Traffic & Transportation

Optimisation of Multi-Type Logistics UAV Scheduling under High Demand

Hong JIANG[1], Tong WU[2], Xinhui REN[3], Lizhen GOU[4]

Original Scientific Paper
Submitted: 26 Mar. 2023
Accepted: 4 Aug. 2023

[1] jh109424@163.com, Civil Aviation University of China
[2] 1917266631@qq.com, Civil Aviation University of China
[3] xinhui9596@sina.com, Civil Aviation University of China
[4] goulizhen97@163.com, Civil Aviation University of China

Publisher:
Faculty of Transport and Traffic Sciences, University of Zagreb

ABSTRACT

At present, interest in the application of unmanned aerial vehicles (UAV) for delivery is growing. A new "multi-type of UAV collaborative delivery" mode has been proposed. Through a combination of large, medium and small UAVs, the delivery capabilities of the UAV logistics system are significantly improved. Sometimes there is high demand, resulting in planned delivery routes that are no longer feasible, and even cause a shortage of distribution centre capacity and drones. This study explores logistics delivery strategies to solve problems caused by high demand. In this study, a multitype and multidistribution UAV model was established with the objective of minimising the total cost of distribution by considering factors such as the UAV energy consumption, load and distribution centre conditions. An improved ant colony algorithm was designed and its effectiveness was verified through the variability of the calculation time and multiple calculation results of different-scale examples. Finally, the classic vehicle routing problem (VRP) case is used in three scenarios to analyse the UAV scheduling optimisation problem. The results indicate that assisted delivery can reduce costs by 3% while ensuring delivery timeliness. The results of this study can provide guidance and benchmarks for the application of UAVs in urban logistics delivery systems.

KEYWORDS

logistics distribution; logistics UAVs; improved ant colony algorithm; delivery path.

1. INTRODUCTION

In dense urban environments, the efficiency of parcel delivery logistics is hampered by traffic congestion, differences in customer location and accessibility. Furthermore, customer demand for time-sensitive package delivery services is growing, prompting various countries to investigate ways to expedite delivery tasks. An entity that can provide superior service and faster delivery speeds can gain competitive advantages in the instant delivery domain. Unmanned aerial vehicles (UAVs) are emerging technologies that stand out in the field of instant delivery, owing to their small size, speed and flexibility. They have been applied to scenarios such as medical rescue material delivery [1], island product delivery [2], food delivery [3–5] and e-commerce logistics parcel delivery [6]. At present, the delivery application modes of UAVs can be classified into three categories: independent UAV delivery [7], independent UAV and truck delivery, and joint UAV and truck delivery [8, 9], which overcome the limitations of the UAV flight range and insufficient payload.

UAVs are not constrained by complex ground conditions and can avoid issues such as congestion, traffic control and delivery vehicle-related problems, which exist in ground-based delivery systems. UAVs can reduce the delivery cycle, completion time and transportation costs, thereby making the delivery process more sustainable. They have become effective alternative transportation tools to support the delivery process and can adapt to the increasing demand for delivery while reducing labour costs. Currently, most logistics UAVs are small and have limited payloads and endurance, resulting in small delivery ranges. However, large and medium-sized UAVs have strong payloads and long endurance, which can complement the shortcomings of small UAVs and expand their transportation range. This can improve the delivery capability of the logistics UAV system and save costs while improving the timeliness of logistics delivery.

Currently, most studies on UAV delivery do not address the dynamic uncertainties that may arise during transportation, which can lead to changes in user demand and make it difficult to execute the original delivery plans [8]. The immaturity of the UAV technology and imperfect policies pose challenges to the flexibility and timeliness of delivery. For example, sudden increases in demand may result in insufficient storage capacity or unmanned aerial vehicle (UAV) transportation capacity, making it difficult to provide effective solutions quickly, which can result in customer dissatisfaction with delivery timeliness and serious impacts on logistics and delivery services. When the demand exceeds the capacity of the delivery centre, the urgent problem in practical UAV applications is how to adjust quickly and effectively, generate a minimum-cost solution and coordinate the interests of all parties.

To address these challenges, we propose a novel multi-type cooperative UAV delivery system that can handle high-demand scenarios. We propose a delivery mode consisting of a two-level delivery system that generates optimal delivery plans for multiple large-sized and medium-sized UAVs at first-level delivery centres according to the demand situation. Our system leverages the advantages of large and small UAVs using a hybrid fleet that can perform different delivery tasks according to their capabilities. The main contributions of this study are as follows.

- We formulated a multitype cooperative UAV delivery problem under high-demand situations as a mixed-integer linear programming (MILP) model that minimises the total delivery cost while satisfying various constraints, such as demand, capacity, range and safety.
- We developed an improved ant colony algorithm that iteratively solves the MILP model using customer demand forecasts and incorporates high-demand scenarios.
- We designed a decentralised control protocol that allows each UAV to communicate with the decision-making module and other UAVs, and to update its delivery plan dynamically based on real-time information and events.
- We conducted extensive simulations using various datasets and scenarios to evaluate the performance of the proposed system. We demonstrated that our system could achieve significant improvements in terms of delivery efficiency, robustness and customer satisfaction.

The remainder of this paper is organised as follows: section 2 reviews the literature and describes the contributions of this study. Section 3 describes the problem, presents a mathematical model and introduces graphs to illustrate the model. Section 4 describes the construction of the UAV scheduling model based on demand changes and the built UAV energy consumption model. Section 5 presents the design and verification of the improved algorithm. Section 6 presents the numerical tests and analyses. Finally, section 7 concludes the paper.

2. LITERATURE REVIEW

This section reviews the literature on demand-driven delivery problems and drone delivery. Scholars have roughly divided research on demand-driven delivery problems into three categories. The first category uses stochastic dynamic knowledge to predict demand and minimise interference with the entire delivery system [9, 10], but because of the inability to accurately predict customer demand, the target and applicability of such research results are often poor. The second category involves re-optimising the original path problem [11]; however, such research results can easily deviate significantly from the original plan, resulting in significant deviations in delivery paths and customer service time, which can negatively impact customer satisfaction. To overcome these problems, scholars have proposed a third research approach based on the concept of interference management [12, 13], which involves real-time adjustments to the original plan to meet customer delivery requirements. The concept of interference management was first applied to aircraft scheduling and has since been widely used in air transportation because flight delays or cancellations can result in high costs. Later, it was gradually applied to other transportation tools such as vehicles and ships. The basic theory is relatively mature and can overcome the shortcomings of the first two methods; however, this theory has not yet been applied to multilevel UAV delivery scenarios. During the operation of the drone, it will be interfered by a variety of uncertain factors and cause failures, which will affect the safe delivery of the package. For the delivery problem of logistics drones, Ren et al. (2022) constructed the drone delivery model under uncertain failure [14]. Subsequently, a recovery model is constructed based on the interference problem caused by the disturbed capacity in drone delivery to the terminal parcel delivery [15].

The operation of UAVs is influenced not only by their own structural design, payload limitations and dynamic spatiotemporal characteristics of the environment [9] but may also be subject to external factors and customer requirements. Significant progress has been made in the application of stochastic programming and robust optimisation techniques to address the uncertainty associated with demand.

Glaudel et al. [12] developed basic flight missions for electric vertical take-off and landing (eVTOL) vehicles and proposed eight potential unconventional scenarios and corresponding solutions. Some scholars considered the reliability of UAV failures during delivery. Torabbeigi et al. [13, 16] proposed minimising the expected demand loss and compared the minimum time required to establish more reliable scheduling plans. Sawadsitang et al. [17–19] investigated the uncertainties of UAV package delivery and formulated a three-stage stochastic integer programming model with multiple objectives, such as delivery costs, percentage of unsuccessful deliveries and on-time delivery bonuses. They also considered the uncertainty of the credibility of cooperative consignors and applied multistage stochastic programming and dynamic Bayesian game optimisation. Due to the uncertain nature of the traffic system, it is not trivial for delivery companies to reliably satisfy customers' time windows. To guarantee the reliability of the pickup and delivery service under stochastic and time-dependent travel times, we consider a pickup and delivery problem with hard time windows considering stochastic and time-dependent travel times [20].

