

Truck-Drone Collaborative Delivery Route Optimization for Urban Flood Emergency Logistics Under Regional Constraints

Yirong Zhao^{1*}

¹ Business School, University of Shanghai for Science and Technology, Shanghai, China

Received: 19 December 2025; **Accepted:** 16 January 2026; **Published:** 12 February 2026

Abstract:

Aiming at urban flood emergency distribution, this paper optimizes truck-drone collaborative delivery under regional constraints. A dual-objective mixed-integer linear programming model is constructed to minimize maximum delivery time and total cost, considering spatial zoning and drone service radius. The improved MO-RHGA-GCD algorithm is adopted, and TC collaboration mode is proposed. Case tests show the model outperforms traditional modes in efficiency and cost, providing effective emergency logistics decision support.

Keywords:

Urban Flood, Emergency Logistics, Truck-drone Collaboration, Route Optimization, Dual-objective Optimization, Regional Constraints

1. Introduction

The intensifying global climate change has triggered frequent extreme precipitation events. As a country prone to floods, China faces disasters characterized by high frequency, intensity, and widespread overlap, posing severe threats to public safety and social stability. With the low-altitude economy penetrating logistics and the industry's growing demand for cost reduction, efficiency improvement, and scenario expansion, the truck-drone collaborative delivery model has become a key research focus in academia and industry. Studies cover both conventional and emergency logistics scenarios, forming an optimization framework with multiple objectives and constraints, along with a diversified algorithm system.

From specific application scenarios, both conventional logistics and emergency logistics face urgent optimization needs, while collaborative delivery models provide targeted solutions across various scenarios. In conventional logistics, core demands focus on cost reduction, efficiency enhancement, and customer experience upgrades. For urban last-mile delivery, traditional models suffer from long waiting times and high costs. The collaborative solution [1] featuring dynamic drone takeoffs and landings at any truck route position reduces waiting time and improves delivery efficiency through multi-drone configurations. Fresh cold chain delivery has long been constrained by freshness loss and high costs. The collaborative model [2] enabling drones to serve multiple customers per trip offers new solutions. In mountainous areas with poor road conditions, the first-mile collection efficiency for fresh agricultural products remains low. The truck-drone joint collection model [3]

effectively ensures product freshness and quality. Meanwhile, enterprises' pursuit of profit maximization and customers' demand for service quality drive the refinement of collaborative models. Multi-trip deliveries with revenue and time windows [4], considering urban area restrictions [5], establish optimization models that balance cost, customer value, and satisfaction. In emergency logistics, the core objectives are rapid response, risk mitigation, and social benefit optimization. Natural disasters like earthquakes and floods often cause road damage, making it difficult for traditional transport to deliver supplies efficiently. To address these scenarios, collaborative solutions are designed, such as incorporating psychological costs for affected populations [6], quantifying social benefits through deprivation costs [7], or developing robust models to handle environmental uncertainties [8]. During infectious disease outbreaks, contactless distribution and risk-based tiered control in affected areas are critical, requiring differentiated collaborative approaches [10]. Additionally, equitable distribution at disaster sites is prioritized [12], further enhancing the social benefits of emergency logistics.

The optimization of truck-drone collaborative delivery routes adapts to diverse scenarios, with its objectives and constraints exhibiting multi-dimensional characteristics that evolve from single-dimensional to comprehensive optimization. Early research primarily focused on single-objective minimization—such as minimizing weighted total cost [1], optimizing total collection costs [3], or shortening total delivery time [8]—which effectively addressed core requirements in specific contexts. As research progressed, multi-objective optimization became mainstream, better aligning with real-world logistics demands. Typical scenarios include: cost-time-customer satisfaction for fresh food delivery [2]; rescue satisfaction-path length for disaster relief [7]; logistics cost-deprivation cost for emergency support [11]; and cost-customer value-satisfaction for urban last-mile delivery [5].

To enhance the practical significance of research, scholars have introduced specialized objectives, such as incorporating psychological costs for disaster victims into the objective function [6], considering fairness in disaster-affected areas [12], and prioritizing corporate profit maximization [4], thereby aligning optimization goals with core scenario requirements. The design of constraints closely aligns with the characteristics of delivery tools and scenario limitations, forming three core constraint categories: First, physical constraints of the tools themselves, including drone payload capacity, flight range, speed, truck capacity, and travel speed [6,3,13], which serve as the foundational premise for collaborative model design; Second, scenario-specific constraints, such as road damage in disaster zones, risk classification in epidemic areas, and urban spatial limitations, which directly determine the feasibility of collaborative strategies [8,10,5]; Third, operational and customer constraints, including time windows, dynamic takeoff and landing of unmanned vehicles, and multi-trip restrictions, which are key to improving delivery service quality [1].

In summary, existing research has established a multi-scenario optimization framework for truck-drone collaborative delivery, clarifying target systems, constraint conditions, and algorithmic pathways. Particularly in emergency logistics, beneficial explorations of collaborative strategies for disaster scenarios have been conducted, laying a solid foundation for subsequent studies. However, considering the unique characteristics of urban flood disasters and the research objectives of this paper, existing achievements still exhibit significant adaptability gaps: First, most studies fail to precisely differentiate between waterlogged areas obstructed by trucks and urban-specific drone no-fly zones, making it difficult to meet delivery demands under

complex spatial constraints. Second, in multi-objective optimization, there is a lack of systematic consideration for the critical constraint of drone service radius. Third, there remains a gap in the design of vehicle-machine coordination logic for urban flood scenarios. Based on this, this paper focuses on emergency delivery scenarios for urban flood disasters. By integrating spatial zoning of restricted and no-fly zones with drone service radius constraints, it constructs a dual-objective mixed-integer linear programming model that minimizes both maximum delivery time and total costs. The core constraints and time synchronization rules for vehicle-machine coordination are clarified to fill the gap in adaptability of existing research for specific disaster scenarios, providing theoretical support and decision-making solutions for efficient and equitable distribution of emergency supplies during urban floods.

