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Two-Level Location-Routing Optimization for Truck-Drone Emergency Logistics with Road Reliability and Time Windows

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Abstract: After sudden disasters, emergency material distribution must satisfy strict timeliness requirements under disrupted road conditions. Truck-only delivery is vulnerable to road damage, while drone-only delivery is limited by payload and endurance; therefore, truck-drone collaboration provides a practical alternative. This paper studies a two-level location-routing optimization problem for emergency logistics in which candidate distribution centers are selected and truck-drone collaborative routes are planned under payload constraints, coordination time constraints, hard time windows, road reliability, and distribution-center failure risk. A mixed-integer programming model is formulated to minimize a weighted objective combining demand coverage and total distribution time. To solve medium-scale instances efficiently, a simulated annealing algorithm is developed with problem-specific encoding/decoding, neighbourhood operators (route reversal, truck-drone service swap, and location fine-tuning), and an adaptive temperature control strategy. Computational experiments based on the Zhengzhou "July 20" flood scenario and instances with 15, 25, and 50 demand points show that the algorithm consistently returns feasible solutions within short CPU times, while sensitivity analysis on drone speed, drone payload, and road reliability quantifies their impacts on completion time and coverage. The proposed model and heuristic provide an implementable decision tool for rapid planning of truck-drone emergency distribution under reliability and time-window constraints.

Keywords: distribution-center disruption; emergency logistics; truck-drone collaboration; mixed-integer programming; road reliability; simulated annealing; two-echelon location-routing problem; time windows

1 INTRODUCTION

Against the backdrop of rapid socio-economic development and continuous growth in population density, natural disasters such as floods and earthquakes occur frequently, and they are prone to triggering secondary disasters like landslides and mudslides. These disasters not only pose a severe threat to people's lives and property safety but also often lead to the paralysis of ground transportation, making the timely supply of emergency materials a key part of disaster relief work. As a core link in ensuring the delivery of materials, the efficient operation of emergency logistics is directly related to the efficiency and effectiveness of disaster rescue. Therefore, the importance of emergency logistics has become increasingly prominent and has also received high attention from national policies. In July 2022, the Chinese National Disaster Reduction Commission issued the 14th Five-Year Plan for National Comprehensive Disaster Prevention and Mitigation, which clearly proposed to improve and perfect the aviation emergency rescue system to provide policy support for emergency material transportation.

Different from traditional ground transportation methods, drones are not restricted by topographical conditions and can reach disaster-stricken areas that are difficult for human resources to access. Especially when ground transportation is interrupted due to disasters, drone delivery can achieve fast, timely and accurate delivery of emergency materials, effectively making up for the shortcomings of ground transportation. At the same time, the national plan also clearly emphasizes the need to strengthen the research, development and application promotion of equipment such as plateau-type large-load drones and aerial hoisting equipment for large-scale devices in complex plateau terrain, further highlighting the important role of drones in emergency rescue.

However, relying solely on drones or traditional truck transportation has its limitations: although drones can overcome topographical obstacles, they are restricted by load capacity and endurance, making it difficult for them to undertake large-scale and long-distance material transportation tasks; although trucks have a large load capacity, they are easily affected by road damage caused by disasters and cannot reach some disaster-stricken areas directly. Therefore, in order to achieve efficient coordination in emergency material transportation and give full play to the respective advantages of drones and trucks, the problem of distribution center location and route planning for truck-drone collaborative emergency logistics has emerged. Reasonable distribution center location can provide an efficient transfer hub for the two transportation methods, and scientific route planning can optimize the transportation process of materials from distribution centers to the frontline of disaster relief, thereby improving the response speed and operation efficiency of the overall emergency logistics system. This has become an important issue that needs to be studied and solved urgently in the current field of emergency logistics.

2 LITERATURE REVIEW

2.1 Emergency Logistics

Location and route planning are crucial components of emergency logistics management. The rationality of the former directly affects the efficiency of the latter, while the efficiency of the latter, in turn, influences the decision-making of the former. The two are complementary and play a decisive role in the effectiveness of emergency logistics management. Wang and Ma (2011) conducted an in-depth analysis of the emergency logistics system, established a material scheduling model for the emergency logistics system, and studied location and route planning models for different types of disasters. Li et al. (2013) took the uncertainty of emergency demand into account and analyzed how to maximize the satisfaction degree of emergency materials while ensuring the optimal efficiency of emergency material transportation. Zheng et al. (2017) analyzed the emergency logistics network system under

post-disaster material shortage, considered different levels of demand urgency, and comprehensively factored in material transportation time satisfaction and distribution fairness to construct a location and route planning model. Zhu et al. (2018) considered the heterogeneity of disaster-stricken areas based on different material demands and comprehensively addressed the material distribution problem by balancing response time and total cost.

In terms of joint optimization algorithms for emergency logistics location and route planning: Najafi et al. (2014) developed a dynamic model for vehicle scheduling and route optimization targeting sudden incidents such as earthquakes. This model can receive updated information in real time and adjust plans accordingly. Ahmadi-Javid and Seddighi (2013) explored the location-routing problem in supply chain networks that might cause product disruptions. Trivedi and Singh (2016) established an LRP model to minimize distance, risk, the number of warehouses, and unmet material demand. The model also fully considered constraints related to demand, capacity, utilization, and budget, and maximized suitability to identify the optimal shelter locations and material distribution plans for post-disaster recovery projects. Huali et al. (2021) classified post-disaster casualties into two levels: mild and severe. They used the increase in injury severity scores to reflect the deterioration of casualties' conditions over time, thereby improving the performance of medical services. Meanwhile, they constructed an emergency logistics location and route planning optimization model to address the uncertainty of the number of disaster victims. Chang et al. (2022) proposed the location of distribution centers based on Fuzzy Correlation (FC) and the assignment of retailers and customers in LRP. Gao et al. (2016) put forward a K-means Ant Colony Optimization (KACO) algorithm with three migration schemes to solve the dynamic location and route planning problem. Bashiri et al. (2016) suggested that auxiliary vehicles could be added to the transportation system as an alternative strategy to compensate for capacity limitations. Hemmelmayr (2015) used a large Neighborhood Search (LNS) algorithm, which can effectively solve the Periodic Location-Routing Problem (PLRP). Roghanian et al. (2021) propose a two-stage robust stochastic location-routing-inventory model to jointly optimize facility location and operational decisions for goods requiring rapid delivery under demand uncertainty, while enhancing solution stability by controlling variability.

