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Bi-level collaborative optimization for unmanned aerial vehicle logistics hub location and delivery routing

Zhenhe YU[1], Xiuguo ZOU[1], Li LI[2]✉

[1]*College of Smart Agriculture (College of Artificial Intelligence), Nanjing Agricultural University, Nanjing 210095, China*
[2]*Department of Automation, Tsinghua University, Beijing 100084, China*

Abstract: In view of problems associated with existing unmanned aerial vehicle (UAV) logistics systems, such as poor coupling between logistics hub locations and delivery routes and insufficient responsiveness to dynamic service demands, in this paper, a bilevel coupled model-based method for the collaborative optimization of UAV logistics hub location selection and route planning is proposed. In the lower level of the model, the adaptive large neighborhood search (ALNS) algorithm combined with the A* algorithm is employed to optimize the delivery path for a given logistics hub location. In the upper level of the model, a genetic algorithm (GA) is employed to optimize the hub location on the basis of the optimal path that is provided by the lower layer, together with the surrounding environmental conditions and the logistics hub construction costs. The scheme undergoes continuous iterative optimization via the dynamic coupling of the upper and lower layers. Experimental results demonstrate that the proposed method yields rational hub locations and effectively integrates the optimization of hub siting and transportation routing, achieving superior performance compared to baselines.

Key words: unmanned aerial vehicle (UAV); logistics hub location selection optimization; route optimization; bilevel collaborative optimization

1 Introduction

Efficient regional logistics reduces the operating costs of enterprises, greatly improves people's livelihoods, and is highly important for promoting local development and optimizing resource allocation.(Imran and Li, 2025) Therefore, efficient regional logistics occupies an important position in the economy of modern society.(Shakhatreh et al., 2019) With the rapid development of low-altitude technology, regional low-altitude logistics that combines unmanned aerial vehicles (UAVs) with logistics and transportation considerations has unique advantages. First, in terms of efficiency, UAV logistics can effectively shorten the delivery cycle and significantly improve the response speed of regional delivery. Second, in terms of the economy, UAV logistics helps reduce the transportation and labor costs of enterprises and optimize the overall operation structure. Third, in terms of accessibility, UAV delivery transcends ground road network constraints and can effectively serve geographically challenging areas, such as mountainous regions and islands, which are difficult to access through traditional logistics channels. Fourth, in terms of flexibility and environmentally friendly, low-carbon operations, small UAVs require minimal takeoff and landing space and consume less energy, making them well-suited for high-density urban environments while meeting sustainable development requirements. Consequently, regional low-altitude logistics is gradually becoming an essential component of modern smart logistics systems.

With the rapid development of low-altitude logistics, the operational complexity has gradually increased. The academic community has carried out multidimensional research on key issues and has focused on the following four main areas:

1. Research on multimodal combined transport

✉ Li LI, li-li@mail.tsinghua.edu.cn
Li LI, https://orcid.org/0000-0002-9428-1960

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modes. Studies have included research on airspace division and traffic management(He et al., 2025; Zheng et al., 2025), the cooperative mechanisms underlying the operation of UAVs and ground vehicles such as trucks for diverse goods and distribution needs(Gao et al., 2023), and improvements of the efficiency and flexibility of the logistics mode by full integration of low-altitude and ground resources through "medium- and low-altitude integration" and "air–ground integration" delivery. In addition, regarding single-dimensional ground and air transport, a model in which multiple agents coordinate with the corresponding hubs to form collaborative operations is proposed, thereby increasing the overall intelligence of the logistics system.

2. Research on UAV detailed flight path planning(Lin et al., 2021; Jiang et al., 2024; Li and Jiang, 2024; Liu et al., 2024a; Chan et al., 2025; Lve et al., 2025). With the Euclidean distance used as a rough given path, corresponding models and heuristic algorithms are used to optimize specific objectives, such as maximizing obstacle avoidance safety and airspace compliance and minimizing energy consumption and time cost; therefore, the global flight path of a UAV can preliminarily meet operational goals while balancing economic viability, safety, and efficiency.

3. Research on UAV mission route planning(Bruni et al., 2023; He et al., 2024; Pina-Pardo et al., 2024; Jiang et al., 2025; Li et al., 2025; Meng et al., 2025). On the basis of the requirements of user order distribution and timeliness of the delivery of goods, time cost and path cost are the main optimization objectives in this approach. To improve high-efficiency "last-mile" transportation, the logistics system can rationally schedule UAV resources on the basis of the model, generate flight schedules and service sequences, and achieve efficient path planning for scenarios that involve multiple demand points and batches by integrating real-world constraints that are encountered by UAVs.

4. Research on hub location–path coordination design(Chauhan et al., 2019; Salama and Srinivas, 2020; Pinto and Lagorio, 2022; Liu and Ma, 2023; Liu et al., 2024b; Wan and Ye, 2024; Xie, 2024). The main goal is to jointly optimize the logistics hub location selection and regional route planning as a whole, i.e., to balance between the total cost of the system and the scope of logistics services while considering the geographical environment, demand distribution, and infrastructure limitations. On the one hand, in UAV logistics hub location selection, various factors, such as the geographical environment, logistics demand distribution, airspace control policies, and supporting infrastructure, need to be comprehensively considered; hence, hub location selection is subject to multiple natural constraints that are imposed by the environment, and the logistics hub location can determine regional logistics coverage and transportation efficiency. On the other hand, once a logistics hub is selected, transportation time, flight resource costs, and energy consumption could become specific constraints that affect UAV route planning, and these factors are often closely and continuously linked to the company's core operational objectives and the specific performance requirements of UAVs. Therefore, conducting research on the collaborative optimization of UAV logistics hub locations and routes is imperative.

Mohamed Salama et al.(Salama and Srinivas, 2020) developed a joint optimization framework for performing multi objective optimization for client location clustering and UAV path planning. The number of UAVs, the locations and number of truck docking points, and UAV path planning were collaboratively optimized, and constraints such as flight distance of the effective load were combined; however, research on dynamic demand and intelligent obstacle avoidance in real-world scenarios was not conducted. Darshan Chauhan et al.(Chauhan, et al., 2019) chose UAV logistics hub location selection as the main research target, maximized the service area while considering the energy consumption and range constraints of UAVs, and used the efficient three-stage heuristic (3SH) algorithm to conduct facility location allocation, to solve multiple-knapsack problems, and to perform a final local search. Although this model emphasizes the advanced nature of multi-objective collaborative optimization, it does not consider low-level functions such as intelligent obstacle avoidance. Roberto Pinto et al.(Pinto and Lagorio, 2022) proposed the rational construction of intermediate charging stations to coordinate the total cost of charging station construction and the minimum travel distance of

UAVs, and the dual-objective coordination was solved through a mixed-integer linear programming model and a heuristic for a multi-objective shortest-path problem. However, the limitation of this approach is the lack of consideration of additional costs, such as queuing at intermediate charging stations and charging time in real-world scenarios; optimizing these factors would increase the complexity of the algorithm, which would hinder the practical application of this model. Wan et al.(Wan and Ye, 2024) used the adaptive immune optimization algorithm to solve for the location of the lowest-cost distribution center in the upper level and the ant colony algorithm to solve for the shortest travel time of vehicles in the lower level, incorporating real-time traffic congestion and driving speed as ant colony pheromones to establish a dynamic adjustment model. This bilevel model can provide an effective solution for dynamic path planning in logistics and transportation and achieve single-objective optimization of time costs; however, applying this method to simulation analysis in 3D space and with a large amount of data may be difficult. Xie et al.(Xie, 2024) proposed the use of a genetic algorithm (GA) embedded in a particle swarm optimization (PSO) algorithm to solve the problem of logistics hub location selection with UAV performance and cost as constraints. This optimization model can fully optimize the objective of cost minimization; however, it falls short in considering the state of the UAVs in real-world scenarios. For instance, it is assumed that each UAV travels at a constant speed, thereby limiting the ability to make path planning decisions under dynamic conditions. Liu et al.(Liu, et al., 2024b) applied fuzzy demand processing to costs and the number of locations, used a GA embedded in a PSO algorithm to perform simulations, explored post-disaster relief center location selection with strong uncertainty, and significantly optimized the problem of UAV logistics hub selection with the constraints of payload and maximum distance coverage. However, the objective function for the time calculation in the simulation was based only on the Euclidean distance, and the obstacle avoidance and path planning of UAVs in the environment were not fully considered. Liu et al.(Liu and Ma, 2023) integrated the simulated annealing algorithm with GA to leverage the global optimization capabilities of the former and the local search efficiency of the latter. They constructed an objective function incorporating both the latest arrival time of items and delivery costs, while introducing multiple constraints to enhance the model's resemblance to real-world scenarios. However, the UAV delivery mechanism that was used required that UAVs deliver to only one demand point at a time, which significantly reduces the transport efficiency and does not consider dynamic demand or environmental changes.

