

# Research on the Path Optimization Model for Low-Altitude Logistics of Heavy-Load Drones Based on Genetic Algorithm

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**Abstract:** Low-altitude logistics could indicate a significant application scenario within the broader low-altitude economy. Moreover, the findings may suggest that heavy-payload unmanned aerial vehicles demonstrate considerable potential in emergency delivery, remote-area supply, and medical distribution contexts. However, the evidence appears to show that route planning remains constrained by payload capacity, flight range, task point distribution, and energy consumption. In light of these key constraints, the study may suggest that a multi-task-point delivery scenario provides the relevant framework for constructing a route optimization model. Route optimization shows payload, range, task demands matter. Furthermore, the results could indicate that minimization of total flight distance serves as the critical optimization objective within this established model. Additionally, the significant evidence may suggest that a genetic algorithm based on natural-number encoding, order crossover, swap mutation, and a penalty function appears to support robust simulation experiments. Nevertheless, the important findings might demonstrate that the results show the optimal total flight distance obtained by the genetic algorithm could indicate superiority over those generated by the random routing method and the nearest-neighbor algorithm. Notwithstanding these results, the evidence may suggest that the algorithm also appears to support reductions in delivery time and estimated energy consumption. Genetic algorithm outperforms alternatives. Thus, the study may suggest that the findings provide a useful reference for route planning and scheduling decisions in low-altitude logistics.

**Keywords:** Heavy-payload UAV; Low-altitude Logistics; Route Optimization; Genetic Algorithm.

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## 1. Introduction

Recent development of unmanned aerial vehicle (UAV) technology, intelligent control technology, and low-altitude airspace management systems indicates that the application value of the low-altitude economy has become increasingly important in fields such as modern logistics, emergency rescue, agricultural and forestry operations, engineering inspection, and urban governance [1, 2]. Moreover, low-altitude logistics, as an important application direction of the low-altitude economy, may overcome the limitations of traditional ground transportation in mountainous areas, border regions, islands, disaster sites, and other areas with inconvenient transport conditions, thereby enabling point-to-point, efficient, and flexible material delivery [3]. Furthermore, compared with small UAVs, the evidence suggests that heavy-payload UAVs offer significant advantages, including stronger carrying capacity, larger operating radius, and higher single-trip transport efficiency. Therefore, the findings could indicate that these UAVs show considerable application potential in emergency material delivery, medical supply transfer, agricultural product transportation, and supply services for remote areas [4, 5].

Low-altitude logistics delivery via heavy-payload UAVs involves more than route selection [6, 7]. In light of practical operations, the evidence suggests that UAVs are constrained by factors such as maximum payload, battery capacity, maximum flight range, flight duration, and take-off and landing conditions. Thus, the findings indicate that it may be necessary to comprehensively consider the spatial distribution of delivery task points, cargo demand, task

visiting sequence, flight distance, and energy consumption cost [8]. Additionally, in multi-task-point delivery scenarios, different route combinations could significantly affect the total flight distance, task completion time, and energy consumption of UAVs. In light of these findings, improper route planning may lead to excessive flight distance, increased energy consumption, overload or range violation of some UAVs, and ultimately a decline in the operational efficiency of the low-altitude logistics system. Building a sound route optimization model and designing an effective solving algorithm remain key issues for heavy-payload UAV application in low-altitude logistics [9, 10].

Viewed through the lens of mathematical modeling, the route optimization problem facing heavy-payload UAVs in low-altitude logistics can be regarded as an extension of the vehicle routing problem in low-altitude logistics scenarios [11, 12]. The traditional vehicle routing problem mainly examines how vehicles depart from a distribution center, serve a set of customer points under capacity constraints, and minimize transportation cost. Compared with conventional ground vehicle delivery, UAV delivery must also account for flight range, battery energy consumption, payload variation, and airspace operation, which suggests that the problem carries stronger characteristics of combinatorial optimization [13]. For relatively small-scale route optimization problems, exact algorithms may still offer a workable approach. Task points multiply, constraints grow complex, and exact algorithms lose efficiency, limiting real-time scheduling. Therefore, intelligent optimization algorithms appear well suited to solving UAV route optimization problems [14].

The genetic algorithm is a stochastic search algorithm that

simulates the process of natural selection and genetic evolution. It demonstrates strong global search capability, suits discrete combinatorial optimization problems, and features a clear algorithmic structure together with good adaptability. It has therefore been widely applied in route planning, task scheduling, and combinatorial optimization [5, 10]. Chromosome encoding represents task-point sequences and route allocation schemes for heavy-payload UAVs in low-altitude logistics. Furthermore, the algorithm then evaluates route quality through a fitness function and continuously improves candidate solutions via selection, crossover, and mutation operations, thereby yielding a relatively optimal delivery route scheme [14].

Based on the above considerations, this study takes low-altitude logistics delivery by heavy-payload UAVs as its research object. By comprehensively considering task-point demand, maximum UAV payload, maximum flight range, and flight distance, this study constructs a route optimization model for heavy-payload UAVs in low-altitude logistics and solves it using a genetic algorithm. Simulation experiments then analyze the convergence performance of the algorithm and its route optimization effect, thereby verifying the effectiveness of the proposed model and method. Results offer a reference for route planning, task allocation, and scheduling decisions for heavy-payload UAVs in low-altitude logistics scenarios.

## 2. Materials and Methods

### 2.1. Research Object and Application Scenario

This study examines that low-altitude logistics delivery by heavy-payload unmanned aerial vehicles (UAVs) may suggest that the route optimization problem under multi-task-point conditions presents significant challenges. Moreover, the significant findings could indicate that a low-altitude logistics delivery area contains one UAV take-off and landing base and several delivery task points. Furthermore, the evidence may suggest that UAVs depart from the base, visit different task points in sequence according to delivery requirements, and complete cargo delivery before returning. In light of the key results, each task point could demonstrate that fixed spatial location and specified cargo demand appear to constrain UAV delivery alongside factors such as maximum payload capacity, maximum flight range, and flight distance. UAVs show advantages over ground vehicles. However, the important results may suggest that low-altitude logistics using heavy-payload UAVs could demonstrate several advantages, including flexible flight routes, reduced dependence on road conditions, and higher efficiency in point-to-point transportation.