Robust optimisation involves considering uncertain events in advance when devising initial plans so that the plans can be executed regardless of whether interference events occur. Kim et al. [21, 22] argued that the flight time of UAVs is affected by changes in air temperature, which introduces uncertainty in flight duration during package delivery. They proposed a robust optimisation method that accounted for three types of uncertain time sets and produced scheduling outcomes that not only considered transportation costs but also incorporated the probability of incompletely scheduled tasks. Under adverse weather conditions such as wind and rain, Pugliese et al. [23] posited that UAVs require more energy to maintain stability. They developed a vehicle routing problem with a time window (VRPDTW) model that accounts for uncertain energy consumption and considers the maximum constraint of energy consumption under worst-case scenarios to ensure energy safety. However, the results of this conservative approach may be overly cautious. Thus, decision-makers must adjust the risk associated with the solution to maximise reliability. Kim et al. [21] considered the effect of temperature changes on battery capacity and found that, without accounting for uncertain weather conditions, UAVs are more likely to fail to return to the warehouse owing to battery energy consumption constraints. They analysed the flying path results corresponding to the flying time under three different uncertainty sets (polyhedron, box and ellipsoid) using a robust optimisation method, which reduced the probability of the UAV failure to return to the warehouse and enhanced the ability of the system to cope with uncertain risks. Patel et al. [24] considered the possibility of UAV delivery failure in the initial plan and aimed to plan a more robust route by considering the initial plan cost and the cost of recovering from failure. Sung et al. [25] addressed uncertain factors such as weather, moving objects and unknown threats in the battlefield environment of UAVs, which often deviate from their planned operations in reality. They considered operational threats when assigning UAV missions and planning paths with minimal risk.

Therefore, this study examines UAV urban instant delivery practices under changing customer demands. First, we consider the impact of payload on the energy consumption of UAVs to reduce discrepancies in actual energy consumption while optimising UAV types and delivery stages, thereby increasing their service range and utilisation rates. Finally, a route recovery model is constructed to account for demand changes in a multitype, multicentre and multistage scheduling problem to mitigate the negative effects caused by demand interference. Kang et al. [26] proposed a time-coordination algorithm for multiple UAVs performing collaborative tasks that does not depend on the assumption that communication between UAVs is bidirectional. The simulation results show that the proposed algorithm can achieve the goal of coordination and significantly reduce the amount of communication between UAVs compared to previous methods.

This study contributes to the field by expanding upon the problem of limited range in UAV delivery from the perspective of multi-UAV cooperation and networking, in a similar manner to the works of Rabta [27] and Huang et al. [28]. Large UAVs can transport goods from warehouses to distribution centres, whereas small-sized and medium-sized UAVs can perform secondary transportation to deliver goods to airport nodes. By strategically deploying distribution centres and nodes, the operating range of UAVs can be expanded to more distant locations from fewer departure hubs, compared with the case of direct delivery from hubs.

In addition, the design of a delivery network must consider both the costs and high customer demand. The storage capacity of distribution centres is limited, and prompt responses are necessary when demand suddenly increases within their coverage area. This type of problem is also very common in practical applications such as takeout, convenience products and medical samples. To solve this problem, it is necessary to consider the load, endurance, speed, cost and other factors of the UAV as well as the geographical, meteorological, traffic and other conditions of the distribution area. Zhang et al. [29] proposed a path-planning method for multiple UAVs with a time window based on the grey wolf optimisation algorithm (GWO). This method considers the flight time, energy consumption, safety and other constraints of UAVs as well as the task priority and time window constraints, with the goal of enabling UAVs to reach the target point within a specified time and minimising the total flight time and total energy consumption. This method uses the global search ability and fast convergence of the grey wolf optimisation algorithm to find the best path scheme.

To address the problems of insufficient UAV capacity and warehousing caused by high demands [30], this study proposes three assisted delivery strategies. An improved ant colony method is also introduced to solve the problem of selecting delivery strategies based on high demand. Moreover, the distribution centre serves as an intermediate point for battery charging or goods storage to reach all potential delivery points for the logistics company's services.

3. PROBLEM DESCRIPTION

In urban environments, small UAVs are commonly utilised for delivery; however, they pose a range of issues such as limited flight distance and duration, which hinder delivery to customers located far away. Consequently, only a subset of customers within a specific delivery range can be served, as illustrated in *Figure 1*.

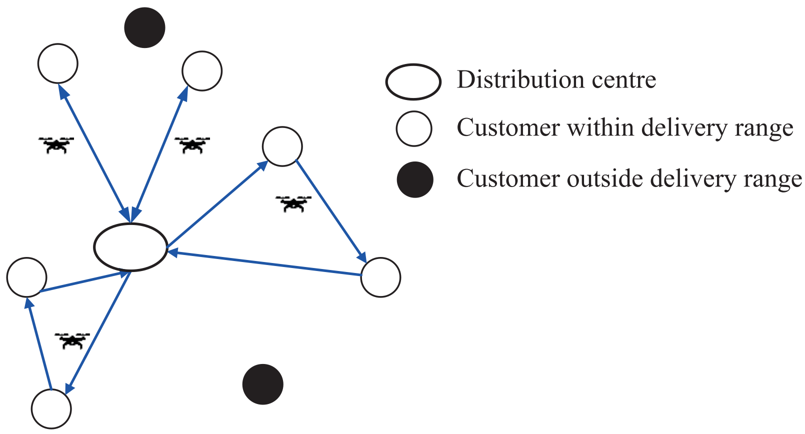

Figure 1 – Schematic diagram of the traditional delivery mode

In a decentralised delivery network, a central control warehouse is established with multiple UAV airports and customers are assigned to a particular airport based on specific service principles. To further minimise the delivery distance from the warehouse to the airport, a first-level distribution centre was placed in the middle of the facility for zone-based goods transfer. Ultimately, a multilevel logistics delivery network comprising a single warehouse, multiple distribution centres and multiple fully automated airports was formed, as shown in *Figure 2*. Once the packages were collected in the warehouse, the UAV delivery process was initiated. Large UAVs are typically employed for package transfers and distributing goods from warehouses to major distribution centres, whereas small UAVs are used for end-package distribution and delivering packages to their respective local airports based on orders. The distribution centre not only provides docking and charging services for large, medium and small UAVs but also serves as a storage facility for scheduling.

Each distribution centre has a limited storage capacity and a finite number of UAVs available for deployment. Logistics companies pre-plan delivery routes for end-demand points, including UAV fleet size and flight paths, provided that the demand at the end does not exceed the storage capacity of the distribution centre or the number of UAVs available. However, special occasions, such as holidays, may cause a surge in demand, rendering one or more of the planned routes infeasible and causing a shortage of distribution centre capacity

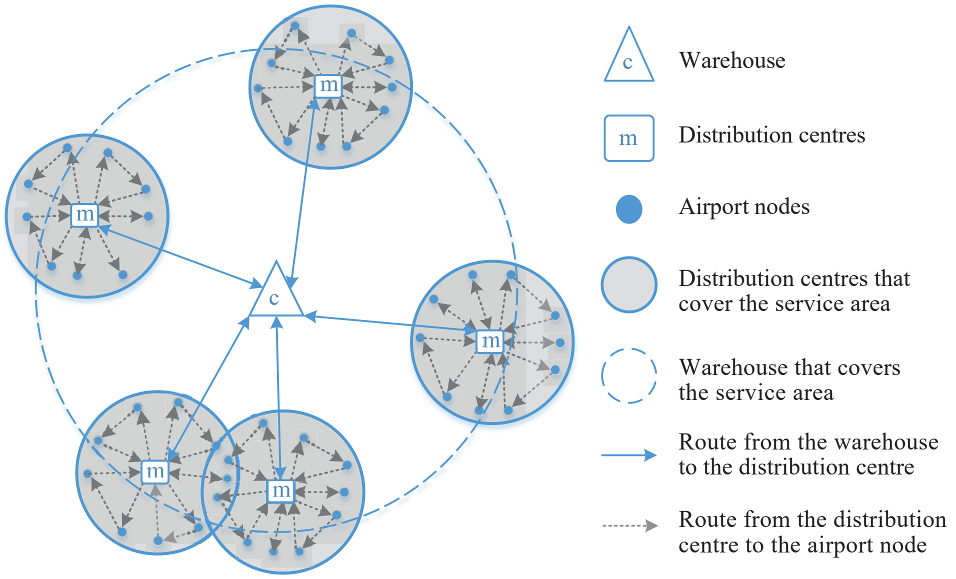

Figure 2 – 2-level UAV delivery mode

and UAV resources. In such cases, a new set of adjusted routes, as depicted in *Figure 3*, is generated, with the added demand being an uncertain quantity that could lead to the following scenarios:

1) *Added demand falls within the distribution centre's capacity*. A new delivery plan was formulated based on the new objective function for the new demand. The increased demand does not exceed the resource limitations of the distribution centre and the original route remains unchanged, as shown in *Figure 3a*. Each distribution centre has a limit on the number of UAVs and the original plan has sufficient UAVs at each

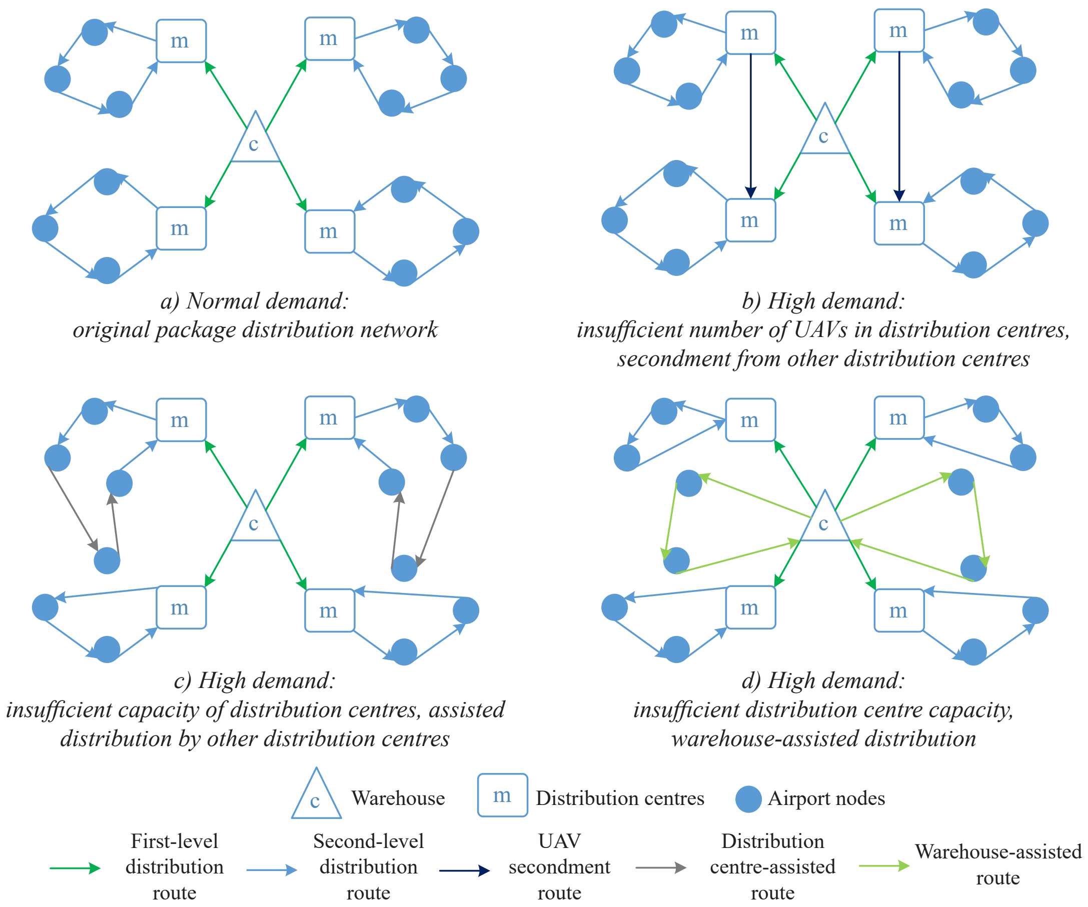

Figure 3 – Illustration of UAV delivery route changes under high-demand conditions

centre. In the new plan, if there is a shortage of UAVs at a particular airport, secondary UAVs from nearby airports are considered. Otherwise, some demand points may not be served, as shown in *Figure 3b*.

2) *The added demand exceeds the capacity of the distribution centre*. If the demand increases significantly and the storage capacity of the distribution centre is insufficient, nearby centres with sufficient capacity share the delivery capacity, as shown in *Figure 3c*. The location of the airport nodes and the resource status of the warehouse UAVs were considered and the warehouse was delivered directly, as shown in *Figure 3d*.

This study makes the following assumptions:

- Only the delivery process of logistics distribution is considered, and after completing the delivery task, logistics UAVs must return to the original distribution centre.
- The impact of weather on the battery life of UAVs was ignored.
- The times required for battery replacement, battery charging and UAV take-off and landing were ignored.
- Within the carrying range, a single UAV can serve multiple demand points.
- The flight speed of the same type of UAV between two nodes was constant.
- The UAVs begin delivery tasks using fully charged batteries.
- Only one central warehouse is established.
- The warehouse and airport capacities were not considered.

4. UAV SCHEDULING MODEL BASED ON DEMAND CHANGES

The definitions and explanations of the model symbols based on the problem descriptions are listed in *Table 1*.

4.1 Construction of UAV energy consumption model

The maximum UAV flight range is closely related to its energy consumption. During UAV delivery, the amount of energy consumed per unit of time depends on the weight of the UAV and the weight of the payload it carries. Imposing limits on a UAV's flight time or distance can result in insufficient battery power, leading to ineffective or unsafe delivery missions. Alternatively, if the battery energy efficiency is low during a single flight, more UAVs may be scheduled to complete the task, resulting in a waste of resources. Therefore, it is essential to consider the energy consumption of UAVs during the delivery phase. A model was established based on the energy consumption of UAV delivery [31, 32].

The battery power required for a UAV to fly from node i to node j is described as *Equation 1*:

$$P_{ij} = \frac{(W+u)V_{ij}}{370\eta\gamma} + \mathrm{e} \tag{1}$$

where W is the weight of the UAV, u is the weight of the payload, V_{ij} is the speed of the UAV from node i to node j, η is the propeller power-transmission efficiency, γ is the lift-to-drag ratio of the UAV and e is the energy consumption of the electronic components of the UAV. The time and energy required for the UAV to fly from node i to j are given by *Equations 2 and 3*, respectively.

$$t_{ij} = \frac{d_{ij}}{V_{ijb}} \tag{2}$$

$$E_{ij} = P_{ij} t_{ij} \tag{3}$$

To maximise delivery efficiency, we assume that the UAV operates at its maximum power throughout the flight, as shown in *Equation 4*. The energy consumption of the UAV from node i to node j is given by *Equation 5*:

$$P_{ij} = P_{max} \tag{4}$$

$$E_{ij} = P_{ijmax} \tag{5}$$

Therefore, the speed and time required for the UAV to fly from node i to node j can be expressed in *Equation 6*. The maximum flight power of the UAV and the energy consumption of the electronic components are constants. *Equations 5 and 6* can be represented by *Equations 7 and 8*, and by conversion, *Equation 7* can be expressed as *Equation 9*: The value of k depends on the UAV type.

