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Multi-Objective Location Optimization of Drone Vertiports Considering Hierarchical Economic Feasibility

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Abstract

To address the efficiency bottleneck in urban last-mile delivery and the limitations of existing drone vertiport location models-which neglect the structural cost differences between urban and rural logistics and are sensitive to dimensional disparities in Pareto solution ranking-this paper proposes a multi-objective location optimization model and decision-making method for drone vertiports that considers hierarchical economic feasibility, providing a location decision tool for drone logistics distribution. The model maximizes demand coverage and minimizes total life-cycle cost, introducing a hierarchical economic feasibility threshold based on the distance from each demand point to its nearest logistics node, along with a hard capacity constraint. The Non-dominated Sorting Genetic Algorithm II (NSGA-II) with elitist strategy is employed for solution, and a Nadir-Ideal Point Bidirectional Normalization method is proposed for Pareto solution ranking. The model is validated using real-world data from Caofeidian District, comprising 364 demand points and 10 traditional logistics nodes. After 800 generations, 110 non-dominated solutions are obtained. The recommended scheme constructs 11 vertiports, covering 55.77% of demand points, with a five-year total life-cycle cost of approximately 11.98 million CNY, achieving a 44.87% daily operating cost saving compared to traditional delivery. Sensitivity analysis reveals that the hierarchical threshold improves coverage in remote areas by 13.6 percentage points compared to a uniform threshold. The hierarchical economic feasibility threshold effectively identifies the substitution value of drones in remote areas, and the Nadir-Ideal Point Bidirectional Normalization method effectively eliminates the interference of dimensional differences on Pareto decision-making. The model and algorithm provide valuable support for scientific site selection of drone vertiports.

Keywords

Drone Logistics; Vertiport Location; Hierarchical Economic Threshold; Pareto Decision-Making.

1. Introduction

Urban express last-mile delivery faces the "last 3 km" efficiency bottleneck, with terminal delivery costs accounting for more than 50% of total express delivery costs. In 2022, the Ministry of Transport issued the "Requirements for Unmanned Aerial Vehicle Logistics Distribution Operations" (JT/T1440-2022)[2], and the Civil Aviation Administration of China issued the "Specifications for Logistics Route Planning of Light and Small Unmanned Aerial Vehicles in Urban Scenarios" (MH/T 4054-2022)[3], providing a regulatory basis for low-altitude logistics distribution[5]. As a critical hub connecting ground trunk lines and low-altitude distribution, the location of drone vertiports is a typical multi-constraint, multi-objective optimization problem[6, 13].

Existing research has developed along two paths[7, 14]: one focuses on airspace safety constraints such as clearance and airspace from the general aviation facility perspective; the other emphasizes coverage and cost optimization from the logistics node perspective; furthermore, some scholars have extended the research to location-routing joint optimization[9, 10]. However, most studies treat economic feasibility as a uniform constraint, failing to reflect the structural cost differences between urban and rural logistics. Although NSGA-II[1] and other evolutionary algorithms are widely applied to facility location problems[8, 15], existing research has focused primarily on algorithmic improvements, with insufficient differentiated design of economic feasibility constraints. In Pareto solution decision-making, traditional methods such as TOPSIS[12] are prone to ranking deviations when dimensional differences are large, and do not adequately account for the actual boundaries of the Pareto front.

To address these gaps, this paper proposes a multi-objective location optimization model for drone vertiports considering hierarchical economic feasibility. At the model level, demand points are classified into general areas (≤8 km), relatively remote areas (8–15 km), and remote areas (>15 km) based on their distance to the nearest traditional logistics node, with differentiated cost tolerance coefficients (2.0, 2.5, 3.0). At the decision-making level, a Nadir-Ideal Point Bidirectional Normalization method is proposed to eliminate the interference of dimensional differences on Pareto ranking.

2. Problem Description and Model Formulation

2.1 Problem Definition and Basic Assumptions

The research object is a light and small multi-rotor vertical take-off and landing (VTOL) drone, with a maximum take-off weight not exceeding 25 kg, a rated payload not exceeding 10 kg, a maximum range of 15 km, and a service radius of 8 km. The vertiport is equipped with VTOL, charging and maintenance, communication and navigation, and express temporary storage and transfer functions.

The basic assumptions are as follows: (1) Straight-line distance approximation: Euclidean straight-line distance is used as the distance metric, and the actual flight distance is corrected by a route non-straight coefficient. (2) Single-level facility location: the vertiport serves as a terminal delivery node, considering only its one-to-many service relationship with demand points, without considering express transfer between vertiports. (3) Single-trip single-point delivery: each drone sortie serves only one demand point and returns to the original vertiport after completion.