2. Problem Description and Analysis

2.1. Regional Limitation Analysis

Following urban flooding disasters, factors such as road collapses and waterlogging may cause partial road network failures. The traditional ground-based emergency supply distribution system struggles to cover all flooded areas. Meanwhile, due to dense buildings, electromagnetic interference, and airspace control regulations, drones cannot safely operate in certain urban zones. This makes relying solely on a single transportation method inadequate for meeting emergency distribution demands in complex disaster scenarios.

Against this backdrop, the truck-drone collaborative delivery model has emerged as a critical technical approach for urban emergency material distribution, combining the heavy-duty capacity of ground transportation with the agility and speed of aerial delivery. Focusing on flood disaster response logistics, this study investigates collaborative route optimization under regional waterlogging conditions, accounting φ_{ij} for spatial accessibility constraints between trucks and drones. To characterize the continuum of road network impacts transitioning from unimpeded to obstructed and ultimately disrupted during urban flooding, we introduce a road traffic coefficient that quantifies flood-induced capacity degradation. A coefficient of 1 indicates fully accessible roads with unaffected truck traffic; a coefficient of 0 signifies complete road failure (e.g., severe flooding or structural collapse); while coefficients below 1 represent varying degrees of restricted conditions (e.g., shallow water accumulation, localized congestion, reduced capacity), which proportionally diminishes effective truck speeds along affected routes. This framework aligns with the real-world scenario where flood events cause partial road network failure and impassable conditions in flooded areas.

Combined with the flood disaster scenario and urban spatial characteristics, the study area is divided into the following three functional areas:

Restricted Area:

An area where trucks are unable to access due to road collapse, severe water accumulation, or other reasons. Emergency supply distribution points within this area can only be reached via drone delivery, and trucks are prohibited from entering the flooded zone directly.

No-Fly Zone:

Designated as an area where drones are prohibited due to factors such as dense construction, electromagnetic interference, or airspace restrictions. Emergency supply points within this zone can only be delivered via trucks, and drones are not permitted to enter the airspace above the no-fly zone.

General area:

The zone permitting both truck passage and drone flight can function as a coordinated interface between them. Every node within the waterlogged area must have at least two non-congestion-avoiding curved connections to the outside, enabling trucks to access drones.

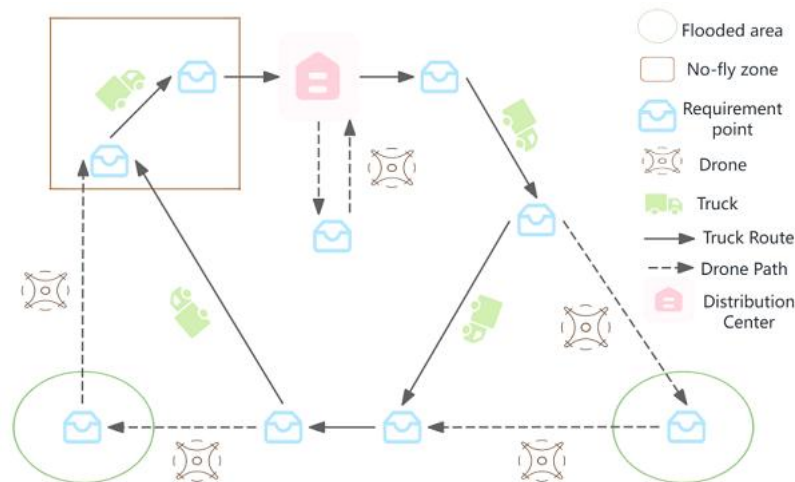


Figure 1. Schematic diagram of truck-drones end-to-end delivery routes considering regional constraints.

Assuming each drone can only serve one node per mission, every node within the flooded area must have at least two arcs connecting it to the outside that meet regional requirements. When the flooded area contains multiple nodes, drones are highly likely to take off and land directly from the distribution center. According to the model's constraints, each truck can only be equipped with one drone, and the number of truck routes must not exceed the actual number of trucks. Therefore, when all nodes are located within the flooded area, the total number of drone deployments cannot exceed the number of trucks (since each drone deployment corresponds to one truck deployment). This indicates that if the number of nodes in the flooded area exceeds the total number of trucks, the optimization problem will have no feasible solution. It should be noted that while standalone drones independent of trucks could be deployed for such scenarios, this situation falls outside the scope of this study.

Based on the spatial division, the public facilities with temporary shelter functions such as schools are selected as emergency material demand points. The geographical coordinates of each demand point are obtained based on the real data of the "7·20" rainstorm and flood disaster in Zhengzhou, and the material demand of each demand point is assumed to be known and indivisible.

2.2. Description of Graph Theory Problems

The Vehicle Routing Problem with Truck and Drone Considering Regional Restriction (VRP-TDR) can be formulated as a graph theory problem. Let $G=(V,A)$ be an undirected incomplete graph, where the node set $V=\{0,1,2,...,n\}$ and the arc set

$A = \{(i,j) | i,j \in V\}$. The node set V contains $n+1$ nodes, with node 0 representing the distribution center and the remaining nodes being customers, denoted $V_C = \{1, 2, \dots, n\}$. Define $AT \subseteq A$ as the arc set permitted for trucks, and $AD \subseteq A$ as the arc set permitted for drones. For any edge (i,j) in AT , assign a non-negative weight to represent the distance from node i to node j for the truck; for any edge (i,j) in AD , assign a non-negative weight to represent the distance from node i to node j for the drone. Introduce a road capacity coefficient in AT to quantify the reduction in passage capacity of the arc (i,j) due to flooding. The distribution center is equipped with multiple identical delivery trucks, each carrying a corresponding drone. The trucks have maximum payload capacities GT and maximum driving ranges LT , while the drones have maximum payload capacities GD and maximum single-mission flight distances LD .

3. Model Construction

3.1. Model Symbol Explanation

Table 1. Symbol Description.