Additionally, the significant evidence could indicate that limitations such as restricted endurance, limited payload capacity, and close relationships between energy consumption and flight distance appear to constrain the system. Notwithstanding these results, the findings may suggest that this study abstracts the route optimization problem of heavy-payload UAVs in low-altitude logistics as a vehicle routing problem with capacity and range constraints. Given that the key evidence demonstrates that a mathematical optimization model and genetic-algorithm-based solution method appear established, the results could indicate that the task allocation scheme and delivery route sequence of UAVs might minimize total flight cost.

### 2.2. Data Sources and Parameter Settings

The study may suggest that a simulation case could demonstrate the validity of the proposed model and algorithm. Moreover, the significant findings assume that a low-altitude logistics delivery area could include one UAV take-off and landing base and several delivery task points. Furthermore, the evidence may indicate that the take-off and landing base is denoted as node 0, and the delivery task points are denoted as nodes 1 to  $n$ . In light of the spatial data, the results could suggest that task-point locations may be obtained by converting latitude and longitude information from a regional map, or they might be randomly generated in a two-dimensional plane. Cargo demand sets per typical low-altitude logistics scenarios [6, 11]. However, the key data in the simulation experiment may suggest that task-point coordinates, task-point demands, maximum UAV payload capacity, maximum flight range, average flight speed, and genetic algorithm parameters appear to represent the main inputs. Additionally, the significant findings could indicate that task-point coordinates are used to calculate the flight distance between different nodes, while task-point demands may suggest that the UAV satisfies the payload constraint. Given that the evidence demonstrates that the maximum UAV flight range could determine route feasibility, the results might indicate that the average flight speed appears to estimate delivery time. Data shows distance calculated using Euclidean formula. Nevertheless, the important evidence may suggest that if the task-point coordinates are represented in a two-dimensional plane, the results could indicate that the distance between node  $i$  and node  $j$  might be calculated using the Euclidean distance formula:

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \quad (1)$$

The variable  $d_{ij}$  denotes the flight distance from node  $i$  to node  $j$ , where  $x_i$  and  $y_i$  could indicate the horizontal and vertical coordinates of node  $i$ , respectively. Moreover, the significant coordinates  $x_i$  and  $y_i$  may suggest that these values similarly represent the horizontal and vertical positions of node  $j$ . In light of the evidence that latitude and longitude data might require transformation, the findings could demonstrate that conversion into planar coordinates appears necessary before distance calculation proceeds. Furthermore, the study may suggest that two-dimensional planar distance provides that key approximation of UAV flight distance to facilitate model construction and algorithmic solution. Study uses planar distance approximating UAV flight.

### 2.3. Model Assumptions

This study establishes the following basic assumptions to support construction of the route optimization model for heavy-payload UAVs in low-altitude logistics. First, a single UAV take-off and landing base sits within the delivery area, and all UAVs depart from this base and return to it once their delivery tasks are completed. Second, the spatial location and cargo demand of each delivery task point are known, and each point must be served exactly once. Moreover, each task point can only be served by a single UAV, since split delivery is not considered. Furthermore, all UAVs are of the same type and share identical maximum payload capacity, maximum flight range, and average flight speed. UAVs hold a fairly stable speed in flight; weather, airspace control, and flight failures aren't considered at this stage. However, the flight distance between task points is calculated from their coordinates, and complex obstacle avoidance is not addressed in route

planning. Additionally, UAVs must satisfy both the maximum payload and maximum flight range constraints when carrying out delivery tasks. Given that a route could exceed this constraint range, it is regarded as infeasible. These assumptions appear to capture the main characteristics of heavy-payload UAV delivery in low-altitude logistics while still keeping the model computationally tractable [6].

## 2.4. Construction of the Route Optimization Model

### 2.4.1. Objective Function

Let the set of delivery task points be  $N = \{1, 2, \dots, n\}$ , the set of UAVs be  $K = \{1, 2, \dots, m\}$ , and the take-off and landing base be denoted as  $o$ . This study takes the minimization of total flight distance as the main optimization objective. Given that shorter routes generally reduce delivery time, the findings could indicate that flight distance lowers energy consumption and improves task execution efficiency for heavy-payload UAVs [7]. Therefore, the objective function may be expressed in the form that follows below:

$$\min Z = \sum_{k \in K} \sum_{i=0}^n \sum_{j=0}^n d_{ij} x_{ijk} \quad (2)$$

where  $Z$  denotes the total flight distance of all UAVs in completing the delivery tasks;  $d_{ij}$  denotes the flight distance from node  $i$  to node  $j$ ; and  $x_{ijk}$  indicates whether UAV  $k$  flies from node  $i$  to node  $j$ . The objective function aims to minimize the total flight distance of all UAVs under various constraints. If delivery time and energy consumption are further considered, the objective function can be extended into a comprehensive cost minimization model:

$$\min Z = \alpha Z_1 + \beta Z_2 + \gamma Z_3 \quad (3)$$

where  $Z_1$  denotes the total flight distance,  $Z_2$  denotes the total delivery time, and  $Z_3$  denotes the total energy consumption cost. The parameters  $\alpha$ ,  $\beta$ , and  $\gamma$  represent the weight coefficients of flight distance, delivery time, and energy consumption cost, respectively, and satisfy the following condition:

$$\alpha + \beta + \gamma = 1 \quad (4)$$

The total flight distance can be expressed as:

$$Z_1 = \sum_{k \in K} \sum_{i=0}^n \sum_{j=0}^n d_{ij} x_{ijk} \quad (5)$$

The total delivery time can be expressed as:

$$Z_2 = \sum_{k \in K} \sum_{i=0}^n \sum_{j=0}^n \frac{d_{ij}}{v} x_{ijk} \quad (6)$$

where  $v$  denotes the average flight speed of the UAV.