2.2 Vehicle-Drone Collaboration

In the "vehicle + drone" last-mile delivery mode, regarding the optimal routing problem of drones and trucks, several domestic and international studies have proposed a new delivery model. This model incorporates the classic vehicle routing problem (VRP) into last-mile drone delivery, where drones and vehicles collaborate to fulfil deliveries. It effectively reduces labour dependence while compensating for the limitation of drones in terms of sustainability when used for delivery alone. Waleed et al. (2023) were the first to integrate the tandem delivery of trucks and drones into VRP. Luo et al. (2023) studied the multi-objective truck-drone collaborative VRP. Gao et al. (2023) proposed a scheduling decision method for trucks and drones to collaborate in delivery and pickup operations. During emergency material delivery in epidemic-stricken areas or disaster zones, some road sections may be inaccessible to vehicles or drones due to road damage, blockades, or regional contamination. To address such scenarios, Yan et al. (2022) constructed a mixed-integer linear programming model for the truck-mounted drone VRP under regional constraints.

In terms of joint delivery by multi-type heterogeneous drones and trucks: Wen and Wu (2022) proposed a new logistics delivery problem using multiple heterogeneous drones. In this approach, large drones transport multiple small drones to the delivery area, while the large drones themselves do not participate in delivery. Francesco et al. (2022) introduced the problem of scheduling conflicting deliveries based on the joint delivery of drones and trucks. The goal is to find a schedule for drones that maximizes their battery capacity while ensuring that the delivery tasks performed by the same drone do not have overlapping intervals. The authors designed an integer linear programming model, and separately developed a pseudo-polynomial time optimization algorithm for the single-drone scenario, as well as additional approximation algorithms for both single-drone and multi-drone scenarios. Hongqi et al. (2021) addressed the issue of how to coordinate trucks and drones, especially under uncertain traffic conditions. They proposed and solved the truck-drone hybrid routing problem with time-dependent road travel times, and put forward an iterative local search heuristic algorithm based on internal and external customer exchanges and arc re-optimization. Andrea et al. (2022) evaluated the environmental and economic sustainability of a last-mile delivery solution involving electric trucks equipped with drones, and compared it with traditional logistics systems. They used a comparative life cycle assessment method to quantify the greenhouse gas emissions per package, and demonstrated that the truck-drone alternative can significantly reduce emissions, while its cost performance is mainly affected by the level of drone automation. Salama and Sharan (2022) studied the coordination problem of last-mile package delivery using one truck and multiple heterogeneous drones. They established a mixed-integer linear programming model with the objective of minimizing the delivery completion time to jointly optimize three decisions. To handle large-scale problem instances, they developed a two-stage optimization search algorithm combining simulated annealing and variable neighbourhood search.

Ying et al. (2025) applied truck-drone collaborative distribution to the flood location and routing optimization problem and designed an improved tabu search algorithm, but they did not consider the two-stage optimization solution. Based on the above studies, this paper considers the two-stage location and route optimization problem for truck-drone emergency distribution centers. Specifically, in the location selection stage, there are candidate distribution centers, and it is necessary to select which distribution centers will perform delivery tasks. This ensures that after vehicles depart from the hub center, they distribute goods to the selected distribution centers. In the route optimization stage, there is a two-stage route optimization process from the hub center to distribution

centers, and then to demand points. It is determined which distribution centers and demand points will be served by drones, and which will be served by trucks, so as to optimize the collaborative delivery routes of vehicles and drones. Meanwhile, this paper considers the impact of distribution center failure probability and road reliability based on the flexibility of drones.

3 RESEARCH METHOD

3.1 Problem Statement

The research problem of this study can be described as follows: The locations of emergency demand points and the material demand quantity of each demand point are known. There is a hub center and multiple candidate distribution centers providing material delivery services, and both the hub center and distribution centers are equipped with truck fleets. Each truck works in collaboration with one drone, and the drone must take off from and return to the truck. After departing from the hub center, the trucks deliver materials to the distribution centers in sequence and then return. Drones can either deliver materials to the distribution centers or directly to the demand points. The trucks and drones at the distribution centers conduct collaborative delivery: when a truck transports goods between different demand points, the drone on the truck picks up a package from the truck and delivers it to another demand point. While the drone is delivering the package, the truck continues to move forward to deliver goods to the next demand point. After completing the delivery, the drone returns to the truck at the next demand point. This process is repeated continuously until the delivery tasks for all demand points are completed, as shown in Fig. 1.

This study focuses on the joint planning problem of emergency distribution center location selection and vehicle-drone collaborative delivery route optimization. In the location selection stage, objectives such as the maximum coverage problem and the minimum delivery time problem are considered, while influencing factors including the demand quantity of demand points, road damage and road reliability, the potential failure risk of distribution centers, and the maximum flight distance of drones are also taken into account. In the route planning stage, the objective is to minimize delivery time. Specifically, in the first-echelon transportation, large trucks and large drones are used to transport emergency materials from the hub center to the distribution centers, while large drones may also deliver materials directly to demand points. In the second echelon, small trucks and small drones collaborate to deliver materials from distribution centers to demand points. For the transportation from distribution centers to demand points, small drones and small vehicles are used for collaborative material delivery. Meanwhile, constraints such as the load and mileage limits of vehicles and drones, as well as road restrictions, are considered. On this basis, a mathematical model for location selection and route planning is established, and a heuristic algorithm is designed to solve the model.

3.2 Assumptions

To clarify the research scope, the following assumptions are proposed:

(1) The locations and distances of candidate distribution centers and demand points are known. Such information is accessible and pre-provided by the emergency management department during the decision-making process.

(2) Without loss of generality, it is assumed that the trucks and drones used in each stage are of the same type. Vehicles of the same type have identical load capacities and speeds.

(3) Each truck is equipped with only one drone; the drone is unloaded and launched from the truck, and each drone delivery mission serves only one demand point. This assumption is consistent with real-world operational scenarios.

(4) To ensure clear resource allocation, each demand point is served by only one drone for material delivery.

(5) Considering the feasibility of practical operations and the capacity constraints of distribution centers and vehicles, each selected distribution center must serve at least one demand point. The total delivery volume of a distribution center shall not exceed its inventory capacity, and the delivery volumes of trucks and drones shall not exceed their respective capacity limits.