Symbol Type	Symbolic Representation	Symbol Description
gather	$V_C = \{1, 2, \dots, n\}$	Set of all requirement points
	V_0	DC
	V_T	All trucks are assembled.
superscript	$i, j, k \in V$	Node label
	$t, t' \in V_t$	Truck Numbering
parameter	GT	maximum load capacity of truck
	LT	maximum driving distance of truck
	GD	maximum payload of UAV
	LD	Maximum flight distance of UAV in a single sortie
	$gt_{ij}(=1)$	The path from node i to node j does not pass through the truck waterlogged area.
	$gd_{ij}(=1)$	The path from node i to node j does not pass through the drone no-fly zone.
	VT	truck speed
	VD	drone flight speed
	ct_{ij}	The truck travel distance from node i to node j
	cd_{ij}	The flight distance of a drone from node i to node j
	C_t	unit distance vehicle transportation cost
	C_d	Unit distance UAV transportation cost
	C_1	vehicle start-up cost
	ω_1	Weight coefficient of time target (timeliness of disaster relief)
	ω_2	Weight coefficient of cost objective (economy)
	C_2	drone start-up cost
	d_i	Customer i 's demand for goods
	ϕ_{ij}	traffic flow coefficient
	M	A sufficiently large positive integer
bivariate	x_{ij}^t	The truck t travels from node i to node j .
	z_{ikj}^t	The truck t carries a drone that departs from node i to deliver goods to customer k and returns at node j .

	u_i^t	Customer i's goods are delivered by truck t.
	v_i^t	Customer i's goods are delivered by a drone carried on truck t.
	$T_{truck_0^t}$	Time when truck t arrives at node i

3.2. Model Assumptions

(1) Each truck can carry one drone, and each drone can only visit one customer at a time.

(2) When the UAV is launched and retrieved at the node, if the UAV arrives at the retrieval node later than the truck, the truck must wait for the UAV to arrive before it can proceed again;

(3) During each drone deployment, the truck continues its journey, and the drone can rendezvous for recovery at subsequent nodes.

(4) Drones can either depart from the distribution center or return to it independently.

(5) Drones and trucks cannot revisit any customer nodes;

(6) Sub-circuits are prohibited in drone flight paths, while trucks are not allowed to form sub-circuits at customer nodes. Each truck may have up to one sub-circuit in the distribution center.

(7) Both the drone and the truck maintained a constant speed, with the drone outpacing the truck.

(8) The drone's flight duration is fixed, with a maximum safe service radius R from the distribution center, and the effects of flight speed and cargo load on the drone's endurance are not considered.

(9) Ignoring both the drone's charging duration and the loading/unloading time between the drone and the truck;

(10) Drones are prohibited from entering no-fly zones, and trucks must avoid flooded areas.

(11) When the distance between the d_{0k} water accumulation point k and the distribution center is $\leq R$, the drone may take off directly from the distribution center to execute the task and return. In this mode, according to the coordination constraints, the truck must wait or load/unload at the distribution center to maintain coordination consistency.

(12) When the distance between demand d_{0k} point k and the distribution center exceeds R , drones are strictly prohibited from taking off directly from the distribution center to serve this point. Instead, they must be transported by trucks to nodes within the service radius for collaborative delivery, or delivered directly by trucks via ground transportation.

(13) Emergency distribution aims to maximize fairness by minimizing the maximum completion time, rather than focusing on the shortest total driving distance.

(14) Within a single scheduling cycle, the flood inundation area and meteorological conditions remain stable, with no secondary disasters or extreme weather disturbances.

3.3. Model Formula

The mixed integer linear programming model constructed in this paper mainly includes the objective function, the routing constraints and the time synchronization constraints, and the specific formulas are as follows:

$$\min F = \omega_1 F_1 + \omega_2 F_2 \quad (1)$$

$$\min F_1 = \max \{T_{truck_i} \mid t \in V_t\} \quad (2)$$

$$\min F_2 = \sum_t x_t C_1 + \sum_{i,j} x_j^t C_t c t_{ij} + \sum_d x_d C_2 + \sum_{i,j} x_j^d C_d c d_{ij} \quad (3)$$

s.t.

$$u_i^s = \sum_{\forall j \in V_C} (x_{ij}^s + x_{ji}^s), \forall i \in V_C, \forall s \in V_S \quad (4)$$

$$v_k^t = \sum_{\forall i \in V'} \sum_{\forall j \in V'} Z_{ikj}^t, \forall t \in V_t \quad (5)$$

$$\sum_{v_i \in V_C} (u_i^t + v_i^t) = 1, i \in V \quad (6)$$

$$\sum_{j \in V'} x_{0j}^t = \sum_{j \in V'} x_{j0}^t \leq 1, \forall t \in V_t \quad (7)$$

$$\sum_{j \in V'} x_{ji}^t = \sum_{j \in V'} x_{ij}^t = u_i^t, \forall i \in V, \forall t \in V_t \quad (8)$$

$$\sum_{i \in V'} \sum_{j \in V'} z_{ij}^{t,k} \leq 1, \forall k \in V_C, \forall t \in V_t \quad (9)$$

$$z_{ij}^{t,k} \leq 1, \forall i, j, k \in V, \forall t \in V_t \quad (10)$$

$$x_{ij}^t \leq g t_{ij}, \forall i \in V, \forall j \in V, \forall t \in V_t, \quad g t_{ij} = \begin{cases} 1, & \phi_{ij} > 0 \\ 0, & \phi_{ij} = 0 \end{cases} \quad (11)$$

$$z_{ij}^{t,k} \leq 0.5(g d_k + g d_j), \forall i \in V, \forall j \in V, \forall k \in V_C, \forall t \in V_t \quad (12)$$

$$x_{ij}^t \geq z_{ij}^{t,k}, \forall i \in V, \forall j \in V, \forall k \in V, \forall t \in V_t \quad (13)$$

$$\sum_{\forall i \in V_C} d_i u_i^t + \sum_{\forall i \in V_C} d_i v_i^t \leq G T, \forall t \in V_t \quad (14)$$

$$d_i v_i^t \leq G D, \forall i \in V_C, \forall t \in V_t \quad (15)$$

$$\sum_{\forall i \in V'} \sum_{\forall j \in V'} c t_{ij} x_{ij}^t \leq L T, \forall t \in V_t \quad (16)$$

$$(c d_{ik} + c d_{kj}) z_{ij}^{t,k} \leq L D, \forall t \in V_t \quad (17)$$

$$z_{0k0}^t = 0, \forall t \in V_t, \forall k \in \{v \in V_C \mid c_{0v}^d > R\} \quad (18)$$

$$t_{Truck_i^t} > \frac{c_{0i}}{V_T \phi_{ij}} M (1 - x_{0i}^t), \forall i \in V_C, \forall t \in V_t \quad (19)$$

$$t_{Truck_i^t} \geq \frac{cd_{0k} + cd_{ki}}{VD} M (1 - z_{0k}^t), \forall k \in V_C, \forall i \in V_C, \forall t \in V_t \quad (20)$$

$$t_{Truck_j^t} \geq t_{Truck_i^t} + \frac{cl_{ij}}{V_T \Phi_{ij}} M (1 - x_{ij}^t), \forall i \in V_C, \forall j \in V, \forall t \in V_t \quad (21)$$

$$x_{ij}^t, z_{ij}^{t,k}, u_i^t, v_i^t \in \{0,1\}, t_{Truck_i^t} \geq 0 \quad (22)$$