Various problems with UAV logistics hub location selection and path planning still exist. First, although many models use cost, route, and hub locations as clear optimization objectives, most of them can optimize only a single objective. Second, most of the existing models rely on only the Euclidean distance to solve the path planning problem and lack consideration of obstacles and no-fly zones in actual situations. Third, most models require UAVs to operate under ideal conditions; however, in real-world logistics scenarios, UAVs inevitably face certain constraints. In conclusion, current UAV logistics systems lack multi-objective optimization, bottom-layer path calculations are unsuitable for actual scenarios, and the actual states of the UAVs are not considered.

Therefore, in this paper, a new bi-level coupled model is presented. The model is divided into upper and lower levels(Ning et al., 2024).Under the premise that the logistics hub location is given by the upper level, the lower level optimizes the UAV delivery path with the objective of minimizing the total distance. On the basis of the optimal path information that is returned by the lower level, a multi-objective optimization model that considers the density of obstacles in the surrounding environment, the total path length, and fixed construction costs is established in the upper level. In this study, the A* algorithm is used to obtain the optimal feasible distance between any two points; the adaptive large neighborhood search (ALNS) algorithm(Hou et al., 2025) is used to rapidly solve for the optimal delivery plan for each UAV in the lower level, including the affiliation relationship among the demand points, the logistics centers, and the service sequence; and the GA is used for iteration to continuously optimize the logistics hub locations in the upper level. Through the nested application of the ALNS algorithm and the GA, the algorithm considers both local and global optima and finally obtains a safe and feasible UAV logistics delivery scheme with optimal delivery cost.

The contribution is threefold:

1. A novel bi-level collaborative optimization model is proposed to simultaneously address the integrated problem of UAV logistics hub location selection and delivery routing, effectively coupling the upper-level hub siting decisions with the lower-level path planning optimization.

2. An effective hybrid algorithmic framework is developed, combining the Adaptive Large Neighborhood Search (ALNS) and A* algorithm for the lower-level route optimization and a Genetic Algorithm (GA) for the upper-level hub location optimization, enabling dynamic iterative refinement between the two levels.

3. The proposed method demonstrates superior performance in generating rational hub locations and efficient, obstacle-aware delivery routes, effectively integrating hub siting and routing optimization compared to baseline approaches.

2 Modeling of the Problem

The task of a logistics hub is to dispatch UAVs to deliver goods promptly and accurately to each demand point. Proper logistics hub locations improve delivery efficiency and reduce delivery costs. In this section, the mathematical expression for the bilevel model of "logistics hub location selection–UAV path collaborative optimization", including set and parameter definitions, decision variable descriptions, objective function construction and constraint conditions, is described in detail. The model consists of upper-level location selection and lower-level path planning. The upper level determines n logistics hub locations within continuous space, and the lower level plans closed delivery paths of multiple UAVs for each logistics hub. Through location selection and planning, all the discrete demand points in the region are ensured to be served exactly once, and the UAVs are ensured to eventually return to their logistics centers.

For the convenience of modeling, the following reasonable assumptions are made in this study: The range of spatial regions to be studied is Ω, regional geographic information is known, and the obstacle density can be quantified; the number of logistics centers to be constructed is a positive integer n that is specified in advance; each logistics hub is equipped with sufficient homogeneous UAVs, and the maximum load capacity per UAV is Q; and each demand point is served exactly once by a single UAV from one logistics hub. Therefore, to visually illustrate the relationship between logistics centers and demand points within the regional space and the logic of UAV path planning and to establish a preliminary reference for subsequent bilevel architecture simulation modeling, this paper presents a schematic diagram of UAV logistics within the region, as shown in Fig. 1.

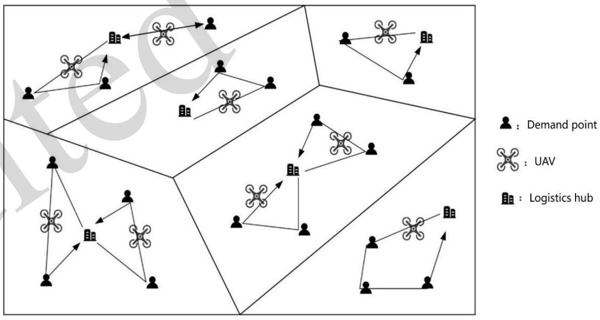


Fig. 1. Schematic diagram of UAV logistics in the region.

We further conduct a preliminary deduction of the model. The principal symbols are listed below, and the complete nomenclature is provided in Appendix A.

Table 1 Description of the main symbols

Parameter	Description
$\mathcal{H}=\{1,2,\ldots,n\}$	Collection of logistics centers
$\mathcal{P}=\{1,2,\ldots,m\}$	Demand point set, with coordinates (a_j,b_j) of demand point j and demand quantity $q_j>0$
Q	Maximum payload of a single UAV
w_1,w_2,w_3	Multi-objective weight coefficient
F_i	Fixed construction and operating costs of logistics hub i
(x_i,y_i)	Location coordinates of logistics hub i
$z_{ij}\in\{0,1\}$	Boolean variable that equals 1 if demand point j is assigned to logistics hub i and equals 0 otherwise
$A_{uv}^{(i,k)}\in\{0,1\}$	Boolean variable that equals 1 if the kth UAV in logistics hub i passes through

	service demand points u and v along path (u,v) and equals 0 otherwise
$u_j^{(i,k)} \in \mathbb{R}^+$	Variable for eliminating the auxiliary sequence of the subloop; indicates the order in which the *k*th UAV serves the *j*th demand point within the service area of logistics hub i

The objective of upper-level location selection is to achieve an optimal balance among the density of obstacles near the UAV logistics centers, the total delivery distance, and the overall cost by selecting appropriate logistics hub locations. The decision variables are the location coordinates of each logistics hub, and the objective function is as follows:

$$\text{Minimize} \quad F_u = w_1 \sum_{i=1}^{n} \rho(x_i, y_i) + w_2 F_l(x, y, z) + w_3 \sum_{i=1}^{n} F_i \tag{1}$$

$$\rho(x_i, y_i) = S_{\text{obs}}^i \big/ S_{\text{T}}^i \tag{2}$$

$$\text{s.t.} \ \sum_{i=1}^{n} z_{ij} = 1, \quad \forall j \in \mathcal{P}, \tag{3}$$

where the first term of the objective function is the spatial obstacle density, which reflects overall location safety; the second term is the actual total route cost under the given hub coordinates and the distribution scheme, which reflects the delivery efficiency; and the third term is the total fixed cost of the logistics hub, which includes construction and operating costs. Equation (2) is used to calculate the spatial obstacle density. Equation (3) ensures that each demand point is uniquely assigned to a logistics hub.

