

ROUTING OPTIMIZATION FOR THE TRAVELING SALESMAN PROBLEM WITH DRONES (TSP-D) IN MEDICAL SUPPLY DISTRIBUTION

Yutong Ha and Tae Seung Kim*

Graduate School of Logistics
Inha University
Incheon, Republic of Korea

*Corresponding author's e-mail: todaykim@gmail.com

The integration of drones into last-mile logistics has emerged as a transformative solution to address the inefficiencies of traditional truck-based delivery in smart cities. This study investigates the Traveling Salesman Problem with Drones (TSP-D) specifically within the context of medical supply distribution in Qingdao, China. A hierarchical two-stage optimization methodology is proposed: first, the service area is partitioned into optimal subregions using the k-means clustering algorithm, with the number of clusters determined by the silhouette coefficient. Second, a mixed-integer programming model is formulated and solved using Gurobi to optimize synchronized routing within each cluster. Based on a dataset of 169 customer locations, computational experiments demonstrate that the framework identifies seven efficient clusters and significantly enhances delivery performance. The findings indicate that the proposed framework has the potential to reduce response time and improve operational efficiency in medical supply distribution.

Keywords: Traveling Salesman Problem with Drone; K-means; Drone; Medical Supply Distribution.

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1. INTRODUCTION

The rapid convergence of automation, artificial intelligence, and advanced communication frameworks has catalyzed the deployment of drones across diverse industrial landscapes. Beyond their established roles in reconnaissance, drones have emerged as a transformative force in civil sectors, particularly within urban traffic management and emergency logistics. Drone-assisted logistics represents a paradigm shift in addressing the "last-mile" delivery dilemma, offering the potential to enhance operational throughput while mitigating environmental footprints. This potential has prompted global industry leaders, including Amazon, Google, DHL, and Walmart, alongside Chinese e-commerce giants such as SF Express, JD.com, and Meituan, to transition from conceptual pilot programs to large-scale, dynamic service models (Agatz et al., 2018; Chung et al., 2020; Jung et al., 2017). These initiatives are fundamentally transforming conventional logistics frameworks into more dynamic and responsive service architectures (Chen et al., 2025; Liu et al., 2025).

However, accelerating urbanization and the global rise in e-commerce have placed unprecedented strain on conventional truck-based logistics, which often struggle to balance temporal responsiveness with cost-effectiveness. In response, hybrid delivery models combining trucks and drones have garnered intensive academic scrutiny. Early conceptual frameworks introduced by Dorling et al. (2017) and Murray and Chu (2015) laid the foundation for integrating drones into vehicle routing problems (VRPs). At the theoretical core of these hybrid systems is the Traveling Salesman Problem (TSP) framework. As the foundational paradigm for routing optimization, the strategic advantage of a TSP-based scheme in medical logistics lies in its capacity for rigorous sequential optimization and latency minimization. Unlike loosely coupled scheduling heuristics, the TSP formulation ensures a strictly optimized service sequence that minimizes cumulative travel distance, a metric that is mission-critical when transporting time-sensitive supplies such as blood products, vaccines, or emergency medications. In healthcare distribution, where every second correlates with patient outcomes, the TSP framework provides the mathematical determinism necessary to guarantee the fastest response time and mitigate operational uncertainty.

Although metaheuristic approaches have been widely applied in collaborative delivery optimization, challenges remain in balancing solution quality with model transparency. Methods such as Adaptive Large Neighborhood Search (ALNS) and genetic algorithms are effective for large-scale problems, but often suffer from limited interpretability and relatively high computational cost. Rather than pursuing increasingly sophisticated metaheuristic structures, this study focuses on developing a computationally tractable and operationally interpretable framework for large-scale urban medical logistics. To this end, a hierarchical optimization framework integrating spatial decomposition and exact mathematical programming is proposed. Specifically, an adaptive K-means clustering method is first employed to partition customer locations into geographically

compact service regions, after which each subproblem is solved independently using the Gurobi optimizer. The proposed framework aims to improve scalability and computational tractability for large-scale urban delivery problems. Numerical experiments based on a 169-customer medical distribution network demonstrate the practical applicability of the proposed framework for coordinated truck-drone logistics operations.