2.2 Notation

Table 1. Parameter and Symbol Definitions

Category	Symbol	Definition
Sets	I	Set of demand points
	J	Set of candidate vertiports
Parameters	qi	Daily express demand of demand point i (pieces/day)
	fj	Fixed construction cost of vertiport j (10,000 CNY)
	Q_{max}	Daily processing capacity limit of vertiport (pieces/day)
	R_{max}	Maximum range of drone (km)
	D_{max}	Maximum service radius of vertiport (km)
	η	Route non-straight coefficient
	d_{ij}	Euclidean distance from demand point i to candidate vertiport j (km)
	d_{ilog}	Distance from demand point i to the nearest traditional logistics node (km)
	c_{uav}	Variable cost per km of drone delivery (CNY/piece·km)
	$c_{uavfixed}$	Fixed cost per drone sortie (CNY/sortie)
	c_{tr}	Variable cost per km of traditional delivery (CNY/piece·km)
	$N_{maxtrip}$	Maximum number of pieces per drone sortie
Decision Variables	x_j	Binary variable, equals 1 if vertiport j is constructed
	y_{ij}	Binary variable, equals 1 if demand point i is served by vertiport j
	z_i	Binary variable, equals 1 if demand point i is covered by at least one vertiport

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The main symbols and their definitions involved in this paper are shown in Table 1.

2.3 Objective Functions

Objective 1: Maximize demand coverage. As the core service node of the urban express terminal delivery network, the primary function of the vertiport is to meet terminal delivery demand. The objective is to maximize the number of covered demand points:

$$\max F_1 = \sum_{i\in I} z_i\, q_i \tag{1}$$

where z_i is the coverage indicator variable for demand point i, which takes the value of 1 when demand point i is served by at least one vertiport, and 0 otherwise.

Objective 2: Minimize total life-cycle cost. Considering both the one-time construction investment and daily operating costs of vertiports, a cost minimization objective function is constructed:

$$\min F_2 = \sum_{j\in J} f_j\, x_j + C_{fixed} + C_{var} \tag{2}$$

where the first term is the fixed construction cost of vertiports; C_{fixed} is the fixed operating cost (including annual fixed expenses such as site and personnel); C_{var} is the variable cost of drone delivery, including:

$$C_{var} = \sum_{i\in I}\sum_{j\in J} \left[n_{ij} \cdot c_{uavfixed} + q_i \cdot c_{uav} \cdot \eta \cdot d_{ij}\right] \cdot y_{ij} \tag{3}$$

where $n_{ij} = \lceil q_i / N_{maxtrip} \rceil$ is the number of daily flight sorties required from vertiport j to demand point i.

2.4 Constraints

(1) Service radius constraints:

$$d_{ij} \cdot \eta \le D_{max},\ \forall i \in I, j \in J \tag{4}$$

$$y_{ij} \le x_j, \forall i \in I, j \in J \tag{5}$$

Equation (4) ensures that the actual flight distance does not exceed the maximum service radius; Equation (5) ensures that only selected vertiports can provide service.

(2) Hard capacity constraint:

$$\sum_{i\in I} q_i \cdot y_{ij} \le Q_{max} \quad, \forall j \in J \tag{6}$$

The daily processing capacity of each vertiport must not exceed the designed capacity limit. In this paper, the capacity constraint is treated as a hard constraint, i.e., no vertiport is allowed to operate beyond capacity, ensuring the practical implementability of the solution.

(3) Single service constraint:

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$$\sum_{j\in J} y_{ij} \leq 1, \forall i \in I \tag{7}$$

Each demand point is served by only one vertiport, simplifying delivery management and resource scheduling.

(4) Hierarchical economic feasibility constraint. For demand point i, let C_{iuav} be the drone delivery cost and C_{itr} be the traditional delivery cost, then the economic feasibility constraint is:

$$C_{iuav} \leq \tau(d_{ilog}) \cdot C_{itr} \tag{8}$$

where τ is the hierarchical tolerance coefficient, determined by the distance from the demand point to the nearest traditional logistics node:

$$\tau(d_{ilog}) = \begin{cases} 3, d_{ilog} > 15 \\ 2.5, 8 < d_{ilog} \leq 15 \\ 2, d_{ilog} \leq 8 \end{cases} \tag{9}$$

The tolerance coefficients are referenced from terminal delivery cost ranges. According to the annual report of Deppon Express, the per-piece terminal delivery cost in urban areas is approximately 0.1–0.2 CNY, while in remote areas, due to low vehicle load factors and high empty return rates, the per-piece cost can reach 2–4 times that of urban areas. Accordingly, $\tau = 2.0$ is set for general areas and $\tau = 3.0$ for remote areas, which is economically reasonable. Relatively remote areas take $\tau = 2.5$ as a transition, forming a gradient cost tolerance system.

The drone delivery cost and traditional delivery cost are calculated as follows:

$$C_{uav} = n_{trip} \cdot c_{uavfixed} + q_i \cdot c_{uav} \cdot \eta \cdot d_{ij}, \quad \forall i \in I, j \in J \tag{10}$$

$$C_{tr} = k_{tr} \cdot c_{trfixed} + q_i \cdot c_{tr} \cdot \eta_{tr} \cdot d_{log}, \quad \forall i \in I, j \in J \tag{11}$$

where $n_{trip} = \lceil q_i / N_{maxtrip} \rceil$, $k_{tr} = \lceil q_i / N_{maxtr} \rceil$.