Formula (1) represents the dual objective function; Formula (2) minimizes the maximum delivery time to characterize fairness maximization; Formula (3) represents total cost minimization; Formulas $u_i^s v_i^s z_{0k}^t u_k^t = 1 \neq 0 z_{ikj}^t c_{0k}^d \leq R$ (4) and (5) establish relationships between decision variables, where defining variables can significantly simplify the model; Formula (6) states that each customer can only be served once, meaning the total delivery attempts by drones and trucks to the same customer must equal 1; Formula (7) specifies that trucks must depart from and return to the center; Formula (8) mandates that all nodes must be exited upon entry; Formulas (9) and (10) indicate that each customer can be served by drones at most once; Formula (11) ensures truck routes avoid flooded areas; Formula (12) prohibits drone flight paths through no-fly zones; Formula (13) restricts drone operations to two consecutive nodes served by trucks (with takeoff preceding landing) while limiting each drone's service to one customer; Formulas (14), (15), and (16) respectively represent truck load capacity, drone payload capacity, and drone endurance constraints; Formula (17) imposes flight distance constraints on drones; Formula (18) mandates that for any customer node k beyond the distribution center's radius, the decision variable (i.e., drone launching from 0, serving k , and returning to 0) must be forcibly set to 0. This forces the model to choose between two scenarios: trucks delivering directly to () or trucks launching drones at intermediate points i ($i = 1$). Conversely, if the constraint is not enforced, the model may freely decide whether to have the drone fly directly from the distribution center for delivery (depending on whether it is more time-efficient than truck delivery). Formula (19) states that the truck's arrival at the first customer node i cannot precede its travel time from the distribution center to i . Formula (20) specifies that if the drone departs from the distribution center, the truck's arrival at i cannot precede the drone's return time to i . Formula (21) indicates that the truck's arrival at node j cannot precede its travel time from the previous node i to node j . Formula (22) defines the variables.

3.3. Definition of Two Modes (TS/TC)

To evaluate the effectiveness of the proposed Collaboration (TC) mechanism, this study constructs a Truck-Support (TS) model within a unified modeling framework. Both models are identical in terms of customer sets, demand, vehicle/drone parameters, and cost structures, with the sole distinction being whether trucks must wait during drone missions and whether cross-node drone recovery is permitted. This design enables the isolation of marginal benefits derived from the collaboration mechanism.

TS (Support): Enables drones to take off from the truck's current location to serve customers and return to the original takeoff point for recovery. The truck must wait for the drone to return before proceeding.

TC (Collaboration, proposed in this paper): This system allows trucks to continue driving while drones are performing tasks, with drones meeting trucks at subsequent nodes for recovery, enabling ground-air parallel operation.

The comparison between TS and TC further isolates the gains from the 'wait-free, cross-node rendezvous' collaborative mechanism, which is the focus of this comparative analysis.

In TS mode, drone missions must return to their original release point for recovery, i.e., $k=i$. To implement the truck's on-site support mechanism, a synchronous waiting constraint must be added:

$$t_{dep(i)}^T \geq t_{arr(i)}^D \quad (23)$$

This constraint prevents the truck from proceeding to the next node during the drone's flight, directly increasing the total completion time. In the TC mode, the drone permits cross-node retrieval, where the pickup point k may be a subsequent access node. To ensure retrievable operations, a rendezvous constraint must be introduced, enabling the drone to complete retrieval with the truck upon arrival at the pickup node.

$$t_{arr(k)}^T \geq t_{arr(k)}^D \quad (24)$$

This mechanism enables trucks to continue moving during drone flights, enabling ground-air parallel operations. Compared to TS, TC's primary advantages lie in reducing truck waiting time and offering more flexible selection of recovery nodes.

4. Model Solving

4.1. HGA-GCD algorithm

This study employs the HGA-GCD algorithm to solve the model. The hybrid genetic algorithm based on greedy collaborative decoding is a hybrid optimization algorithm that combines the global search capability of genetic algorithms with the local optimization advantages of greedy collaborative decoding. Its core mechanism enhances solution quality and convergence efficiency through greedy collaborative decoding during the decoding phase, making it suitable for complex problems such as combinatorial optimization and path planning, particularly excelling in scenarios with multiple constraints and large solution spaces. The algorithm first sets parameters and randomly generates the first generation of chromosomes (integer-encoded sequences). The greedy collaborative decoding (GCD) and fitness evaluation form the core components. Both the initial population and subsequent offspring require this step to convert chromosomes (sequences) into practical collaborative paths for trucks and drones. This process includes customer classification, constructing truck routes based on greedy strategies, attempting to insert drone tasks to reduce costs and time, and finally calculating two objective function values (total cost and maximum completion time). Genetic operations: These include standard selection, crossover (e.g., OX sequence crossover), and mutation (e.g., exchange mutation) to generate new potential solutions. Local search (VNS): To overcome the poor local development capability of genetic algorithms, variable neighborhood search (VNS) is introduced. This involves applying small-scale perturbations (e.g., 2-opt, swap, relocate operators) to excellent solutions, aiming to find better neighboring solutions. Population Update: An elite strategy is employed to cross-fertilize parent and newly generated offspring, selecting

the top N individuals for the next generation to ensure continuous improvement in population quality.