In lower-level planning, an optimal UAV collaborative delivery scheme for each logistics hub is independently designed on the basis of the logistics hub coordinates $\{(x_i, y_i)\}$ and distribution variable $\{z_{ij}\}$. The delivery plan defines the demand points that are served by each UAV and their order and eventually generates a completely closed path that departs from the logistics hub, passes through the demand points that need to be served, and returns to the hub. The core objective is to minimize the actual total flight distance of all the UAVs, and the objective function is as follows:

$$\text{Minimize} \quad F_u = w_1 \sum_{i=1}^{n} \rho(x_i, y_i) + w_2 F_l(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{z}) + w_3 \sum_{i=1}^{n} F_i \tag{4}$$

$$s.t. \sum_{j \in \mathcal{P}} q_j z_{ij} \le k_i \cdot Q, \quad \forall i \in \mathcal{H} \tag{5}$$

$$\sum_{k=1}^{k_i} \left[\sum_{v:(j,v) \in E_i} A_{jv}^{(i,k)} + \sum_{u:(u,j) \in E_i} A_{uj}^{(i,k)} \right] = 2 z_{ij}, \quad \forall i \in \mathcal{H}, \forall j \in \mathcal{P} \tag{6}$$

$$\sum_{v \in \mathcal{P}} A_{0_i v}^{(i,k)} = 1, \quad \sum_{u \in \mathcal{P}} A_{u 0_i}^{(i,k)} = 1, \quad \forall i \in \mathcal{H}, \forall k \tag{7}$$

$$\sum_{v:(u,v) \in E_i} A_{uv}^{(i,k)} = \sum_{v:(v,u) \in E_i} A_{vu}^{(i,k)}, \quad \forall u \in \mathcal{P}, \forall i \in \mathcal{H}, \forall k \tag{8}$$

$$u_j^{(i,k)} - u_\ell^{(i,k)} + m_i \cdot A_{j\ell}^{(i,k)} \le m_i - 1, \quad \forall j \ne \ell, \forall i, k \tag{9}$$

$$1 \le u_j^{(i,k)} \le m_i, \quad \forall j, i, k \tag{10}$$

where Equation (4) is the objective function, which solves for the total path cost. Equation (5) ensures that the total demand of each logistics hub does not exceed the total transport capacity of all the UAVs. Equations (6)–(7) ensure that each demand point is served by one UAV exactly once, and the UAVs successively serve the demand points and return to the logistics hub after completing a whole loop of logistics. Equation (8) ensures that each node has an equal number of incoming and outgoing paths, thus guaranteeing continuous and uninterrupted connectivity. Equation (9) ensures that each path is a simple link that does not have subloops.

The bilevel planning model is tightly coupled with the logistics hub coordinates (x_i, y_i) and distribution plan z_{ij}. Specifically, the logistics hub locations that are output by the upper level are used as the input parameters for the lower level, and the coordinated UAV paths from the lower level are fed back to the upper level for decision-making. The optimal solution of the system is eventually obtained by iteratively solving the bilevel coupled planning problem, thus completing the collaborative optimization of UAV logistics hub location selection and the delivery route.

2 Model solution

In view of these problems, in this study, the A* algorithm is used to solve for the lower-level path cost, and a mixed metaheuristic algorithm that is based on a GA that is embedded with ALNS is used to solve the bilevel model.

2.1 Path cost solved by the A* algorithm

In actual logistics delivery, the flight paths of UAVs need to avoid static obstacles, and the distance between logistics centers and demand points is not a simple Euclidean distance. Therefore, the A* algorithm is used in this study to accurately calculate the flight distance between points, which is used as an important basis for subsequent evaluation.

The A* algorithm is a heuristic search algorithm whose core cost function is $f(n) = g(n) + h(n)$, where $f(n)$ represents the total cost, $g(n)$ is the current cost, and $h(n)$ is the heuristic estimated cost. By comprehensively considering the heuristic estimated cost and the accumulated path cost, it selects the next position to move toward, enabling a rapid search toward the destination. This makes it suitable for shortest path planning problems. Specifically, the continuous airspace is first discretized into a grid system. Based on the actual airspace conditions, each grid cell is assigned a value: if a cell belongs to a no-fly zone or contains an obstacle, it is assigned a value of 0; if the cell is unconstrained, it is assigned a value of 1. Subsequently, a path search is executed within this constructed grid model. As shown in Fig. 2, starting from the current grid cell where the UAV is located (the parent node), the algorithm searches into the surrounding 8 adjacent grid cells. Whether a cell is converted into the next parent node is determined by its assigned value. Starting from the initial node, the algorithm continuously expands the node with the smallest total cost $f(n)$ until the target node is reached. Finally, by backtracking, all nodes forming the path from the start node to the end node are retrieved. The Euclidean distance for each segment is calculated, yielding the shortest feasible path and thereby obtaining the actual path cost c_{uv} between the origin and destination.

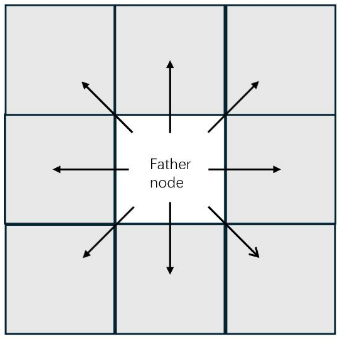


Fig. 2. Schematic Diagram of Path Search Directions

Before the iterative optimization of the bilevel architecture, the A* algorithm is employed in this model to precalculate the path costs between all logistics centers and demand points. These costs are then stored as a path cost matrix $\boldsymbol{C}$. This matrix serves as the fundamental data source for subsequent model solving, reflecting the spatial environment constraints and path cost information.

2.2 ALNS algorithm-based lower-level path collaborative optimization

Under the premise of a given upper-level decision, i.e., the determination of the specific location of each logistics hub, the lower-level problem can be regarded as multiple independent vehicle routing problems with capacity constraints. In this study, the ALNS algorithm is used to solve the lower-level problem, which gradually approaches the optimal solution through continuous destroy and repair operations. The specific process of the algorithm is provided in Appendix B.

2.3 Upper-level location selection optimization based on the GA

The GA is used in this study to solve the upper-level logistics hub location problem. A global search is performed in the solution space by simulating the genetic evolution behavior in nature to gradually approach the optimal solution. The GA continuously advances the individuals in the population through various operations, such as selection, crossover, and mutation, and ultimately obtains the optimal or near-optimal location selection scheme. The specific process is provided in Appendix C.

The figure below illustrates the specific solving process of the bilevel model. The upper level is optimized by the GA algorithm, while the lower-level path planning is handled by the ALNS algorithm. Before entering the coupled GA-ALNS algorithm, path costs are first solved using the A* algorithm as the underlying algorithm. Moreover, as clearly shown in Fig. 3, logistics center location and path planning rely on the GA and ALNS algorithms to achieve collaborative optimization within the bilevel architecture.

