, and our research object has changed from trucks and distribution centres to drones and vertical take-off and landing airports (VTOL). Additionally, we transform the last mile of logistics activities into secondary cargo transportation, using specialised docking stations as important facilities in UAV transit operations. We propose a hierarchical delivery system for logistics distribution based on the actual operation of delivering goods in layers, different from the single-layer delivery in previous research, and suggest a three-tier layout plan for UAV take-off and landing points in the city. To optimise the overall distribution network considering factors such as UAV performance, multi-types of UAV, and multi-level facilities from an economic perspective, we construct a three-tier take-off and landing point layout planning model for urban logistics UAVs. We design a suitable heuristic algorithm to solve the proposed model, and finally optimise the facility location and route decision as a whole and present a comprehensive distribution network solution.

3. PROBLEM DESCRIPTION

As an emerging air transport tool, UAVs have gradually attracted extensive attention from various demand service providers. However, due to the impact of weather dependence, endurance, load limitation and infrastructure needs in the logistics distribution of drones, in order to expand the flight range of drones and reduce the impact of long-distance flights, a safe take-off and landing platform in urban scenes should be provided. This study proposes a delivery method of "UAV and vertical take-off and landing (VTOL) airports" joint distribution. In the two stages of the location-routing problem (LRP), our research background is set in a complex urban scenario. We refer to the idea of hierarchical design of UAV airports according to the scale in the NASA research report [51], in this scenario, after the customer terminal (VTOL point) sends out the demand for goods, the cloud service platform receives the instruction and sends it to the city's central warehouse (VTOL hub airport), which then dispatches the goods and sends them to the customer terminal through intermediate stations (VTOL airport). In this delivery process, the UAV airport can serve as both a distribution centre for cargo schedules and a docking or charging station for UAVs.

The UAV location-routing problem (UAV LRP) for delivery is a complex logistics distribution system that requires consideration of location decisions and route planning. In location decisions, we propose a three-tier UAV VTOL airport location layout, consisting of a primary (the first-tier) VTOL hub airport (vertihub), a secondary (the second-tier) VTOL airport (vertiport) and a tertiary (the third-tier) VTOL point (vertistop). The vertihub is responsible for interregional cargo turnover and transportation by using regional UAVs on the route. It has large-capacity storage space, hardware facilities such as automated three-dimensional warehouses, automated sorting equipment, large-scale UAV automatic charging service areas, UAV intelligent automatic guidance and landing equipment, weather detection equipment, and software functions such as warehouse management, control, sorting and UAV operation service platforms. The vertiport is responsible for city-level cargo turnover and transportation, with medium-sized storage space that can accommodate both regional and terminal UAVs for parking and transportation on the route. It has hardware facilities such as automated or semi-automated warehouses, automated sorting equipment, medium-sized UAV automatic charging service areas, UAV automatic landing equipment and weather detection equipment, and software functions similar to those of the vertihub. The vertistop is responsible for cargo turnover and transportation within the city and is also a facility for customers to pick up and deliver goods. It has a small-capacity storage space and uses terminal UAVs for logistics transportation on the route. It has hardware facilities such as automated sorting equipment, customer interaction equipment, cameras, landing guidance equipment and software that mainly includes intelligent systems for customer interaction.

The joint delivery logistics network of UAVs and vertiports, as shown in *Figure 1*, consists of a hybrid route composed of three-tier VTOL airport facilities and two types of UAVs cooperating together to solve the UAV delivery routing problem. Given the six alternative vertiports in a certain area of the logistics network, after calculating the total cost of the logistics distribution network, five candidate sites (B1~B5) are determined. Regional UAVs 1~5 depart from the vertihubs, delivering goods to each vertiport, then complete unloading, finally returning to the starting point for charging and exchanging batteries along the flight route (vertihub → vertiports (B1~B5) → vertihub). Each vertiport covers a certain range of vertistops. For example, vertistops (C1~C3) are all within the delivery coverage of the vertiport B1, and the end UAV 1 departs from vertiport B1, which completes the second-level path of cargo delivery along the flight route (B1 → C1 → C2 → C3 → B1).

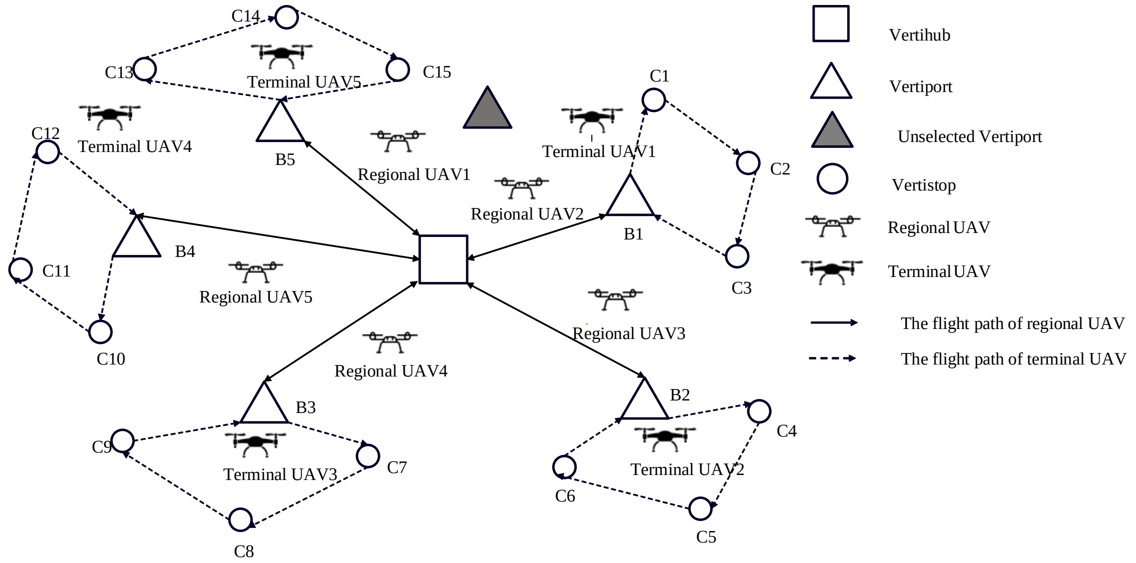


Figure 1 – Joint distribution logistics network of UAVs and VTOL airports

In this research, UAV LRP is an incomplete directed graph $G=(V,E)$ consisting of several sets of nodes $V_{(i)}, i=1\cdots\cdots j$ and arcs $E_{(i,j)}$. The nodes $V_{(i)}$ consist of three types of VTOL airports, and each arc $E_{(i,j)}$ represents a route between a pair of nodes $E_{(i)}, E_{(j)}$. A type of UAV is required for delivery service between each pair of arcs. The goal is to obtain feasible facility locations to allocate UAV flight routes and minimise the total delivery network cost, including the cost of establishing facilities and the transportation cost of serving end customers.