$$V_{ij} = \frac{370(P_{max} - e)\eta\gamma}{W+m} \tag{6}$$

Table 1 – Symbols definitions and explanations in the model

Symbol type	Symbol	Explanation
Subscript	i, j	Node index
	k	UAV index
	b	UAV types index
	m	Distribution centre index
Set	$C_a=\{1,2,3\ldots,n_a\}$	Set of all airport demand nodes
	$C_m=\{1,2,3,\ldots,n_m\}$	Set of all distribution centres
	$C_b=\{1,2,\ldots,n_b\}$	Set of UAV types
	$K_{bm}=\{1,2,\ldots,k_m\}$	Number of UAVs of type b corresponding to distribution centre m
	$K_{bc}=\{1,2,\ldots,k_c\}$	Number of UAVs of type b corresponding to warehouse c
	$C_d=\{1,2,\ldots,n_d\}$	Set of nodes for warehouses, distribution centres and airports
	$C_e=\{1,2,\ldots,n_e\}$	Set of warehouses and distribution centres
Parameter	c	Warehouse location point
	f_b	Fixed cost of using type b
	R_m	Maximum cargo capacity allowed at distribution centre m
	q_m	Demand at distribution centre m
	V_{ij}	Speed of UAV of type b flying from node i to node j
	d_{ij}	Distance from node i to node j
	t_i	Time of arrival at node i
	t_{ij}	Cruise time from node i to node j
	P_{ij}	Power of UAV flying from node i to node j
	E_{ij}	Energy consumption of UAV flying from node i to node j
	P_{max}	Maximum flight power of UAV
	Q_b	Maximum load capacity of UAV type b
	E_b	Maximum energy of UAV battery for type b
	q_i	Demand at node i
	W	UAV weight
	u	Payload
	e	Energy consumption of electronic components during flight
	η	Propeller power transmission efficiency
	γ	Lift-to-drag ratio
Binary variable	x_{ijbk}	If UAV of type b and index k delivers from node i to node j, x_{ijbk}=1, otherwise x_{ijbk}=0
	y_{ibk}	If demand at node i is delivered by UAV k of type b, y_{ibkm}=1, otherwise y_{ibkm} =0
	u_{ibk}	If demand at node i is delivered by UAV k of model b in the original route, u_{ibkm}=1, otherwise u_{ibkm}=0
	Z_{ibk}	If UAV k of type b serves node i in the original route but not in the new route, Z_{ibk}=1, otherwise Z_{ibk}=0

$$t_{ij} = \frac{d_{ij}\left(W+m\right)}{370\left(P_{max}-e\right)\eta\gamma} \tag{7}$$

$$V_{ij} = \frac{k}{W+m} \tag{8}$$

$$t_{ij} = \frac{d_{ij}}{k}\left(W+m\right) \tag{9}$$

4.2 Construction of a UAV scheduling recovery model under demand changes

Based on the problem description and related assumptions above and considering the energy consumption characteristics of UAVs in different stages and changing demand scenarios, the UAV scheduling recovery model is constructed as follows.

Objective function 10 minimises the fixed cost and distance cost of the UAVs. *Objective function 11* minimises the ratio of unserved demand to total demand. *Objective function 12* minimises the ratio of demand nodes on the original route that cannot be served on the new route to the total demand nodes on the original route.

$$\min F1 = \sum_{b=1}^{n_b}\sum_{\substack{j=1\\j\neq i}}^{n_a+n_m}\sum_{k=1}^{k_c} f_b x_{cibk} + \sum_{b=1}^{n_b}\sum_{i=1}^{n_m}\sum_{\substack{j=1\\j\neq i}}^{n_a+n_m}\sum_{k=1}^{k_m} f_b x_{ijbk} + \sum_{i=1}^{n_d}\sum_{j=1}^{n_a+n_m}\sum_{b=1}^{n_b}\sum_{k=1}^{k_m+k_c} d_{ij} x_{ijbk} \tag{10}$$

$$\min F2 = 1 - \frac{\sum_{i=1}^{n_a}\sum_{b=1}^{n_b}\sum_{k=1}^{k_m+k_c} y_{ibk}}{n_a} \tag{11}$$

$$\min F3 = \sum_{i=1}^{n_a}\sum_{b=1}^{n_b}\sum_{k=1}^{n_m} \frac{z_{ibk}}{u_{ibk}} \tag{12}$$

UAVs departing from any distribution centre must return to the original distribution centre. UAVs may travel to other distribution centres to rescue or directly to airport nodes (*Equation 13*).

$$\sum_{\substack{j=1\\j\neq i}}^{n_a+n_m} x_{ijbk} = \sum_{j=1}^{n_a} x_{jibk} \qquad \forall i \in C_m, \forall b \in C_b, \forall k \in K_{bm} \tag{13}$$

UAVs departing from the warehouse must eventually return to the original warehouse (from the warehouse to the distribution centre or from the warehouse to the airport node) (*Equation 14*).

$$\sum_{j=1}^{n_a+n_m} x_{cjbk} = \sum_{j=1}^{n_a+n_m} x_{jcbk} \qquad \forall b \in C_b, \forall k \in K_{bc} \tag{14}$$

For any airport node, the number of inputs is equal to the number of outputs and it can only be accessed once (*Equation 15*).

$$\sum_{\substack{i=1\\i\neq j}}^{n_d}\sum_{b=1}^{n_b}\sum_{k=1}^{k_m+k_c} x_{ijbk} = \sum_{\substack{i=1\\i\neq j}}^{n_d}\sum_{b=1}^{n_b}\sum_{k=1}^{k_m+k_c} x_{jibk} \leq 1 \qquad \forall j \in C_a \tag{15}$$

The warehouse and distribution centres may be visited multiple times. In the original plan, the demand for each distribution centre can be met exactly once. In the case of interference involving a distribution centre with insufficient rescue capacity, multiple accesses may be required (*Equation 16*).

$$\sum_{b=1}^{n_b}\ \sum_{k=1}^{k_c} x_{cmbk} \geq 1 \qquad \forall m \in C_m \tag{16}$$

The capacity of each distribution centre must be considered (*Equation 17*).

$$\sum_{j=1}^{n_a}\sum_{b=1}^{n_b}\sum_{k=1}^{k_m} q_j x_{mjbk} \leq R_m \qquad \forall m \in C_m \tag{17}$$

The capacity constraint for type *b* UAVs travelling from warehouses or distribution centres to airport nodes (*Equation 18*).

$$q_j \sum_{i=1}^{n_e} \sum_{j=1}^{n_a} \sum_{k=1}^{k_m} x_{ijbk} \le Q_b \qquad \forall b \in C_b \tag{18}$$

The capacity constraint for type b UAVs travelling from warehouse to distribution centre (point-to-point service) (*Equation 19*).

$$q_m x_{cmbk} \le Q_b \qquad \forall m \in C_m, \forall b \in C_a, \forall k \in K_{bc} \tag{19}$$

Energy constraint for UAVs (transportation from the warehouse to the distribution centre is point-to-point and the distance between the warehouse and the distribution centre is within the range of UAV energy consumption, which is not considered in this case. The energy consumption of delivery from the distribution centre to the airport node involves three situations: UAVs travel from the warehouse to the airport node, from the distribution centre to the airport node or from one distribution centre to another before arriving at the airport node) (*Equation 20*).

$$q_j \sum_{i=1}^{n_d} \sum_{\substack{j=1 \\ j \ne 1}}^{n_a+n_m} t_{ij} x_{ijbk} P_{ij} \le E_b \qquad \forall b \in C_b, \forall k \in K_{bm} \cup K_{bc} \tag{20}$$

Time constraints for arriving at each airport node (*Equation 21*).

$$t_i + t_{ij} + \left(1 - x_{ijbm}\right) D \le t_j \qquad \forall b \in C_b, \forall k \in K_{bm} \cup K_{cm} \tag{21}$$

The decision variables are defined as 0-1 variables (*Equation 22*).

$$\begin{gathered} x_{ijbk} \in [0,1],\ y_{ibk} \in [0,1],\ u_{ibk} \in [0,1],\ z_{ibk} \in [0,1] \\ \forall i, j \in C_d, \forall b \in C_b, \forall k \in K_{bm} \cup K_{bc} \end{gathered} \tag{22}$$

5. ALGORITHM DESIGN

Various optimisation methods are involved in UAV path planning [33], including traditional methods such as the artificial potential field method, dynamic programming and Dijkstra's algorithm, and modern intelligent algorithms that are established by imitating one or more natural phenomena and processes, such as A*, particle swarm optimisation and ant colony algorithms. Research on the application of intelligent optimisation algorithms to UAV task-planning technology can better leverage the positive effects of task allocation and flight path planning.