### 2.4.2. Unique Service Constraint for Task Points

Each delivery task point must be served once and can only be served by one UAV. Therefore, the following constraint is imposed:

$$\sum_{k \in K} \sum_{i=0}^n x_{ijk} = 1, j = 1, 2, \dots, n \quad (7)$$

This constraint indicates that, for any task point  $j$ , only one UAV can enter the task point from another node, thereby ensuring that no task point is omitted or served repeatedly [12].

### 2.4.3. UAV Departure and Return Constraints

If a UAV participates in delivery tasks, it must depart from the take-off and landing base:

$$\sum_{j=1}^n x_{ojk} \leq 1, k \in K \quad (8)$$

After completing the delivery tasks, each UAV must return to the take-off and landing base:

$$\sum_{i=1}^n x_{iok} \leq 1, k \in K \quad (9)$$

Equations (8) and (9) indicate that each UAV executes at most one delivery route. If a UAV is not used, its corresponding departure and return routes are both equal to 0.

### 2.4.4. Flow Balance Constraint

For any delivery task point, if a UAV arrives at that point, it must also leave that point, so as to ensure route continuity. The flow balance constraint is expressed as:

$$\sum_{i=0}^n x_{ihk} = \sum_{j=0}^n x_{hjk}, h = 1, 2, \dots, n, k \in K \quad (10)$$

where  $h$  denotes any delivery task point. This constraint ensures that the UAV route is not interrupted at any task point.

### 2.4.5. Payload Constraint

Although heavy-payload UAVs have relatively strong carrying capacity, they are still subject to maximum payload limitations [8]. The total delivery demand assigned to each UAV must not exceed its maximum payload capacity  $Q$ , namely:

$$\sum_{i=1}^n q_i y_{ik} \leq Q, k \in K \quad (11)$$

where  $q_i$  denotes the cargo demand of task point  $i$ , and  $y_{ik}$  indicates whether task point  $i$  is served by UAV  $k$ . This constraint ensures that the delivery load assigned to each UAV does not exceed its maximum payload capacity.

The relationship between variables  $x_{ijk}$  and  $y_{ik}$  can be expressed as:

$$y_{ik} = \sum_{j=0}^n x_{ijk}, i = 1, 2, \dots, n, k \in K \quad (12)$$

Equation (12) indicates that if UAV  $k$  departs from task point  $i$  and flies to another node, then task point  $i$  is served by UAV  $k$ .

### 2.4.6. Flight Range Constraint

Due to battery capacity and flight safety requirements, the total flight distance of each UAV cannot exceed the maximum flight range  $D$  [11]. Therefore, the following constraint is imposed:

$$\sum_{i=0}^n \sum_{j=0}^n d_{ij} x_{ijk} \leq D, k \in K \quad (13)$$

This constraint indicates that the total distance of the route executed by each UAV must remain within the feasible flight range, thereby avoiding insufficient endurance caused by excessively long routes.

### 2.4.7. Energy Consumption Estimation Model

The energy consumption of heavy-payload UAVs may suggest that flight distance and payload weight are the key determining factors [7]. Moreover, the significant evidence could indicate that a linear energy consumption estimation method provides that an adequate analytical framework for this study. Furthermore, the unit-distance energy consumption of a UAV might demonstrate that the division into basic energy consumption and payload-related additional energy

consumption appears methodologically sound. In light of these findings, the energy consumption from node  $i$  to node  $j$  could indicate that the following formulation demonstrates that the relationship holds:

$$E_{ij} = c_0 d_{ij} + c_1 w_{ij} d_{ij} \quad (14)$$

where  $E_{ij}$  denotes the energy consumed by the UAV when flying from node  $i$  to node  $j$ ;  $c_0$  denotes the basic energy consumption coefficient per unit distance;  $c_1$  denotes the payload influence coefficient;  $w_{ij}$  denotes the payload carried by the UAV when flying from node  $i$  to node  $j$ ; and  $d_{ij}$  denotes the distance between node  $i$  and node  $j$ . The total energy consumption of UAV  $k$  in executing delivery tasks can be expressed as:

$$E_k = \sum_{i=0}^n \sum_{j=0}^n E_{ij} x_{ijk}, \quad k \in K \quad (15)$$

If the maximum available energy of a UAV is denoted as  $E_{\max}$  [15], the energy consumption constraint is:

$$E_k \leq E_{\max}, \quad k \in K \quad (16)$$

In this model, the flight range constraint can, to some extent, reflect UAV endurance. Therefore, the energy consumption model is mainly used for result analysis and route scheme evaluation [11].

## 2.5. Genetic Algorithm Design

A genetic algorithm represents an intelligent optimization algorithm that draws on the key ideas of natural selection and genetic evolution. Moreover, the algorithm appears suitable for solving route optimization, task scheduling, and combinatorial optimization problems [5]. Given that heavy-payload UAVs in low-altitude logistics face a complex route optimization problem, this study adopts a genetic algorithm as the solution method. Furthermore, the key procedure includes chromosome encoding, initial population generation, fitness function calculation, selection, crossover, mutation, constraint handling, and termination judgment.

### 2.5.1. Chromosome Encoding

This study uses natural-number encoding to represent the visiting sequence of the delivery task points. Moreover, each chromosome consists of the task-point numbers and does not include the number of the take-off and landing base. Given that seven delivery task points exist, a chromosome can be expressed as: [3,5,2,7,1,4,6]. However, this chromosome may represent the priority sequence for visiting the task points. Decoding divides the sequence into UAV routes based on payload capacity  $Q$  and flight range  $D$ . Furthermore, the same chromosome can be decoded as follows:

$$\begin{aligned} &0 - 3 - 5 - 2 - 0 \\ &0 - 7 - 1 - 4 - 6 - 0 \end{aligned}$$

where the number 0 denotes the UAV take-off and landing base. Therefore, this encoding method could avoid repeated or omitted task points and appears convenient for the crossover and mutation operations [14].