(6) According to the characteristics of the problem, a truck-drone collaborative delivery mode is adopted to respond to environmental changes. The truck can continue to depart after the drone's take-off point according to the actual situation, and rendezvous with the drone at subsequent demand points for delivery.

(7) Given the urgency of emergency material demand, deliveries to demand points must satisfy hard time window constraints.

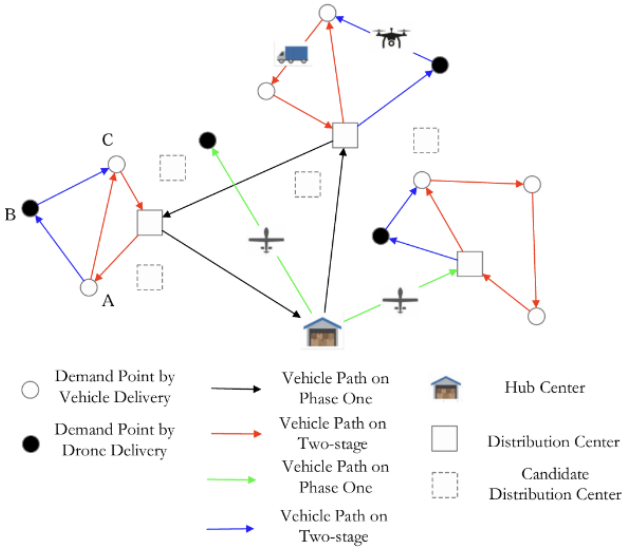


Figure 1 Two-stage route planning for drone-vehicle collaborative delivery with distribution center location selection

3.3 Mathematical Model

The Mathematical Model is shown below.

(1) Sets

I_0 : Hub center

I_1 : Set of candidate distribution centers

I_2 : Set of demand points

I : Set of all nodes, where $I = I_0 \cup I_1 \cup I_2$

K : Set of trucks, with $k \in K$

U : Set of drones, with $u \in U$

(2) Parameters

Q_0 : Inventory quantity of the hub center

Q_i : Inventory quantity of candidate distribution center i, where $i \in I_1$

q_i : Emergency material demand quantity of node i, where $j \in I_2$

h_{ik} : Quantity of materials delivered by truck k to candidate distribution center i, where $i \in I_1$

Q_k : Maximum capacity limit of truck k

Q_{ku} : Maximum capacity limit of drone u carried by truck k

v_k , v_u : Speeds of truck k and drone u, respectively

d_{ij} : Distance from node i to node j

$\widetilde{t_{ijk}}$: Time taken by truck k to travel from node i to node j

t_{ijku} : Time taken by drone u carried by truck k to travel from node i to node j

h_u^g : Departure preparation time of drone u (including material assembly time for the drone)

h_u^a : Receiving time of drone u

L_{jk} : Latest arrival time of truck k at node j

Ljku: Latest arrival time of drone u carried by truck k at node j

D_u : Maximum flight distance of drone u (round trvel distance)

p_{jk} : Reliability of road from node i to node j (probability of no damage)

r_i : Failure probability of candidate distribution center i

Δ : Maximum acceptable coverage distance of demand points

(3) Variables

$$B_i = \begin{cases} 1, \text{ if candidate distribution center } i \text{ is} \\ \text{selected,} \\ 0, \text{ otherwise} \end{cases}$$

$$\mu_{ik} = \begin{cases} 1, \text{ if distribution center } i \text{ is served} \\ \text{by truck } k, \\ 0, \text{ otherwise} \end{cases}$$

$$w_{iu} = \begin{cases} 1, \text{ if distribution center } i \text{ is served} \\ \text{by drone } u \\ 0, \text{ otherwise} \end{cases}$$

$$\alpha_{jk} = \begin{cases} 1, \text{ if demand point } j \text{ is served by truck } ku \\ 0, \text{ otherwise} \end{cases}$$

$$\gamma_{ju} = \begin{cases} 1, \text{ if demand point } j \text{ is served by drone } u \\ (\text{applicable to two types of drones}) \\ 0, \text{ otherwise} \end{cases}$$

$$x_{ijk} = \begin{cases} 1, \text{ if truck } k \text{ travels from demand point } i \\ \text{to demand point } j \\ 0, \text{ otherwise} \end{cases}$$

$$y_{ijku} = \begin{cases} 1, \text{ if drone } u \text{ (carried by truck } k) \\ \text{travels from demand point } i \text{ to} \\ \text{demand point } j \\ 0, \text{ otherwise} \end{cases}$$

$$s_{ijfku} = \begin{cases} 1, \text{ if drone } u \text{ on truck } k \text{ is launched} \\ \text{from demand point } i, \text{ then delivers} \\ \text{to demand point } j, \text{ and} \\ \text{subsequently rendezvou, with the} \\ \text{truck at demand point } f \\ 0, \text{ otherwise} \end{cases}$$

$$\beta_{ijk} = \begin{cases} 1, \text{ if truck } k \text{ serves demand point } i \\ \text{before demand point } j \\ 0, \text{ otherwise} \end{cases}$$

$$z_{ijk} = \begin{cases} 1, \text{ if drone } u \text{ (carried by truck } k) \text{ travels} \\ \text{from demand point } i \text{ to } j \\ 0, \text{ otherwise} \end{cases}$$

ϑ_{ik} , representing the position of node i in the route of truck k

(4) Model

$$\text{Min}Z = \lambda_1 \times \left(1 - \frac{\left(\sum_{j \in I_1} q_j \left(\sum_{k \in K} \alpha_{jk} + \sum_{u \in U} \gamma_{ju} \right) \right)}{\sum_{j \in I_2} q_j} \right) +$$

$$\lambda_2 \times \left(\sum_{k \in K} \sum_{i \in I_1} \tilde{t}_{0ik} \mu_{ik} + \sum_{u \in U} \sum_{i \in I_1} \left(h_u^g + t_{0iu} + h_u^a \right) w_{iu} + \right. \quad (1)$$

$$\left. \sum_{k \in K} \sum_{i,j \in I_2} \tilde{t}_{ijk} x_{ijk} + \sum_{u \in U} \sum_{i,j \in I_2} \left(h_u^g + t_{ijku} + h_u^a \right) y_{ijku} \right)$$

$$\sum_{k \in K} \sum_{i \in I_1} h_{ik} \mu_{ik} + \sum_{u \in U} \sum_{j \in I_2} q_j \gamma_{ju} \le Q_0 \quad (2)$$