4.2. Improved HGA-GCD Algorithm

To address stringent constraints in urban flood emergency distribution—including restricted traffic in flooded areas, flight bans in no-fly zones, and drone safety service radius limitations—this study proposes a region-restricted and fairness-oriented multi-objective hybrid genetic algorithm (MO-RHGA-GCD) based on the HGA-GCD framework.

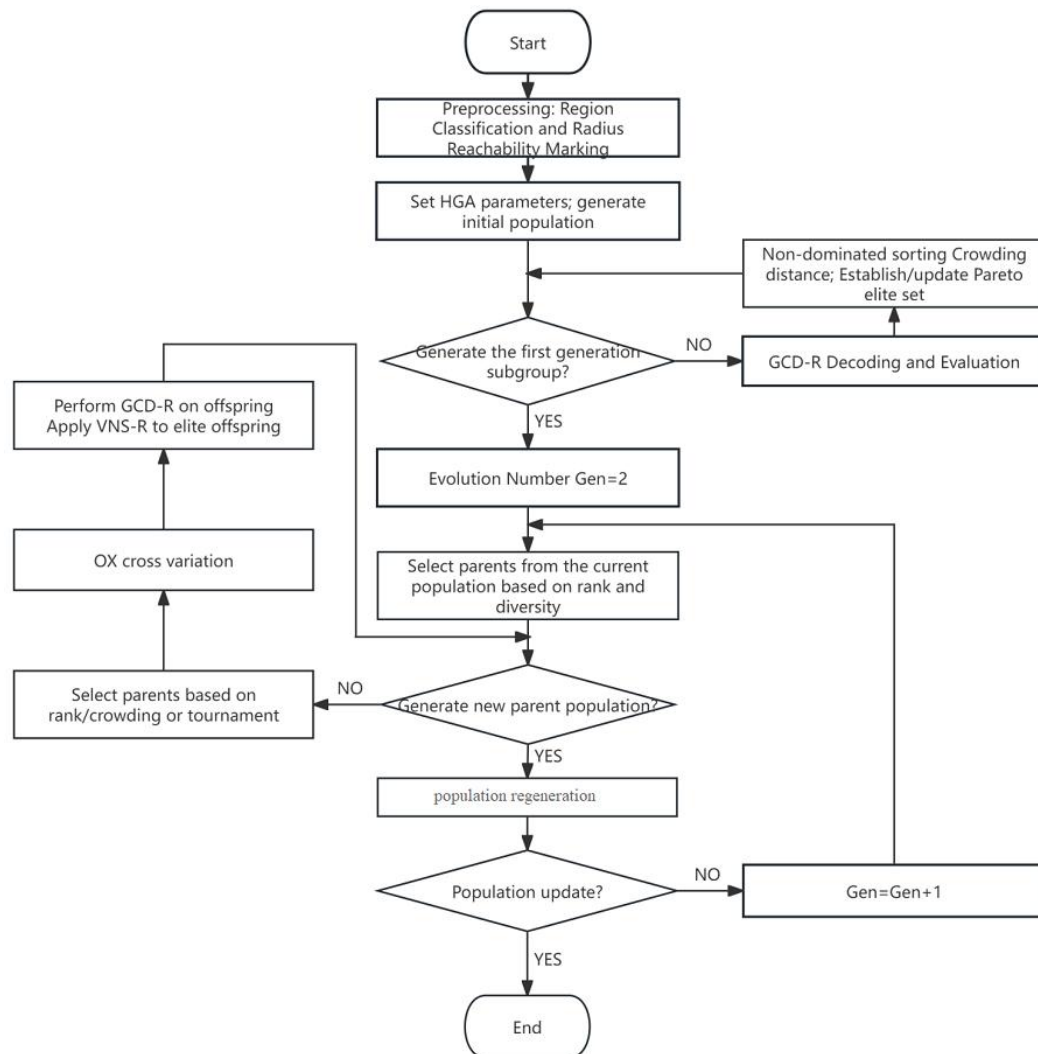


Figure 2. Flowchart of the Improved HGA-GCD Algorithm.

The upper layer employs NSGA-II for multi-objective evolutionary search within customer access priority and collaborative strategy spaces, while the lower layer designs a region-restricted greedy collaborative decoder (GCD-R) to map chromosomes into feasible collaborative paths satisfying regional accessibility, radius, and vehicle-machine synchronization rules. Through sequential simulation, the algorithm calculates dual objectives: “maximum arrival/completion time (fairness) versus total cost.” During decoding, customers in no-fly zones are assigned to truck services, while those in flooded areas are assigned to drone services. For customers exceeding R distance from distribution centers, drone direct flights are prohibited, requiring truck relays or direct truck deliveries. To characterize the differences

between TS (truck service) and TC (truck collaboration) mechanisms, the decoder uniformly models drone recovery rules and truck waiting logic: under TS, drones must return to original launch points with trucks waiting; under TC, cross-node rendezvous recovery and ground-air parallel operations are permitted. To enhance local development capabilities, the algorithm incorporates a joint neighborhood VNS that simultaneously perturbs and real-time repairs truck routing structures and drone launch/recovery points, thereby obtaining a well-distributed, high-quality Pareto approximate optimal solution set under strict constraints. The specific algorithm flow is illustrated in Figure 2.

5. Case Analysis

5.1. Relevant Geographic Data

From July 17 to 23, 2021, Henan Province was hit by an unprecedented torrential rainstorm, with Zhengzhou at its epicenter. Dubbed the "July 20 Zhengzhou Super Flood," this disaster became a landmark case in China's emergency management of urban flooding, characterized by extreme severity, complex response challenges, and far-reaching social impacts. Official reports revealed 1.8849 million affected residents, 292 fatalities, and direct economic losses totaling 53.2 billion yuan. Over 10,000 municipal roads and arterial highways were damaged, while 143 reservoirs exceeded flood levels, with multiple levees and dams at risk of breaching. The Jingguang Expressway tunnel was flooded, trapping over 200 vehicles, and the collapse of a water barrier wall on Subway Line 5 forced trains to stop, leaving 500+ passengers stranded and 14 dead. Designated as a liability incident, it exposed critical gaps in emergency preparedness and infrastructure. In response, the State Council formed a special investigation team, issued a report with rectification requirements, and accelerated upgrades to urban flood control, drainage, and emergency management systems nationwide.