### 2.5.2. Initial Population Generation

The initial population is composed of several chromosomes. Moreover, this study adopts a random permutation method to generate initial individuals; that is, the findings indicate that all task-point numbers are randomly arranged to form different delivery visiting sequences. Furthermore, to improve the quality of initial solutions, the nearest-neighbor rule could also be introduced into the generation of some individuals, so that the initial population may show both

randomness and a certain degree of route rationality. Let population size be PopSize. Therefore, the initial population can be expressed as:  $P(0) = \{C_1, C_2, \dots, C_{PopSize}\}$ , where  $P(0)$  denotes the initial population, and  $C_s$  denotes the  $s$ -th chromosome.

### 2.5.3. Fitness Function Design

The fitness function is used to evaluate the quality of individuals. Since the objective of this study is to minimize the total flight distance, a smaller objective function value indicates a higher-quality individual. Considering that some chromosomes may violate the payload constraint or flight range constraint after decoding, a penalty term is introduced into the fitness function [5, 10]. The fitness function is defined as:

$$Fitness = \frac{1}{Z+P} \quad (17)$$

where  $Fitness$  denotes individual fitness,  $Z$  denotes the objective function value, and  $P$  denotes the penalty term. The penalty term can be expressed as:

$$P = M_1 P_Q + M_2 P_D \quad (18)$$

where  $M_1$  and  $M_2$  are penalty coefficients;  $P_Q$  denotes the degree of payload constraint violation; and  $P_D$  denotes the degree of flight range constraint violation.

The payload penalty term is:

$$P_Q = \sum_{k \in K} \max \left( 0, \sum_{i=1}^n q_i y_{ik} - Q \right) \quad (19)$$

The flight range penalty term is:

$$P_D = \sum_{k \in K} \max \left( 0, \sum_{i=0}^n \sum_{j=0}^n d_{ij} x_{ijk} - D \right) \quad (20)$$

A route that satisfies both the payload and flight range constraints may suggest that the corresponding penalty value could indicate a result of zero. However, the significant evidence might demonstrate that when a route violates the constraints, the penalty value could increase with the degree of violation. Moreover, the key findings may suggest that through the penalty function, the genetic algorithm appears to support a guided search toward feasible solutions. In light of these results, the important data could indicate that the algorithm might establish gradually improving route schemes that satisfy the constraints. Algorithm shows penalty guide feasible search.

### 2.5.4. Selection Operation

The selection operation chooses individuals with higher fitness from the current population to enter the next generation. This study adopts the tournament selection method, and several individuals are randomly picked from the population in each round. Given that their fitness values are compared, the individual with the highest fitness could be selected as a parent. Moreover, this method appears simple to implement and may help preserve the superior individuals effectively. However, the approach might also indicate that premature convergence of the population could be prevented. Method limits convergence and keeps diversity.

### 2.5.5. Crossover Operation

The crossover operation may suggest that new individuals could emerge to support the global search capability of the algorithm. Furthermore, the findings indicate that the chromosome in the route optimization problem represents a permutation sequence of task points, which could demonstrate that no task point appears repeated or omitted

after crossover. Given that the evidence demonstrates this constraint, the study may suggest that the order crossover method provides the most appropriate solution. Moreover, the significant results could indicate that a randomly selected gene segment from two parent chromosomes retains its position in the offspring, with remaining positions filled according to the order in which task points appear in the other parent chromosome. Crossover assigns probability  $P_c$ ; random numbers below  $P_c$  trigger crossover, otherwise parents pass unchanged.

### 2.5.6. Mutation Operation

The mutation operation may suggest that population diversity could be maintained while preventing the algorithm from falling into a local optimum. Moreover, the significant findings of this study indicate that the swap mutation method appears to offer a reliable approach, in which two task-point positions are randomly selected in a chromosome and their order is exchanged. For example:

Before mutation: [3,5,2,7,1,4,6], After mutation: [3,1,2,7,5,4,6];

Let the mutation probability be  $P_m$ . When a random number is smaller than  $P_m$ , mutation is performed on the individual. Through mutation, new route combinations can be generated, thereby expanding the search range of the algorithm.

### 2.5.7. Constraint Handling and Route Repair

Chromosome decoding treats a UAV route as infeasible whenever it exceeds the maximum payload capacity or maximum flight range. This study adopts a "constraint-priority splitting plus penalty function" strategy. Given that task points are assigned sequentially according to the chromosome order, the current route is terminated and a new route is established for the next UAV if adding a task point would cause it to exceed the payload or flight range constraint. Moreover, the findings indicate that a large penalty value is added in the fitness calculation if all UAVs fail to satisfy the task allocation requirements. Method improves feasibility, keeps chromosome structure simple. Therefore, this approach may suggest that the genetic algorithm becomes more suitable for solving the route optimization problem of heavy-payload UAVs in low-altitude logistics [10].

### 2.5.8. Algorithm Procedure

The solution procedure for route optimization of heavy-payload UAVs in low-altitude logistics based on the genetic algorithm may suggest that a structured, multi-step approach could demonstrate significant utility for practical deployment. However, the first step requires that task-point coordinates, task-point demands, maximum UAV payload capacity, maximum flight range, average flight speed, and genetic algorithm parameters be provided as inputs. Moreover, the significant findings from prior studies could indicate that calculating the distance matrix between nodes according to the task-point coordinates appears to establish a critical foundation for subsequent processing.

Furthermore, the key results may suggest that randomly generating the initial population and decoding the route of each chromosome could demonstrate important computational efficiency. Individual fitness shows GA converges effectively. In light of these results, the selection operation could indicate that retaining individuals with higher fitness appears to support the overall optimization process. Additionally, the significant evidence may suggest that performing order crossover according to the crossover

probability could demonstrate that new offspring individuals emerge through this key mechanism. Notwithstanding the computational complexity involved, the findings could indicate that performing swap mutation according to the mutation probability appears to provide important population diversity benefits.