Dijkstra's algorithm was used to search for the distance between nodes and remaining nodes. It begins from the starting point, continues to expand outwards until the search ends and finds the shortest path. However, the algorithm is based on node squares for calculation, and in the process of path searching, it is necessary to search all points, which leads to increased computational complexity and low efficiency. Dynamic programming is based on the special nature of tasks that divide decision stages that are not influenced by previous decisions. However, dynamic programming has strong limitations, targeting only the solution of optimal problems, and its theoretical design is complex. During the practical simulation of the A* algorithm path planning, there may be situations where the path turns repeatedly and the planned path can quickly find redundant points; however, this will greatly increase the algorithm's operating time and other defects. Genetic algorithms require active encoding, a search for optimal solutions, decoding and other operations during solution processing. As the complexity of the problem gradually increases, the computational complexity significantly increases and exacerbates the difficulty of encoding. A comprehensive comparison with the corresponding algorithms revealed the significant difficulty of encoding in the actual application process.

Traditional optimisation methods have prominent issues in practical applications, including difficulties in initialisation and significant constraints on algorithms that escape local optima, owing to the movement method. Biomimetic intelligent algorithms can effectively overcome these limitations and their advantages are more apparent.

The ant colony algorithm (ACO) was originally invented by Italian scholars such as Marco Dorigo [34, 35]. It is a biomimetic algorithm proposed by simulating the behaviour of ant colonies searching for food in nature and has basic characteristics such as heuristics, distributed computation and positive feedback.

5.1 Algorithm steps and procedures

The ant colony algorithm selects the next delivery location for each individual based on the pheromone concentration along the path to plan the optimal delivery route. This approach shares the same physical meaning and modelling method as the unmanned aerial vehicle (UAV) delivery scheduling described in this study. Therefore, the ant colony algorithm was adopted to plan the UAV delivery scheme, and its objective function was improved by adding constraints related to UAV flight and delivery station capacity. We propose a multi-objective [36] optimisation algorithm for delivery planning that considers both the high demand for delivery and the limited resources of the warehouse, as well as the dual constraints of demand for UAV and customer and service costs.

In this algorithm, each individual ant starts from the starting point and calculates the probability of selecting a neighbouring delivery station (distribution warehouse) based on the UAV, warehouse and customer demand constraints, as well as the multi-objective function. The next service customer is then determined using the roulette-wheel selection method until the ant reaches its destination or a local optimal solution. After multiple (multi-generation) iterations, multiple optimal routes are obtained that meet the constraints of the UAV, warehouse resources and customer demands and minimise the multi-objective cost. During the planning process, it was found that some planned routes became infeasible owing to the high demand from customers within the delivery station service radius, leading to insufficient capacity at the delivery centre and UAV resources. The improved ant colony algorithm was used to decide whether to implement the UAV secondment strategy or the assisted delivery strategy according to the constraints of the UAV, warehouse resources and customer demand, and the optimal delivery route was calculated.

The search ability of the algorithm is insufficient and the convergence speed is low because the transfer probability formula of the basic ant colony algorithm contains less feature information. To address this issue, the ant colony algorithm is improved by adding customer demand within the service radius of the distribution centre and total demand within the service radius of the warehouse to the state transition formula.

The ant selects the next delivery location based on the pheromone concentration and visibility while considering the partial and total demand and prioritising customers with high demand. The information pheromone strategy for the improved ant colony algorithm is expressed by *Equations 23 and 24*.

$$j=\begin{cases}\arg\ \max\left[\tau_{ij}(t)\right]^{x}\left[\eta_{ij}(t)\right]^{\beta}\cdot\left[1/width_j\right]^{\gamma}\cdot\left[1/wait_j\right]^{\delta}, & q\le q_0\\ P_{ij}^{k}, & q>q_0\end{cases}\tag{23}$$

$$p_{ij}^{k}=\begin{cases}\dfrac{\left[\tau_{ij}\right]^{\chi}\left[\eta_{ij}\right]^{\beta}\left[1/width_j\right]^{\gamma}\left[1/wait_j\right]^{\delta}}{\sum\limits_{s\in allow_k}\left(\left[\tau_{is}\right]^{\chi}\left[\eta_{is}\right]^{\beta}\left[1/width_s\right]^{\gamma}\left[1/wait_s\right]^{\delta}\right)}, & j\in allow_k\\ 0, & j\notin allow_k\end{cases}\tag{24}$$

In these equations, τ_{ij} is the pheromone concentration along the path from i to j, η_{ij} is the visibility of the path, the greater the visibility, the smaller the distance between customers. $wait_j$ is the demand that requires assistance within the service radius of the distribution centre j and $width_j$ is the difference between the distribution centre's capacity and demand, representing the amount of demand that requires assistance. The importance factor of the pheromone is denoted by χ, the importance factor of the visibility is denoted by β, the capacity factor of the distribution centre is denoted by γ and the demand factor of the assistance is denoted by δ. $allow_k$ is the node to be accessed by ant k.

To expand the solution space and avoid local optima and random solutions resulting from overly large or small values, we set q and q_0 as constants between 0 and 1 in the above equation, which is a dynamic adjustment strategy for the pheromone evaporation factor ρ, as shown in *Equations 25 and 26*. A flowchart of the improved ant colony algorithm is shown in *Figure 4*.

$$q_0=\begin{cases}a_1, & iter\le\frac{1}{4}\max iter\\ a_2, & \frac{1}{4}\max iter<iter\le\frac{3}{4}\max iter\\ a_3, & \frac{3}{4}\max iter<iter\le\max iter\end{cases}\tag{25}$$

$$q_0=\begin{cases}0.2, & iter\le\frac{1}{4}\max iter\\ 0.5, & \frac{1}{4}\max iter<iter\le\frac{3}{4}\max iter\\ 0.85, & \frac{3}{4}\max iter<iter\le\max iter\end{cases}\tag{26}$$

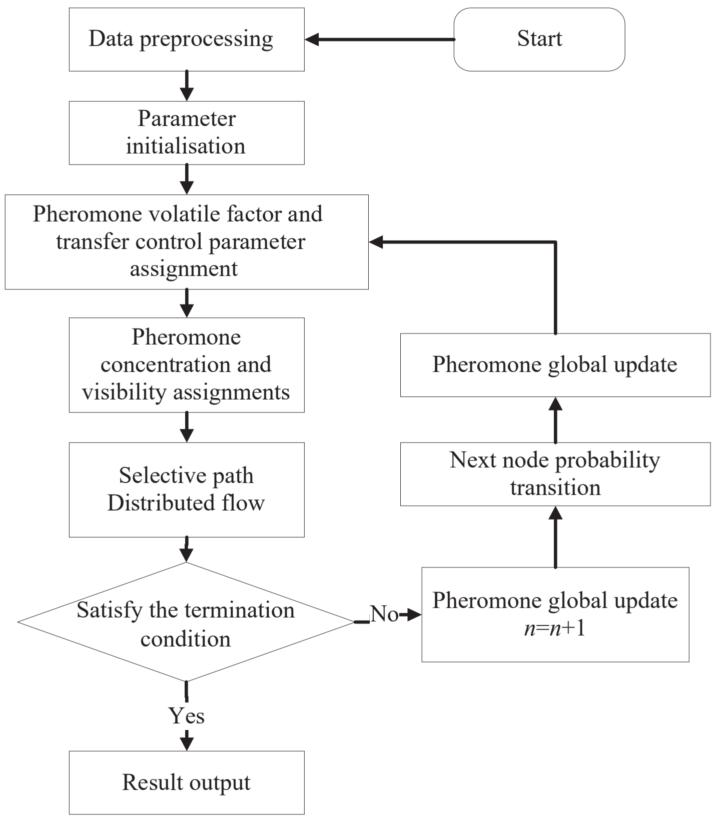

Figure 4 – Improved ant colony algorithm flow chart

5.2 Algorithm performance testing

To verify the convergence and stability of the improved ant colony algorithm, Solomon standard test cases R101 and C101 were first used for conducting tests. The primary purpose is to investigate the impact of customer distribution on the improved algorithm. Subsequently, standard Solomon test cases with 10, 20 and 30 customers are tested to evaluate the effect of the number of customers on the calculated results of the improved algorithm. MATLAB R2016b was utilised for programming in a 64-bit Windows 10 operating system environment, using an AMD Ryzen 5 3500U quad-core eight-thread processor with a main frequency of 2.10 GHz and 12 GB of RAM. The number of ants was set to 100 and the maximum number of iterations was set to 100. The results are shown in *Figure 5* and *Table 2*.