The energy consumption of UAVs during flight is determined by the power required at different stages of flight, which consists of climbing, cruising, hovering and descending. According to the flight profile of UAVs shown in *Figure 2*, which is performing a mission in an urban area, each UAV used will have one or more flight trajectories. Each trajectory can consist of climbing, cruising and descending stages.

During the climbing stage, UAVs will climb to a certain altitude from the VTOL platform provided by the airport and adjust the forward direction of the UAV at the highest point. During the cruising stage, UAVs adjust the angle of attack and gradually accelerate to a constant speed, then begin to cruise. When they are about to reach the task point, they start to reduce their speed. We use g_{acc} , g_{int} and g_{dec} to represent the percentage of cruising stage occupied by the acceleration, uniform speed and deceleration phases of the UAV, respectively. The parameters p_u^{acc} , p_u^{int} and p_u^{dec} represent the power of UAVs during acceleration, uniform speed and deceleration, respectively.

Finally, during the descending stage, when UAVs reach the airspace above the airport, they first hover. At this time, UAVs will search for the platform position provided by the airport. Then UAVs gradually descend until they approach the airport platform. If UAVs miss the platform position along the way, they will also hover until they find the platform position before continuing to descend. Since the climbing power (p_u^a), descending power (p_u^d) and motor speed (λ_u) of different types of UAVs are different, each type of UAV has a maximum payload (τ_u) and an average flight speed ($\overline{v}_u$). In this study, we will divide UAVs into two types: regional UAVs and terminal UAVs, each with different parameters.

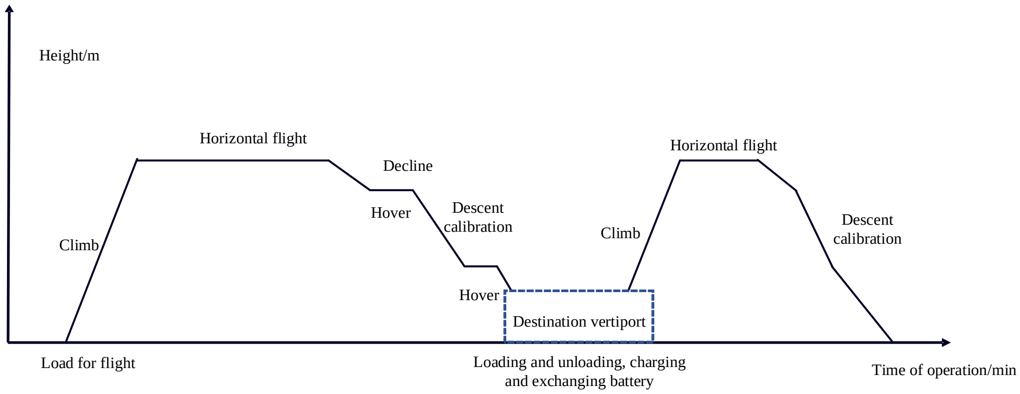


Figure 2 – Flight profile of UAV performing a mission

4. CONSTRUCTION OF A DUAL-LAYER PROGRAMMING MODEL FOR UAV-LRP

4.1 Assumptions

This study makes the following assumptions:

1) UAV delivery process is aligned with regulatory requirements, flying in the established route, without considering the route conflict or obstacle avoidance issues;
2) The locations of the vertihubs and vertistops are known;
3) The demand and time window requirements of the vertistops are known;
4) The vertihub can cover all candidate locations for vertiports;
5) Each UAV is equipped with a fully charged battery that can provide full power throughout the departure and transfer processes;
6) The battery of the UAV is fully filled during each mission, and the UAV does not need to replace the battery, regardless of the battery change time;
7) In the UAV flight task, the severity of the meteorological environment is within the controllable range, and the current task can be completed according to the planned route.

4.2 Symbol definitions

The model parameters and symbol definitions and explanations are presented in *Table 1* and *Tables 2–4* below.

Table 1 – Variable definitions

	Variable	Definition
Set variables	$I=\{i\mid i=1,2,3\cdots n\}$	Set of candidate vertiports
	$J=\{j\mid j=1,2,3\cdots n\}$	Set of vertistops
	$U=\{u\mid u=1,2,3\cdots n\}$	Set of UAVs
	$K=\{k\mid k=1,2\}$	Set of UAVs type
Decision variables (Binary variable)	x_i	whether an alternative vertiport is enabled, $x_i=1$, otherwise $x_i=0$
	y_{ij}	whether vertiport i delivery to Vertispot j, $y_{ij}=1$, otherwise $y_{ij}=0$
	s_u^k	whether the u-th UAV of type k of UAV is used, $s_u^k=1$, otherwise $s_u^k=0$

Table 2 – Model parameter variable definition

Parameter	Definition	Parameter	Definition
n_i	Number of transfers at vertiport i	t_i	Storage time of a package at vertiport i
o	Location of the vertihub	d_{oi}	Flight distance from the vertihub to a candidate vertiport
d_{ij}	Flight distance from a candidate vertiport to vertistop	t_j^u	Time when a UAV arrives at vertistop
T_j^{accept}	Earliest start time vertistop can be served	ET_j^{accept}	Latest end time vertistop can be served
T_{js}	Ideal start time for vertiport service	ET_{js}	Ideal end time for vertiport service
Z_s	Penalty coefficient for violating time windows	t_{sj}^u	Service time of UAV at vertistop
N	Number of candidate vertiports	n_j	Logistics demand of a vertistop
l_i	Capacity of Vertiport	w_{load}	Weight of packages carried by UAV during departure
ω_o^u	Battery capacity of UAV when departing from the vertihub	q_u	Battery capacity of UAV