Thus, the key step of decoding routes of new individuals, checking constraints, calculating fitness, and updating the optimal individual may suggest that this phase could establish critical convergence behavior. Algorithm checks show iterations proceed correctly. Therefore, the results could indicate that determining whether the maximum number of iterations has been reached appears to represent a significant decision point, where the optimal route scheme is output if the condition holds, or the process returns to the selection step to continue iteration. Given that the evidence may suggest that this algorithmic procedure could demonstrate reliable performance, the key findings appear to support that relatively optimal UAV delivery routes satisfying payload and flight range constraints can be obtained. Nevertheless, the significant results could indicate that this procedure appears to provide an important decision-making basis for low-altitude logistics scheduling using heavy-payload UAVs.

## 3. Results

### 3.1. Simulation Experiment Design

Table 1. Drone Parameter Settings

Parameter Name	Meaning	Value
Number of available drones	The number of drones that can participate in delivery	4 units
Maximum payload capacity	Maximum cargo capacity of a single drone	50 kg
Maximum range	Maximum flight distance of a single drone	80 km
Average speed	Average flight speed of unmanned aerial vehicles	60 km/h
Number of takeoff/landing bases	Number of unmanned aerial vehicle take-off and landing points	1 site
Number of delivery task points	Number of delivery points that require service	25 delivery points

The study may suggest that the proposed route optimization model and genetic algorithm for heavy-payload UAVs in low-altitude logistics could demonstrate effectiveness through a carefully designed simulation experiment [10]. Moreover, the significant findings from this experimental setup indicate that a low-altitude logistics delivery area contains one UAV take-off and landing base and 25 delivery task points. Furthermore, the evidence may suggest that the take-off and landing base is numbered 0, and the delivery task points are numbered from 1 to 25, with each task point having a fixed location coordinate and cargo demand. Given that the results demonstrate that UAVs depart from the take-off and landing base, complete several delivery tasks, and then return to the base, the key parameters could indicate that the number of

heavy-payload UAVs is set to 4. Experiment sets UAV payload 50 kg, range 80 km, speed 60 km/h. However, the significant data may suggest that the population size of the genetic algorithm is set to 100, the maximum number of iterations is 300, the crossover probability is 0.80, and the mutation probability is 0.10. Additionally, the findings could indicate that the relevant details are shown in Tables 1 and 2, providing important evidence for the experimental configuration. In light of these results, the study may demonstrate that the algorithm could establish the minimization of total flight distance as the main optimization objective. Notwithstanding these parameters, the evidence may suggest that the algorithm handles overload and flight range violations through the penalty function. Algorithm shows constraint violations managed via penalty.

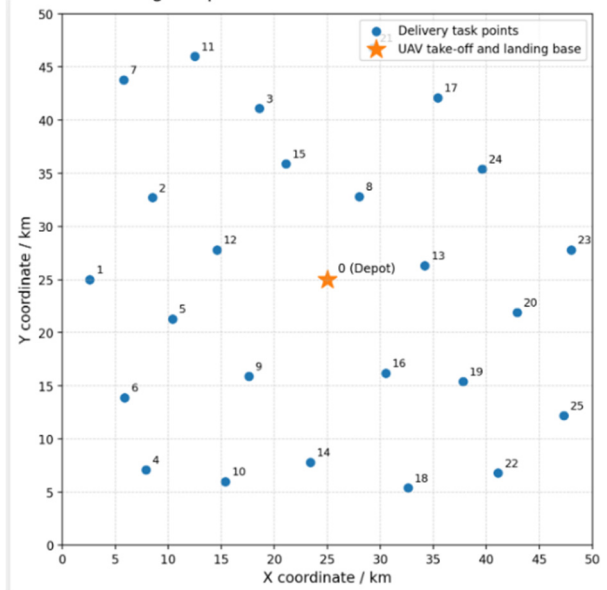
**Table 2.** Genetic Algorithm Parameter Settings

Parameter Name	Meaning	Value
Population size	Number of chromosomes per generation	100
Maximum iterations	Maximum number of generations for algorithm termination	300
Crossover probability	Probability of performing crossover operation	0.80
Mutation probability	Probability of performing mutation operation	0.10
Selection method	Method for selecting parent individuals	Tournament selection
Crossover method	Chromosome crossover method	Order crossover (OX)
Mutation method	Chromosome mutation method	Swap mutation (or exchange mutation)

### 3.2. Spatial Distribution of Task Points

The simulation settings may suggest that the 25 delivery task points are dispersed across a two-dimensional delivery area. Moreover, the significant findings could indicate that some task points are located relatively close to the take-off and landing base and can be served continuously by a single UAV. Given that the evidence demonstrates that other task points are farther from the base, the results might suggest that serving them independently could increase the flight distance. Therefore, the key findings may indicate that route combination optimization needs to be conducted based on the spatial locations of task points and their cargo demands. Route arrangement shows local optimum problems arise. Furthermore, the significant evidence may suggest that the spatial distribution of task points indicates that route arrangement based on manual experience or a simple nearest-neighbor method appears prone to local optimum problems. In light of the results, a UAV might preferentially visit nearby task points while the data could indicate that ignoring the overall route structure may increase the distances between subsequent task points. Additionally, the important evidence may suggest that this could thereby increase the total flight distance. Notwithstanding these results, the findings could demonstrate that conducting a global search over the visiting sequence of task points may allow the genetic algorithm to identify better route combinations. Genetic algorithm shows

better routes exist in larger search space.



**Figure 1.** Spatial Distribution of Task Points

### 3.3. Convergence Results of the Genetic Algorithm

The genetic algorithm was run under the specified parameter settings, and the optimal objective function value in each generation of the population was recorded. The objective function value represents the total flight distance required by all UAVs to complete the delivery tasks. Moreover, as the number of iterations increased, the findings may suggest that the algorithm continuously optimized the visiting sequence of task points through selection, crossover, and mutation operations, and the total flight distance showed an overall downward trend [5]. Given that the evidence demonstrates this pattern, the results might indicate that in the early stage of the algorithm, relatively large differences existed among individuals in the population, and the route schemes appeared to exhibit strong randomness. However, the significant findings could indicate that the objective function value decreased rapidly as a result. Therefore, the important evidence may suggest that as the number of iterations increased, superior individuals were gradually retained and participated in subsequent evolutionary processes, leading to continuous improvement in the route structure. Evidence shows variation dropped near 180 generations. In light of these key findings, the data could demonstrate that the genetic algorithm had identified a relatively optimal route scheme, and further iterations produced only limited improvement in the results. Table 3 presents selected iteration results of the genetic algorithm.