2. LITERATURE REVIEW

The Traveling Salesman Problem (TSP) serves as a fundamental framework in the field of combinatorial optimization. Its primary goal is to determine the minimum-length Hamiltonian circuit that traverses each location exactly once and returns to the origin point. Its rigorous structure and broad applicability have made it a fundamental abstraction for a wide range of real-world applications, including vehicle routing, circuit design, logistics scheduling, and network planning. In response to increasing demands for cost efficiency and sustainability in last-mile delivery, classical TSP formulations have evolved to incorporate emerging delivery technologies, most notably drone-assisted logistics. A significant contribution in this area was made by Murray and Chu (2015), who introduced two innovative variants of the traditional Traveling Salesman Problem: the Flying Sidekick Traveling Salesman Problem (FSTSP) and the Parallel Drone Scheduling Traveling Salesman Problem (PDSTSP). These models extended the classical framework by incorporating coordinated operations between trucks and drones. These models enable a delivery vehicle to dispatch drones during its route, allowing for a decoupling of delivery tasks and a notable increase in operational efficiency. Building upon this foundation, Agatz et al. (2018) formulated an integer programming model based on the FSTSP, which was later extended by Murray and Raj (2020) to accommodate scenarios where a single truck can launch multiple drones concurrently. From an economic perspective, Campbell et al. (2017) demonstrated the cost-effectiveness of such hybrid delivery systems. In an effort to enhance computational efficiency, Moshref-Javadi et al. (2020) proposed a mixed-integer linear programming (MILP) formulation to improve computational tractability. Further enhancing the model's realism, Murray and Raj (2020) developed a mixed-integer linear programming (MILP) model that aimed to improve the tractability of solving such complex routing problems.

At the system level, efforts have been made to enhance the operational coordination between trucks and drones. Mourelo Ferrandez et al. (2016) developed a synchronized truck-drone transportation framework, emphasizing real-time coordination for drone launches and recoveries. Complementarily, Salama and Srinivas (2020) proposed a bi-objective optimization model integrating customer clustering with hybrid routing, yielding a Pareto frontier of trade-off solutions balancing cost and time. The integration of spatial clustering techniques, particularly the k-means algorithm, has emerged as a crucial strategy for managing large-scale routing complexities by partitioning delivery nodes into manageable sub-regions. By leveraging k-means to decompose extensive service areas, researchers can significantly reduce the computational search space, effectively bridging the gap between customer spatial distribution and synchronized truck-drone coordination (Mourelo Ferrandez et al., 2016). Such decomposition strategies are increasingly recognized for their ability to maintain computational tractability in complex, multi-modal logistics systems as the problem scale expands (Carlsson and Song, 2018). To further refine drone deployment strategies, De Freitas and Penna (2020) introduced a two-stage hybrid approach, where an initial MILP solution is subsequently improved using Variable Neighborhood Search (VNS).

Given the NP-hard complexity of the Truck-Drone Collaborative Routing Problem (TSP-D), traditional exact approaches, such as branch-and-bound, branch-and-price, and mixed-integer linear programming (MILP), typically face difficulties in scaling and are often constrained to solving only small-sized instances. To overcome this challenge, Bouman et al. (2018) introduced a dynamic programming algorithm specifically designed for the TSP-D model originally proposed by Agatz et al. (2018). Their empirical analysis revealed that this approach outperformed standard MILP solvers, offering notable improvements in both solution accuracy and computational speed. In a similar vein, Poikonen et al. (2019) presented four heuristic strategies based on branch-and-bound techniques, which were developed to enhance efficiency for medium-sized problems, thereby broadening the practical scope of exact and hybrid optimization methods.

As the scale and complexity of TSP-D instances increase, heuristic and metaheuristic approaches have gained prominence due to their computational efficiency and flexibility. For instance, a hybrid metaheuristic that integrates Genetic Algorithms (GA) with Ant Colony Optimization (ACO) has shown enhanced performance in optimizing both truck and drone routes simultaneously. This approach has produced more reliable solutions compared to traditional methods (Gunay-Sezer et al., 2023). In another study, a Variable Neighborhood Tabu Search (VNTS) approach was employed to reduce total delivery time by explicitly accounting for truck waiting periods at rendezvous points (Tong et al., 2022). Additionally, the General Variable Neighborhood Search (GVNS) metaheuristic outperformed existing methods in over 80% of benchmark instances, highlighting its effectiveness across diverse scenarios (Freitas et al., 2023). Complementing these efforts, a hybrid genetic algorithm designed to minimize both cost and delivery time has shown promising results when applied to complex TSP-D configurations (Gansterer and Hartl, 2017). Beyond consumer-oriented last-mile delivery, routing models have also been extended to healthcare logistics. In this domain, Acar and Altin (2025) formulated the medication distribution problem as a Multi-Depot General Colored Traveling Salesman Problem with Time Windows (MD-GCTSP-TW), capturing the

operational constraints and growing demand associated with home healthcare services. In summary, the integration of drones into last-mile delivery has profoundly reshaped classical routing problems, giving rise to new challenges and opportunities in optimization. Metaheuristic frameworks, owing to their adaptability and scalability, offer a viable pathway for solving large-scale TSP-D instances and hold significant promise for the future of intelligent urban logistics.

3. PROBLEM DESCRIPTION AND MODEL

3.1. Problem description

The fundamental configuration of a last-mile delivery system traditionally involves dispatching ground-based vehicles, primarily trucks, from a central distribution facility to sequentially serve a series of spatially distributed customer locations, as illustrated in Figure 1. In the illustrative case, a single depot is responsible for fulfilling delivery tasks to ten customer nodes. However, due to urban infrastructure constraints, such as narrow roadways or restricted vehicular access, traditional trucks may encounter severe operational inefficiencies or may be entirely incapable of accessing certain customer sites. To overcome spatial constraints and regulatory challenges, recent studies have focused on incorporating drones as a supplementary delivery solution. This integration has notably improved the flexibility of routing and expanded geographic coverage. In such hybrid configurations, customer locations that are challenging for truck access are reassigned to drones, which can effectively reduce total travel time and expand service reach in complex environments.