Table 3 – Cost parameter variable definition

Parameter	Definition	Parameter	Definition
C_1	Operating cost of vertiport	C_2	Storage cost of a vertiport
g_i	Construction cost of vertiport	p	Storage unit price of a package at vertiport
f_u^k	Fixed usage cost of the u-th UAV of type k	C_u^a	UAV maintenance cost
C_u^b	Depreciation cost of a UAV	C_u^c	Cost of maintaining/replacing a UAV battery

Table 4 – UAV performance parameter variable definition

Parameter	Definition	Parameter	Definition
h_u	Flight altitude of UAV	v_u^a	Ascending speed of UAV
p_u^a	Motor power required for UAV ascent	v_u^d	Descent speed of UAV
p_u^d	Motor power required for UAV descent	p_u^{hover}	Hovering power of UAV
λ_u	Motor speed of UAV	$\bar{v}_u$	Average flight speed of UAV
τ_u	Maximum payload of UAV	p_u^{acc}	Power during acceleration stage of UAV
p_u^{dec}	Power during deceleration stage of UAV	p_u^{int}	Power during cruising stage of UAV
g_{acc}	Percentage of acceleration time during cruising stage of UAV	g_{dec}	Percentage of deceleration time during cruising stage of UAV
g_{int}	Percentage of cruising time during cruising stage of UAV	C_{iju}	Cost of UAV battery consumption per unit

4.3 Model construction

Based on the above assumptions and variable definitions, a mathematical model is proposed for the problem, which is divided into two parts: an upper-level model and a lower-level model.

$$MinC = C_{top} + C_{bottom} \tag{1}$$

$$MinC_{top} = \sum_{i=1}^{i} g_i x_i + \sum_{i=1}^{i} pn_i t_i x_i \tag{2}$$

$$\begin{aligned} MinC_{bottom} = C_3 + C_4 + C_5 = &\sum_{k=1,2} \sum_{u}^{U} f_u^k s_u^k + \sum_{i}^{I} \sum_{j}^{J} \sum_{u}^{U} (C_u^a + C_u^b + C_u^c)(d_{oj} + d_{ij}) x_i + \\ &\sum_{k}^{K} \sum_{u}^{U} \sum_{i}^{I} C_{oiuk} (\frac{h_{uk}}{v_{uk}^a}) p_{uk}^a x_i + \sum_{k}^{K} \sum_{u}^{U} \sum_{i}^{I} \sum_{j}^{J} C_{ijuk} (\frac{h_{uk}}{v_{uk}^a}) p_{uk}^a x_j + \\ &\sum_{k}^{K} \sum_{u}^{U} \sum_{i}^{I} C_{oiuk} (\frac{h_d}{v_{uk}^d}) p_{uk}^d x_i + \sum_{k}^{K} \sum_{u}^{U} \sum_{i}^{I} \sum_{j}^{J} C_{ijuk} (\frac{h_{uk}}{v_{uk}^d}) p_{uk}^d x_j + \\ &\sum_{k}^{K} \sum_{u}^{U} \sum_{i}^{I} C_{oiuk} \left((p_{uk}^{hover} + \lambda_{uk} h_{uk})(\frac{d_{oi}}{\bar{v}_{uk}}) + \left(\sqrt{\tau_{uk} \bar{v}_{uk} p_{uk}^{acc}} g_{acc} + (\frac{2 p_{uk}^{\text{int}}}{\bar{v}_{uk}}) g_{\text{int}} + \sqrt{\tau_{uk} \bar{v}_{uk} p_{uk}^{dec}} g_{dec} \right) d_{oj} \right) y_{oi} + \\ &\sum_{k}^{K} \sum_{u}^{U} \sum_{i}^{I} \sum_{j}^{J} C_{ijuk} \left((p_{uk}^{hover} + \lambda_{uk} h_{uk})(\frac{d_{ij}}{\bar{v}_{uk}}) + \left(\sqrt{\tau_{uk} \bar{v}_{uk} p_{uk}^{acc}} g_{acc} + (\frac{2 p_{uk}^{\text{int}}}{\bar{v}_{uk}}) g_{\text{int}} + \sqrt{\tau_{uk} \bar{v}_{uk} p_{uk}^{dec}} g_{dec} \right) d_{ij} \right) y_{ij} \end{aligned} \tag{3}$$

$$1 \le \sum_{i}^{I} x_i \le N \tag{4}$$

$$\sum_{i}^{I} g_i x_i \le C_{total} \tag{5}$$

$$\sum_{i}^{I} \sum_{j}^{J} n_j y_{ij} \le \sum_{i}^{I} l_i x_i \tag{6}$$

$$\sum_{i}^{I} x_i y_{oi} = \sum_{i}^{I} x_i y_{io} \le 1 \tag{7}$$

$$\sum_{i}^{I} \sum_{j}^{J} y_{ij} = \sum_{i}^{I} \sum_{j}^{J} y_{ji} \le 1 \tag{8}$$