$$Q_i B_i + \sum_{k \in K} h_{ik} \mu_{ik} \ge \sum_{k \in K} \sum_{j \in I_2} q_j \alpha_{jk} + \sum_{u \in U} \sum_{j \in I_2} q_j \gamma_{ju}, \forall i \in I_1 \quad (3)$$

$$\sum_{i \in I_1} h_{ik} \mu_{ik} + \sum_{j \in I_2} q_j \alpha_{jk} \le Q_k, , \ \forall k \in K \quad (4)$$

$$\sum_{j \in I_2} q_j \gamma_{ju} \le Q_{ku}, \forall k \in K, u \in U \quad (5)$$

$$\mu_{ik} \le B_i, \forall i \in I_1, k \in K \quad (6)$$

$$w_{iu} \le B_i, \forall i \in I_1, u \in U \quad (7)$$

$$\alpha_{jk} + \gamma_{ju} \le \sum_{i \in I_1} B_i \times \mathbb{I}\left(d_{ij} \le \Delta \right), \forall j \in I_2, k \in K, u \in U \quad (8)$$

$$d_{ij} \times y_{ijku} \le D_u, \forall i, j \in I, k \in K, u \in U \quad (9)$$

$$h_u^g + t_{ijku} + t_{jfu} + h_u^a \le \widetilde{t_{ifk}}, \forall i, j, f \in I_2, k \in K, u \in U \quad (10)$$

$$s_{ijfku} \le x_{ifk}, \forall i, f \in I_2, k \in K, u \in U \quad (11)$$

$$\sum_{i \in I_1 \cup I_2, i \ne j} x_{ijk} = \sum_{f \in I_2, f \ne j} x_{jkf}, \forall j \in I_2, k \in K \quad (12)$$

$$\sum_{i \in I_1 \cup I_2, i \ne j} y_{ijku} = \sum_{f \in I_2, f \ne j} y_{jkfu}, \forall j \in I_2, k \in K, u \in U \quad (13)$$

$$\vartheta_{jk} \ge \vartheta_{ik} + 1 - (n+2)(1-\beta_{ijk}), \forall i, j \in I_2, k \in K \quad (14)$$

$$\sum_{k \in K} \alpha_{jk} + \sum_{u \in U} \gamma_{ju} = 1, \forall j \in I_2 \quad (15)$$

$$x_{ijk} \le p_{ij} \times z_{ijk}, y_{ijku} \le p_{ij} \times z_{ijk}, \forall i, j \in I, k \in K, u \in U \quad (16)$$

$$\sum_{i \in I_2} \widetilde{t_{ijk}} x_{ijk} \le L_{jk}, \forall j \in I_2, k \in K \quad (17)$$

$$h_u^g + \sum_{i \in I_2} t_{ijku} y_{ijku} + h_u^a \le L_{jku}, \forall j \in I_2, k \in K, u \in U \quad (18)$$

$$\sum_{i' \in I_1, i' \ne i} B_{i'} \times \mathbb{I}(d_{i'j} \le \Delta) \ge 1 - B_i(1-r_i), \forall j \in I_2, i \in I_1 \quad (19)$$

The objective function combines the two core objectives of maximum coverage problem and minimum delivery time using weight coefficients λ_1 and λ_2, ultimately minimizing the weighted total objective. The first part represents the maximum coverage rate of demand points, while the second part respectively represents the time for truck k to serve candidate distribution centers, the time for drone u to serve candidate distribution centers, the time for truck k to serve demand points, and the time for drone u carried by truck k to serve demand points. Constraint (2) states that the total outbound volume of the hub center - including materials delivered by trucks and drones - must not exceed the hub's total inventory. Constraint (3) states that for each candidate distribution center, the sum of its own inventory (if selected) and materials delivered by trucks must be at least the total materials it distributes to demand points by trucks and drones. Constraint (4) states that the total materials transported by each truck-including those delivered to candidate distribution centers and directly to demand points - must not exceed the truck's maximum load capacity. Constraint (5) states that the total volume of materials delivered by each drone (carried by a specific truck) to demand points must not exceed the drone's maximum load capacity. Constraint (6) states that a truck can only be assigned to serve a candidate distribution center if that distribution center has been selected. Constraint (7) states that a drone can only be assigned to serve a candidate distribution center if that distribution center has been selected. Constraint (8) states that a demand point can only be served by a truck or drone if there is at least one selected distribution center within the demand point's maximum acceptable coverage distance. Constraint (9) states that for any travel between two nodes, the flight distance of a drone (carried by a specific truck) must not exceed the drone's maximum round-trip flight distance. Constraint (10) states that the total time for a drone (on a specific truck) to take off from one demand point, deliver to another, and rendezvous with the truck at a third demand point must not exceed the truck's direct travel time from the take-off point to the rendezvous point. Constraint (11) states that a drone can only execute the "take-off-deliver-rendezvous" process if the truck it belongs to travels directly from the drone's take-off demand point to the rendezvous demand point. Constraint (12) states that for each demand point, the number of times a truck arrives at the point must equal the number of times it departs. Constraint (13) states that for each demand point, the number of times a drone (on a specific truck) arrives at the point must equal the number of times it departs. Constraint (14) states that if a truck serves one demand point before another, the position number of the first demand point in the truck's route must be smaller than that of the second. Constraint (15) states that each demand point must be served by exactly one entity - either a truck or a drone - with no missed or repeated services. Constraint (16) states that a truck or drone can only use the road between two nodes if the road is marked as available. Constraint (17) states that the total travel time of a truck to reach each demand point must not exceed the latest acceptable arrival time for that demand point. Constraint (18) states that the total time of a drone (on a specific truck) to reach each demand point - including preparation, flight, and receiving time - must not exceed the latest acceptable arrival time for that demand point. Constraint (19) states that if a selected distribution center fails, there must be at least one other selected distribution center that can cover the demand points originally served by the failed center.

3.4 Algorithm Design

The joint optimization problem of two-stage emergency distribution center location selection and routing with vehicle-drone collaboration is a typical NP-hard problem. Exact algorithms can obtain valid solutions for small-scale problems but require a long solution time, while heuristic algorithms are more suitable for solving this problem.

The Simulated Annealing (SA) algorithm is derived from the principle of solid annealing, simulating the physical process of "high-temperature melting slow cooling low-temperature crystallization". First, it controls the acceptance probability of inferior solutions through temperature attenuation to achieve wide-range exploration of the solution space; then, it focuses on local optimization through low temperature and low acceptance rate of inferior solutions, balancing "exploration" and "exploitation". With the mechanism of "random search + probabilistic acceptance of inferior solutions", the algorithm can jump out of local optima. Through this mechanism, the SA algorithm can exhibit strong performance in solving complex combinatorial optimization problems.