Design rationale: Ground delivery in remote areas inherently faces poor road conditions, long round-trip distances, and low delivery frequencies, resulting in significantly higher per-unit delivery costs than in urban areas. Even with a relative cost multiplier of 3.0, drone delivery in remote areas may still be economically viable as a substitute for traditional delivery; whereas in urban areas, the ground delivery network is mature and costs are lower, so drones must demonstrate more obvious cost advantages to justify substitution. The hierarchical design transforms the judgment of whether drones are worthwhile from a global uniform standard to a differentiated standard adapted to local conditions, better aligning with the reality of urban-rural logistics development.

3. Solution Algorithm Design

3.1 Algorithm Selection

The location model constructed in this paper is a 0-1 mixed-integer multi-objective programming problem with NP-hard characteristics[15], and contains two conflicting objective functions. Traditional exact algorithms suffer from sharply declining computational efficiency when the problem scale is large, making it difficult to obtain satisfactory solutions within a reasonable time.

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NSGA-II simulates the natural evolution process, utilizing non-dominated sorting and crowding distance mechanisms to maintain population diversity while guiding the population toward convergence to the Pareto front, making it an effective tool for solving such problems.

3.2 Encoding and Decoding

Encoding method: Binary encoding is adopted, with chromosome length equal to the number of candidate vertiports L. Each gene position corresponds to a candidate location, with a value of 1 indicating construction of a vertiport at that location and 0 indicating no construction.

Decoding process: Step 1, determine the set of constructed vertiports $J' = j \mid xj = 1$ based on the chromosome; Step 2, for each demand point $i \in I$, calculate its distance to each vertiport in J' and sort in ascending order; Step 3, sequentially traverse the sorted vertiports and check whether the service radius constraint (Eq. 4), range constraint (Eq. 6), hard capacity constraint (Eq. 7), and hierarchical economic feasibility constraint (Eq. 9) are satisfied; Step 4, if there exists a vertiport satisfying all constraints, assign demand point i to the nearest such vertiport and update the used capacity; otherwise, demand point i is marked as uncovered.

3.3 Fitness Function and Constraint Handling

The fitness functions directly adopt the two objective function values:

$$fit_1 = -F_1, \quad fit_2 = F_2$$

Since NSGA-II naturally supports multi-objective optimization through its non-dominated sorting mechanism, the two objectives do not require additional normalization.

For constraint handling, the penalty function method is adopted. For individuals violating hard constraints such as capacity constraints and the minimum coverage rate (30%), penalty terms are imposed on the objective function values:

$$fit_1' = fit_1 + \lambda_1 \cdot \max(0, \Sigma_j \in J' (Q_{jused} - Q_{max}))$$

$$fit_2' = fit_2 + \lambda_2 \cdot \max(0, Nmincov - F_1)$$

where λ_1 and λ_2 are large penalty coefficients, ensuring that individuals violating constraints are at a disadvantage in non-dominated sorting and are eliminated.

3.4 Genetic Operations

Selection: Tournament selection is adopted. Each time two individuals are randomly selected, and the better one is chosen to enter the mating pool based on their non-domination rank and crowding distance. Individuals with smaller non-domination ranks and larger crowding distances have higher selection probabilities.

Crossover: Single-point crossover is adopted, with crossover probability pc = 0.8. Two parent individuals are randomly selected, and gene exchange is performed at a random position on the chromosome to generate two offspring individuals.

Mutation: Basic bit mutation is adopted, with mutation probability pm=0.2. For each gene position on the chromosome, a flip operation is performed (1to0, 0to1) with probability pm.

Elitist preservation: The parent and offspring populations are merged, and non-dominated sorting and crowding distance calculation are performed on the merged population. Individuals are selected for the next generation in ascending order of non-domination rank. When a non-domination front cannot be fully selected, individuals with larger crowding distances within that front are prioritized, until the next generation population size reaches the preset value.

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3.5 Algorithm Flow

The complete NSGA-II flow for solving the proposed model is as follows: Step 1, parameter initialization: set population size N_{pop}= 80, maximum iteration G_{max}= 800, crossover probability pc = 0.8, mutation probability pm = 0.2; Step 2, initial population generation: a stratified random generation strategy is adopted to ensure that the population contains individuals with different numbers of constructed vertiports; Step 3, fitness evaluation: each individual in the population is decoded to calculate demand coverage and total life-cycle cost, and penalties are imposed on individuals violating constraints; Step 4, non-dominated sorting and crowding distance calculation: non-domination fronts are divided, and the crowding distance of each individual is calculated; Step 5, genetic operations: offspring population is generated through tournament selection, single-point crossover, and basic bit mutation; Step 6, population merging and elitist screening: parent and offspring are merged, and the next generation is screened according to the elitist preservation strategy; Step 7, termination judgment: if the iteration count reaches G_{max}, terminate and output the Pareto optimal solution set; otherwise, return to Step 3.