$$s_u^k w_{load} \le \tau_u \tag{9}$$

$$M, t_j^u < T_j^{accept} \tag{10}$$

$$Z_s (T_{js} - t_j^u), T_i^{accept} \le t_j^u < T_{js} \tag{11}$$

$$0, T_{js} \le t_j^u \le ET_{js} \tag{12}$$

$$Z_s (t_j^u - ET_{js}), ET_{js} < t_j^u < ET_j^{accept} \tag{13}$$

$$M, t_j^u > ET_j^{accept} \tag{14}$$

$$T_i = t_{oi}^u + t_{si}^u + t_{io}^u \tag{15}$$

$$t_{ij}^u = t_{ij}^u + t_{sj}^u + t_{jj'}^u + t_{sj'}^u + t_{j'i}^u \tag{16}$$

$$\omega_o^u = \omega_i^u = q_u \tag{17}$$

The objective function expression of the problem is presented in *Equation 1*, which consists of the upper and lower-level objective functions. The upper-level objective function, *Equation 2*, includes the operational and storage costs of the VTOL airports. The operational costs include airport leasing fees, utility expenses, facility and equipment purchase costs, while the storage costs mainly comprise equipment maintenance and depreciation costs, packaging and processing costs and labour costs. *Equation 3* includes three types of costs, including eight costs. Among them, C3 is the fixed input cost of drones, that is, the cost of purchasing or leasing a new drone, the cost of pilots or background supervision resources. C4 is the UAV operating cost, that is, the loss and depreciation cost generated by the UAV in the long-term flight, including the UAV maintenance cost, depreciation cost and battery maintenance/replacement cost. C5 is the UAV flight energy cost, which mainly includes the UAV's energy cost when climbing from the vertical hub airport and VTOL airport, the energy cost generated when descending from the VTOL airport and VTOL point, and the energy cost during the horizontal flight stage between the vertical hub airport and VTOL airport and the vertical take-off and landing point. This includes the cost of energy consumption during the four stages of hovering, acceleration, uniform speed and deceleration during flight. The UAVs also have two stages of flight, from the vertihub to the vertiport and from the vertiport to the vertistop. *Equation 4* indicates that there should be at least one vertiport location and no more than the maximum pre-selected number of vertiport locations. *Equation 5* indicates that the cost of selecting vertiport locations should not exceed the total investment cost. *Equation 6* indicates that the capacity of any alternative vertiport should be sufficient to meet the demand for services. *Equations 7 – 8* indicate that UAVs should return to their initial points after completing their delivery services. *Equation 9* indicates that the weight of the packages loaded on UAVs should not exceed their maximum payload capacity. *Equations 10 – 14* represent the time window penalty constraint. *Equations 15 – 16* indicate that the drones should continuously provide services to the vertistops during the delivery of goods and the drones should provide point-to-point service for the vertiports. *Equation 17* indicates that the UAV should be fully charged before departing from the vertihub or the vertiport.

4.4 Bi-level genetic algorithm

There are many optimisation methods to solve the site-path planning problem, including integer programming, dynamic programming, branch and bound method and nonlinear programming. Modern heuristic algorithms that are now widely used are also built by imitating one or more phenomena and processes in nature, including simulated annealing algorithm, particle swarm optimisation algorithm, genetic algorithm [37] and so on. Through the study of the application of the heuristic algorithm to the location – path of UAVS VTOL airport, the problems of location selection, task assignment and flight path planning can be solved quickly. In the face of large-scale problems, integer programming methods need highly complex algorithms and techniques, and it takes a long time to calculate the results, which requires high computer performance. The dynamic programming method divides the problem to be solved into several sub-problems, and the solution of the original problem is obtained after solving the sub-problems, but the generation of sub-problems is often not independent of each other and is subject to certain limitations. At the same time, the dynamic programming method is only aimed at solving the optimal problem, and the theoretical design is complicated. The simulated annealing algorithm is affected by the cooling rate of temperature. If the cooling rate is not suitable, the search time between the current point and the next point is longer, although a better solution can be obtained, it will take a lot of time. In addition, if the cooling rate is too fast, the optimal solution may be skipped to search for the suboptimal solution.

There are some outstanding problems in the application of traditional optimisation methods, mainly due to the difficulty of initialisation and the great constraint effect of moving mode on the algorithm jumping out of the local area. The bionic intelligent algorithm can solve the limitation problem effectively, and the advantage effect is obvious.

The emergence of genetic algorithm (GA) is inspired by biological evolution, which provides a better solution to the global optimisation problem. The genetic algorithm is based on biological genetic and evolutionary mechanisms, combined with an adaptive probabilistic optimisation algorithm, to find the optimal solution in the global search range. Each chromosome in the upper-layer genetic algorithm of this model selects and iteratively inherits the optimal individual by means of biological inheritance such as selection, crossover and variation, so as to plan the optimal location scheme. In the lower genetic algorithm, each chromosome represents a route scheme, and the optimal distribution route is preserved through the selection mechanism of the survival of the fittest in nature. Its physical significance is consistent with the modelling method studied in this paper. Therefore, the two-layer genetic algorithm is selected to solve the site-path problem of VTOL airport.

The UAV urban delivery LRP based on dual-layer programming is an NP-hard problem. Traditional exact-solving algorithms are slow and cannot converge quickly. Therefore, this paper proposes a dual-layer genetic algorithm to solve this problem. Genetic algorithm (GA) is a population-based metaheuristic algorithm that utilises the genetic mechanism of individuals. These individuals follow genetic rules to breed new offspring, and GA selects genetic operators (selection, crossover and mutation) to find better solutions from a set of solutions for each iteration.

The bi-level UAV LRP is divided into two layers: the upper layer model focuses on the operating and storage costs of vertiports, which mainly solves the location problem of vertiports. The lower layer model aims to minimise the total flight route cost, which needs to solve the assignment problem of vertistops and the UAV flight route problem. The solving approach is described as follows:

1) Use the upper layer model to determine the location and number of vertiports.
2) Based on the location results of the upper layer model, solve the route planning problem in the lower layer model.
3) Return the route planning results of the lower layer model to the upper layer to calculate the storage cost.
4) Iterate the overall objective of the upper layer and terminate the loop calculation if the termination condition is met.

According to the above-solving approach, the overall algorithmic framework of the UAV urban delivery LRP based on the bi-level programming model in *Figure 3* can be constructed.