3.4.1 Encoding

A two-layer integer coding structure is adopted, with the total coding length being 1 (hub center I_0) + $|I_1|$(candidate distribution centers) + $|I_2|$(demand points).

The hub center is coded as I_0, and the candidate distribution centers are coded as $1\sim|I_1|$. Nodes $|I_1|+1\sim|I|$ are divided into two types of demand nodes according to routing rules, namely demand points where trucks perform delivery tasks and disaster-stricken points where drones perform delivery tasks. The coding is divided into two layers: the location selection layer and the routing layer, as detailed in Tab. 1.

Table 1 Coding rules with risk adaptation

Coding Layer	Content Definition	Example (Assuming $I_0=0$, $I_1=\{1,2,3,4\}$, $I_2=\{5,6,7,8\}$)
First Layer (Location Selection)	1. "0-1" indicates selection status: 1 = selected, 0 = not selected; 2. Risk labels for selected centers: H (high risk, $r_i>0.3$), M (medium risk, $0.1<r_i\le 0.3$), L (low risk, $r_i\le 0.1$)	$[0,1(M),0,1(L)]\rightarrow$ Selected centers: 2 (medium risk) and 4 (low risk); Unselected centers: 1 and 3
Second Layer (Route Coding)	1. Integer sequence representing truck-drone delivery order, starting/ending with I_0; 2. Road reliability labels: $R_H(\text{high}, p_{ij}\ge 0.8)$, $R_M(\text{medium}, 0.5<p_{ij}<0.8)$ $R_L(\text{low}, p_{ij}\le 0.5)$; 3. Drone range redundancy (to ensure $D_u\ge d_{round-trip}$)	$[I_0,2M,4L,I_0;$ $2(M),5(R_H),(u_1\rightarrow 6D_i$ ……] $I_0\rightarrow$ DC2 (medium risk) → DC4 (low risk) $\rightarrow I_0$; DC2→ Demand point 5 (truck via high-reliability road) → Demand point 6 (drone u_1) → Demand point 7 (truck via medium-reliability road) → DC2.

3.4.2 Decoding

Step 1: Initialize Parameters

Extract coding information: Obtain selected distribution centers K_{selected} and their risk levels from the first layer; obtain route sequences with reliability and redundancy information from the second layer.

Initialize truck-drone parameters: Each truck k paired with one drone u; initial truck load $load_k=0$, initial departure time $t_k=0$; drone preparation time $t_u^g=h_u^g$.

Initialize node information: Current node $curr_node=I_0$; as sign backup distribution centers for high-risk nodes.

Step 2: Traverse the Route Coding and Parse the Delivery Process

Traverse each node in the order of the second-layer coding (starting from I_0), and handle three types of scenarios to ensure all routes start and end with I_0, as shown in Tab. 2.

Step 3: Calculate the Objective Function Value

The primary objective is to minimize the maximum completion time across all trucks:

$$f(S)=\max(t_k\mid k\in K)$$

where t_k includes the return time to I_0.

Feasibility penalty for constraint violations:

$$f(S)=f(S)+\sum_{m=1}^{5}M\times\mathbb{I}(\text{constraint } m \text{ violated})$$

where $M=10^6$ and $\mathbb{I}(\cdot)$ is the indicator function.

Table 2 Initial routes processing logic for truck-drones

Node Type	Processing Logic	Time/Load Update Formula
Selected distribution center ($k\in K_{\text{selected}}$, $k\in I_1$)	1. Truck travels from $curr_node$ (previous node, e.g., I_0 or previous demand point) to k; 2. Check distribution center capacity: total materials allocated to k $\le Q_kQ_k$ is the inventory of k); 3. Update current associated distribution center to k.	Time: $t_k=t_k+d(curr_node,k)/v_k$ (d is distance between nodes, v_k is truck speed) Load: $load_k$ = total materials allocated to k ($\le Q_k$)
Demand point delivered by truck ($i\in I_2$, no (u →marker))	1. Truck travels from $curr_{node}$ to i; 2. After unloading, check load: $load_k-q_i\ge 0$ (q_i is demand of i); 3. Check time window: $t_k\le L_{ik}$ (L_{ik} is latest arrival time of truck at i)	Time: $t_k=t_k+d(curr_node,i)/v_k$ Load: $load_k=load_k-q_i$
Demand point delivered by drone ($(u\rightarrow j), j\in I_2$))	1. Drone takes off from $curr_node$ (current position of truck) to deliver to j; check drone load ($q_j\le Q_{ku}$) and time window ($t_u\le L_{jku}$); 2. Truck continues to $next_node$ (subsequent node of j in coding); 3. After delivery, drone flies to $next_node$ to rendezvous with truck, ensuring drone eventually returns to truck; 4. Rendezvous time is the maximum of truck's and drone's arrival time at $next_node$.	Drone time: $t_u=t_{ug}+d(curr_node,j)/v_u+d(j,next_node)/v_u$ (v_u is drone speed); Truck time: $t_k=t_k+d(curr_node,\ next_node)/v_k$ Rendezvous time: $t_k=\max(t_k,t_u)$

3.4.3 Operator Design

Operator 1: In-path Reversal Operator (for single truck routes, without changing the position of I_0)

Randomly select route segments containing low-reliability roads or high-risk centers, reverse their order, and update reliability information:

Example:

Original: $I_0=0\rightarrow 2(R_L)\rightarrow 5\rightarrow(u_1\rightarrow 6)\rightarrow 7\rightarrow I_0=0$

Modified: $I_0 = 0 \rightarrow (u_1 \rightarrow 6) \rightarrow 5 \rightarrow 2(R_H) \rightarrow 7 \rightarrow I_0 = 0$

Operator 2: Truck-Drone Delivery Subject Swap Operator (for individual demand points, adapted to I_0 routes)

Swap delivery subjects between truck-served points on low-reliability roads and drone-served points with sufficient range redundancy:

Example:

Original: $I_0 = 0 \rightarrow 2 \rightarrow 5$ (truck, R_L) $\rightarrow (u_1 \rightarrow 6$, redundancy = 6 km) $\rightarrow I_0 = 0$

Modified: $I_0 = 0 \rightarrow 2 \rightarrow (u_1 \rightarrow 5$, redundancy = 4 km) $\rightarrow 6$ (truck, R_H) $\rightarrow I_0 = 0$

Operator 3: Distribution Center Location Fine-tuning Operator (for nodes in I_1, with synchronous adjustment of I_0 routes)

Replace high-risk selected centers with low-risk unselected ones, adjusting material allocation and routes accordingly:

Example:

Original: $k = 2$ (high risk) with route $I_0 = 0 \rightarrow 2 \rightarrow 5 \rightarrow I_0 = 0$

Modified: $k' = 4$ (low risk) with route $I_0 = 0 \rightarrow 4$ (R_H) $\rightarrow 5 \rightarrow I_0 = 0$.