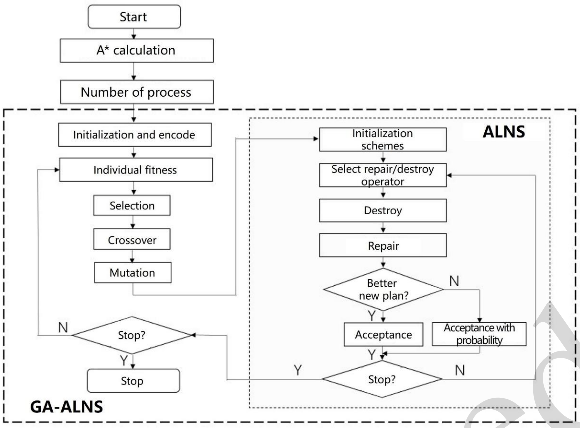


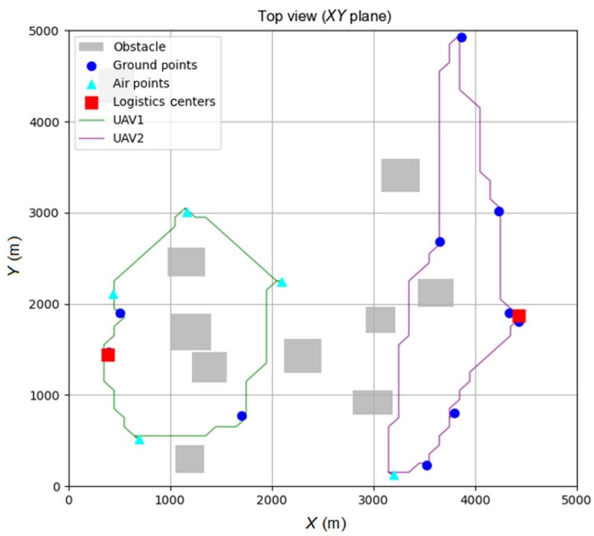
Fig. 3. Flowchart of the model solution algorithm.

3 Experimental results and analysis

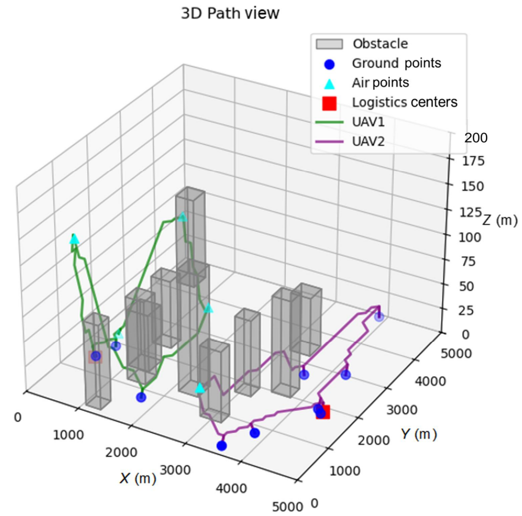
Based on the above deduction, we proceed to conduct experimental modeling. The algorithms involved in the bilevel architecture are implemented using Python 3.9. The experiments are carried out in a limited airspace, with 15 demand points and 2 logistics centers. The weights in the cost function are set to $w_1 = 0.2, w_2 = 0.6, w_3 = 0.2$. The GA is run for 200 iterations, and the ALNS is run for 300 iterations. For other parameter settings, please refer to Appendix D.

In the experimental results visualization, the simulation outputs a 3D front view, a 2D top view, and the total cost function convergence curve. The convergence curve is used to evaluate whether the optimal cost can be achieved through multiple iterations of optimization. The 3D and 2D views, from multiple perspectives, demonstrate whether the UAV successfully completes basic obstacle avoidance maneuvers, whether all demand points are serviced under the shortest path cost, and whether a closed-loop path returning to the logistics center is formed. Please refer to the figure below.

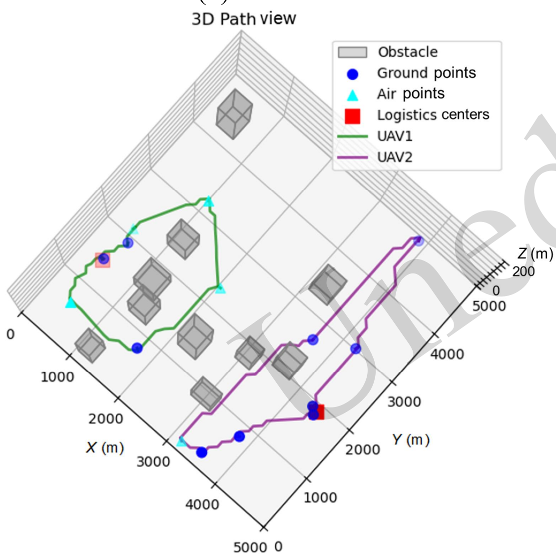
On the basis of the experimental settings and data, the optimal location and path planning results of UAV logistics centers finalized under the bilevel coupled optimization model are shown in Fig. 4. In areas near obstacles, the UAV does not blindly choose the shortest straight-line path. Instead, it relies on the underlying A* algorithm and detours around obstacles based on spatial constraints, with the specific detour method chosen to minimize path cost. Each UAV departs from the logistics hub to which it belongs, successively serves the designated demand points, and then returns to the logistics hub, thus forming a closed path, and no demand points are missed. In addition, the distribution of the logistics hub locations is reasonable, and there is no situation for which the selected locations are too concentrated or scattered, which reflects good coupling between location selection and route planning. To summarize, the bilevel coupled optimization model proposed in this paper effectively solves the collaborative optimization problem of UAV logistics hub location selection and route planning under multiple factors, including obstacles, path costs, and fixed construction costs, and achieves a good balance of multiple objectives through a dynamic feedback mechanism between the upper and lower levels.



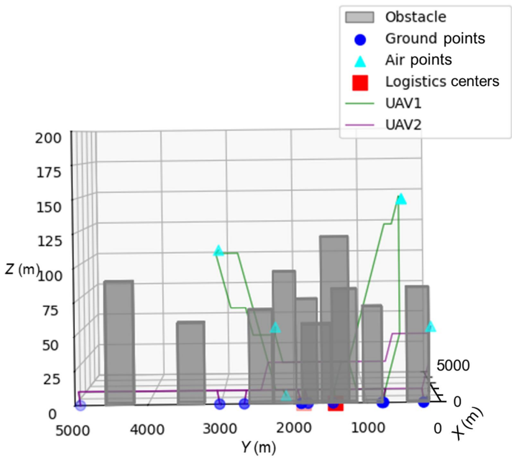
(a) Top view



(b) Front view

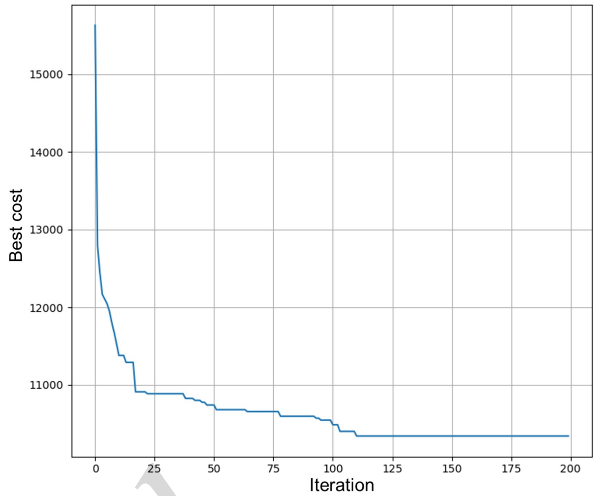


(c) Multiperspective reference 1

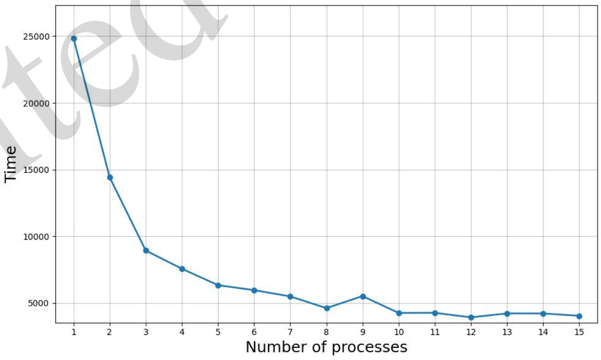


(d) Multiperspective reference 2

Fig. 4. Location selection and path optimization results of the bilevel coupled model.