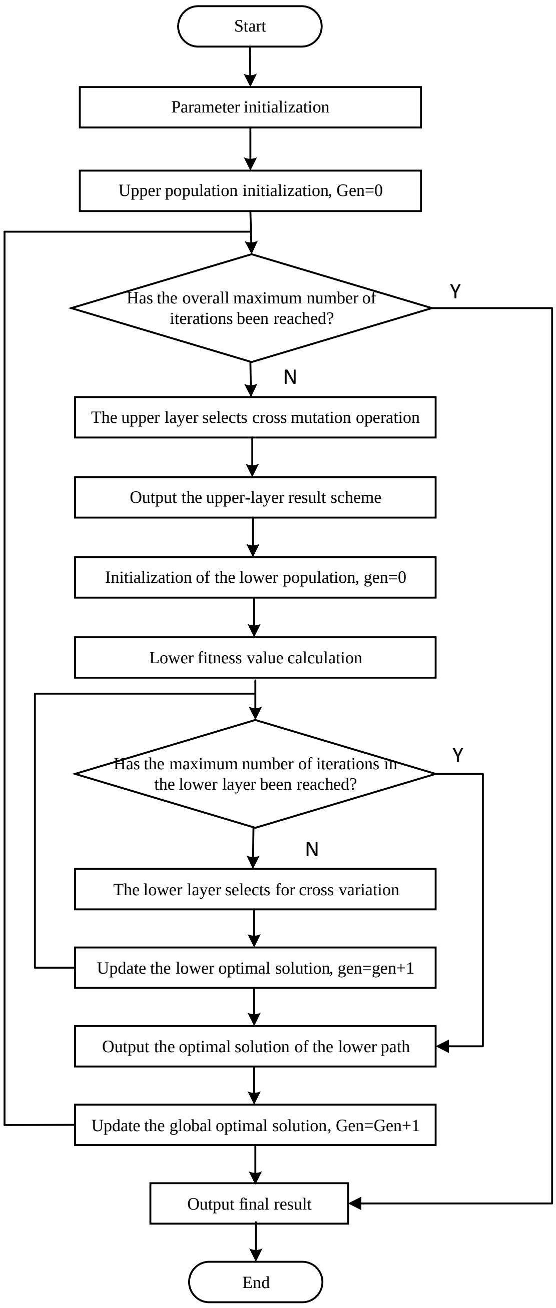


Figure 3 – Bi-level genetic algorithm solution approach

5. EXPERIMENTAL RESULTS AND ANALYSIS

This section describes the following: first, a brief explanation of the data required for the case is provided; second, the optimal model results based on an example study are analysed; and finally, a sensitivity analysis is conducted to investigate the impact of the scale of the case, the layout of vertihub location, and the payload capacity of the UAVs on the total cost. All experimental analyses were conducted on a computer (Inter(R) Core (TM) i7-6700HQ CPU @ 2.60GHz with RAM 16GB) using MATLAB R2019b (64-bit).

5.1 Description of relevant data

Taking Tianjin City as an example, this paper studies the LRP of UAV logistics distribution in urban areas. The related data include: take-off and landing airport node information, UAV basic information, other parameter settings and algorithm parameter settings.

Airport node information for UAV VTOL

There are three levels of VTOL airports, namely, vertihub, vertiport and vertistop. The node information of each level of the airport is introduced below.

The vertihub location is referenced from the Tianjin JD Asia No.1 Logistics Centre. Due to its large-scale construction and advanced hardware and software facilities, such as automated three-dimensional warehouses, automatic sorting machines and intelligent information systems, it lays a certain foundation for its future development as a VTOL hub airport. Therefore, it is used as a vertihub. Its node information includes airport ID numbers and latitude and longitude coordinates (using the WGS84 coordinate system). The details are shown in *Table 5*.

Table 5 – Vertical take-off and landing hub airport parameter information

Airport ID	Longitude coordinate	Latitude coordinate
0	117.370306	39.177247

Alternative vertiports are randomly distributed within the experimental area. In this case, 5 alternative locations were randomly selected as vertiports. The node information includes airport ID, longitude and latitude coordinates, service time window and service time. The service time window is 20 hours and the service time is randomly generated between 20 and 30 minutes. *Table 6* shows the details of these alternative airports.

Table 6 – Alternative vertical take-off and landing airport parameter information

Airport ID	Longitude coordinate	Latitude coordinate	Service start time	Service end time	Service time (minutes)
1	117.2314279	39.10728245	0	1200	25
2	117.323999	39.10728245	0	1200	24
3	117.2777134	39.16955663	0	1200	24
4	117.323999	39.23187577	0	1200	26
5	117.3702846	39.16955663	0	1200	25

Vertistops are obtained through POI data crawling of residential and commercial buildings within the Tianjin urban area, which form the data information of the VTOL points. The node information includes airport ID, longitude and latitude coordinates, demand, service time window and service time. The specific information is summarised in *Table 7*.

Basic information on UAVs

UAVs are classified into regional UAVs and terminal UAVs. As a carrier, UAVs avoid ground traffic congestion and rely on the route network and air transportation advantages to transport goods from vertihubs to vertistops. Referring to the UAV operating status of Antwork Technology, the flight speed of UAVs is set to 25 km/h. The fixed cost of UAVs is 4,000 RMB. The maintenance, depreciation and battery maintenance/replacement costs incurred during UAV operation are 0.1 RMB, 0.2 RMB and 0.23 RMB, respectively. Other specific parameters of UAVs [52] are shown in *Table 8*.

Table 7 – Vertical take-off and landing point parameter information

Airport ID	Longitude coordinate	Latitude coordinate	Demand (kg)	Service start time	Service end time	Service time (minutes)
6	117.3442	39.1439	0.2	912	967	12
7	117.3112	39.12554	0.1	825	870	14
8	117.2907	39.19667	0.3	65	146	14
9	117.3162	39.12328	0.2	727	782	12
10	117.2822	39.15077	0.3	235	357	8
11	117.3211	39.18096	0.2	621	702	3
12	117.3511	39.21777	0.4	170	225	6
13	117.2738	39.11184	0.3	255	324	5
14	117.2974	39.08282	0.5	345	389	4
15	117.4124	39.17257	0.3	346	567	6
16	117.2594	39.14785	0.6	458	578	12
17	117.2377	39.12237	0.1	256	587	4
18	117.3114	39.08701	0.3	348	556	12
19	117.3105	39.1394	0.4	348	678	15
20	117.3252	39.13701	0.3	234	658	7
21	117.2754	39.13303	0.1	256	485	6
22	117.2598	39.13017	0.3	364	678	5
23	117.2906	39.1075	0.3	456	687	6
24	117.2393	39.12532	0.1	552	687	13
25	117.2453	39.14942	0.3	359	548	8
26	117.3279	39.11454	0.1	237	568	20
27	117.2653	39.10604	0.6	358	685	13
28	117.3021	39.11364	0.3	248	658	17
29	117.27	39.12856	0.1	348	685	16
30	117.3056	39.1065	0.6	458	658	5
31	117.2674	39.12396	0.3	354	585	16
32	117.2567	39.14118	0.1	458	658	6
33	117.2969	39.13718	0.4	225	547	13
34	117.311	39.12743	0.6	358	658	4
35	117.2827	39.13125	0.1	258	658	18

Other related parameter settings

The numerical values of other related parameters involved in the UAV urban delivery location route planning model are shown in *Table 9*.