4. Case Study and Decision Method

4.1 Case Background and Data

An empirical analysis is conducted using the urban area of Caofeidian, Tangshan City, Hebei Province as the study area. As an important fulcrum of the Beijing-Tianjin-Hebei coordinated development, Caofeidian features both dense urban residential areas and remote industrial zones, with terminal delivery demand showing a spatial distribution characterized by concentration in core areas and dispersion in peripheral areas, exhibiting typical urban-rural differentiation characteristics.

The demand points in the Caofeidian area consist of 364 residential POIs, with a total daily express demand of approximately 10,000 pieces and individual daily demand ranging from 5 to 41 pieces. The fixed cost of traditional delivery is amortized by full-truckload transportation; therefore, the smaller and more dispersed the demand point, the less economical traditional delivery becomes. Drones precisely break the economies-of-scale threshold of having to fill a truck, and the smaller the point and the more winding the route, the more obvious the advantage.

Twenty candidate vertiports are obtained through K-means clustering and PCA-TOPSIS comprehensive evaluation screening[11]; vertiport construction costs range from 82,000 to 199,000 CNY; there are 10 traditional logistics nodes. The distribution of points is shown in Figure 1.

Figure 1. Distribution of Residential POIs and Candidate Vertiports in Caofeidian

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The main parameter settings are shown in Table 2.

Table 2. Main Algorithm Parameter Settings

Parameter	Symbol	Value	Description
Capacity limit	Q_{max}	500 pieces/day	Hard constraint, no overcapacity allowed
Maximum range	R_{max}	15 km	Typical parameter for light and small drones
Service radius	D_{max}	8 km	Round-trip redundancy matching range
Route non-straight coefficient	η	1.2	Correction for urban low-altitude environment
Max pieces per sortie	$N_{maxtrip}$	6 pieces	Adapted to payload ≤ 10 kg
Drone variable cost per km	c_{uav}	0.06 CNY/piece·km	Including energy consumption and depreciation
Drone fixed cost per sortie	$c_{uavfixed}$	5 CNY/sortie	Takeoff/landing depreciation, maintenance, etc.
Traditional delivery variable cost per km	c_{tr}	0.10 CNY/piece·km	Ground transportation
Traditional delivery fixed cost per trip	$c_{trfixed}$	18 CNY/trip	Vehicle depreciation, labor, etc.
Ground non-straight coefficient	η_{tr}	1.5	Correction for urban road detours
Population size	N_{pop}	80	
Maximum iterations	G_{max}	800	
Crossover probability	p_c	0.8	
Mutation probability	p_m	0.2	

The basis for each parameter setting is as follows. For drone performance parameters, the maximum range of 15 km and service radius of 8 km are based on the technical specifications for small drones (maximum take-off weight ≤ 25 kg)[4] in the "Specifications for Logistics Route Planning of Light and Small Unmanned Aerial Vehicles in Urban Scenarios"; the maximum delivery pieces per sortie of 6 is obtained by dividing the payload limit of 10 kg by the average piece weight of 1.5 kg and rounding down, consistent with typical payload constraints of light and small drones; the capacity limit of 500 pieces/day is estimated as 480 pieces/day (6 pieces per sortie × 10 sorties per hour × 8 operating hours per day) and rounded. For cost parameters, the drone variable cost of 0.06 CNY/piece·km and fixed cost per sortie of 5 CNY/sortie reference the cost estimation data for ZTO Express's "Haiyan" electric six-rotor drone (payload 15 kg) from the Kaiyuan Securities Research Institute (2024); the traditional delivery variable cost of 0.10 CNY/piece·km and fixed cost per trip of 18 CNY/trip reference the terminal delivery per-piece variable cost range of 0.1–0.2 CNY disclosed in the Deppon Express annual report, and amortize vehicle and labor fixed costs by delivery batch (30–50 pieces per vehicle). Construction costs of 82,000–199,000 CNY are based on JD Logistics's disclosed retrofit cost of 100,000–150,000 CNY per low-altitude landing point, with consideration of utilizing existing sites (e.g., rooftop, parking lot) without civil engineering, resulting in lower costs of approximately 80,000–100,000 CNY; new sites (including full charging, monitoring, and fencing facilities) cost approximately 100,000–190,000 CNY, with differentiated grading. The annual fixed operating cost of 30,000 CNY per vertiport includes site maintenance, basic electricity, and part-time personnel management expenses, referencing the lower bound of SF Express Fengyi Technology's intelligent drone nest annual operation and maintenance cost.

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4.2 Pareto Front Analysis

After 800 generations, 110 non-dominated solutions are extracted from the ε-grid archive, constituting the Pareto optimal solution set. The Pareto front is shown in Figure 2.