Figure 3. Distribution map of water accumulation areas.

Based on practical considerations, the flood-prone zones utilize data from the National Earth System Science Data Center, while the no-fly zones are based on actual controlled areas. The coordinates are obtained through Python calls to the AutoNavi Map API, with the spatial distribution of heavy rainwater accumulation shown in Figure 3.

5.2. Parameter Settings

This study employs medium-sized compound-wing drones, a standard equipment in emergency logistics, with transport parameters specified in Table 2. The algorithm parameters are configured as follows: 40 demand points are randomly generated based on Zhengzhou's urban density data from the Seventh National Population Census, each with demand values ranging from 80 to 300.

Table 2. Transport vehicle parameters.

parameter	short-cut process
truck speed	60km/h
drone flight speed	80km/h
Truck load capacity per unit	2000 kg
UAV payload per unit	200 kg
Truck fuel consumption per yuan/km	4.5
Power consumption per yuan/km for drones	1.2
fixed cost of truck	800
fixed cost of UAV	300
Maximum flight radius of UAV/km	30km

5.3. Result Analysis

To validate the model's effectiveness, this study performed TS and TC model simulations on the same dataset, comparing their Pareto solution sets and path structures of typical optimal solutions under dual-objective criteria. To minimize randomization effects, each experimental group was independently run multiple times under identical parameters, with optimal values and statistical results documented. The TC model achieved a Pareto frontier solution set after 300 iterations, as illustrated in Figure 4 and Figure 5.

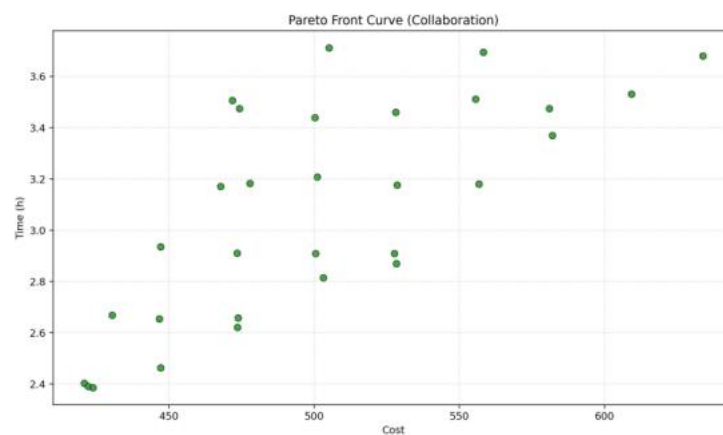


Figure 4. Pareto frontier solution of TC mode.

Figure 5 demonstrates that the TC model outperforms both T and TS models in achieving both total cost and maximum completion time objectives. Specifically, the TC model significantly reduces overall delivery time by enabling cross-node drone recovery and allowing trucks to continue operating during drone missions, while optimizing resource utilization efficiency to lower operational costs. Furthermore, comparative analysis of path structures across different models reveals that the TC model enables more flexible task allocation, reduces truck idling rates and waiting times, thereby enhancing the overall efficiency of collaborative delivery.

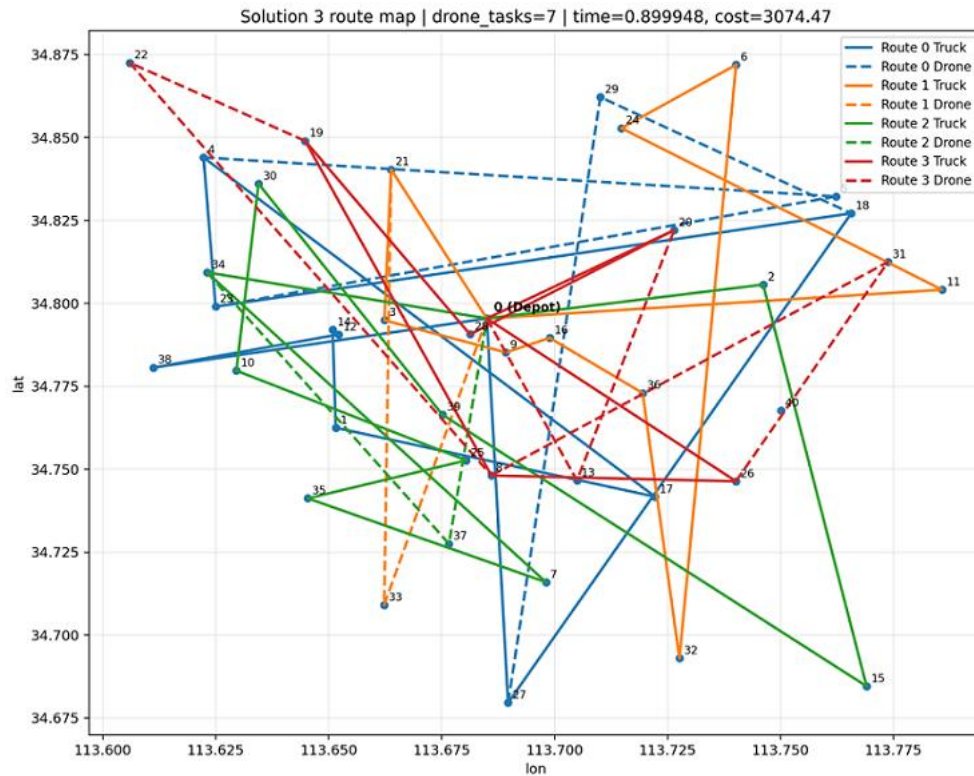


Figure 5. Path diagram of the optimal solution for TC mode.

The experimental results further demonstrate that the TC model exhibits greater advantages as the number of distribution nodes increases. For instance, in a scenario with 40 demand points, the TC model achieves approximately 15% shorter maximum completion time and nearly 28% lower total costs compared to the TS model. This improvement is primarily attributed to the effective implementation of the ground-air parallel operation mechanism, which enhances the delivery system's adaptability and robustness in complex geographical environments. Meanwhile, the T model, which relies entirely on trucks for task completion, demonstrates significantly higher maximum completion time and total costs than the other two models.