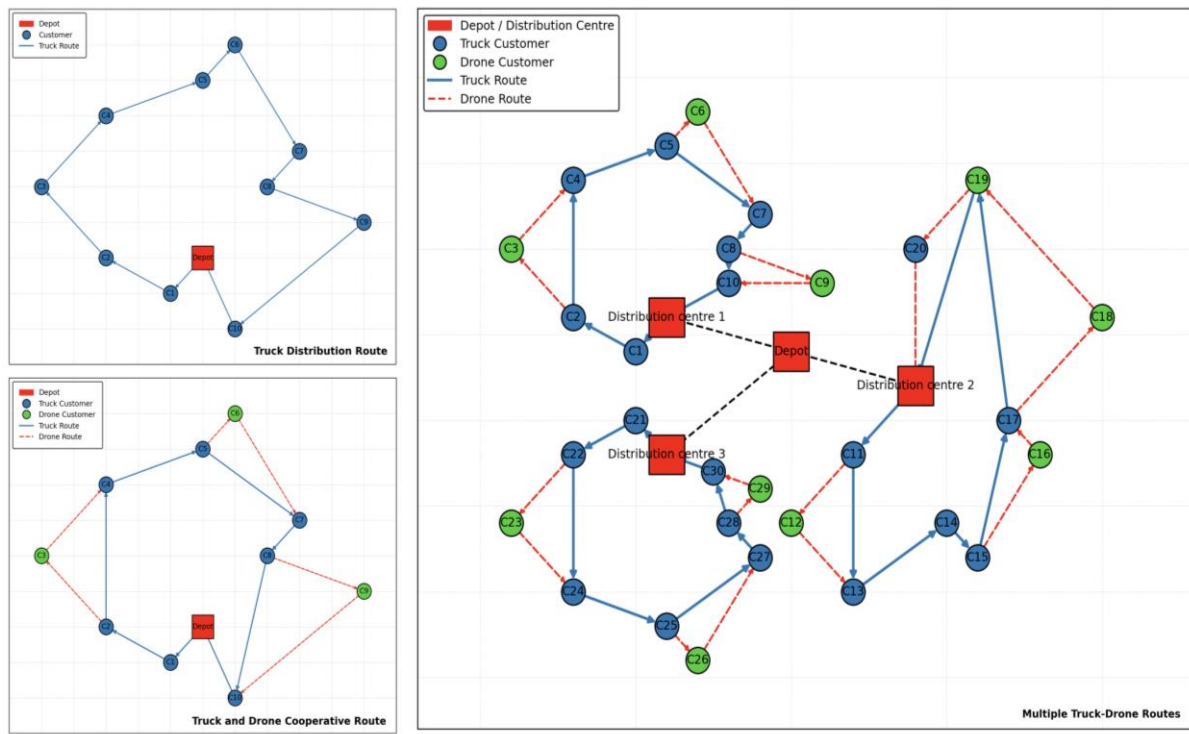


Figure 1. Multiple truck-drone distribution routes

In pursuit of improved operational efficiency, particularly in dense urban delivery contexts, this study implements a K-means clustering approach to partition the entire service area into K operational subregions. Each cluster is assigned an independent local depot to act as a secondary distribution center. Based on node characteristics and feasibility constraints, delivery responsibilities are allocated to either trucks or drones. Both delivery modes operate under a closed-loop paradigm, whereby vehicles and drones are required to depart from and return to their respective depots, ensuring operational continuity. In the coordinated mode, the drone is transported by the truck and launched at predetermined release points, thereby conserving its limited battery power for essential delivery segments. As shown in Figure 1, a single drone may perform multiple sorties within a truck route. Each sortie begins and ends at a designated customer location, with the truck driver assisting in package deployment and drone recovery operations. This synergistic architecture significantly enhances routing

agility, energy efficiency, vehicle utilization, and service responsiveness, particularly in constrained or inaccessible delivery environments.

To maintain computational tractability and isolate the impact of synergistic routing logic between ground and aerial vehicles, several fundamental assumptions are established. The distribution facility is assumed to possess sufficient inventory and transport carriers to fulfill all customer demands without shortage, providing a benchmark for optimal routing performance. Each truck is equipped with at most one drone, and each drone sortie is restricted to serving a single customer per trip, a constraint that aligns with current industry safety protocols and mission reliability standards. All customer demands are assumed to be within the truck's maximum capacity and must be fully satisfied. Provisions for drone maintenance, including battery replacement and reloading, are conducted at rendezvous points to ensure operational continuity. The drone fleet is considered homogeneous in terms of range and energy consumption, and the model omits stochastic variables such as charging durations and fine-grained loading times to focus on synchronization efficiency. Finally, each customer location is visited exactly once, ensuring a non-redundant delivery schedule.