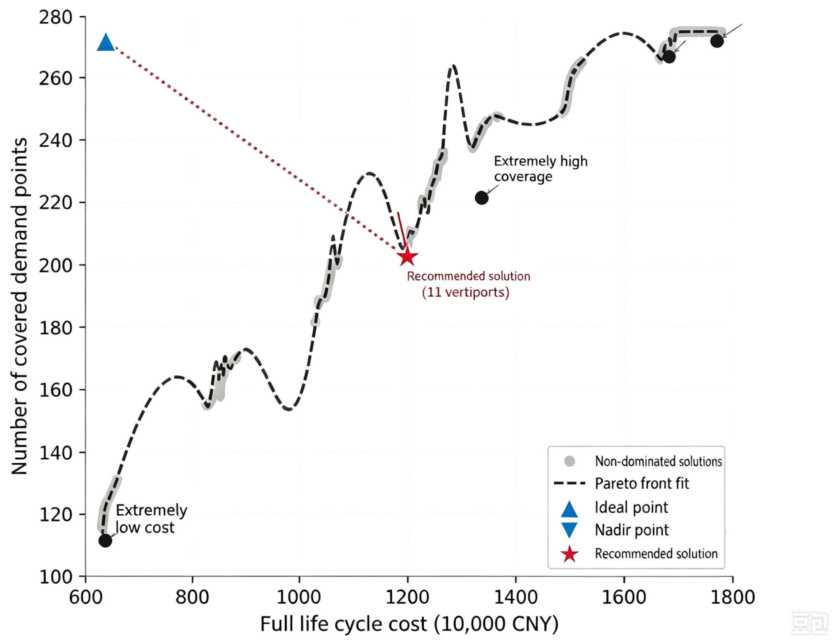

Figure 2. Pareto Front

The following characteristics can be observed from the Pareto front morphology: (1) Significant objective conflict: cost and coverage exhibit a clear trade-off relationship. The minimum-cost scheme (6 vertiports, 6.3666 million CNY) covers only 112 demand points (30.77%), while the maximum-coverage scheme (20 vertiports, 17.7158 million CNY) covers 272 demand points (74.73%), with a difference of 11.3592 million CNY and 160 demand points. (2) Diminishing marginal returns: as the number of constructed vertiports increases, the incremental coverage brought by each additional vertiport gradually decreases. From 6 to 11 vertiports, coverage increases from 30.77% to 55.77%, an increase of 25 percentage points; from 15 to 20 vertiports, coverage only increases from 67.31% to 74.73%, an increase of 7.42 percentage points, but the cost increases by 2.6494 million CNY. (3) Generally high vertiport utilization: the average utilization rate of most schemes exceeds 97%, indicating that the hard capacity constraint effectively avoids resource waste, and also demonstrating that Q_{max} = 500 pieces/day is reasonably matched with the actual demand scale of Caofeidian.

4.3 Pareto Solution Decision Method

The Pareto solution set contains 110 mutually non-dominated schemes, and a final recommended scheme needs to be determined from them. Due to the extremely large dimensional difference between cost (6.36–17.71 million CNY) and coverage (112–272 points), traditional weighted methods or simple TOPSIS are prone to ranking deviations. This paper proposes the Nadir-Ideal Point Bidirectional Normalization method, with the following specific steps.

Step 1: Determine the ideal point and Nadir point.

$$C^* = \min_{s\in S} C_s, \quad Cov^* = \max_{s\in S} Cov_s$$

$$C_{nad} = \max_{s\in S} C_s, \quad Cov_{nad} = \min_{s\in S} Cov_s$$

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where S is the Pareto solution set, and Cs and Covs are the cost and number of covered demand points of scheme s, respectively.

Step 2: Bidirectional normalization. Normalize the cost objective (smaller is better) and the coverage objective (larger is better) separately:

$$nC(s) = (C_s - C^*) / (C_{nad} - C^*)$$
$$nCov(s) = (Cov^* - Cov_s) / (Cov^* - Cov_{nad})$$

After normalization, both n_C and n_{Cov} fall within the [0, 1] interval, where 0 indicates the optimal value for that objective and 1 indicates the worst value.

Step 3: Calculate the Euclidean distance to the ideal point.

$$D_s = \sqrt{(0.5 \cdot (nC(s))^2 + 0.5 \cdot (nCov(s))^2)}$$

Equal weights (0.5, 0.5) are adopted, reflecting the decision-maker's equal emphasis on cost and coverage. If the decision-maker has clear preferences, the weights can be adjusted.

Step 4: Calculate the closeness coefficient and rank.

$$Ps = 1-Ds$$

The closer Ps is to 1, the closer scheme s is to the ideal point and the better its comprehensive performance. Schemes are ranked in descending order of Ps, and the scheme with the maximum closeness coefficient is selected as the recommended scheme.