3.4.4 Temperature Update Strategy

Temperature T is a core parameter of the SA algorithm, balancing exploration and exploitation through "initial temperature → cooling → termination temperature". The specific design is as follows:

(1) Initial temperature T_0

Calculated based on risk-weighted standard deviation of initial solutions:

$$T_0 = -\sigma / \ln(p_0)$$

where σ is risk-weighted standard deviation and $p_0 = 0.85$ (high-risk scenarios).

(2) Cooling Function

Adaptive cooling with risk-dependent coefficients:

$$T_{t+1} = \alpha_t \times T_t$$

where $\alpha_t = 0.99$ (high risk), 0.97 (medium risk), and 0.95 (low risk).

(3) Termination Conditions

Algorithm terminates when $T < 10^{-5}$ or maximum iterations reached (1200 for high-risk, 1000 for medium-risk, 800 for low-risk scenarios).

3.4.5 Simulated Annealing Algorithm Flow

Step 1: Input Parameters and Initialization

a) Input basic data:

Hub center I_0: location (fixed start/end point);

Candidate distribution centers I_1: locations, inventory Q_i, failure probability r_i;

Demand points I_2: locations, demand q_i, hard time windows $[a_i, b_i]$, maximum acceptable coverage distance Δ;

Truck-drone parameters: truck speed v_k, load capacity Q_k; drone speed v_u, load capacity Q_{ku}, takeoff preparation time h_u^g, maximum round-trip range D_u;

Road network parameters: inter-node distance d_{ij}, road reliability p_{ij};

b) Set SA algorithm parameters:

Initial inferior solution acceptance probability p_0 = 0.85 (high-risk scenarios) / 0.8 (low-risk scenarios); dynamic cooling coefficient α (0.99 for high-risk/0.97 for medium-risk / 0.95 for low-risk); termination temperature $T_{\text{end}} = 10^{-5}$; maximum iterations MaxIter (1200 for high-risk/1000 for medium-risk/800 for low-risk); number of initial solutions $N = 80$; penalty coefficient $M = 10^6$;

c) Generate initial solution:

Randomly generate N two-layer coding sequences, all satisfying "the second layer starts and ends at I_0"; the first layer includes risk labels $(H / M / L)$ for distribution centers; the second layer includes road reliability labels ($R_H / R_M / R_L$) and drone range redundancy; Screen feasible solutions S_0 through decoding (with additional checks: road reliability ≤ 0.3, drone range redundancy ≤ 2 km); calculate its objective value $f_0 = f(S_0)$; Set current solution $S_{\text{curr}} = S_0$, optimal solution $S_{\text{best}} = S_0$, optimal objective value $f_{\text{best}} = f_0$.

Step 2: Initialize Temperature and Iteration Counter

Calculate initial temperature T_0: Divide N initial solutions into high/medium/low risk groups based on average risk of selected centers;

Calculate standard deviations $\sigma_1, \sigma_2, \sigma_3$ for each group;

Compute weighted total standard deviation $\sigma = 0.4\sigma_1 + 0.3\sigma_2 + 0.3\sigma_3$;

Compute $T_0 = -\sigma / \ln(p_0)$;

Set current temperature $T = T_0$ and iteration counter $t = 0$.

Step 3: Iterative Search

When $T > T_{\text{end}}$ and $t <$ MaxIter, repeat the following operations:

a) Generate new solution S': Randomly select one neighborhood operator to operate on S_{curr}:

Risk-oriented in-path reversal operator: Prioritize reversing segments with low-reliability roads ($p_{ij} \le 0.6$) or high-risk centers, update road reliability labels;

Truck-drone collaborative swap operator: Swap truck-served points on low-reliability roads with high-redundancy drone-served points, recalculate drone range redundancy;

Location-backup synchronous fine-tuning operator: Replace high-risk selected centers with low-risk unselected ones, adjust backup centers and associated routes;

Ensure the second-layer coding of S' still starts and ends at I_0; check feasibility through decoding (additional checks: high-risk centers must have backups, roads with

$p_{ij} \le 0.5$ must switch to alternatives); if infeasible, assign penalty value $f(S') += M$; Calculate objective difference $\Delta f = f(S') - f(S_{\text{curr}})$;

b) Accept new solution:

If $\Delta f \le 0$: Accept S' set $S_{\text{curr}} = S'$; if $f(S') < f_{\text{best}}$, update $S_{\text{best}} = S'$ and $f_{\text{best}} = f(S')$;

If $\Delta f > 0$: Generate $r \in [0, 1]$, compute $P = \exp(-\Delta f / T)$; if $r \le P$, accept S' , set $S_{\text{curr}} = S'$;

c) Update temperature and counter:

Adjust cooling coefficient α based on risk level of current solution S_{curr} ; $T = \alpha \times T$, $t = t + 1$.

Step 4: Terminate Algorithm and Output Results

When $T \le T_{\text{end}}$ or $t \ge \text{MaxIter}$, terminate iteration and output the following results:

Optimal location scheme: candidate distribution centers (nodes in I_1) corresponding to "1" in the first-layer coding of S_{best} , with risk levels and backup center information; Optimal route scheme: truck-drone collaborative route in the second-layer coding of S_{best} , including road reliability labels, drone range redundancy, and key node time stamps; Optimal objective value: f_{best} (the latest completion time of all demand points, i.e., the maximum time for trucks to depart from I_0 and return to I_0), with risk scenario adaptability assessment (e.g., proportion of low-reliability roads, backup coverage rate for high-risk centers).

4 RESULTS AND DISCUSSION

4.1 Computational Study

This study takes the flood disaster caused by the Zhengzhou "July 20" rainstorm as the main research object. The dataset mainly covers two core aspects: candidate distribution centers, which are used to study the location selection problem in trunk transportation; disaster impact data, which is combined with the established model to implement location selection and route optimization.