3.2. Modeling

The truck and drone vehicle routing problem can be framed as a graph-based problem. Let $G = (N, A)$ represent an undirected, incomplete graph, where $N = \{0, 1, 2, 3, 4, \dots, n+1\}$ is the set of all vertices, encompassing both the start and end points. In this graph, node 0 corresponds to the distribution center, while the other nodes represent the customer locations. The customer locations are denoted as $c = \{1, 2, 3, 4, \dots, n\}$, and the set of points accessible by drones is represented by $M = \{0, 1, 2, 3, 4, \dots, n\}$. The coefficient c_2 represents the cost of drone delivery, while d_{ij} denotes the travel distance between node i and node j . The model parameters and decision variables are summarized in Table 1.

Table 1. Model parameters and Decision variables

	Parameter	Type	Meaning
Parameters	N		The set of all points (including start and end points)
	M		The set of points that can be delivered using a drone
	O		Start and end points
	c_1		Distance cost coefficient for truck delivery
	c_2		Distance cost coefficient for drone delivery
	d_{ij}		Traveling distance from node i to node j
Decision variables	x_{ij}	$\{0, 1\}$	Whether the truck passes through the path from node i to node j
	y_{ij}	$\{0, 1\}$	Whether a drone passes through the path from node i to node j
	s_i	$\{0, 1\}$	Whether node i is delivered by a truck
	a_{ij}	$\mathbb{Z}_{\geq 0}$	For sub-loop elimination, the number of antecedent arcs of the path (arc) from node i to node j

This paper formulates a mathematical optimization model based on Mixed Integer Programming (MIP), as detailed below. The objective of the model is to tackle the truck and drone vehicle routing problem by combining both truck and drone deliveries in order to minimize the overall travel costs. The problem is specifically framed as follows:

$$\text{Min } \sum_{i \in N} \sum_{j \in N} (x_{ij} d_{ij} c_1 + y_{ij} d_{ij} c_2) \quad (1)$$

$$\sum_{j \in N} x_{ij} = 1, \quad \forall i \in N \setminus M \quad (2)$$

$$\sum_{j \in N} x_{ji} = 1, \quad \forall i \in N \setminus M \quad (3)$$

$$\sum_{j \in N} (x_{ij} + y_{ij}) = 1, \quad \forall i \in M \quad (4)$$

$$\sum_{j \in N} (x_{ji} + y_{ji}) = 1, \quad \forall i \in M \quad (5)$$

$$\sum_{j \in N} y_{ij} = \sum_{j \in N} y_{ji}, \quad \forall i \in M \quad (6)$$

$$x_{ii} = 0, \quad \forall i \in N \quad (7)$$

$$y_{ii} = 0, \quad \forall i \in M \quad (8)$$

$$s_i = \sum_{j \in N} x_{ij}, \quad \forall i \in N \quad (9)$$

$$\sum_{j \in N, j \neq i} a_{ij} - \sum_{j \in N, j \neq i, j \neq 0} a_{ji} = s_i, \quad \forall i \in N \quad (10)$$

$$a_{ij} \leq |N| x_{ij}, \quad \forall i \in N \setminus 0, \forall j \in N \quad (11)$$

$$y_{ij} + y_{jk} \leq 2x_{ik} + 1, \quad \forall i \in N, j \in M, k \in N \quad (12)$$

$$\sum_{j \in N} y_{ij} \leq 1, \quad \forall i \in N \quad (13)$$

$$\sum_{j \in N} y_{ji} \leq 1, \quad \forall i \in N \quad (14)$$

$$y_{ij} \in \{0,1\}, \quad \forall i, j \in N \quad (15)$$

$$x_{ij} \in \{0,1\}, \quad \forall i, j \in N \quad (16)$$

The truck and drone vehicle routing problem is formulated as an optimization model aimed at minimizing the total delivery cost. The objective function (1) seeks to minimize the combined costs associated with both truck and drone deliveries. Regarding the constraints, Constraints (2) and (3) ensure that each customer is visited exactly once by the truck, thereby adhering to the fundamental principles of the vehicle routing problem by ensuring that the truck departs from and returns to each customer location precisely once. Constraints (4) and (5) impose that, for customers eligible for drone service¹³, the drone is allowed to visit each customer only once, thus eliminating any potential for service duplication. Furthermore, Constraint (6) specifies that a customer served by the drone must also be departed from by the drone, ensuring that the drone completes its delivery cycle for every customer it serves. Constraints (7) and (8) prevent self-loops for both the truck and drone, ensuring that neither vehicle revisits a node without serving it, thus preventing unnecessary travel and ensuring an efficient route. Constraint (9) defines the truck's visiting status, indicating whether the truck is assigned to visit a particular customer node or not. To prevent the formation of disjoint subtours, we adopt a flow-based Gavish-Graves (GG) formulation, represented by the pair of Constraints (10) and (11). Constraint (10) enforces the conservation of a dummy commodity flow at each customer node i visited by the truck (where $s_i = 1$). Constraint (11) ensures that this flow can only traverse through active arcs where $x_{ij} = 1$. Together, these constraints force all truck-served nodes to be connected to the depot in a single continuous route. Furthermore, the operational synchronization between the truck and the drone is strictly governed by Constraint (12), which synchronizes the launch and rendezvous locations. This time-coordination condition ensures seamless collaboration between the truck and drone, allowing for efficient joint operations. Constraints (13) and (14) impose the restriction that each drone can only be assigned to one mission at any given time, preventing overlapping or conflicting drone operations. Constraints (15) and (16) enforce binary variable constraints on x_{ij} and y_{ij} ensuring that these decision variables take only valid binary values (0 or 1), thus guaranteeing proper operational assignments for the truck and drone.