Table 8 – Parameters of UAVs

Parameter	Symbol	Regional UAV	Terminal UAV	Unit
UAV unit consumption cost	C_{iju}	0.43	0.43	RMB
UAV flight altitude	h_u	120	120	meter
UAV ascent speed	v_u^a	48	48	km/h
UAV motor power required for ascent	p_u^a	12	12	kW
UAV descent speed	v_u^d	32	32	km/h
UAV motor power required for descent	p_u^d	5	5	kW
UAV hover power	β_u	90	90	kW
UAV motor speed	λ_u	1	1	
Maximum UAV payload	τ_u	2	1.2	kW
Power required for UAV acceleration	p_u^{acc}	90	90	kW
Power required for UAV cruising	p_u^{int}	85	85	kW
Power required for UAV deceleration	p_u^{dec}	70	70	kW
Percentage of acceleration phase during cruising	g_{acc}	5%	5%	%
Percentage of uniform speed phase during cruising	g_{int}	90%	90%	%
Percentage of deceleration phase during cruising	g_{dec}	5%	5%	%

Table 9 – Other parameter information

Parameter Name	Symbol	Value	Unit
Construction Cost of Vertiport	g_i	2000	RMB
Storage Unit Price in Vertiport	p	0.005	RMB/kg/minute

Algorithm parameter information

The bi-level genetic algorithm established in Section 4 is divided into upper and lower layers, and relevant parameters in the genetic algorithm are set separately, as shown in *Table 10*.

Table 10 – Double-layer genetic algorithm parameter settings

Upper layer genetic algorithm parameters	Value	Lower layer genetic algorithm parameters	Value
Population size	100	Population size	100
Crossover probability	0.9	Crossover probability	0.9
Mutation probability	0.3	Mutation probability	0.1
Iteration number	200	Iteration number	200

5.2 Experimental results

The proposed model was solved using the data described above, and the iterative convergence graph of the algorithm is shown in *Figure 4*. From the graph, it can be seen that the algorithm converged to the optimal value at the 66th iteration. The solution of the location-routing model using the bi-level genetic algorithm showed that the total optimal cost of the UAV delivery network was 250,701.08 RMB. The facility location cost accounted for approximately 39.90% of the total cost, while the UAV route operation cost accounted for approximately 60.10%. The total number of UAVs required was 15, of which 7 were needed for the first phase (regional) of network distribution, accounting for approximately 46.67% of the total UAVs, and 8 were needed for the second phase (terminal), accounting for approximately 53.33%. The total flight distance of the UAVs was 189.06 km, with 70.19 km (approximately 37.13%) flown during the first phase and 118.86 km (approximately 62.87%) flown during the second phase. Next, we will analyse the upper and lower layers separately.

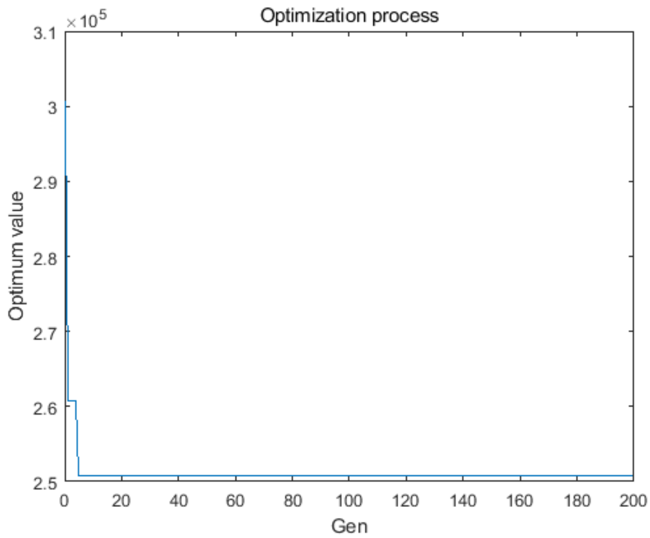


Figure 4 – Iterative convergence graph of the bi-level genetic algorithm.

After calculation, the upper layer location results indicate that the optimal total cost was achieved when selecting the alternative with ID numbers 1 and 2. The location scheme is illustrated in *Figure 5*, where the empty circles represent the vertiports that were not selected, the larger solid circles represent the selected vertiports, and the smaller solid circles represent the vertistops.

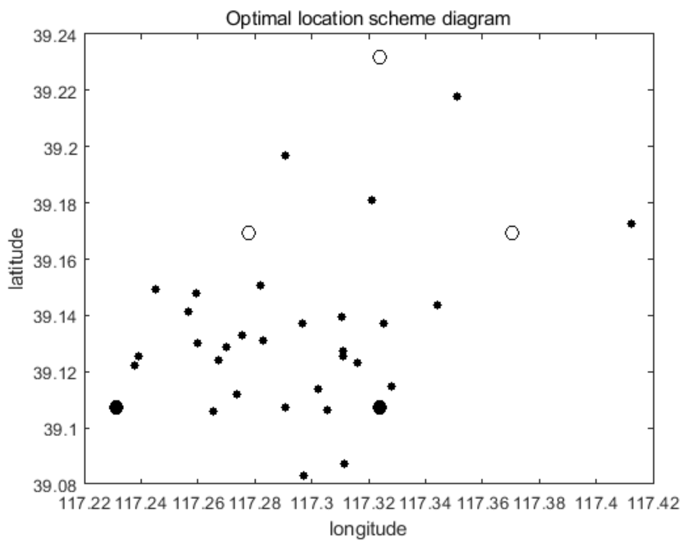


Figure 5 – UAV vertical take-off and landing airport location results

At this point, the sum of the vertiport operating cost and storage cost in the upper layer model objective function was 100,019.41 RMB, with specific values shown in *Table 11*.

Regarding the route results, the sum of the fixed input cost, operation cost, and flight energy consumption cost in the lower-level model was 150,681.67 RMB. The route was divided into two parts: from vertihub to vertiport and from vertiport to vertiports. The specific path results are shown in *Figure 6*.