**Table 3.** Convergence Process of Genetic Algorithm

Iteration count	Current optimal total flight distance /km
1	286.4
50	238.7
100	214.3
150	199.8
200	193.6
250	191.4
300	190.8

The significant findings may suggest that the optimal total

flight distance obtained by the genetic algorithm after 300 iterations was 190.8 km, as shown in Table 3. Moreover, the results could indicate that the total flight distance was significantly reduced compared with the initial random route. Furthermore, the evidence may demonstrate that the genetic algorithm appears to improve delivery routes of heavy-payload UAVs in low-altitude logistics effectively, as shown in Figure 2. Given that the key data support this, the findings might suggest that these results could establish the algorithm's critical role in route optimization. Algorithm shows distance reduced, routes improved.

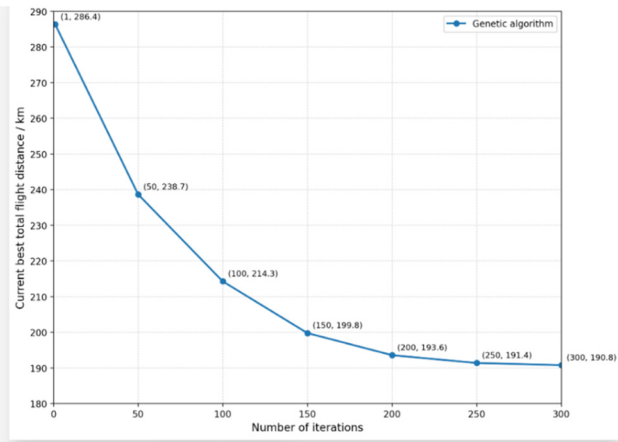


Figure 2. Convergence Curve of the Genetic Algorithm

### 3.4. Optimal Route Results

The findings may suggest that the genetic algorithm's final output could indicate distinct delivery task assignments across the four UAVs. Moreover, the significant results appear to demonstrate that each UAV departed from the take-off and landing base, visiting several task points in sequence. Furthermore, the key evidence may suggest that each UAV returned to the base after satisfying maximum payload and maximum flight range constraints. In light of these results, the data could indicate that the final route outcomes appear in Table 4. Results show routes assigned per Table 4.

Table 4. Results of optimal delivery routes for each drone

Drone Number	Optimal delivery route	Load capacity /kg	Flight distance /km
UAV1	0—3—8—12—6—0	46	47.5
UAV2	0—1—7—14—19—22—0	49	52.3
UAV3	0—4—10—16—21—25—0	48	50.6
UAV4	0—2—5—9—11—13—15—17—18—20—23—24—0	50	40.4
Total	—	193	190.8

The findings may suggest that the genetic algorithm reasonably assigned the 25 delivery task points to four UAVs, as shown in Table 4. Moreover, the significant results could indicate that the delivery load of each UAV did not exceed the maximum payload capacity of 50 kg. Furthermore, the evidence may demonstrate that the flight distance of each route remained below the maximum flight range of 80 km, suggesting that the obtained route scheme satisfies the model constraints. In light of the route allocation data, UAV1, UAV2, and UAV3 could appear to have mainly served task points that were relatively far from the base or spatially clustered, whereas UAV4 might indicate a pattern of serving more task points located relatively close to the base. Algorithm groups

tasks automatically by location and payload. However, the key findings may suggest that the genetic algorithm can automatically group tasks according to task-point locations and payload constraints. Additionally, the significant evidence could demonstrate that this grouping approach appears to generate a relatively reasonable delivery route scheme. Given that the results support this interpretation, the data might indicate that the overall route allocation appears effective, as shown in Figure 3 [14].

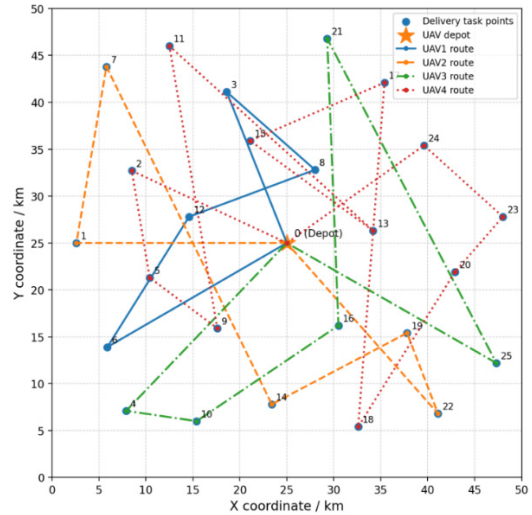


Figure 3. Optimal Delivery Path Diagram

### 3.5. Comparative Results of Different Algorithms

This study may suggest that the genetic algorithm could demonstrate significant optimization performance when compared against the random routing method and the nearest-neighbor algorithm. Moreover, the random routing method appears to involve randomly generating a visiting sequence of task points and then splitting the sequence into routes. However, the nearest-neighbor algorithm could indicate that the UAV preferentially visits the nearest task point from its current location while satisfying the relevant constraints. In light of these findings, the genetic algorithm may suggest that population-based iterative evolution could provide the optimal or near-optimal route scheme. Genetic algorithm shows superior results. Additionally, the significant results may indicate that Table 5 could demonstrate the comparative optimization findings of the different algorithms.