3.3. Algorithmic Framework for Cluster-Based Coordinated Truck–Drone Delivery Optimization

To enhance the computational efficiency and scalability of the proposed integrated truck-drone delivery system, a spatial decomposition strategy was employed, utilizing the K-means clustering algorithm. The optimal number of clusters was determined through the Silhouette Coefficient (SC), a metric that assesses clustering quality by balancing the cohesion within clusters and the separation between them. Upon determining the optimal cluster structure, customer nodes were grouped into geographically contiguous subregions, each served independently by a coordinated truck and drone pair. Within each zone, customers located in areas deemed logistically unsuitable or inefficient for ground transportation, due to physical or infrastructural constraints, were designated as drone-exclusive service targets. This hierarchical framework combines a data-driven clustering module with a two-stage truck–drone routing optimization process, implemented in a Python–Gurobi hybrid environment. The proposed method enhances both workload balance across service regions and delivery mode differentiation. A formal pseudocode outlining the algorithm, referred to as SC-KMeans Clustering and TSP-D Optimization with drone Integration, is provided below.

Algorithm: SC-KMeans Clustering and TSP-D Optimization

Input: Node set N , Depot candidate set D , Cluster range K_{range} , Distance matrix d_{ij} , Drone cost coefficient c , Drone-eligible nodes $M \subseteq N$, Depot node(s) $O \subseteq N$

Output: Optimal number of clusters k^* , Final clustering result $Cluster[]$, Cluster centers $Centro[]$, Truck route list $route$, Drone route plan $dict_drone_route$

Initialize empty list $sil_values \leftarrow []$

For each k in K_range :

 Select depot locations from set D as initial cluster centers $Centro[1, \dots, k]$

 Initialize empty cluster list $Cluster[1, \dots, k]$

 Set $Changed \leftarrow \text{True}$

 While $Changed == \text{True}$:

 Clear all clusters $Cluster[i]$

 For each node x in N :

 Compute distance from x to all $Centro[i]$; assign x to closest cluster i

 End For

 Recalculate $Centro[i]$ as mean of points in $Cluster[i]$

 If all $Centro$ unchanged: set $Changed \leftarrow \text{False}$

 End While

 For each node x in N :

 Compute silhouette value $s(x)$ based on current cluster assignment

 Compute average silhouette score $S(k)$ over all nodes

 Append $S(k)$ to sil_values

End For

Let $k^* \leftarrow \text{argmax}(sil_values)$

Re-run KMeans with k^* to obtain final $Cluster[k^*]$ and $Centro[k^*]$

Define TSP-D input:

$N \leftarrow$ all nodes;

$M \leftarrow$ drone-eligible nodes;

$O \leftarrow$ depot nodes

$d_{ij} \leftarrow$ pairwise distances

$c_1 \leftarrow$ truck distance cost coefficient

$c_2 \leftarrow$ drone distance cost coefficient

Create Gurobi model

Define variables:

$x_{ij} \in \{0,1\}$ // truck travels from i to j

$y_{ij} \in \{0,1\}$ // drone flies from i to j

$s_i \in \{0,1\}$ // node i is served by truck

$a_{ij} \in \mathbb{Z}_{\geq 0}$ // Gavish–Graves(GG) flow variable for subtour elimination

For all $i \in N \setminus M$:

$\sum_{j \in N} x_{ij} = 1, \sum_{j \in N} x_{ji} = 1$

For all $i \in M$:

$\sum_{j \in N} (x_{ji} + y_{ij}) = 1, \sum_{j \in N} (x_{ij} + y_{ji}) = 1$

$\sum_{j \in N} y_{ji} = \sum_{j \in N} y_{ij}$

For all $i \in N$:

$\sum_{i \in N} x_{i,i} = 0, \sum_{i \in N} y_{i,i} = 0$

For all $i \in N \setminus O$:

$s_i = \sum_{j \in N} x_{ij}$

$\sum_{j \in N \setminus \{i\}} a_{ij} - \sum_{j \in N \setminus \{O, i\}} a_{ji} = s_i$

 For all $j \in N$:

$a_{ij} \leq |N| * x_{ij}$

For all $j \in M$:

 For all $i \in N, k \in N$:

$y_{ij} + y_{jk} \leq 2 * x_{ik} + 1$

For all $j \in N$:

Algorithm: SC-KMeans Clustering and TSP-D Optimization

$$\begin{cases} \sum_{j \in N} y_{ij} \leq 1 & \forall i \in N \\ \sum_{j \in N} y_{ji} \leq 1 & \forall i \in N \end{cases}$$

Define objective function:

$$\text{Minimize } \sum_{i \in N} \sum_{j \in N} x_{ij} \cdot d_{ij} \cdot c_1 + y_{ij} \cdot d_{ij} \cdot c_2$$

Solve the model using Gurobi.optimize()

Extract truck path from $x_{ij} = 1 \rightarrow \text{list_route}$

Extract drone routes from $y_{ij} = 1 \rightarrow \text{dict_drone_route}$

Return k^* , Cluster[k^*], Centro[k^*], list_route, dict_drone_route

4. RESULTS

The proposed coordinated delivery model involving both trucks and drones was implemented through a hybrid computational framework that integrates the Gurobi optimizer and Python programming environment, running under a standard operating system. To enhance the computational efficiency of the problem and improve the scalability of the algorithm, a spatial decomposition strategy was adopted by clustering customer nodes into distinct regional zones. Each zone is managed independently and serviced by a dedicated truck–drone pair.

To determine the optimal number of operational clusters, the Silhouette Coefficient (SC), a well-known metric for evaluating clustering quality, was used. As shown in Figure 2, the SC value reaches its highest when the number of clusters is set to seven, indicating that this configuration strikes the best balance between inter-cluster dispersion and intra-cluster cohesion. Consequently, the optimal number of clusters was determined as seven, and the 169 customer nodes were partitioned into seven service regions with corresponding depot locations, as illustrated in Figure 2.

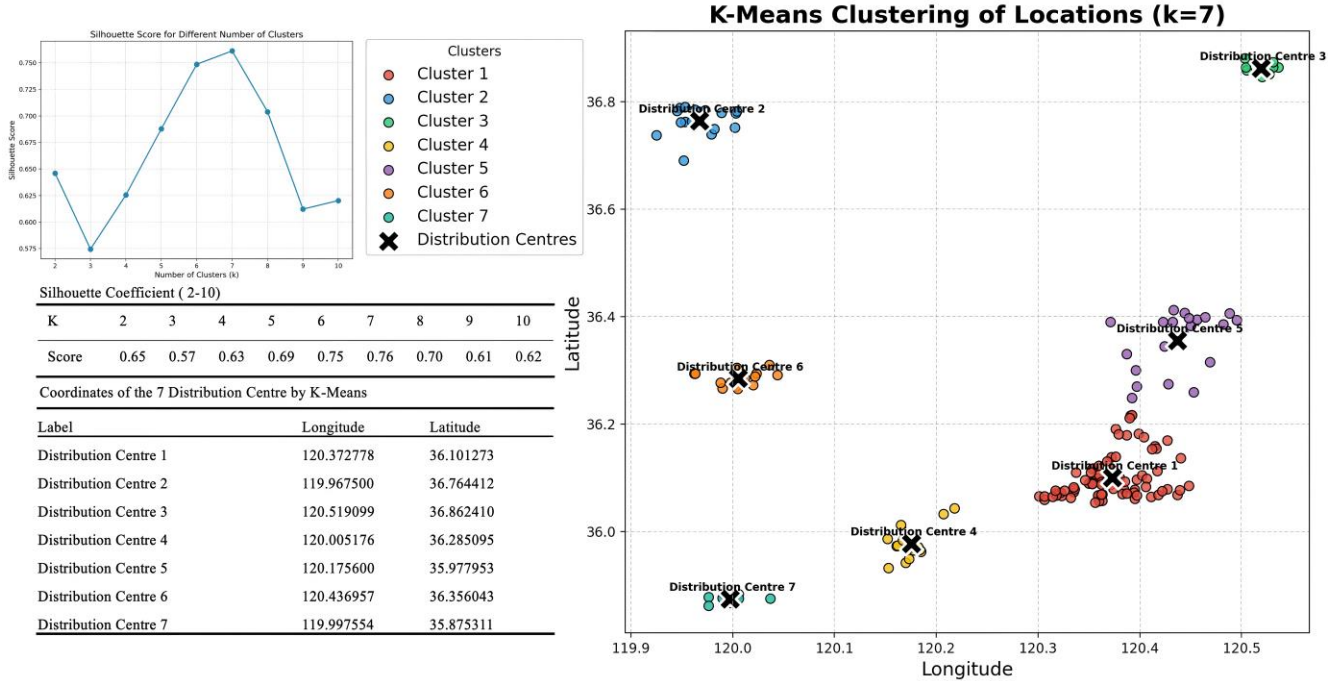
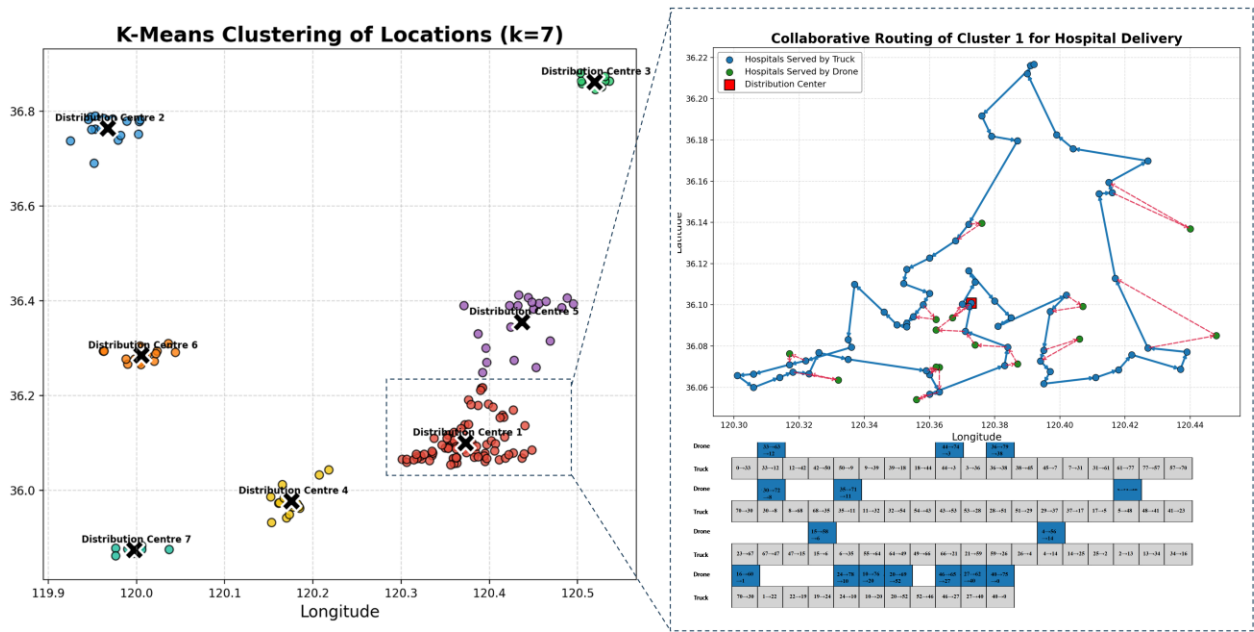