Table 11 – Upper-level model costs

Cost category	Value (RMB)
Operating cost	100,000
Storage cost	62.41
Total upper layer cost	100,062.41

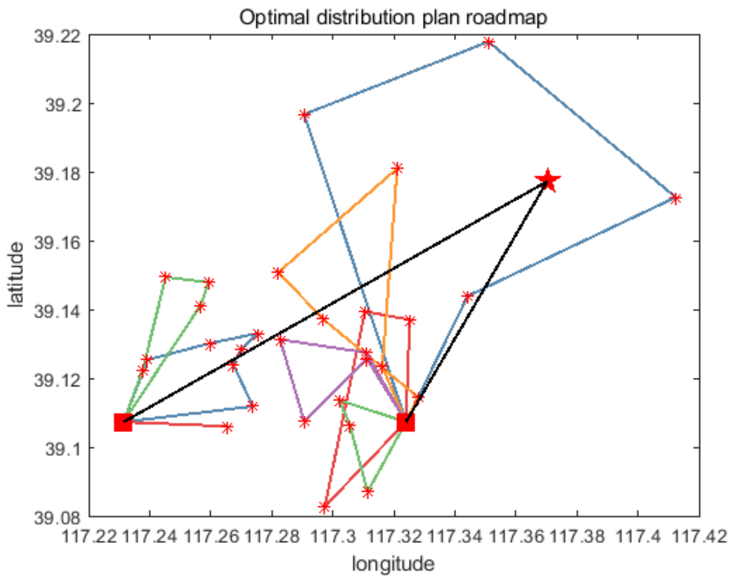


Figure 6 – Delivery path results

The lower layer path model was solved by the bi-level genetic algorithm. The vertihub with ID 0 dispatched 7 regional UAVs to serve vertiports 1 and 2, and vertiports 1 and 2 dispatched 3 and 5 terminal UAVs to serve vertistops, respectively. The specific UAV delivery scheme is shown in *Table 12*.

Table 12 – UAV flight path results and delivery scheme costs

Starting airport ID number	Delivery path	Number of UAVs	Flight distance (km)	Delivery scheme cost (RMB)
0	0→1→0,0→2→0	7	70.19	70378.60
1	1→13→31→29→21→22→24→1	3	31.14	30094.97
	1→27→1 1→17→25→16→32→1			
2	2→8→12→15→6→2	5	87.72	50208.11
	2→14→19→20→2			
	2→18→30→28→2			
	2→26→33→10→11→9→2			
	2→34→35→23→7→2			

5.3 Sensitivity analysis of parameters

By analysing various parameters of the established model, the influence of each parameter on the model's objectives is studied. Since large-scale operational scenarios have not yet emerged, it is necessary to expand the data scale to explore the impact on the total cost. Additionally, the location of the vertihub is predetermined in the premise assumption, and the selected location will also affect the overall results. Finally, the impact of the payload capacity of the UAV on the model is considered.

Sensitivity analysis of distribution scale in the cases

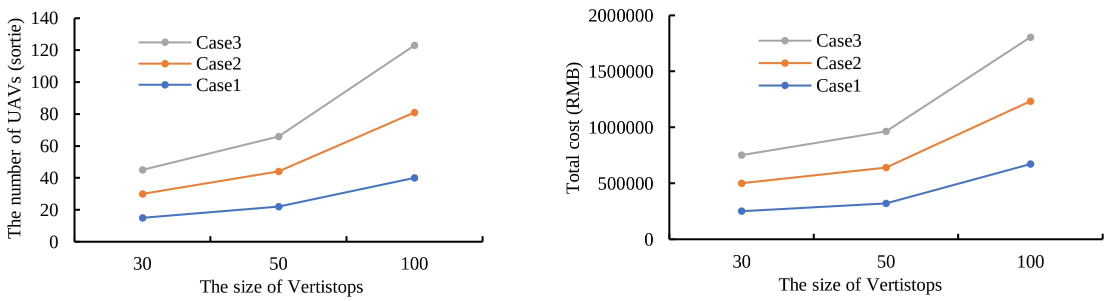
The scale of the vertistop in the research is set to 30, 50 and 100, respectively. Furthermore, under each scale, the model is calculated using three different types of location layout: uniform layout (Case1), clustered layout (Case2) and semi-clustered layout (Case3). The calculation results are shown in *Table 13*.

Table 13 – Calculation results for different distribution scales

Scale	Layout type	Location selection	Number of UAVs	Total flight distance (km)	Location selection cost (RMB)	Path cost (RMB)	Total cost (RMB)
30	Case1	1,2	15	189.06	100019.41	150681.67	250701.08
	Case2	1,2	15	174.74	100020.50	150661.75	250682.25
	Case3	1,2	15	204.69	100019.51	150703.42	250722.93
50	Case1	1,3	22	345.28	100026.78	221141.97	321168.76
	Case2	2,3	22	202.56	100029.44	220891.31	320920.75
	Case3	2,3	22	252.51	100028.86	220960.81	320989.67
100	Case1	1,2,3	40	524.72	150044.04	521959.53	672003.57
	Case2	1,2,3	41	306.69	150043.85	411567.70	561611.54
	Case3	1,2,3	42	430.97	150043.92	421778.69	571822.60

From *Table 11*, it was found that the distribution of vertistops has an impact on the delivery network. When the vertistops are clustered, the number of UAVs required and the total delivery cost of the delivery network are lower than those of other distribution methods. The results in *Figure 7* show that the number of vertistops is directly related to the total number of UAVs used and the total delivery cost of the delivery network. When the number of vertistops increased from 30 to 50 and from 50 to 100, the number of UAVs and the total delivery cost of the delivery network increased by 46.67% and 81.82%, 28.11% and 109.24% for Case1, 46.67% and 86.36%, 28.02% and 75.00% for Case2, and 46.67% and 90.91%, 28.06% and 78.14% for Case3, respectively.

It can be seen that as the number of vertistops increases, the impact of the three types of layouts on the increase or decrease in the number of UAVs is relatively small. However, for the total delivery cost, the growth rate of the delivery network total cost under the clustered layout is smaller than that under the other two types of location layout.



(a) *(b)*

Figure 7 – The impact of the number and layout of vertistops on the model: a) impact on the number of UAVs; b) impact on delivery network cost

Sensitivity analysis of vertihub location

To explore the impact of changes in the location of vertihub on the overall network cost, the location of the vertihub was placed at the edge of vertistops, the edge of the vertiport, the centre of the vertistops, and the centre of the vertiport, respectively. Before the experiment, it was ensured that the scale of this case was 30 vertistops, and the positions of the vertistops and the vertiport remained unchanged. From the experimental results in *Table 14*, it can be seen that the change in the location of the vertihub will cause adjustments to the location scheme. When the layout of the vertihub is located at the edge of the vertistops, the total cost of flight distance and distribution network relatively increases. This is mainly because the location of the vertihub has a significant impact on the service time window of the vertistops. It is worth noting that the change in the location of the vertihub does not cause a change in the number of UAVs, but it does affect the total flight distance and path cost of the UAVs.