(a)



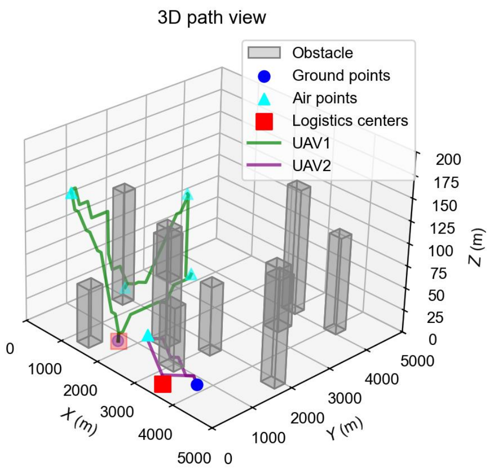
(b)

Fig. 5. (a) Iteration process of a single simulation algorithm when the number of processes is 1. (b) Time taken for a single simulation when the number of processes is 1–15.

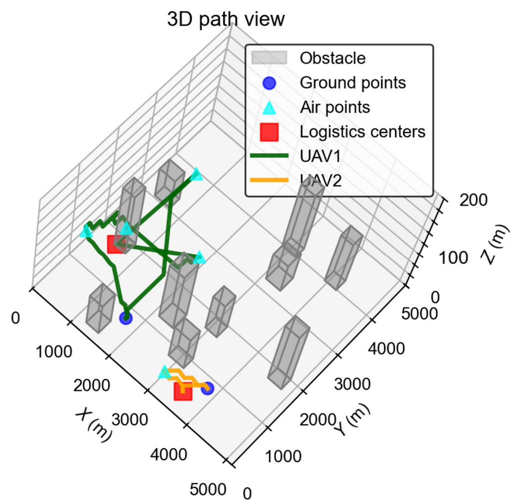
The experimental results show that if there is only one process, as shown in Fig. 5(a), the algorithm gradually converges after 111 iterations; 200 iterations take approximately 14 hours; and after 111 iterations, the total cost function eventually stabilizes at approximately 10,399. First, the algorithm can rapidly decrease in the early iteration stage and gradually stabilize at approximately 105 iterations, which indicates that the algorithm has good convergence and stability. Second, in terms of the cost, the weights of the objective function are set as: $w_1 = 0.2, w_2 = 0.6, w_3 = 0.2$, which indicates that the UAV path cost is prioritized throughout the entire solution process, meeting the conceptual requirement of using the logistics path as the core in calculating the final operating cost in the actual scenario. During the 14 hours of total algorithm operation, an analysis of the time required by its different modules shows that ALNS occupies approximately 98.5%–99% of the total time. The main reason is that the ALNS algorithm always requires a large amount of time when calculating the capacitated vehicle routing problem (CVRP)(Fan et al., 2020). When the problem is iteratively solved, the time consumption increases exponentially with the number of solution objects that are involved, and investigation of the destroy and repair factors in ALNS increases in complexity during global analysis, thereby resulting in greater time consumption. In terms of the surface-level computational load, the lower-level ALNS algorithm optimizes the logistics hub to which the demand point belongs and the delivery sequence. Compared with the upper-level GA algorithm, which optimizes only the logistics hub location, the lower-level algorithm requires more time during the iterative process.

To further reduce the time that is required to determine the logistics centers, the effect of the number of processes on convergence is tested. The test results show the following: On the Intel Core i7-14700KF processor (20 cores and 28 threads), by simultaneously evaluating the fitness of individuals in a GA population through 19 parallel processes and obtaining the optimized algorithm using a time statistics module and an acceleration ratio calculation module, the original serial computation time of approximately 14 hours is reduced to approximately 1.3 hours. Thus, a 10.77-fold increase in speed is achieved, thereby improving the single-simulation efficiency of the algorithm. In addition, to explore the specific relationship between the number of processes in parallel computing and the solution efficiency of the algorithm, a process number control module is added into the algorithm so that the number of processes increases by only one compared with the previous run, and the statistics module records the time of a single simulation. To compress the experimental time, the numbers of iterations for the GA and ALNS algorithm are set to 55 and 15, respectively, and the remaining values are the same as those in the previous settings. A line chart with the number of processes and single-simulation time as causal variables is shown in Fig. 5(b). The time that is taken for a single simulation significantly decreases as the number of processes increases. This is because multiprocess parallel computing fully leverages the computational power of multicore processors, distributes computational loads evenly across all cores, and avoids the resource wastage that is inherent in serial computing, where a single core handles all the tasks while others remain idle. This approach effectively resolves the limitation of serial modes that individual fitness must be computed sequentially and significantly increases algorithmic solution efficiency, thereby providing reliable support for rapid decision-making in practical applications.

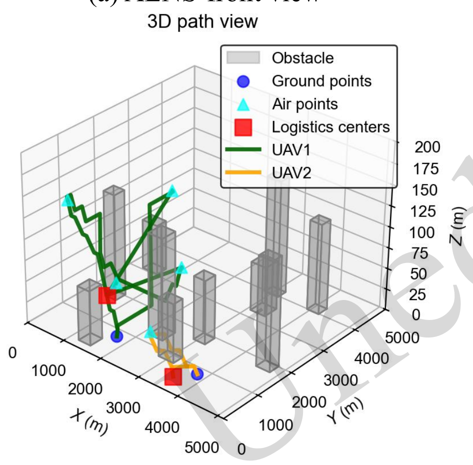
In this study, to verify the performance of the GA-ALNS bilevel architecture model, another bilevel model is introduced for comparison. The upper level of the new model solves the logistics hub location selection problem and uses the GA for iterative optimization. However, although the lower level retains route planning as the solution target, the ALNS algorithm is replaced by another type of heuristic search algorithm: the PSO algorithm. The new model ensures that the solution approach remains unchanged, as shown in Fig. 3, and the cost calculation continues to be based on Equations (1)–(10). To simplify the solution process and ensure that the algorithm converges as quickly as possible, the GA algorithm is set to iterate 50 times, whereas both PSO and ALNS are set to iterate 10 times, and the number of demand points is reduced to 7, with all other parameters remaining unchanged. The bilevel GA-ALNS and GA-PSO models are compared after undergoing the same number of iterations, and single-simulation time, algorithm convergence, and the quality of the lower-level path planning are evaluated. The specific results are shown in Fig. 5 and Fig. 6.