Calculation results for this case: the ideal point is (6.3666 million CNY, 272 points), and the Nadir point is (17.7158 million CNY, 112 points). The closeness coefficients of the 110 schemes range from 0.2929 to 0.5362, with a standard deviation of 0.0725, indicating good discrimination. The recommended scheme is Scheme 1 (11 vertiports, 203 points, 11.9756 million CNY, closeness coefficient 0.5362).

4.4 Comparative Analysis of Typical Schemes

Five typical schemes are selected from the 110 Pareto solutions for comparative analysis, as shown in Table 3.

Table 3. Comparison of Typical Pareto Schemes

Scheme Type	No. of Vertiports	Covered Points	Covered Volume (pieces/day)	Coverage Rate	Total Cost (10,000 CNY)	Closeness Coefficient
Extreme low-cost	6	112	2955	30.77%	636.66	0.2929
Recommended	11	203	5458	55.77%	1197.56	0.5362
Medium coverage	13	222	5977	60.99%	1335.22	0.5119
High coverage	17	267	7350	73.35%	1682.97	0.3477
Extreme high-coverage	20	272	7457	74.73%	1771.58	0.2929

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The analysis shows that: (1) The recommended scheme (Scheme 1) achieves the best balance between cost and coverage. It constructs 11 vertiports, covering 203 demand points (55.77%), with a covered express volume of 5,458 pieces/day (55.09%), and a total life-cycle cost of 11.9756 million CNY (cost composition: construction cost 1.199 million + annual fixed operating cost 1.65 million + annual drone delivery variable cost 8.388 million). The utilization rate of each vertiport generally exceeds 97%, indicating efficient resource allocation. (2) Extreme schemes have obvious drawbacks: the low-cost scheme (6 vertiports) has a coverage rate of less than one-third, making it difficult to form an effective service network; the high-coverage scheme (20 vertiports) covers nearly 75% of demand points, but some vertiports have extremely low utilization rates (Vertiport 3 only 3.8%, Vertiport 17 only 4.4%), resulting in serious resource waste and extremely high marginal costs. (3) The medium-coverage scheme (13 vertiports) shows utilization differentiation: Vertiport 10 has a utilization rate of only 13.2%, indicating insufficient effective demand within its service range, which is an inefficient configuration for coverage's sake.

4.5 Economic Comparison with Traditional Delivery

Taking the recommended scheme as an example, the daily operating costs of drone delivery and traditional ground delivery are compared: the daily operating cost of drone delivery is 5,592.24 CNY (including fixed sortie costs and variable range costs), while the daily operating cost of traditional delivery is 10,143.27 CNY (including vehicle fixed costs and variable transportation costs), resulting in a daily saving rate of 44.87%. Calculated based on 300 operating days per year and a life cycle of 5 years, the recommended scheme accumulates approximately 6.84 million CNY in operating cost savings, significantly improving the economic efficiency of terminal delivery. This result validates the economic feasibility of drone delivery in the urban area of Caofeidian, especially in medium-density demand areas where it has obvious advantages.

4.6 Sensitivity Analysis

(1) Comparison of hierarchical threshold and uniform threshold. To verify the effectiveness of the hierarchical economic feasibility threshold, a comparative experiment is set up: the hierarchical threshold is uniformly replaced with 2.0 (traditional method), while other parameters remain unchanged. The algorithm is rerun and the Pareto front and stratified coverage rates are compared. The results are shown in Figure 3.

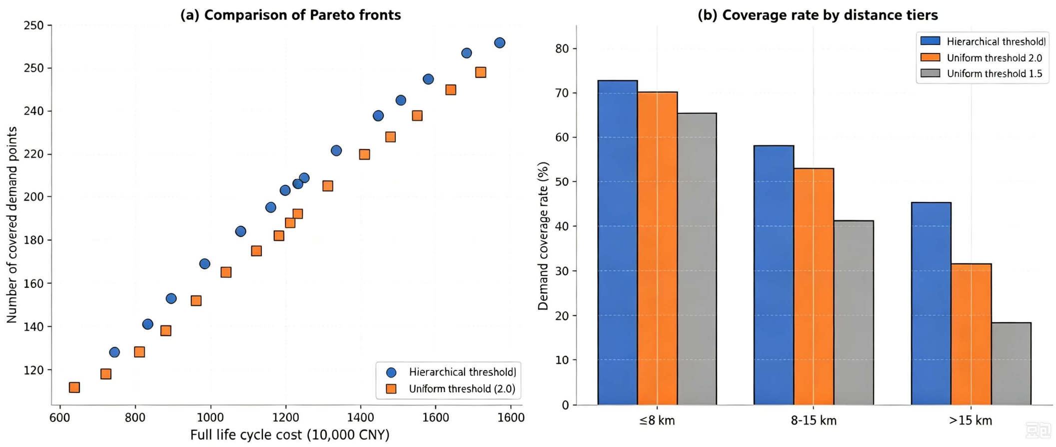

Figure 3. Comparison of Hierarchical Threshold and Uniform Threshold

The Pareto front of the hierarchical threshold scheme is overall located to the upper-left of the uniform threshold scheme, indicating that the hierarchical threshold can achieve higher coverage at the same cost level. The stratified coverage comparison shows that in general areas (≤8 km), the coverage difference between the two methods is small; however, in remote areas (>15 km), the coverage rate