Table 14 – Impact of Vertihub Location on Distribution Network Cost

Location layout	Location Selection	Number of UAVs	Total Flight Distance (km)	Location Selection Cost (RMB)	Path Cost (RMB)	Total Cost (RMB)
Edge of vertistops	1,2	15	189.06	100019.41	150681.67	250701.08
Edge of vertiports	1,3	15	167.02	100020.42	150506.42	250526.84
Center of vertistops	1,2	15	149.19	100020.27	150509.23	250529.50
Center of vertiports	1,3	15	171.46	100020.35	150520.71	250541.05

Sensitivity analysis of UAV payload capacity

The purpose of this experiment is to investigate the impact of UAV payload capacity on the number of UAVs and total cost in a delivery network. The payload capacity ranges of the regional UAV (Cap1) and terminal UAV (Cap2) are set between 4 to 10 kg and 1.5 to 4 kg, respectively, while keeping other parameters constant. The experimental results are shown in *Table 15*.

Table 15 – The impact of drone payload capacity on delivery network cost

Payload classification	UAV payload	Location selection	Number of regional UAV	Number of terminal UAV	Total flight distance (km)	Location selection cost (RMB)	Path cost (RMB)	Total cost (RMB)
Cap1	4	1,2	4	8	189.06	100019.41	120542.10	220561.51
	6	2,3	3	8	171.45	100019.59	110472.51	210492.09
	8	2,3	3	8	171.45	100019.59	110478.36	210497.95
	10	2,3	3	8	171.45	100019.59	110483.52	210503.10
Cap2	1.5	1,2	7	6	180.28	100019.41	130680.11	230699.52
	2	1,2	7	5	175.40	100019.41	120688.93	220708.34
	2.5	1,3	7	4	182.97	100019.33	110710.74	210730.06
	3	1,2	7	3	166.12	100019.41	100702.22	200721.63
	3.5	1,2	7	3	165.49	100019.41	100712.77	200732.18
	4	1,2	7	3	161.69	100718.13	100019.41	200737.54

From *Table 15*, it can be seen what is the impact of two types of UAV payload capacity on the number of UAVs and overall delivery cost. The results indicate that, to some extent, the number of UAVs used decreases as the payload capacity increases. Once a certain level is reached, the number of UAVs used remains constant. This is because the service time at the vertistop limits the number of UAVs used. In addition, changes in payload capacity for terminal UAVs have a more significant impact on the overall network delivery cost compared to regional UAVs. The experimental results demonstrate that the total delivery cost decreases first and then increases as UAV payload capacity increases. Therefore, when operating conditions permit, in order to keep the overall network delivery cost at a low level, the payload capacity of the UAV should be adjusted. Therefore, if the payload capacity of feeder UAVs is set between 6 to 8 kg and the payload capacity of last-mile UAVs is set between 3 to 4 kg, both the number of UAVs used and the network delivery cost can be kept at a lower level.

6. CONCLUSION AND FUTURE DIRECTIONS

This study investigates the UAV delivery location routing problem (LRP) in urban areas. Firstly, design an operational plan for a UAV distribution network using different types of UAVs with multi-level Verti-airports. A bi-level programming model is proposed, considering UAV-related factors, such as UAV depreciation, maintenance and energy costs in different flight stages. Furthermore, a bi-level genetic algorithm is developed based on the dual-layer programming model. Finally, a set of new instances is generated using the urban area of Tianjin as the experimental area.

We further analyse the impact of parameters in the model on the overall distribution network. It is found that the change in the scale of vertistop has a positive correlation with cost. In terms of location layout, a cluster-style layout of vertistop can result in smaller distribution costs and flight distances. When analysing the location of the vertihub, it is found that the layout of the vertihub on the edge of the vertistop results in an increase in flight distance and total distribution costs of the distribution network. When testing the parameter of UAV payload capacity, it is found that the UAV payload capacity has a negative correlation with the overall cost of the distribution network, and with the increase of payload capacity, the number of regional and terminal UAVs tends to be stable. When setting the payload capacity of regional UAVs at 6 to 8 kg and terminal UAVs at 3 to 4 kg, the number of UAVs and network distribution cost can be kept at a low level.

The research of this paper still has some shortcomings and needs to be improved. In the study of UAV delivery, the flight speed of the UAV is set to be uniform, but in the actual delivery process, the UAV is affected by the external environment, and the flight speed and flight power change. Therefore, the UAV flight speed can be used as a variable to optimise the UAV routing problem in the subsequent research. When solving the site-path model of drone city distribution, a double-layer genetic algorithm is designed. Different algorithms can be applied to the solution of the double-layer model in future studies, and new algorithms can be added to speed up the convergence of solutions.

Several potential directions for future research in UAV logistics can be considered. In this study, the demand is assumed to be deterministic, but future research should consider fuzzy demand. In addition, the cost of UAV charging and replacing batteries should be considered in further research. Future research could develop different scenarios to solve logistics distribution problems. Finally, future research can try to study the application of UAV flight trajectory in three-dimensional scenes.

DATA AVAILABILITY

The data used and analysed during the study are available from the corresponding author upon reasonable request.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest regarding the publication of this paper.

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无人机城市物流配送网络中机场选址–路径规划——以天津市为例

摘要：
无人机（UAV）具有快速、零接触和绿色交付等潜力，由于其成本效益和方便快速的交付操作而得到越来越多的关注和应用。为了提高交付效率并提供竞争优势，在未来的城市中，需要一个支持无人机垂直起降（VTOL）的多层机场网络。本文提出了一个考虑无人机飞行能耗和运营成本的多层无人机机场选址问题。目标是在满足服务范围内交付需求的基础上，最大限度地减少机场数量并缩短交付路径。基于传统配送中心站点-路径问题，构建无人机配送网络，采用双层遗传算法解决机场选址和飞行路径规划问题。基于此，以天津市区为例，验证了模型和算法的有效性。实验结果表明，本文构建的模型可用于无人机机场布局规划，适用于大规模、多飞行器类型、多层次的无人机机场布局规划。数据分析结果表明，当垂直枢纽机场布局在 VTOL 选址点的边缘时，配送网络的飞行距离和配送总成本都相对增加。增加有效载荷容量将减少无人机投入数量，但总成本呈先下降后增加的趋势。本研究可为未来无人机城市配送网络中的机场选址和无人机类型选择提供理论依据。

关键词：
无人机城市物流；无人机垂直起降机场；物流配送网络；选址–路径问题；双层遗传算法