Figure 5 illustrates a comparison of algorithm convergence rates. The results indicate that the improved ant colony algorithm exhibits fast convergence and initial results that are close to the optimal results of the original ant colony algorithm, with favourable calculation results.

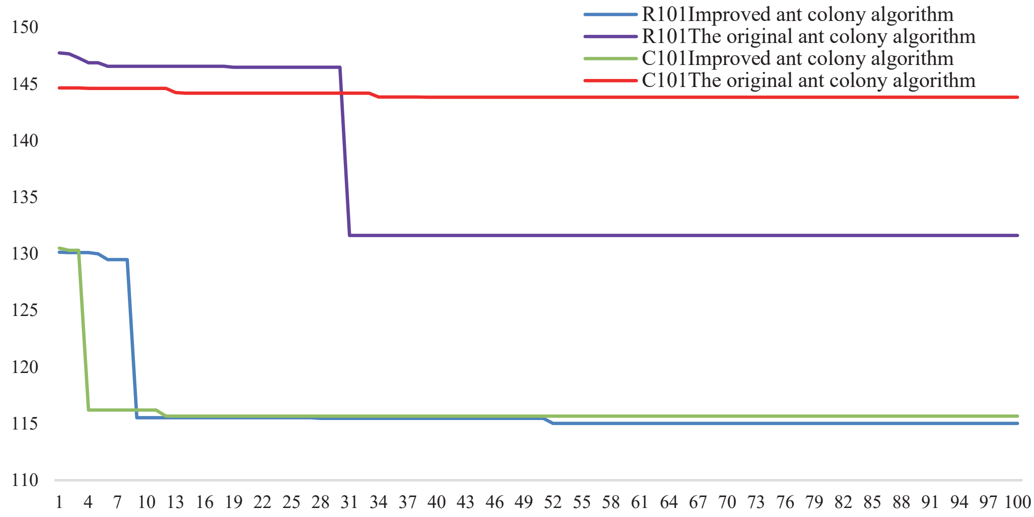

Figure 5 – Algorithm convergence comparison

Table 2 – Comparison of distribution cost reduction rate among different customers

Number of customers	Cost reduction rate
10	31.05%
20	18.15%
30	10.57%

Table 2 presents a comparison of the distribution cost reduction rates for different numbers of customers. As the number of customers increases, the rate of reduction in distribution costs gradually decreases but remains above 10%. These results demonstrate that the improved ACO algorithm performs well when computing small-scale test cases. In addition, the improved algorithm is better suited to the problem itself and exhibits superior convergence.

6. NUMERICAL ANALYSIS OF MULTIPLE TYPES LOGISTICS UAVS

Based on the results of the experiments scheduling multiple types of logistics UAVs under high demand, this study optimised multiple conflicting objectives under specific constraints related to demand size. Decision-makers must balance these objectives to make optimal decisions. The objective of this study was to minimise total costs and maximise the level of service provided to customers. A large UAV was proposed with a large load of 15 kg, equipment cost of 56,000 yuan, range of 20 km per sortie, total operation of 50,000 km during its life cycle, a total of 2,500 sorties and mandatory retirement after reaching the total operating mileage. The unit price of the power battery used by the UAV was 5,200 yuan per set, and it could be recharged and discharged approximately 500 times on average, allowing each set of batteries to be used for an average of 500 sorties. Five sets of power batteries are required for each UAV during its lifespan. It requires 1.5° of electricity to fully charge one set of power batteries and the average electricity price is approximately 1 yuan per degree. During use, the average weight of a single package transported by a UAV was 0.5 kilograms and a single UAV could transport up to 30 packages per sortium. The cost and maximum payload of a small UAV are both one-third those of a large UAV. When implementing the distribution method, unless the storage capacity of the distribution centre reaches the upper limit or the number of small drones is insufficient, we stipulate that large drones are used from the warehouse to the distribution centre, and small drones are used for distribution from the distribution centre to the node.

Four scenarios were analysed in this study: delivery scenario analysis under different demand changes, delivery scenario analysis under different UAV resources, analysis of the impact of distribution centre capacity and optimisation of the use of multiple UAV types compared to the use of a single model.

To investigate the impact of demand on cost and delivery scenarios, the A-n37-k5 data from the CVRP (capacitated vehicle routing problem, CVRP) standard case library on the website http://www.bernabe.

dorronsoro.es/v-rp/ were used in this study. Some data were modified in the multi-model logistics scheduling optimisation model of UAVs proposed in this study to generate a test case named C-n37-k5, which included 37 customers, one warehouse, three distribution centres and eight nodes. Customers were distributed radially around the warehouse. The warehouse, distribution centres, nodes and customers are shown in *Figure 6*, where the warehouse is designated as A, the distribution centres are designated as C1, C2 and C3, the nodes are designated as J1- J8 and the customers are numbered from 1 to 36.

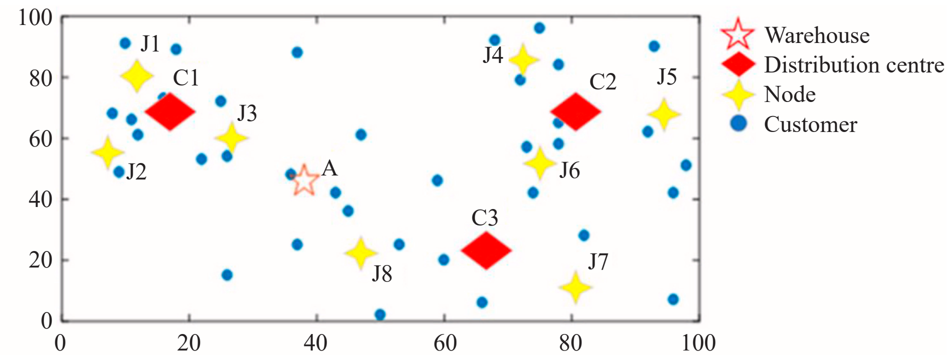

Figure 6 – Distribution of warehouses, distribution centres, nodes and customers

The improved ant colony algorithm was used to calculate the optimal delivery scenario and its cost without interference using the MATLAB R2016b programming language. The operating environment was a 64-bit Windows 10 operating system with an AMD Ryzen 5 3500U quad-core eight-thread processor, a clock speed of 2.10 GHz and 12 GB of RAM. The iteration number was set to 100 and the population size was set to 100 for testing purposes.

6.1 Analysis of capacity-constrained delivery solutions to meet demand

For the C-n37-k5 case, the original package delivery plan was utilised and the results are listed in *Table 3*.

Table 3 – Delivery costs for meeting demand with distribution centre capacity

Case	Warehouse to distribution centre delivery path	Delivery cost (¥)	Distribution centre to node delivery path	Delivery cost (¥)
C-n37-k5	1: A-C1-A 2: A-C2-A 3: A-C3-A	1: 95.41 2: 110.82 3: 100.76	1: C1-J1-J2-C1 2: C1-J3-C1 3: C2-J4-J5-C2 4: C2-J6-C2 5: C3-J8-C3 6: C3-J7-C3	1: 62.15 2: 30.41 3: 71.54 4: 30.01 5: 30.53 6: 28.21

As indicated in *Table 3*, UAVs delivering packages from the warehouse to the distribution centre are only accountable for delivering the goods of one distribution centre, with delivery costs of ¥ 95.41, ¥ 110.82 and ¥ 100.76, respectively. Therefore, the total cost of delivering goods from the warehouse to the distribution centre is ¥ 307. The average delivery cost of the UAVs that deliver from the distribution centre to the nodes is ¥ 42.14, with a total cost of ¥ 252.85 for the six UAVs utilised in delivery. When the distribution centre, node capacity and UAV capacity were satisfied, the total delivery cost for the 36 customers was ¥ 559.85. Three large UAVs and six small UAVs were required, along with three distribution centres and eight nodes.

6.2 Analysis of delivery solutions when UAV capacity does not meet demand

In this case, when the customer demand of case A-n37-k5 in the CVRP standard case library is adjusted to a high demand, situations may arise in which the distribution centre capacity or the number of UAVs is insufficient, requiring assistance from the warehouse or other distribution centres, as shown in *Figures 3b and 3d*. First, when the distribution centre resources are sufficient but UAV capacity at some distribution centres is insufficient under high demand and needs to be seconded. The numbers of small UAVs available for C1, C2 and C3 are three, three and two, respectively, based on the number of nodes covered by each distribution centre. An improved ant colony algorithm was employed to solve this problem and the results are presented in *Table 4*.