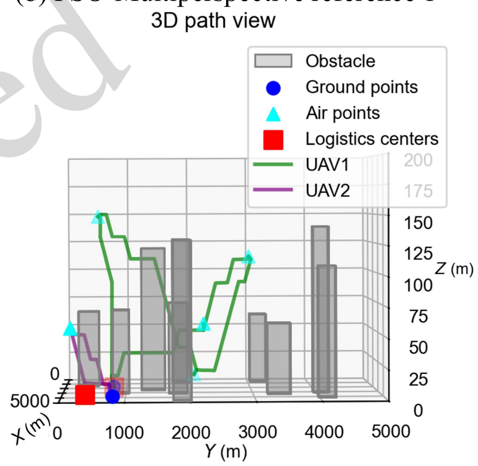
(a) ALNS-front view



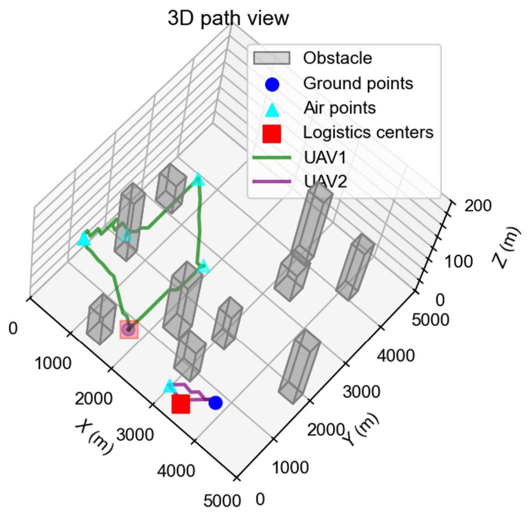
(b) PSO-Multiperspective reference 1



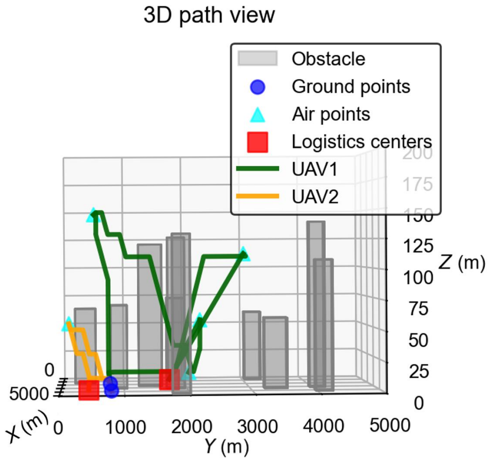
(a) PSO-front view



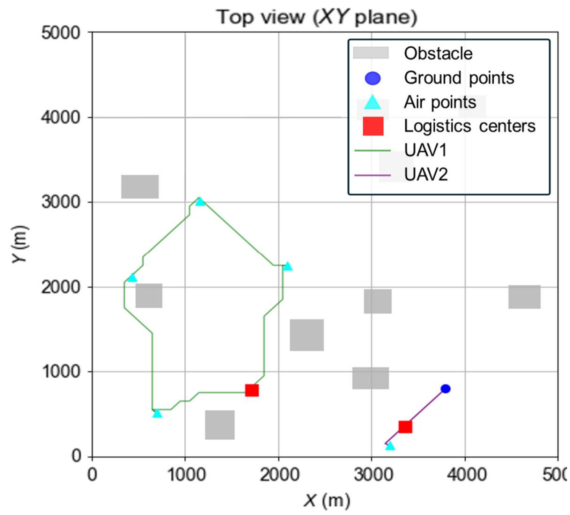
(c) ALNS-Multiperspective reference 2



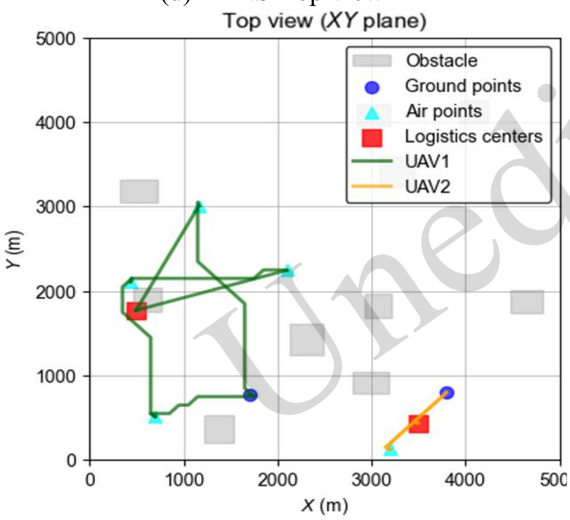
(b) ALNS-Multiperspective reference 1



(c) PSO-Multiperspective reference 2



(d) ALNS-Top view



(d)PSO- Top view

Fig. 6. Comparison Charts of Path Planning Results between ALNS and PSO Algorithms

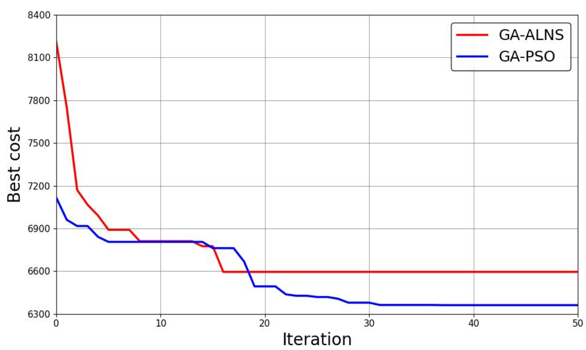


Fig. 7. Convergence Results Comparison Chart

In contrast, if PSO is used as the path planning algorithm for the lower level of the model, there are considerable limitations. First, at the simulation time level, the time statistics module shows that the single-simulation solution time of the PSO algorithm was approximately 5.84 times that of the ALNS algorithm, which indicates that the computational efficiency of the PSO algorithm is significantly lower than that of the ALNS algorithm. First, the PSO algorithm has a weaker local optimization ability than the ALNS algorithm, and the time consumption increases when complex problems such as path optimization are encountered. Second, the PSO algorithm exhibits inferior convergence performance compared with that of the ALNS algorithm (Fig. 7). The PSO algorithm stabilizes after 32 iterations, whereas the ALNS algorithm converges as early as the 16th iteration. Furthermore, the minimum cost that is obtained by the GA-PSO after undergoing a longer iteration process differs only marginally from that achieved by the GA-ALNS. Third, and most importantly, GA-PSO significantly underperformed GA-ALNS in terms of lower-level path planning quality. In the top view of Fig. 6, it can be clearly observed that GA-PSO exhibits pronounced decision-making flaws in delivery sequencing. Compared with GA-ALNS, the UAV generates numerous redundant paths and incurs substantially higher path costs, which directly results in reduced overall delivery efficiency and significantly increased costs. Meanwhile, by comparing the multiperspective view in Fig. 6, we can better observe that the logistics route of GA-ALNS remains a complete closed path and exhibits significantly greater simplicity in the vertical direction compared to GA-PSO, further demonstrating that the GA-ALNS two-layer architecture has higher decision-making capability in path planning and achieves better path quality.

In addition, we also observed the phenomenon of route overlap with obstacles in the GA-PSO architecture. Therefore, based on multiperspective analysis, we established a relationship diagram between the UAV's position and its distance to the nearest obstacle to detect whether collisions occur during UAV logistics transportation.

Table 2 Description of the main symbols

Symbol	Explanation
$P=(x,y,z)$	The path points where the UAV is located

O_i	The i-th individual obstacle around the UAV
$x_{\min}$ / $x_{\max}$	The minimum/maximum boundary value of obstacle O_i on the x-axis
$y_{\min}$ / $y_{\max}$	The minimum/maximum boundary value of obstacle O_i on the y-axis
$z_{\min}$ / $z_{\max}$	The minimum/maximum boundary value of obstacle O_i on the z-axis
$d(P,O_i)$	The distance from the UAV at path point P to obstacle O_i
$D(P)$	The minimum distance from the UAV at path point P to all obstacles

Based on the UAV's path points and the overall distribution of obstacles, we first established a set of obstacles $\{O_1,O_2,...,O_i\}$ and built a formula for calculating the distance from the UAV to a single obstacle based on the Euclidean distance:

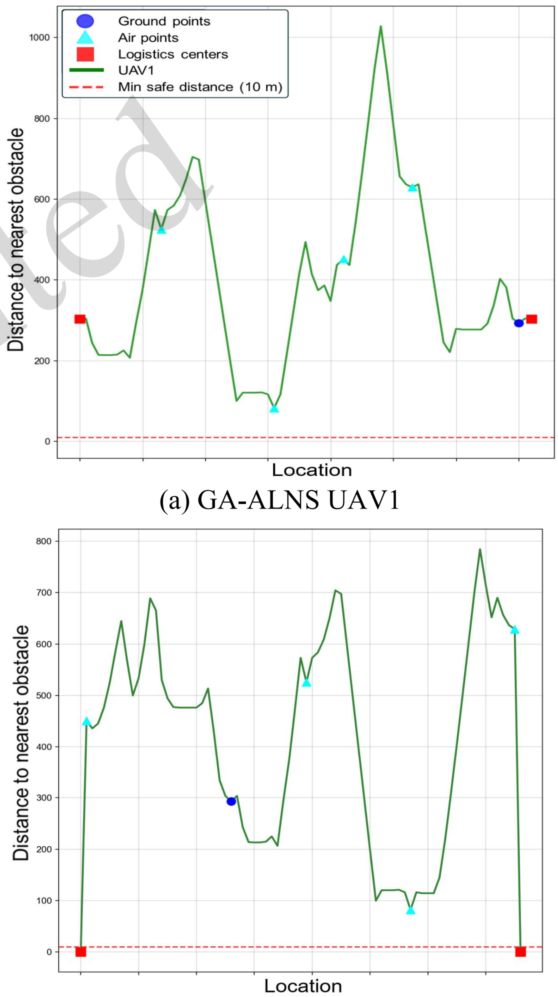
$$\begin{aligned} d(P,O) = [&\max(x_{\min}-x, x-x_{\max}, 0)^2 + \\ &\max(y_{\min}-y, y-y_{\max}, 0)^2 + \\ &\max(z_{\min}-z, z-z_{\max}, 0)^2]^{1/2}. \end{aligned} \quad (11)$$

If the UAV is inside an obstacle, the calculated $d(P,O_i)$ is 0, indicating a collision. Otherwise, the normal distance value is output.