Figure 2. Silhouette Coefficient and K-means

Following this clustering phase, the algorithm proceeds to solve the subproblems corresponding to each cluster independently. Within each region, truck routes are planned in tandem with drone deployments, enabling the drone to be launched and retrieved by the truck at designated nodes. This operational synergy between truck and drone substantially reduces delivery time and enhances overall routing efficiency. The detailed results for each cluster are presented as follows:



Cluster 1 encompasses 64 nodes visited by the truck, supplemented by 15 drone-dispatched deliveries at strategic launch–return pairs such as (4,14), (20,52), and (46,27). Given the region’s high density and complexity, the optimization process took approximately 306.052 seconds to reach convergence. Cluster 2 includes a moderately sized route with 14 truck stops and 2 drone deliveries, namely (5,4) and (6,5). The computational time was relatively minimal at 1.787 seconds. Cluster 3 consists of a compact route containing 10 nodes, with 3 drone missions carried out for (5,2), (2,3), and (3,6). The solution was obtained within 0.673 seconds. Cluster 4 features 14 truck nodes and a single drone operation at (11,0), solved in 1.849 seconds. Cluster 5 includes a larger set of 19 truck stops and 4 drone deliveries, such as (2,15), (3,6), and (6,14). The total time to solve was 2.188 seconds. Cluster 6 presents a balanced topology with 15 truck nodes and 2 drone flights, executed at (0,2) and (3,1), requiring 1.761 seconds for optimization. Cluster 7 is a relatively small region, involving 7 truck nodes and 2 drone launches, namely (0,4) and (3,2), with a runtime of 1.281 seconds.

To provide a comprehensive overview of the optimization performance, the key metrics for all seven clusters, including objective values, travel distances, delivery splits, and computational efficiency, are summarized in Table 2.

Table 2. Summary of Optimization Results Across Seven Clusters

Cluster ID	Objective (Total Dist.)	Drone Deliveries	Truck Deliveries	Drone Split (%)	Truck Split (%)	Computation Time (s)
Cluster 1	121.98	15	64	18.99%	81.01%	306.052
Cluster 2	42.22	2	14	12.50%	87.50%	1.787
Cluster 3	19.19	3	7	30.00%	70.00%	0.673
Cluster 4	30.68	1	14	6.67%	93.33%	1.849
Cluster 5	84.96	4	19	17.39%	82.61%	2.188
Cluster 6	16.56	2	15	11.76%	88.24%	1.761
Cluster 7	10.96	2	7	22.22%	77.78%	1.281
Average	46.65	-	-	17.15%	82.85%	45.036

To examine the impact of operational cost structures on delivery assignment decisions, a sensitivity analysis was conducted with respect to the drone cost coefficient. The results, presented in Table 3, show a substantial change in delivery patterns as the relative cost of drone operations varies. When the drone cost coefficient decreases from 0.4 to 0.1, the proportion of drone-served customers increases from 0% to 30.77%, indicating that drone deployment becomes progressively more attractive as drone operations become less costly. A notable transition occurs when the coefficient reaches 0.4, under which the optimization model completely excludes drone operations and assigns all delivery tasks to trucks. This behavior suggests that the economic viability of drone-assisted delivery is highly dependent on relative operating costs. Under high-cost conditions, the efficiency gains associated with drone deployment are insufficient to compensate for additional coordination and operational requirements. As drone costs decrease, however, the model increasingly utilizes drones, particularly in clusters characterized by dispersed customer distributions and relatively inefficient truck routes. The results also show that computational time remains relatively stable across different parameter settings. This indicates that variations in delivery assignment patterns have limited influence on the overall computational performance of the proposed framework.