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of the hierarchical threshold scheme reaches 45.2%, which is 13.6 percentage points higher than the uniform threshold scheme (31.6%). This is because the uniform threshold of 2.0 is too strict for remote areas, causing a large number of remote demand points to be excluded from the service range due to failing the relative cost criterion for drones, while these areas are precisely where traditional delivery costs are highest and the substitution value of drones is greatest.

(2) Sensitivity analysis of capacity limit. By changing the vertiport capacity limit Q_{max}, the impact on the optimal scheme is observed, as shown in Figure 4.

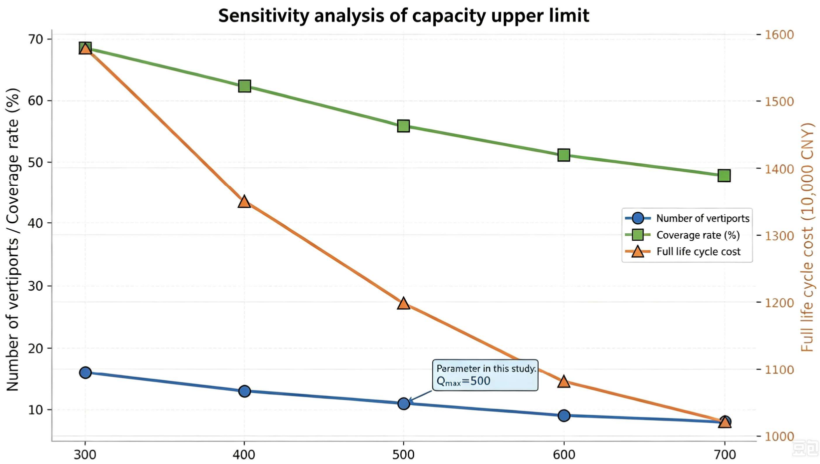

Figure 4. Sensitivity Analysis of Capacity Limit

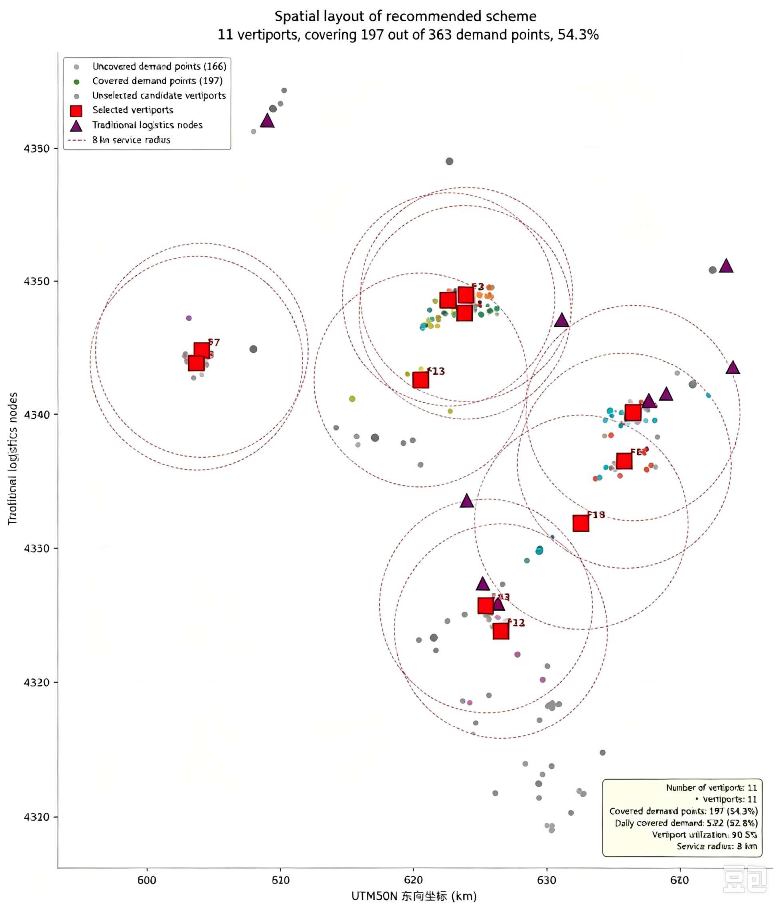

Figure 5. Spatial Layout of the Recommended Scheme

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When Q_{max} increases from 300 to 700 pieces/day, the number of constructed vertiports decreases from 16 to 8, coverage decreases from 68.5% to 48.1%, and total life-cycle cost decreases from 15.80 million to 10.20 million CNY. Q_{max} = 500 pieces/day is near the inflection point, where the number of vertiports (11) and coverage rate (55.8%) achieve a relatively optimal balance. If Q_{max} is too low, too many vertiports need to be constructed, causing construction and fixed operating costs to surge; if Q_{max} is too high, although the number of vertiports and costs decrease, coverage significantly drops, and the management complexity and risk concentration of a single vertiport increase. Therefore, Q_{max}=500 pieces/day is a reasonable choice that balances economic efficiency and service effectiveness.