Through this comprehensive optimization process, the location of distribution centers and the material distribution routes can be finally determined. Currently, there is no standard dataset for the emergency location-routing problem in truck-drone collaborative distribution. This paper uses relevant data from the Zhengzhou "July 20" rainstorm, where the data of candidate distribution centers and demand points refers to the research of Ying et al. (2025). The candidate distribution centers in this paper are: (1.7, 2.0), (6.4, 4.8), (9.0, 3.2), (11.2, 0.6), (13.6, 0.2). The relevant data of the distribution centres and demand points are shown in Tab. 3, while N is the demand point number, C represents the demand coordinates, D represents the material demand (kg) of the demand point, T represents the time window (h) of the demand point.

Table 3 Relevant data of demand points

N	C	D	T	N	C	D	T
0	(7.0, 3.0)	-	-	13	(10.0, 0.0)	33	3
1	(0.0, 4.0)	18	3	14	(10.0, 1.0)	21	3
2	(0.0, 3.0)	33	3	15	(10.0, 3.0)	36	3
3	(1.6, 3.0)	21	3	16	(10.0, 5.0)	15	3
4	(2.5, 5.6)	36	3	17	(10.0, 6.5)	21	3
5	(3.2, 4.7)	33	3	18	(12.0, 0.0)	12	3
6	(3.4, 6.0)	33	3	19	(12.0, 3.0)	18	3
7	(3.8, 2.8)	18	3	20	(12.0, 4.5)	15	3
8	(4.8, 3.5)	12	3	21	(12.5, 4.0)	18	3
9	(6.3, 0.0)	12	3	22	(12.5, 6.5)	42	3
10	(6.3, 3.0)	33	3	23	(14.0, 1.2)	12	3
11	(6.3, 4.6)	15	3	24	(14.6, 2.6)	9	3
12	(6.3, 6.0)	18	3	25	(14.6, 4.3)	33	3

4.2 Algorithm Solution

To meet the requirements of the example analysis in this paper, the following basic data are supplemented: According to the actual conditions of existing trucks and drones, the maximum load capacities of trucks and drones are set as $Q_k = 500$ kg and $Q_{ku} = 50$ kg respectively; their average travel speeds are $v_k = 35$ m/s and $v_u = 50$ m/s respectively. The departure preparation time of the drone is $h_u^g = 20$ s , and the receiving time of the drone is $h_u^a = 20$ s. The maximum perturbation value of the truck's travel time deviation is 20% of the nominal value, i.e., $\widetilde{t_{ijk}} = \overline{t_{ijk}} \cdot 20\%$.

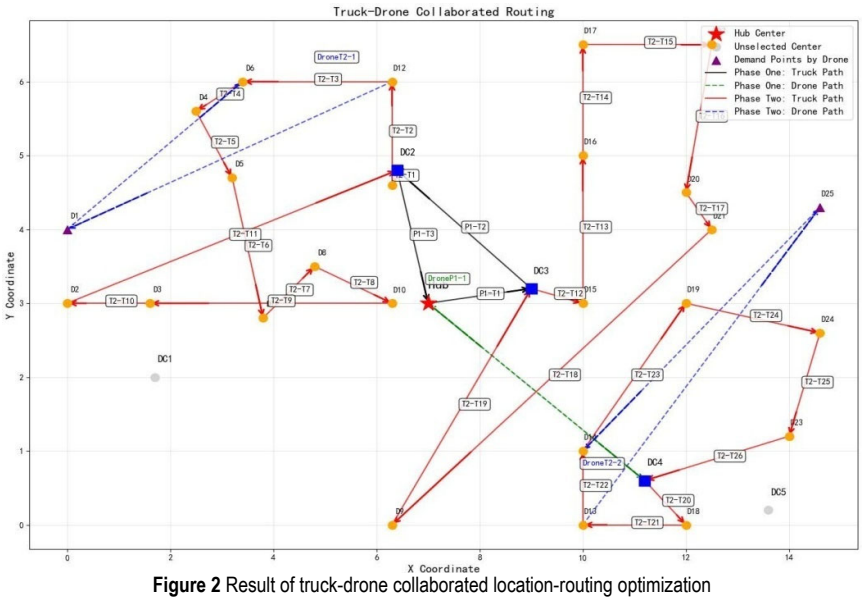


Figure 2 Result of truck-drone collaborated location-routing optimization

The algorithm is programmed in Python and run on a computer with 8 GB of RAM and an i5-8250 U processor. The operation result takes the optimal value among 10 runs. The solution result is shown in Fig. 2.

Among them, in the first stage, the selected distribution centers are DC_2, DC_3, and DC_4, DC_2 and DC_3 are delivered by trucks, while DC_4 is delivered solely by drones. In the second stage, except for demand points 1 and 25 which are delivered by drones, all other demand points are delivered by trucks. The specific results are as follows:

First Stage:

Truck route: $I_0 \rightarrow DC_3 \rightarrow DC_2 \rightarrow I_0$

Drone task: $I_0 \rightarrow DC_4 \rightarrow I_0$

Second Stage:

DC2 truck route: $DC_2 \rightarrow 12 \rightarrow (u_1 \rightarrow 1) \rightarrow 6 \rightarrow 4 \rightarrow 5 \rightarrow 7 \rightarrow 8 \rightarrow 10 \rightarrow 3 \rightarrow 2 \rightarrow DC_2$

DC3 truck route: $DC_3 \rightarrow 15 \rightarrow 16 \rightarrow 17 \rightarrow 22 \rightarrow 20 \rightarrow 21 \rightarrow 9 \rightarrow DC_3$

DC4 truck route: $DC_4 \rightarrow 18 \rightarrow 13 \rightarrow (u_2 \rightarrow 25) \rightarrow 11 \rightarrow 19 \rightarrow 24 \rightarrow 23 \rightarrow DC_4$.

From the solution results, it can be concluded that: (1) In terms of the objective function, the total time for emergency material distribution is 4.86 hours, which meets the time window requirements of each demand point. (2) In terms of algorithm running time, the maximum running time of the algorithm during operation is 4.72 seconds, and the minimum is 3.08 seconds. The algorithm can provide a satisfactory solution in a very short time, demonstrating high efficiency and feasibility.