Table 3. Sensitivity Analysis of Drone Cost Coefficient

Drone Cost Coefficient	Drone Deliveries	Truck Deliveries	Drone Split (%)	Truck Split (%)	Average Computation Time (s)
0.1	52	117	30.77%	69.23%	45.873
0.2	29	140	17.15%	82.85%	45.036
0.3	16	153	9.47%	90.53%	45.721
0.4	0	169	0.00%	100.00%	45.508

5. DISCUSSION

The results provide clear evidence that the proposed spatial decomposition framework substantially improves the tractability of large-scale truck–drone routing problems. By decomposing the 169-node instance into multiple compact service regions according to the Silhouette Coefficient, the model effectively reduces the search complexity associated with large-scale TSP-D formulations. Unlike conventional meta-heuristic approaches, which often exhibit unstable convergence behavior as the problem scale increases, the proposed framework maintains stable computational performance across all sub-regions. In

particular, Clusters 2–7 were solved within 2.2 seconds, while the densest cluster also converged within an operationally acceptable time. These findings indicate that localized decomposition enables the optimization process to focus on structurally similar demand patterns, thereby improving computational efficiency without sacrificing solution quality. The framework therefore offers a practical solution for large-scale urban routing optimization in dense urban logistics systems.

The numerical analysis further demonstrates the operational advantages of integrating drones into truck-based delivery systems. The average drone service ratio reached 17.15%, although substantial variation was observed among clusters, ranging from 6.67% to 30.0%. This heterogeneity reflects the sensitivity of the model to local spatial structures and routing conditions. In areas characterized by high truck detour costs or fragmented customer distributions, the optimization process assigned a larger proportion of deliveries to drones, allowing the system to bypass inefficient ground routes. Under such conditions, the truck primarily functions as a mobile support platform for drone dispatch and recovery. The resulting coordination mechanism improves route flexibility and shortens service completion time through parallel operations between ground vehicles and drones. The consistency of these collaborative patterns across all clusters suggests that the proposed framework remains effective under varying urban delivery environments.

From an operational perspective, the decomposition strategy also improves system robustness by separating the overall network into independently manageable service regions. This structure limits the propagation of localized disruptions and facilitates adaptive rescheduling under dynamic urban conditions. Although the current study assumes constant drone flight speed and does not explicitly model battery degradation or stochastic energy consumption, the relatively low computational burden of the framework provides favorable conditions for future dynamic re-optimization. Future studies may extend the proposed model by incorporating energy uncertainty, payload-dependent flight performance, and time-varying traffic conditions to further enhance its applicability in real-world urban logistics operations.

6. CONCLUSION

This study proposes a two-stage optimization framework for medical supply distribution in Qingdao, China, through a coordinated truck–drone delivery system. In the first stage, the Silhouette Coefficient is used to evaluate clustering performance under different k -values and determine an appropriate partition structure for large-scale customer nodes. Customer locations are then divided into several service regions through the K-means algorithm, with each cluster assigned a localized depot acting as a secondary distribution center. In the second stage, a mixed-integer programming (MIP) model is formulated to minimize total delivery cost under truck–drone collaborative operations. The model explicitly considers feasible rendezvous locations between trucks and drones, as well as truck-accessible service areas, to ensure operational feasibility within each cluster. Due to operational and regulatory constraints, drone services are limited to a subset of designated hospitals.

The computational results generate seven customer clusters and corresponding depot locations, each associated with an independent truck–drone routing plan. Compared with conventional truck-only delivery strategies, the proposed framework improves both delivery efficiency and operational sustainability. The results also indicate that truck–drone coordination can enhance the responsiveness of emergency medical logistics while increasing the flexibility of urban healthcare distribution systems. In addition, the decomposition-based framework improves the tractability of large-scale routing problems by reducing the complexity of the solution space.

Several limitations remain in the current study. Dynamic customer demand, stochastic order arrivals, payload-related energy consumption, and delivery time windows are not considered. To maintain computational tractability and remain consistent with current operational safety requirements, the model adopts a single-drone-per-truck configuration and restricts each drone sortie to a single customer. Future research may extend the framework to multi-drone coordination, multi-stop drone missions, and dynamic routing environments. Incorporating real-time traffic conditions, battery degradation, and demand uncertainty would further improve the applicability of the proposed framework in practical urban medical logistics operations.

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