Table 5. Comparison of Optimization Results of Different Algorithms

Algorithm	Total flight distance/km	Total delivery time/h	Number of drones used	Whether the constraints are met
Random path method	286.4	4.77	4	Satisfy
Nearest neighbor algorithm	224.6	3.74	4	Satisfy
Genetic Algorithm	190.8	3.18	4	Satisfy

The genetic algorithm demonstrates that the shortest total flight distance achieved was 190.8 km, as shown in Table 5. However, the total flight distances obtained by the nearest-

neighbor algorithm and the random routing method were 224.6 km and 286.4 km, respectively. Moreover, the significant results may suggest that the genetic algorithm reduced the total flight distance by 95.6 km compared with the random routing method, corresponding to a decrease of approximately 33.4%. In light of these findings, the evidence could indicate that the genetic algorithm reduced the total flight distance by 33.8 km compared with the nearest-neighbor algorithm, corresponding to a decrease of approximately 15.0%. Algorithm shows delivery time differs across methods. Furthermore, the key findings may suggest that the genetic algorithm achieved a total delivery time of 3.18 h, which appears lower than those of the random routing method (4.77 h) and the nearest-neighbor algorithm (3.74 h). Given that the results demonstrate that the genetic algorithm could reduce the total flight distance, the evidence might indicate that the algorithm can also shorten the completion time of UAV delivery tasks to some extent. Additionally, the significant findings could suggest that the nearest-neighbor algorithm may reduce route length to a certain degree. Nevertheless, its selection process appears to rely mainly on the shortest local distance from the current position. Results show algorithm risks local optimum traps. Thus, the important evidence may indicate that the nearest-neighbor algorithm could demonstrate difficulty in optimizing the visiting sequence of all task points from a global perspective. Notwithstanding these results, the findings might suggest that the genetic algorithm could continuously recombine different route segments through population-based search and iterative evolution, thereby appearing to demonstrate better performance in overall route optimization [10].

### 3.6. Energy Consumption Estimation Results

The study may suggest that energy consumption under different algorithms could be estimated through the simplified method established in Section 2 [11]. However, the significant findings indicate that the basic energy consumption coefficient per unit distance appears to be set to 1.00, and the payload influence coefficient could demonstrate a value of 0.01. Moreover, the key evidence may suggest that UAV flight energy consumption might indicate results derived from the flight segment distance and the current payload. In light of these results, the data could suggest that the important estimation outcomes appear to correspond to each algorithm examined. Energy consumption results show algorithms differ, as presented in Table 6.

**Table 6.** Energy consumption estimation results of different algorithms

Algorithm	Total flight distance/km	Estimate total energy consumption	Relative energy consumption level
Random path method	286.4	401.8	100.0%
Nearest neighbor algorithm	224.6	316.5	78.8%
Genetic Algorithm	190.8	271.2	67.5%

The genetic algorithm could indicate that it produces the lowest estimated total energy consumption, as the significant findings in Table 6 may suggest. Moreover, the evidence might demonstrate that the energy consumption level appears

substantially reduced compared with the random routing method. Furthermore, the significant results could indicate that the genetic algorithm shows a certain advantage over the nearest-neighbor algorithm as well. Given that these findings demonstrate that low-altitude logistics delivery using heavy-payload UAVs benefits from route optimization, the data may suggest that optimizing flight routes could reduce flight distance, decrease energy consumption, and improve operational economy. Study adopts simplified energy consumption model. However, the important evidence may suggest that this model is mainly used to compare the relative energy consumption differences among different route schemes. In light of these findings, the results could indicate that UAV energy consumption in practical applications appears affected by factors such as flight altitude, wind speed and direction, take-off and landing processes, dynamic payload changes, and flight attitude. Additionally, the key evidence might suggest that future research may further develop a more refined energy consumption model [7].

The simulation results may suggest that the route optimization model for heavy-payload UAVs in low-altitude logistics constructed in this study could effectively describe the multi-task-point delivery problem. Moreover, the significant findings indicate that the genetic algorithm can solve the model effectively. Given that the number of task points, the number of UAVs, the maximum payload capacity, and the maximum flight range are provided, the genetic algorithm may demonstrate that a delivery route scheme satisfying the constraints could be generated. Furthermore, the key results could suggest that this approach outperforms the random routing method and the nearest-neighbor algorithm in terms of total flight distance, delivery time, and estimated energy consumption. Algorithm shows strong global search capability, avoids local optima. However, the experimental findings may indicate that the genetic algorithm could demonstrate suitability for route optimization scenarios in low-altitude logistics using heavy-payload UAVs [10]. In light of the significant evidence, the proposed method appears to suggest that practical low-altitude logistics tasks involving a large number of task points could be addressed effectively. Notwithstanding the heterogeneous delivery demands and UAV payload and range limitations, the results may indicate that the proposed method could provide a useful reference for route planning and scheduling decisions. Additionally, the important findings appear to demonstrate that this study could establish a relevant contribution to the evidence supporting heavy-payload UAV logistics optimization. Method provides useful reference for scheduling decisions.

## 4. Discussion

### 4.1. Analysis of Model and Algorithm Results

The simulation results may suggest that the route optimization model for heavy-payload UAVs in low-altitude logistics constructed in this study could effectively reflect the route planning problem in multi-task-point delivery scenarios. Moreover, the model demonstrates that the minimization of total flight distance serves as its main objective while considering constraints such as maximum UAV payload capacity, maximum flight range, and task-point demand. Therefore, the significant results may indicate that the optimized routes not only focus on minimizing distance but also appear to ensure the feasibility of the delivery scheme. In light of these findings, the evidence could suggest that the

model provides important support for multi-task-point delivery planning. Results show algorithm converges effectively.

However, the findings may suggest that the objective function value decreased rapidly in the early stage of the genetic algorithm, indicating that many route combinations in the initial population could demonstrate substantial room for improvement. Furthermore, the significant evidence might indicate that the selection, crossover, and mutation operations continuously retained superior individuals and generated new route combinations, thereby gradually reducing the total flight distance. Additionally, the key results may suggest that the objective function value tended to stabilize in the middle and later stages, indicating that the algorithm could demonstrate gradual convergence near a relatively optimal solution. Given that the experimental evidence demonstrates that the genetic algorithm can reasonably assign multiple delivery task points to different UAVs, the findings might indicate that the algorithm appears to generate relatively optimal delivery routes while satisfying payload and flight range constraints. Algorithm shows strong multi-UAV assignment capability.