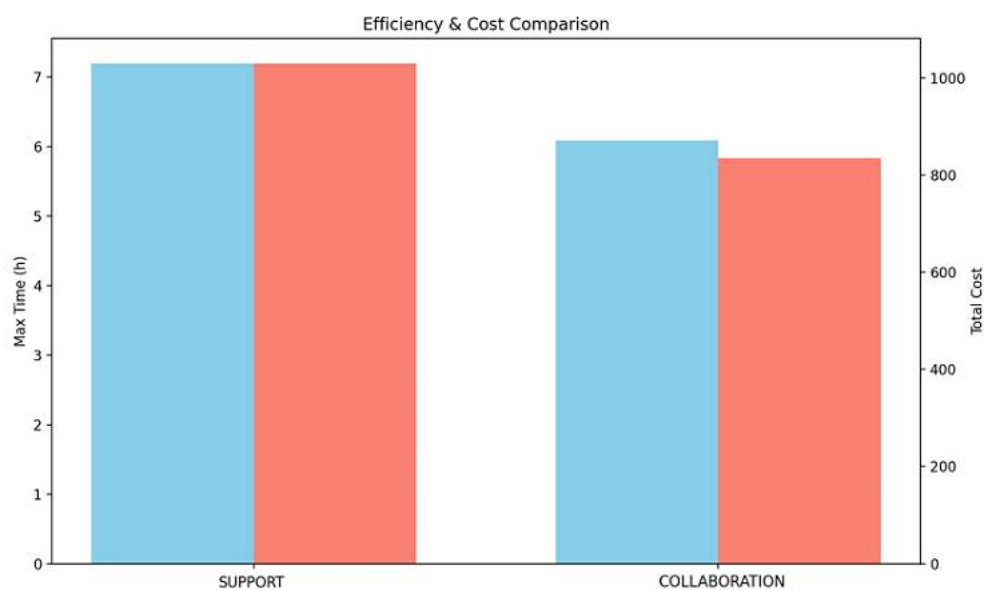


Figure 6. Comparison of Dual Objectives for Optimal Solution.

To further validate the model's stability and algorithm performance, this study conducted statistical analysis on results from multiple independent runs. The findings demonstrate that the improved HGA-GCD algorithm achieves high-quality solution sets with remarkable convergence speed and consistent solution quality, as shown in Figure 7. This indicates the algorithm not only possesses strong global search capabilities but also effectively avoids local optima through its local search strategy. Overall, the TC model combined with the improved algorithm provides reliable technical support for solving complex constraint problems in urban flood emergency distribution, showcasing promising application prospects.

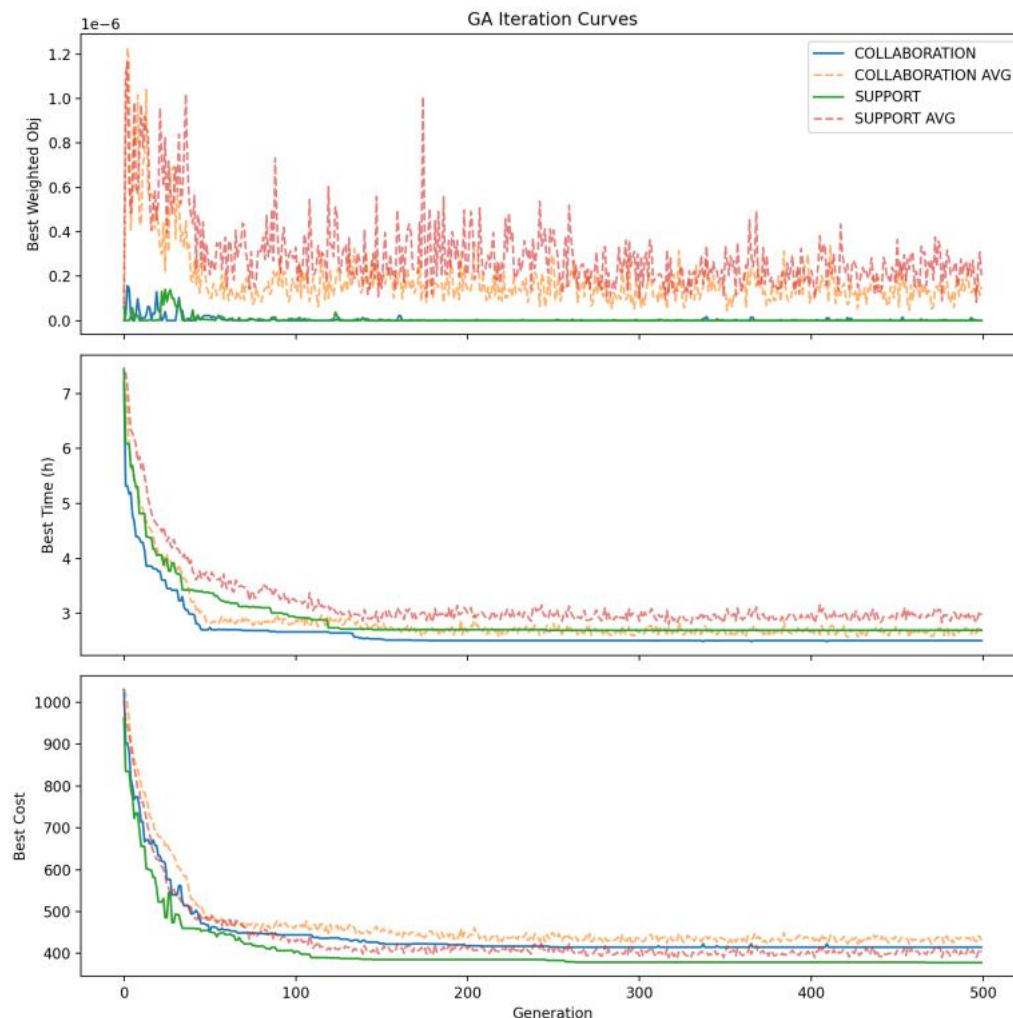


Figure 7. Convergence Curve of the Algorithm.