After calculating the distances from the UAV to each obstacle, a set is established, and the minimum distance from the UAV to the surrounding i obstacles is taken as the minimum distance from the UAV to the nearest obstacle:

$$D(P) = \min\{d(P,O_1), d(P,O_2), ..., d(P,O_i)\} \quad (12)$$

Based on the above minimum distance calculation process, in the two-layer architecture experiments, in addition to analyzing the UAV routes from multiple perspectives, we added a distribution map of the distances between the UAV and obstacles. This map illustrates the real-time distance relationship between the UAV and the nearest obstacle at various positions along the route, where the horizontal axis represents the UAV position and the vertical axis represents the minimum distance to the nearest obstacle, calculated by Equation (12). Specifically, we first used the same legend as in the multidimensional view, and the UAV positions were also kept consistent, allowing for corresponding analysis between the multiview map and the obstacle distance analysis map, thereby more intuitively reflecting the real-time positional relationship between the UAV and obstacles during the logistics process. Second, we set a 10 m minimum safety distance red line to detect whether a collision occurs between the UAV and obstacles during the logistics process. The results are shown in Fig. 8.



(b) GA-PSO UAV1

Fig. 8. Obstacle Distance Profile for GA-ALNS and GA-PSO

Combining Fig. 6 and Fig. 8 further intuitively demonstrates that the UAV serves every demand point during navigation. Moreover, Fig. 8 provides further validation of the phenomenon where UAV1 in the GA-PSO architecture appears to pass through obstacles. The distance distribution results show that during the logistics transportation process, the UAV never crosses below the red line, indicating that the UAV maintains a safety distance greater than 10 m from surrounding obstacles and does not collide with them. This more fully demonstrates that both the GA-ALNS and GA-PSO two-layer architectures strictly adhere to the A* algorithm as the underlying path planning during simulation, achieving intelligent obstacle avoidance capability.

Based on all the above comparisons, it can be concluded that ALNS and PSO, as lower-level path planning algorithms, are not suitable for real-world operational scenarios where low cost and high efficiency are core objectives. Therefore, the GA-ALNS bilevel model proposed in this paper demonstrates a certain level of advancement compared to similar models.

In reality, the location selection for UAV logistics centers and route planning require comprehensive consideration of multiple factors, including site safety, logistics transportation efficiency, and construction/operational costs. As shown in Equation (1), we construct an objective cost function that better aligns with real-world scenarios by weighting three influencing factors: the obstacle density within the space, the total path cost, and the total fixed costs of logistics centers. For further details on the representation of the weight coefficients in the model and their interrelationships, please refer to Appendix E.

This paper analyzes and presents the lowest costs obtained from convergence under five different weight settings for each of the three weight coefficient groups by constructing curve charts:

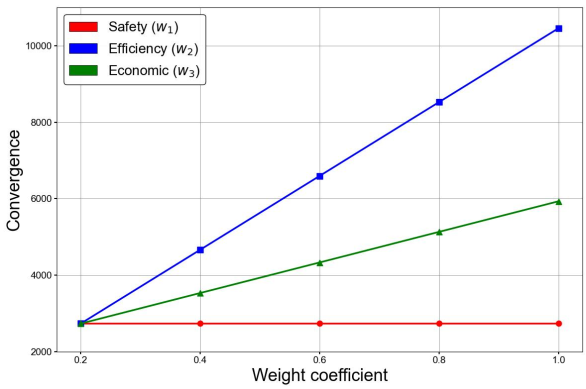


Fig. 9. Comparison Chart of Sensitivity Analysis for Each Weight Coefficient

From Fig. 9, we can clearly derive the sensitivity ranking of the weight coefficients as $w_2(\text{efficiency}) > w_3(\text{economy}) > w_1(\text{safety})$. Similarly, the detailed results and trend analysis of the sensitivity study are provided in Appendix E. From the perspective of the cost function construction, the obstacle density value ranges within [0, 1]. Compared to the orders of magnitude of fixed costs and path costs, the cost variation introduced by the safety weight is almost negligible, resulting in its lowest sensitivity. Therefore, according to the experimental results, relying on the bilevel architecture model proposed in this paper, the safety weight has a limited impact in practical logistics scenarios. Moreover, if aiming for a low-cost and high-efficiency logistics model, compared to the more intuitive fixed costs, businesses should place greater emphasis on the path costs influenced by the efficiency weight and conduct fine-tuned adjustments to w_2.

In addition, in this study, parallel computing is used to solve the case in which there are 7 demand points and 2 logistics centers and that in which there are 25 demand points and 5 logistics centers. To reduce the experimental time as much as possible, the number of iterations of the GA is adjusted to 50. When the number of demand points changes, the algorithm can still converge and stabilize within a certain period to obtain the minimum target cost. Thus, all the experimental results demonstrate that the bilevel model that is proposed in this paper has strong reliability and flexibility and is superior to baseline models; moreover, a solid foundation for the application of this model in actual scenarios is provided.

5 Conclusions

In view of the poor coupling between logistics hub locations and delivery routes and the poor ability to address dynamic delivery demand in low-altitude UAV logistics systems, a bilevel coupled model was constructed in this study to address the collaborative optimization of UAV logistics hub location selection and route planning. In the lower level of the model, the ALNS algorithm is combined with the A* algorithm to optimize delivery route planning for the given logistics hub locations. In the upper level, the

GA is used to optimize the logistics hub location on the basis of the route cost feedback from the lower level. The collaborative optimization of location selection and route planning is achieved through the dynamic coupling of the upper and lower levels. The experimental results show that the proposed method can effectively avoid urban obstacles and generate a closed path that covers all demand points, and the algorithm has a fast convergence speed and high stability. In the simulation model presented in this paper, optimization is proposed for logistics hub location selection, UAV path planning, and intelligent obstacle avoidance.

However, in real-world scenarios, we still need to conduct multiobjective optimization regarding aspects such as endurance capability, dynamic situation handling, battery recycling, and energy replenishment to make the simulations more closely resemble actual conditions. In future work, the optimization will be refined on the basis of the current model.

Acknowledgments

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Author contributions

Yu and Li designed the research. Yu, Zou and Li drafted the paper. Zou supervised the project, provided guidance, and revised the paper. Li reviewed the paper and provided substantial suggestions. Zou assisted in the methodology design. Yu and Li finalized the paper.

Conflict of interest

All the authors declare that they have no conflict of interest.