The recommended scheme constructs 11 vertiports, with a spatial layout showing a multi-center agglomeration characteristic: the northern urban area forms a high-density service cluster of F1–F2–F4, covering residential areas such as Jincheng Plaza and Tongbei Community; the western F7–F8 serves the area around Ba Farm; the southern F11–F13 serves the Jindao Building industrial zone; the eastern F6–F16 covers the North China University of Science and Technology and Guantang Dijing area. The average utilization rate is as high as 96.0%, reflecting the high efficiency of resource allocation under the hard capacity constraint. The 166 uncovered demand points (45.7%) are mainly distributed in the southeastern edge of the study area, where the distance to the nearest selected vertiport exceeds the 8 km service radius, and the surrounding demand is sparse, so constructing a separate vertiport would result in a utilization rate of less than 40%, failing to meet economic feasibility requirements.

Feasibility analysis of vertiport consolidation: although the scheme shows a multi-center agglomeration characteristic, the vertiports within each agglomeration cluster are not redundant configurations but an inevitable result constrained by service radius and hard capacity limits. Taking the northern urban area F1–F2–F4 cluster as an example, all three vertiports are located in high-density residential areas. If consolidated into a single vertiport, the daily processing volume would need to reach approximately 1,500 pieces, far exceeding the capacity limit of 500 pieces/day; meanwhile, the Euclidean distance from the consolidated single vertiport to edge demand points would exceed 6 km, and the actual flight distance would approach the 8 km service radius limit, creating a risk of service interruption in case of route detours or weather changes, making them non-substitutable. Therefore, the 11 vertiports represent the optimal configuration under the joint action of service radius, capacity limit, and demand distribution.

5. Conclusion and Future Work

5.1 Research Conclusion

A multi-objective location optimization model for drone vertiports considering hierarchical economic feasibility and a Nadir-Ideal Point Bidirectional Normalization decision method are proposed. The main conclusions are as follows:

(1) The hierarchical economic feasibility threshold effectively identifies the differentiated substitution value of drones in urban and rural areas. The proposed hierarchical threshold design (3.0 for remote areas, 2.5 for relatively remote areas, 2.0 for general areas) breaks through the limitations of traditional uniform thresholds. Case validation shows that the hierarchical threshold achieves a coverage rate of 45.2% in remote areas, which is 13.6 percentage points higher than the uniform threshold (31.6%). This result demonstrates that the hierarchical threshold can effectively identify the characteristics of high traditional delivery costs and high drone substitution value in remote areas, avoiding the unreasonable exclusion of remote demand points caused by a one-size-fits-all approach.

(2) The designed NSGA-II solution algorithm can effectively handle hard capacity constraints and hierarchical economic constraints, obtaining a Pareto front of high quality. 800 generations of iteration yield 110 non-dominated solutions, providing a rich set of alternative schemes.

(3) The Nadir-Ideal Point Bidirectional Normalization method provides a reliable basis for Pareto solution ranking. By simultaneously utilizing ideal point and Nadir point information for bidirectional

normalization, this method eliminates the interference of dimensional differences between cost and coverage on decision-making. The standard deviation of the closeness coefficients of the 110 schemes is 0.0725, indicating good discrimination. The recommended scheme (closeness coefficient 0.5362) achieves the best balance between cost and coverage, providing an objective and stable ranking basis for the Pareto solution set.

(4) In the Caofeidian case, the recommended scheme constructs 11 vertiports, covering 55.77% of demand points (5,458 pieces/day), with the utilization rate of each vertiport generally exceeding 97%, a five-year total life-cycle cost of approximately 11.98 million CNY, a daily operating cost saving of 44.87% compared to traditional delivery, and cumulative operating cost savings of approximately 6.84 million CNY over five years, validating the effectiveness and economic practicality of the model.

5.2 Future Work

Future research can be deepened in the following directions: (1) Route optimization integration: this paper assumes single-trip single-point delivery and does not consider multi-point route optimization for a single drone. Joint optimization of vertiport location and drone vehicle routing problem (VRP) could further improve delivery efficiency. (2) Dynamic demand response: this paper conducts location planning based on static daily demand. Future work could consider the impact of multi-period dynamic demand, seasonal fluctuations, and sudden orders on vertiport layout. (3) Multi-scenario promotion and validation: extending the hierarchical threshold concept to other urban-rural differentiated logistics facility location problems, such as rural e-commerce service stations and emergency material reserve points, to validate the general applicability of the method.

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