4.3 Results Analysis of Different Instance Scales

Three instances of different scales were set up for analysis, categorized by the number of demand points into three instances: 15, 25, and 50. The coordinates for both 15 and 50 demand points instances are randomly generated based on 25 demand points. The calculation results are shown in Tab. 4. Here, ND represents the number of demand points, NC represents the number of distribution centers, KT represents the total delivery time of truck delivery tasks, UT represents the total delivery time of drone delivery tasks, TT represents the total delivery time to complete all demand points, and CPU time represents the algorithm running time.

Table 4 Analysis results of different instance scales

ND	NC	KT	UT	TT	CPU time / s
15	3	100.8	5.22	106.02	2.88
25	5	269.4	22.2	291.6	4.13
50	7	578.4	66.6	645.0	10.72

From the results in Tab. 4, it can be concluded that: (1) For all instances, the algorithm can converge within the given number of iterations. (2) As the instance scale expands, the solution time becomes longer, and the time required for truck and drone delivery also increases. Overall, the algorithm designed in this paper can provide satisfactory solutions for instances of all scales in a short time, showing practicality.

4.4 Sensitivity Analysis

To further evaluate the algorithm performance, sensitivity analysis was conducted from three aspects: drone speed, drone load capacity, and road reliability, to further analyze the impact of different parameter settings on the solution results. The algorithm terminates when the maximum number of iterations (300) is reached. Each parameter setting was run 10 times, and the average value was taken.

(1) Analysis of the Impact of Drone Speed on Solution Results

As shown in Tab. 5, when the drone speed increases gradually from 10 m/s to 70 m/s, the drone delivery time (UT) decreases from 213.0 minutes to 31.2 minutes, and the total delivery time (TT) decreases from 525.6 minutes to 335.4 minutes. However, when the drone speed exceeds 30 m/s, diminishing marginal returns occur. This is because drones are the bottleneck when their speed is low; when the speed is high, truck trunk transportation becomes the bottleneck, and the proportion of the fixed preparation time of drones increases. The algorithm running time remains basically stable. Tab. 5 shows the sensitivity analysis of drone speed on the solution results.

Table 5 Sensitivity analysis on drone speed

Drone Speed	KT	UT	TT	CPU time / s
10	312.6	213.0	525.6	18.32
20	310.8	116.4	427.2	17.89
30	309.0	78.0	387.0	18.15
40	307.2	54.6	361.8	17.95
50	306.0	42.6	348.6	18.03
60	305.4	35.4	340.8	17.78
70	304.2	31.2	335.4	18.21

(2) Analysis of the Impact of Drone Load Capacity on Solution Results

Tab. 6 shows the sensitivity analysis of drone load capacity on the solution results. In Tab. 6, when the drone load capacity increases from 30 kg to 50 kg, the truck delivery time (KT) decreases from 336.0 minutes to 306.0 minutes, and the total delivery time (TT) decreases from 372.0 minutes to 348.6 minutes. It should be noted that after the drone load capacity reaches 50 kg, KT and TT tend to stabilize. This is because there is no further optimization space for trucks, and the redundancy of load capacity exceeding 50 kg cannot be converted into efficiency. The algorithm running time remains basically stable.

Table 6 Sensitivity analysis on drone load capacity

Drone Load Capacity	KT / min	UT / min	TT / min	CPU time / s
30	336.0	36.0	372.0	18.25
40	312.0	60.0	354.0	17.98
50	306.0	42.6	348.6	18.03
60	304.8	43.2	346.8	17.89
70	303.6	43.8	345.6	18.11
80	302.4	44.4	344.4	17.95

(3) Analysis of the Impact of Road Reliability on Solution Results

In this study, the average level of road reliability between all nodes is used to represent the overall road reliability. The impact of overall road reliability values (0.55, 0.65, 0.75, 0.85, and 0.95) on the solution results was analyzed. Here, P represents the delivery coverage rate.

As shown in Tab. 7, when the road reliability increases from 55% to 95%, the truck delivery time (KT) decreases from 331.2 minutes to 303.6 minutes, the drone delivery

time (UT) decreases from 53.4 minutes to 41.4 minutes, the total delivery time (TT) decreases from 384.6 minutes to 345.0 minutes, and the delivery coverage rate increases from 82.4% to 99.6%. Among them, trucks are more affected by road reliability, and the range of 0.75-0.85 is the optimal interval for truck delivery. There is no significant change in the algorithm running time.

Table 7 Sensitivity analysis on road reliability

Road Reliability	KT / min	UT / min	TT / min	P / %	CPU time / s
0.55	331.2	53.4	384.6	82.4	18.35
0.65	318.6	48.6	367.2	89.6	18.12
0.75	309.0	45.0	354.0	95.2	18.05
0.85	306.0	42.6	348.6	98.8	18.03
0.95	303.6	41.4	345.0	99.6	17.98

5 CONCLUSION

This paper investigated a two-level truck-drone emergency location-routing problem that integrates distribution-center selection and collaborative truck–drone routing to support disaster response. A mixed-integer programming formulation was developed to capture key operational constraints, including truck and drone payload limits, truck-drone rendezvous time feasibility, hard time windows at demand points, road reliability restrictions, and distribution-center failure considerations. To address the NP-hard nature of the joint problem, a simulated annealing approach with two-layer encoding, tailored neighborhood operators, and adaptive cooling was designed to generate high-quality solutions within practical computation times.

Case-based experiments (Zhengzhou "July 20") and multi-scale tests (15/25/50 demand points) indicate that the proposed heuristic can rapidly obtain feasible routing and location decisions that satisfy time-window requirements, while sensitivity analyses demonstrate how increased drone speed and payload reduce completion time up to diminishing-return regions, and how improved road reliability increases coverage and reduces truck travel time. These results support the applicability of truck–drone collaboration for emergency logistics under disrupted transportation networks.

Meanwhile, this paper still has some limitations. Due to the fact that drone emergency logistics has not yet been widely applied on a large scale and actual operational data are lacking, this study primarily conducts research through numerical experiments. The model established cannot fully capture the complexities of real-world emergency environments and unexpected situations. Additionally, factors such as the impact of weather conditions on drone flight, the layout of drone charging stations, and the priority levels and time windows of emergency supplies are not taken into account. Future work should extend the model to multi-drone-per-truck or heterogeneous fleets, incorporate more realistic stochastic road reliability and center-failure scenarios, and evaluate additional objectives such as operating cost and equity of emergency supply, enabling more comprehensive decision support for large-scale disaster relief.

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