Table 4 – Delivery solutions for insufficient UAV capacity at distribution centres under high demand

Case	Warehouse to distribution centre delivery path	Delivery cost (¥)	Distribution centre to node delivery path	Delivery cost (¥)
C-n37-k5	1: A-C1-A 2: A-C2-A 3: A-C3-A	1: 115.61 2: 139.76 3: 140.88	1: C1-J1-J2-C1 2: C1-J3-C1 3: C1-C3-J8-C1 4: C2-J4-J6-C2 5: C2-J5-C2 6: C2-C3-J7-C2 7: C3-J8-C3 8: C3-J7-C3	1: 59.87 2: 39.41 3: 50.09 4: 45.11 5: 39.88 6: 55.87 7: 41.52 8: 39.01

The results indicate that UAVs from distribution centres C1 and C2 were borrowed to perform deliveries at C3, specifically UAVs 3 and 6. In the high-demand scenarios, the UAVs at C1 and C2 could meet their own demands, whereas those at C3 had insufficient capacity and required seconding from other distribution centres. This was mainly due to two factors. First, the customer coverage of C3 is relatively dispersed, resulting in a reduction in the number of customers that can be served by a single UAV. Second, the increased demand led to a shortage of UAV capacity, and a single UAV was unable to meet the delivery requirements of a single node. The use of UAVs for delivery was found to be significantly more expensive than the use of UAVs for distribution centres. For instance, UAV no. 3, which departed from C1, had to fly to C3 to pick up goods before delivery, thereby increasing flight time and distance and reducing delivery efficiency. Consequently, delivery costs were relatively high.

In situations where the distribution centre had sufficient resources but insufficient UAV capacity, the costs of large UAV deliveries from the warehouse to the distribution centre were ¥ 115.61, ¥ 139.76 and ¥ 140.88, respectively. The total cost of delivering goods from the warehouse to the distribution centre was ¥ 395.03. Meanwhile, the average cost of using UAVs for deliveries from the distribution centre to the nodes was ¥ 46.34, with a total cost of ¥ 370.76 for using eight UAVs for deliveries. When the distribution centre and node capacities are met but the UAV capacity is not, the total delivery cost for 36 customers is ¥ 765.79, representing an increase of only 36% compared with the normal demand.

6.3 Analysis of delivery solutions when demand exceeds capacity and resources

When UAV capacity is sufficient, but distribution centre resources and capacity are not, other distribution centres or warehouses may need to assist in delivery. The results of using the improved ant colony algorithm to solve this problem are listed in *Table 5*.

The results indicated that the distribution plan employed both warehouse-assisted and other distribution centre-assisted distributions. Distribution centres C2 and C3 utilised warehouse-assisted distribution, while distribution centre C1 provided support to C3 using large-scale UAV no. 4 and small-scale UAV no. 3. In high-demand situations, distribution centre C1 could satisfy its own requirements, whereas the UAV capacities of distribution centres C2 and C3 were insufficient and required assistance from other distribution centres and warehouses. This was mainly due to distribution centre C3 serving relatively scattered customer areas, resulting in a decrease in the number of customers serviced by a single UAV, and the high demand, leading to a shortage of distribution centre resources. High demand caused a decrease in efficiency and an increase in cost for small UAV distribution, whereas warehouse-assisted distribution had lower costs. The results indicated

Table 5 – Delivery solutions when demand exceeds distribution centre capacity and resources

Case	Warehouse to distribution centre delivery path	Delivery cost (¥)	Distribution centre to node delivery path	Delivery cost (¥)
C-n37-k5	1: A-C1-A 2: A-C2-A 3: A-C3-A 4: A-J6-J8-A	1: 115.61 2: 120.41 3: 140.21 4: 98.99	1: C1-J1-J3-C1 2: C1-J2-C1 3: C1 -J8-C1 4: C2-J4 -C2 5: C2-J5-C2 6: C3-J7-C3	1: 61.55 2: 38.41 3: 43.09 4: 36.11 5: 41.09 6: 39.01

that the cost of the second UAV was significantly higher than that of the distribution centre UAV delivery. The assisted distribution strategy involved warehouse A assisting distribution nodes J6 and J8, and distribution centre C2 assisting distribution centre C3.

When the distribution centre resources were insufficient but the UAV capacity was sufficient, the costs of large-scale UAV distribution were ¥ 115.61, ¥ 120.41, ¥ 140.21 and ¥ 98.99, respectively. The total cost of transporting goods from the warehouse to the distribution centre was ¥ 475.22. The average cost of UAV delivery for centre-to-node distribution tasks was ¥ 43.27, with a total cost of ¥ 259.26. When the distribution centre and node capacities were not met, but the UAV capacity was met, the total distribution cost for 36 customers was ¥ 743.48.

7. CONCLUSION AND FUTURE WORK

This study investigated urban logistics and distribution problems in densely populated city environments, where there is a growing demand for time-sensitive delivery services. A multitype logistics UAV scheduling optimisation model was developed that considered constraints such as distribution centre capacity, UAV energy consumption limitations and the impact of UAV payload on flight energy consumption. A hybrid improved ant colony algorithm was adopted to solve the proposed model considering practical problems. Numerical experiments were conducted using the classic VRP A-n37-k5 dataset to form two differently sized cases and the results demonstrated that the algorithm has high feasibility and practical value. Their experimental results indicated that secondary UAVs and warehouse-assisted delivery increased delivery costs by only 36% under high demand. In addition, under the same high demand, the cost of warehouse-assisted delivery was lower than that of the secondary UAVs. Therefore, ensuring sufficient UAV capacity can reduce costs, ensure timely delivery and improve delivery efficiencies. Warehouse-assisted delivery, other distribution centre-assisted delivery and UAV-seconding delivery are effective solutions for addressing the problems of insufficient storage resources and UAV capacity under high demand. They ensure the timely delivery of goods while increasing costs by only approximately 35%, yielding high economic benefits.

Multi-type collaborative logistics distribution has unique advantages over traditional truck and single-type UAV delivery in densely populated cities with high demand. Multi-type UAVs provide flexible delivery solutions and the advantages of multi-type UAVs collaboration come into play when the delivery centre's UAV capacity or resources are insufficient. Warehouse-assisted delivery and distribution centre-assisted delivery can reduce delivery costs while ensuring timely delivery under high demand. However, external factors, such as tall buildings, can affect UAV safety during urban delivery. Future research can be conducted on UAV obstacle avoidance issues and new logistics delivery modes adapted to different contexts. Furthermore, the design of different search operators for the ant colony algorithm can be explored to improve the solution quality.

ACKNOWLEDGEMENTS

This work was supported by the National Key R&D Program Project (2022YFB4300904); and Fundamental Research Funds for the Central Universities of Education of China (3122021091). The author would like to thank the state funding and all the participants for their assistance.

REFERENCES

[1] Khan SI, et al. UAVs path planning architecture for effective medical emergency response in future networks. *Physical Communication*. 2021;47:101337. DOI: 10.1016/j.phycom.2021.101337.

[2] Song BD, Park K, Kim J. Persistent UAV delivery logistics: MILP formulation and efficient heuristic. *Computers & Industrial Engineering*. 2018;120:418-428. DOI: 10.1016/j.cie.2018.05.013.

[3] Hwang J, Kim I, Gulzar MA. Understanding the eco-friendly role of UAV food delivery services: Deepening the theory of planned behavior. *Sustainability*. 2020;12(4):1440. DOI: 10.3390/su12041440.

[4] Hwang J, Lee J, Kim H. Perceived innovativeness of UAV food delivery services and its impacts on attitude and behavioral intentions: The moderating role of gender and age. *International Journal of Hospitality Management*. 2019;81:94-103. DOI: 10.1016/j.ijhm.2019.03.002.

[5] Liu Y. An optimization-driven dynamic vehicle routing algorithm for on-demand meal delivery using UAVs. *Computers & Operations Research*. 2019;111:1-20. DOI: 10.1016/j.cor.2019.05.024.