Declaration on the use of generative AI tools

We used AI tools to check for grammatical errors within the text and modified the expressions of a few sentences to make them more appropriate

Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

References

Bruni ME, Khodaparasti S, Perboli G, 2023. The drone latency location routing problem under uncertainty. *Transportation Research Part C: Emerging Technologies*, 156:104322. https://doi.org/10.1016/j.trc.2023.104322

Chan YY, Ng KKH, Wang T, et al., 2025. Near time-optimal trajectory optimisation for drones in last-mile delivery using spatial reformulation approach. *Transportation Research Part C: Emerging Technologies*, 171:104986. https://doi.org/10.1016/j.trc.2024.104986

Chauhan D, Unnikrishnan A, Figliozzi M, 2019. Maximum coverage capacitated facility location problem with range constrained drones. *Transportation Research Part C: Emerging Technologies*, 99:1–18. https://doi.org/10.1016/j.trc.2018.12.001

Fan H, Li D, Kong L, et al., 2020. Time-dependent vehicle routing optimization under fuzzy demand. *Control Theory & Applications*, 37(5):950–960. (in Chinese)

Gao J, Zhen L, Wang S, 2023. Multi-trucks-and-drones cooperative pickup and delivery problem. *Transportation Research Part C: Emerging Technologies*, 157:104407. https://doi.org/10.1016/j.trc.2023.104407

He X, Li L, Mo Y, et al., 2024. A distributed route network planning method with congestion pricing for drone delivery services in cities. *Transportation Research Part C: Emerging Technologies*, 160:104536. https://doi.org/10.1016/j.trc.2024.104536

He Z, Shu Z, Wang X, et al., 2025. Research on the architecture of unmanned aircraft system traffic management (utm). *Standard Science*, (1):82–87, 108.

Hou R, Deng X, Chen H, 2025. Coordinated control of large-scale multi-objective rail transit timetables based on an improved alns algorithm. *Automation & Instrumentation*, (3):224–227, 232. https://doi.org/10.14016/j.cnki.1001-9227.2025.03.224 (in Chinese)

Imran, Li J, 2025. Uav aerodynamics and crop interaction: Revolutionizing modern agriculture with drone. translators, Springer Nature Singapore, Singapore, (in en)

Jiang Y, Xu X-X, Zheng M-Y, et al., 2024. Evolutionary computation for unmanned aerial vehicle path planning: A survey. *Artificial Intelligence Review*, 57(10):267. https://doi.org/10.1007/s10462-024-10913-0

Jiang Y, Liu M, Jia X, et al., 2025. The multi-visit vehicle routing problem with multiple heterogeneous drones. *Transportation Research Part C: Emerging Technologies*, 172:105026. https://doi.org/10.1016/j.trc.2025.105026

Li S, Jiang L, 2024. Research on uav intelligent obstacle avoidance path and real-time route planning based on a* algorithm. *Automation & Instrumentation*, (12):67–71. https://doi.org/10.14016/j.cnki.1001-9227.2024.12.067 (in Chinese)

Li S, Zhang T, Xiao Y, et al., 2025. On-demand ridesharing based on dynamic scheduling in urban air mobility. *Transportation Research Part C: Emerging Technologies*, 175:105111. https://doi.org/10.1016/j.trc.2025.105111

Lin X, Wang C, Wang K, et al., 2021. Trajectory planning for unmanned aerial vehicles in complicated urban environments: A control network approach. *Transportation Research Part C: Emerging Technologies*, 128:103120. https://doi.org/10.1016/j.trc.2021.103120

Liu G, Ma Y, 2023. Location and task allocation of urban logistics drone delivery centers. *Flight Dynamics*, 41(3):88–94. https://doi.org/10.13645/j.cnki.f.d.20230403.009 (in Chinese)

Liu H, Tsang YP, Lee CKM, 2024a. A cyber-physical social system for autonomous drone trajectory planning in last-mile superchilling delivery. *Transportation Research Part C: Emerging Technologies*, 158:104448. https://doi.org/10.1016/j.trc.2023.104448

Liu X, Li Z, Zhong Y, 2024b. Optimization of emergency drone delivery station location based on a hybrid ga-pso algorithm. *Fire Science Today*, 9(9):1–3. (in Chinese)

Lve W, Wu S, Chen S, et al., 2025. Path planning for emergency material delivery by drones in urban building complex environments. *Journal of Disaster Science*, :1–9. (in Chinese)

Meng SS, Chen Y, Li D, 2025. Pickup and delivery problem with multi-visit drones considering soft time windows. *Transportation Research Part C: Emerging Technologies*, https://doi.org/10.2139/ssrn.5125258

Ning Z, Zhang L, He J, 2024. A bi-level optimization model for train formation in double-line intersection sections aiming at conflict resolution. *Journal of Tongji University (Natural Science Edition)*, 52(1):18–26. (in Chinese)

Pina-Pardo JC, Silva DF, Smith AE, et al., 2024. Dynamic vehicle routing problem with drone resupply for same-day delivery. *Transportation Research Part C: Emerging Technologies*, 162:104611. https://doi.org/10.1016/j.trc.2024.104611

Pinto R, Lagorio A, 2022. Point-to-point drone-based delivery network design with intermediate charging stations. *Transportation Research Part C: Emerging Technologies*, 135:103506. https://doi.org/10.1016/j.trc.2021.103506

Salama M, Srinivas S, 2020. Joint optimization of customer location clustering and drone-based routing for last-mile deliveries. *Transportation Research Part C: Emerging Technologies*, 114:620–642. https://doi.org/10.1016/j.trc.2020.01.019

Shakhatreh H, Sawalmeh AH, Al-Fuqaha A, et al., 2019. Unmanned aerial vehicles (uavs): A survey on civil applications and key research challenges. *IEEE Access*, 7:48572–48634. https://doi.org/10.1109/ACCESS.2019.2909530

Wan M, Ye C, 2024. Location and distribution optimization of logistics distribution centers based on bi-level programming. *Complex Systems and Complexity Science*, :1–8. (in Chinese)

Xie W, 2024. Location-allocation problem of urban logistics drone delivery centers. *Logistics Engineering and Management*, 46(6):83–86. (in Chinese)

Zheng X, Wu H, Tan X, et al., 2025. Research on low-altitude airspace zoning and route design based on drone airports. *Urban Geotechnical Investigation & Surveying*, (3):168–172. (in Chinese)

Electronic supplementary materials

Sections S1–S5

中文概要

题 目：无人机物流中心选址及运货路径的双层协同优化

作 者： 于镇赫[1]，邹修国[1]，李力[2]

机 构： [1]南京农业大学，智慧农业学院（人工智能学院），中国南京，210031；[2]清华大学，自动化系，中国北京，100084

目 的： 针对现有无人机物流系统中枢纽选址与配送路径耦合性差、对动态服务需求响应不足等问题，本文提出一种基于双层耦合模型的协同优化方法，旨在同时优化枢纽选址与无人机配送路径，以降低物流总成本、提升配送效率，并实现多目标平衡。

创新点： 1. 提出一种新型双层协同优化模型，将上层枢纽选址决策与下层路径规划紧密耦合，实现多目标联合优化；2. 构建融合自适应大邻域搜索算法、A*算法和遗传算法的混合启发式求解框架，实现上下层之间的动态迭代优化；3. 在路径规划中引入真实环境中的障碍物约束，使模型具备智能避障能力，优于仅依赖欧氏距离的传统方法。

方 法： 1. 上层以遗传算法优化枢纽选址，目标函数综合考虑环境障碍密度、总配送路径成本和枢纽固定建设成本；2. 下层采用自适应大邻域搜索算法结合 A*算法，在给定枢纽位置下优化多无人机的带容量约束的配送路径（图 3）；3. 通过 A*算法对离散化空域进行障碍物感知的最短路径预计算，生成路径成本矩阵，供上下层迭代调用；4. 采用多进程并行计算加速遗传算法中个体适应度的评估，显著提升求解效率。

结 论： 1. 所提模型能生成合理的枢纽选址，并规划出避开障碍物、覆盖所有需求点的安全闭合路径；2. 遗传算法-自适应大邻域搜索算法架构在收敛速度、路径质量和总成本方面均优于对比模型；3. 并行计算可将仿真时间从约 14 小时缩短至 1.3 小时，加速比达 10.77 倍。

关键词： 无人机；物流中心选址优化；路径优化；双层协同优化