6. Conclusion and Prospects

This study addresses urban flood emergency distribution challenges by constructing a truck-drone collaborative path optimization model with regional constraints. It tackles practical constraints such as vehicle restrictions caused by road flooding and drone flight bans due to urban airspace control. By categorizing distribution areas into flooded zones, no-fly zones, and standard zones, the model captures spatial accessibility differences between trucks and drones. Incorporating drone safety service radius constraints and vehicle-machine time synchronization rules, it establishes a dual-objective mixed-integer linear programming framework with “maximum fairness (minimizing maximum arrival/completion time)” and “total cost

minimization” objectives. This provides a computable decision-making framework for efficient and equitable emergency distribution during flood disasters. To highlight the synergistic mechanism’s efficiency gains, the study compares two modes under a unified framework: the truck-stationary support (TS) mode and the cross-node rendezvous-recovery (TC) mode. It elucidates how TC reduces completion time and improves resource utilization through “eliminating waiting and enabling ground-air parallel operation.” For solution methods, a region-constrained fairness-oriented multi-objective hybrid genetic algorithm is proposed: the upper layer employs NSGA-II for multi-objective evolutionary search, while the lower layer designs a region-constrained greedy collaborative decoder to map chromosomes into feasible collaborative paths satisfying accessibility, radius, and synchronization constraints. Embedded with a joint neighborhood VNS to enhance local development capabilities, this approach achieves well-distributed, high-quality Pareto approximate solution sets under strict constraints. The results of the example show that TC mode is better than TS mode in both total cost and maximum completion time under the given experimental setting. In 40 scenarios of demand points, the maximum completion time and total cost of TC mode are significantly lower than those of TS mode, which verifies the effectiveness of the model, the cooperation mechanism and the improved algorithm.

For future research, the following directions can be further expanded and refined: (1) Addressing more realistic disaster evolution processes by incorporating temporal variability and uncertainty in water accumulation areas and no-fly zones, establishing stochastic/robust optimization or rolling temporal domain re-optimization mechanisms to enhance solution applicability under dynamic disaster scenarios; (2) At the operational modeling level, further considering time consumption factors such as cargo loading/unloading, drone power replenishment/charging, and takeoff/landing preparations, as well as time-varying road networks with traffic speed changes due to congestion or water depth variations, thereby improving the model's accuracy in depicting real emergency dispatch processes; (3) At the system configuration level, expanding to multi-distribution centers, diverse drone/vehicle types, and more general collaborative systems like “multi-drone per vehicle,” while studying fairness-cost trade-off patterns under different resource allocations; (4) At the algorithmic level, introducing stronger feasibility repair and acceleration evaluation strategies (e.g., segmented evaluation, incremental simulation, learning-based neighborhood selection) to further improve convergence speed and solution set stability under large-scale instances; (5) Conducting multi-scenario comparisons and sensitivity analyses using real urban road and airspace control data to develop parameter recommendations and decision support tools directly applicable to emergency management departments.

Conflicts of Interest

The author declares that there is no conflict of interest regarding the publication of this article.

Funding

This research received no specific grant from any funding agency in the public, commercial or not-for-profit sectors.

References

- [1] Li, Y.; Luo X.R.; Yin, X.R. et al. Optimization of truck-drone collaborative delivery routes considering dynamic synchronization. *Journal of South China University of Technology (Natural Science Edition)*, 2026; pp. 1-11.
- [2] Li, J.T.; Zhou, X.D.; Jiang, J.J. et al. Multi-objective optimization of truck-drone collaborative delivery for fresh produce. *Complex Systems and Complexity Science*, 2026; pp. 1-11.
- [3] Fu, Z.H.; Li, J.Y.; Liu, C.S. Joint truck-drones cargo collection path planning for mountainous fresh produce logistics. *Computer Engineering and Applications*, 2025, 61(14), 332-342.
- [4] Luo, Y.Q.; Chen, Y.R.; Ran, M.L. Multi-trip truck-drones collaborative delivery with revenue and time window. *Control and Decision*, 2025, 40(06), 1817-1826.
- [5] Li, Y.C.; Mou Haibo, Yuan Meng, et al. Multi-objective optimization of truck-drone joint delivery under regional constraints. *Journal of Shenzhen University (Science and Engineering Edition)*, 2025, 42(02), 205-215.
- [6] Cao, Y.C.; Zhai, Y.B.; Geng, S.Q. Research on Post-Earthquake Truck-Drone Collaborative Delivery Path Optimization Considering Disaster Victims' Psychological Factors. *Journal of Safety and Environment*, 2025, 25(12), 4787-4798.
- [7] Liu, Y.; Chen, Z.; Ma, L. Multi-objective collaborative scheduling and optimization algorithm for truck-drones in earthquake emergency rescue. *Computer Application Research*, 2025, 42(12), 3660-3667.
- [8] Zhang, K.Y.; Shi, Y.; Guo, H.X. et al. Research on optimization decision-making of emergency material dispatch for mountainous natural disasters based on truck-drone coordination. *China Management Science*, 2025, 33(02), 150-160.
- [9] Gong, Y.; Tu, M.; Zhou, Y. Robust optimization for emergency site selection and path planning in flood disaster response with truck-drone coordination. *Computer Engineering and Applications*, 2025, 61(14), 307-321.
- [10] Liu, C.S.; Wu, Z.; Zhou, Y.F. et al. Optimization of dynamic collaborative delivery routes for unmanned trucks in emergency material supply in epidemic areas. *Systems Science and Mathematics*, 2022, 42(11), 3027-3043.
- [11] Zhang, L.J.; Ding, Y. Optimization of dual-target emergency material delivery based on truck-drone collaborative distribution. *Journal of Systems Management*, 2025, 34(01), 81-95.
- [12] Han, J.; Liu, Y.Q. Research on Cooperative Delivery Path Optimization for Trucks Considering Road Damage and Fairness. *Operations Research and Management*, 2025, 34(06), 55-62.
- [13] Zhen, L.; Gao, J.J.; Tan, Z.Y. Research on Multi-Truck and Multi-Drone Collaborative Delivery Path Optimization Problem. *Journal of Management Science*, 2024, 27(07), 1-18.



© 2026 by the author(s); licensee International Technology and Science Publications (ITS), this work for open access publication is under the Creative Commons Attribution International License (CC BY 4.0). (<http://creativecommons.org/licenses/by/4.0/>)