[6] Lin Y, Lyu J, Jiang Y. Research on optimization of drone delivery based on urban-rural transportation considering time-varying characteristics of traffic. *Application Research of Computers*. 2020;37(10):2984-2989. DOI:

10.19734/j.issn.1001-3695.2019.07.0210.

[7] Pinto R, Lagorio A. Point-to-point UAV-based delivery network design with intermediate charging stations. *Transportation Research Part C: Emerging Technologies*. 2022;135:103506. DOI: 10.1016/j.trc.2021.103506.

[8] Deng X, et al. Vehicle-assisted UAV delivery scheme considering energy consumption for instant delivery. *Sensors*. 2022;22(5):2045. DOI: 10.3390/s22052045.

[9] Cao Q, Zhang X, Ren X. Path optimization of joint delivery mode of trucks and UAVs. *Mathematical Problems in Engineering*. 2021;2021:1-15. DOI: 10.1155/2021/4670997.

[10] Thibbotuwawa A, et al. UAV mission planning resistant to weather uncertainty. *Sensors*. 2020;20(2):515. DOI: 10.3390/s20020515.

[11] Huang J-L， et al. Fault influence model of swarm UAVs based on cellular automata. *Control and Decision*. 2023;38(1):103-111. DOI: 10.13195/j.kzyjc.2021.0910.

[12] Glaudel HS. Establishing the framework for e-VTOL Flight mission scenario development for urban air mobility research using cognitive task analysis. *AIAA Aviation 2021 Forum*. 2021; p. 2339.

[13] Torabbeigi M, et al. An Optimization approach to minimize the expected loss of demand considering UAV failures in UAV Delivery scheduling. *Journal of Intelligent & Robotic Systems*. 2021;102(1):1-15. DOI: 10.1007/s10846-021-01370-w.

[14] Ren XH, Gou LZ, Wu T. Drone last delivery under uncertainty failure. *Journal of Guangxi University (Natural Science Edition)*. 2022;47(03):732-745. DOI: 10.13624/j.cnki.issn.1001-7445.2022.0732.

[15] Ren XH, Gou LZ, Wu T. Disturbance recovery model of logistics drone with capacity disturbance. *Science, Technology and Engineering*. 2023;23(01):407-413.

[16] Torabbeigi M, Lim GJ, Kim SJ. UAV delivery schedule optimization considering the reliability of UAVs. *2018 International Conference on Unmanned Aircraft Systems (ICUAS)*. IEEE; 2018. p. 1048-1053.

[17] Sawadsitang S, et al. Joint ground and aerial package delivery services: A stochastic optimization approach. *IEEE Transactions on Intelligent Transportation Systems*. 2019;20(6):2241-2254. DOI: 10.1109/TITS.2018.2865893.

[18] Sawadsitang S, et al. Shipper cooperation in stochastic UAV delivery: A dynamic Bayesian game approach. *IEEE Transactions on Vehicular Technology*. 2021;70(8):7437-7452. DOI: 10.48550/arXiv.2002.03118.

[19] Sawadsitang S, et al. Multi-objective optimization for UAV delivery. *2019 IEEE 90th Vehicular Technology Conference (VTC2019-Fall)*. IEEE; 2019. p. 1-5.

[20] Wang Z, Dessouky M, van Woensel T, Ioannou P. Pickup and delivery problem with hard time windows considering stochastic and time-dependent travel times. *EURO Journal on Transportation and Logistics*. Vol. 12. 2023. DOI: 10.1016/j.ejtl.2022.100099.

[21] Kim SJ, Lim GJ, Cho J. Drone flight scheduling under uncertainty on battery duration and air temperature. *Computers & Industrial Engineering*. 2018;117:291-302. DOI: 10.1016/j.cie.2018.02.005.

[22] Kim SJ, Lim GJ, Cho J. A robust optimization approach for scheduling UAVs considering uncertainty of battery duration. *Proceedings of the IIE Annual Conference*. Institute of Industrial and Systems Engineers (IISE); 2017. p. 187-192.

[23] Di Puglia Pugliese L, Guerriero F, Scutellá MG. The last-mile delivery process with trucks and UAVs under uncertain energy consumption. *Journal of Optimization Theory and Applications*. 2021;191(1):31-67. DOI: 10.1007/s10957-021-01918-8.

[24] Patel R, et al. Robust multi-UAV route planning considering UAV failure. *2019 International Conference on Unmanned Aircraft Systems (ICUAS)*. 2019. p. 205-212.

[25] Sung I, et al. A design of a scheduling system for an unmanned aerial vehicle (UAV) deployment. *IFAC-PapersOnLine*. 2019;52(13):1854-1859. DOI: 10.1016/j.ifacol.2019.11.472.

[26] Kang H, et al. Time coordination of multiple UAVs over switching communication networks with digraph topologies. *2021 IEEE International Systems Conference(SysCon)*. 2021. p. 5964-9. DOI: 10.1109/CDC45484.2021.9683619.

[27] Rabta B, Wankmüller C, Reiner G. A drone fleet model for last-mile distribution in disaster relief operations. *International Journal of Disaster Risk Reduction*. 2018;28:107-112. DOI: 10.1016/j.ijdrr.2018.02.020.

[28] Huang H, Savkin AV, Huang C. Drone routing in a time-dependent network: Toward low-cost and large-range parcel delivery. *IEEE Transactions on Industrial Informatics*. 2021;17(2):1526-1534. DOI: 10.1109/TII.2020.3012162.

[29] Zhang C, Liu Y, Hu C. Path planning with time windows for multiple UAVs based on Gray Wolf algorithm. *Biomimetics*. 2022;7:225. DOI: 10.3390/biomimetics7040225.

[30] Nikolić M, Teodorović D. Vehicle rerouting in the case of unexpectedly high demand in distribution systems. *Transportation Research Part C: Emerging Technologies*. 2015;55:535-545. DOI: 10.1016/j.trc.2015.03.002.

[31] Cheng C, Adulyasak Y, Rousseau LM. Drone routing with energy function: Formulation and exact algorithm. *Transportation Research Part B: Methodological*. 2020;139:364-387. DOI: 10.1016/j.trb.2020.06.011.

[32] D'Andrea R. Guest editorial can drones deliver?. *IEEE Transactions on Automation Science & Engineering*. 2014;11(3):647-648. DOI: 10.1109/TASE.2014.2326952.

[33] Aggarwal S, Kumar N. Path planning techniques for unmanned aerial vehicles: A review, solutions, and challenges. *Computer Communications*. 2020;149:270-299. DOI: 10.1016/j.comcom.2019.10.014.

[34] Dorigo M, Birattari M, Stützle T. Ant colony optimization. *IEEE Computational Intelligence Magazine*. 2006;1(4):28-39. DOI: 10.1109/MCI.2006.329691.

[35] Dorigo M, Caro GD. *The ant colony optimization metaheuristic: Algorithms, applications, and advances*. McGraw-Hil Ltd; 2006. DOI: 10.1007/0-306-48056-5_9.

[36] Eitzen H, et al. A multi-objective two-echelon vehicle routing problem. An urban goods movement approach for smart city logistics. *2017 XLIII Latin American Computer Conference (CLEI)*. IEEE; 2017. p. 1-10.

江红，武彤，任新惠，苟利珍

高需求下多机型物流无人机调度优化研究

摘要：
有效平衡地铁站台和车厢的乘客分布对于缓解局部拥堵非常重要。本文探讨了激励机制在鼓励乘客排队行为中的作用。为了定量分析乘客对该政策的遵从情况，在中国福州进行了问卷调查。根据调查数据的初步分析，在激励情景下乘客有各种移动距离上的偏好，即不移动、距离较小和距离较大。此外，本文还建立了一个考虑旅行目的和移动距离的嵌套Logit模型。实证结果表明，虽然货币和积分制度激励可以有效提高乘客对换乘队列定位要求的遵从程度，但当移动距离很小时，人们对奖励的关注度较低。与周末通勤的乘客相比，工作日通勤的乘客则会更遵守政策。

关键词：
遵从性；局部拥堵；激励机制；嵌套Logit模型；等候区