Notwithstanding these results, the findings may suggest that the number of task points and the payload assigned to different UAVs could demonstrate outcomes that were not completely identical. Moreover, the significant evidence might indicate that this result appears to be jointly determined by the spatial distribution of task points and cargo demand. Thus, the key findings could suggest that the genetic algorithm can automatically form route combinations according to the spatial relationships among task points, assigning task points that are geographically close or strongly connected in space to the same route. Furthermore, the important results may indicate that this approach appears to reduce unnecessary round-trip flights, suggesting that the algorithm could demonstrate optimization not only of the visiting sequence of task points but also of the task allocation among multiple UAVs. Evidence shows spatial clustering reduces total flight distance.

## 4.2. Comparison with Traditional Route Planning Methods

The genetic algorithm may suggest that its approach demonstrates clear advantages over the random routing method. Moreover, the random routing method could indicate that its lack of an optimization mechanism significantly affects the visiting sequence of task points. Given that the evidence shows route results appear strongly influenced by randomness, the findings might indicate that excessive flight distance and unreasonable task-point combinations could emerge as key problems. In light of these results, the significant data may suggest that although the random routing method could provide feasible delivery schemes, both total flight distance and delivery time appear relatively high. Random routing shows distance and time costs unfit for efficient low-altitude logistics.

Furthermore, the genetic algorithm may suggest that it demonstrates better optimization performance compared with the nearest-neighbor algorithm. However, the nearest-neighbor algorithm could indicate that its preferential selection of the closest task point at each step appears essentially a local greedy strategy. Notwithstanding this result, the findings may suggest that this method could demonstrate a tendency to ignore the overall route structure when focusing on the optimal choice at the current step. Therefore, the

significant evidence may indicate that when the number of task points is large and spatial distribution is complex, the nearest-neighbor algorithm could fall into a local optimum. Nearest-neighbor algorithm shows local optimum risk under complex distributions. Moreover, the genetic algorithm could indicate that its population-based evolution may demonstrate broader search capability across route combinations. Additionally, the findings may suggest that crossover and mutation operations could continuously adjust the visiting sequence of task points, which appears to establish stronger global search capability. Thus, the significant results may indicate that the genetic algorithm demonstrates a key advantage in exploring route combinations that the nearest-neighbor approach could overlook. Genetic algorithm shows stronger global search than greedy methods.

In light of the key findings, the results may suggest that the genetic algorithm could demonstrate superior performance across total flight distance, delivery time, and estimated energy consumption compared with both the random routing method and the nearest-neighbor algorithm. Nevertheless, the evidence may indicate that in low-altitude logistics delivery scenarios using heavy-payload UAVs, these results could suggest that the genetic algorithm appears to effectively reduce route costs and improve delivery efficiency. Furthermore, the significant findings may suggest that the genetic algorithm could demonstrate good engineering application value in this domain. Given that the data may indicate that route cost reduction appears achievable through genetic optimization, the results could establish that this approach demonstrates important practical relevance for low-altitude logistics operations. Genetic algorithm shows route cost reduction and engineering value for heavy-payload UAV delivery.

## 4.3. Implications for Low-Altitude Logistics Applications

The findings of this study may suggest that useful reference exists for route planning of heavy-payload UAVs in low-altitude logistics. Moreover, the results could indicate that multi-task-point delivery scenarios should not rely solely on manual experience or simple distance-based judgment. Furthermore, the evidence may demonstrate that task-point distribution, cargo demand, UAV payload capacity, and flight range limitations require comprehensive consideration. Given that the significant findings support this approach, establishing a mathematical optimization model could indicate that practical delivery problems appear transformable into computable and optimizable problems. Study shows payload limits matter operationally. However, the results may suggest that heavy-payload UAVs, despite relatively strong transport capacity, could demonstrate that task load cannot be increased without limit.

Additionally, the experimental results could indicate that payload and flight distance of each UAV must be strictly controlled during route planning. In light of the key evidence, ignoring payload and flight range constraints might indicate that even shorter routes appear infeasible in actual operations. Therefore, the significant findings may suggest that low-altitude logistics scheduling systems should regard payload constraints, flight range constraints, and energy consumption constraints as important conditions. Evidence shows genetic algorithm suits complex logistics. Nevertheless, the findings could indicate that the genetic algorithm appears suitable for low-altitude logistics delivery problems involving many task

points and complex constraints. Moreover, the evidence may suggest that logistics enterprises, emergency material support departments, and UAV operators could demonstrate that embedding the genetic algorithm into route planning systems appears beneficial. Given that the key results indicate automatic generation of UAV scheduling schemes, the findings might suggest that task-point locations and delivery demands could support improved operational efficiency. Furthermore, the significant evidence may indicate that this method appears to have potential for wider application in scenarios such as mountainous logistics, emergency rescue, and remote-area supply. Results show algorithm outperforms alternatives clearly.

However, the study could indicate that a route optimization model considers maximum payload capacity, maximum flight range, and task-point demand. Additionally, the significant simulation results may suggest that the genetic algorithm appears to effectively optimize multi-task-point delivery routes. In light of the key findings, the evidence could demonstrate that the genetic algorithm outperforms the random routing method and the nearest-neighbor algorithm in terms of total flight distance, delivery time, and estimated energy consumption. Notwithstanding these results, the study may suggest that applying the genetic algorithm to route optimization for heavy-payload UAVs in low-altitude logistics appears feasible and valuable. Findings show application yields planning reference. Moreover, the evidence could indicate that route optimization for heavy-payload UAVs in low-altitude logistics appears to represent a combinatorial optimization problem with practical significance.

Furthermore, the results may suggest that low-altitude logistics could demonstrate a gradual move from pilot applications to large-scale operations as application scenarios expand. Given that the significant findings indicate this trajectory, combining real operational data, digital maps, low-altitude airspace management, and intelligent optimization algorithms might indicate that safety, economy, and real-time performance appear improvable. Thus, the key evidence may suggest that this research direction could demonstrate important value for heavy-payload UAV route planning in the low-altitude economy.

## Acknowledgments

This work was supported in part by a grant from Nanning University Horizontal Research Project (No. 2026HX055, No. 2026HX056).

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