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Collaborative Truck/Drone Routing Problem: An Application to Disaster Logistics

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Abstract: This study focuses on collaborative UAV/UGV routing problem in emergency logistics aiming to optimize the coordinated delivery efforts of both vehicles during disaster situations. By using a mixed integer model the study identifies the best delivery points and assigns specific drones to transport medical supplies to designated emergency assembly points. The research methodically assesses how UAV speed, UGV stops and cluster numbers affect delivery time. The results show that increasing UAV speeds and reducing stops and clusters generally lead to deliveries but achieving the time requires a careful balance due to their complex interactions. The study suggests that strategic coordination between UAVs and UGVs can significantly improve the efficiency of emergency logistics systems potentially reducing response times in disaster relief and medical supply deliveries. In conclusion the model highlights the potential for enhancements, in emergency response capabilities that could help save lives and lessen disaster impacts. Future studies should consider adapting the model for conditions and unpredictable scenarios to ensure resilience against demands.
Keywords: Disaster Logistic, Autonomous Vehicles, Traveling Salesman Problem, Routing Problem

Introduction

Natural disasters are increasing day by day around the world. Climate change is one of the primary issues contributing to the increase in these disasters. As a result, human life and development are negatively affected. Understanding the nature, stages, and components of these disasters is crucial in effectively dealing with them. Natural disasters often cause significant losses for people. Delivering aid materials to the affected regions is an essential part of disaster relief efforts. However, the post-disaster environment is challenging, and traditional ground-based material delivery is severely affected. In densely populated cities such as Istanbul, where ground transportation is disrupted, alternative disaster logistics plans are necessary. The final stage of delivering aid materials heavily relies on human transportation, which is expensive, risky, and reduces the efficiency of modern disaster relief missions. In Worldwide, there have been numerous natural disasters that resulted in major loss of life and huge financial harm. For instance, the Wenchuan earthquake in China in 2008 caused over 69,000 fatalities [1]. Similarly, in Türkiye, two earthquakes in 1999 led to more than 20,000 deaths [2] and an economic loss of approximately 9 to 13 billion dollars [3]. The two very large earthquakes of February 2023 in southern side of Türkiye caused an estimated $34.2 billion in direct physical damages, the equivalent of 4% of the country’s 2021 GDP, according to a World Bank rapid damage assessment report [4]. These disasters have had a significant impact on governments, civil society organizations, and communities. As a result, the need to develop an effective disaster prevention and relief system has been acknowledged world- wide. Countries, including Türkiye, have recognized the importance of having a well- functioning disaster coordination center based on experiences gained from past disasters,

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particularly in the areas of relief supply distribution and maintaining order after a disaster. Emergency logistics is a specific type of logistics operation that focuses on the urgent provision of materials, personnel, and funding in response to serious disasters [5]. Like regular logistics operations, emergency logistics is also concerned with achieving efficiency. However, emergency logistics places greater emphasis on achieving logistics benefits through logistics efficiency. In serious disaster situations, it is essential to urgently deliver relief materials to the affected area. To ensure that this transportation can be carried out regularly, optimizing the route of emergency delivery vehicles is crucial. Through the disaster coordination center, the route scheduling of delivery vehicles becomes possible, allowing for the distribution of aid materials to assembly areas in the disaster area as quickly as possible, thereby significantly reducing pressure on the rescue operation.

In this study, we tested different scenarios for drone speeds and the number of emergency assembly points. Calculations were performed using the Julia programming language and for the visualization, Python packages were used. The model clearly shows us that there is an optimal balance between assembly point number, UAV speed and number of clusters. The results show that minimal total time depends on not only UAV speed, but also cluster and assembly point numbers. This suggests that increasing the UAV speed beyond a certain point may result in diminishing returns in terms of improving the system's performance. Overall, the results show that the UAV speed parameter is a critical factor in the system's performance and should be carefully considered when optimizing the system. However, we must also consider other parameters to achieve overall system optimization. This study shows that significant time savings can be achieved by adjusting the speed of UAVs and the number of delivery points. Optimizing these factors can lead to shorter truck travel distances, reduced UAV energy consumption, and less UAV circling time.

2. Literature Review

2.1. Humanitarian Relief Logistics

Recently, there has been significant research interest in humanitarian relief logistics and emergency logistics planning. Research field can be divided into two categories. The first category concentrates on readiness and management activities that occur before a disaster or emergency event. These activities involve aspects such as determining facility locations, pre-positioning stocks, and developing evacuation plans. The second category focuses on post-disaster or emergency event operations, including activities related to resource distribution and transportation of medical and other necessary equipment [6]. Understanding these categories helps in identifying the crucial stages in disaster logistics where UAV and UGV integration can enhance efficiency and response time.

Meeting the needs of people after a disaster is a crucial mission for emergency logistics. However, due to the sudden and unforeseeable nature of disasters, it is very difficult to meet the needs of all victims early on. In a real-time situation, planning for disaster transportation, route planning, and material transportation from storage are frequently encountered problems.

In disaster situation, planning for logistics and human transportation via air trans- port greatly improves the quality and efficiency of disaster relief efforts. However, poor post-disaster conditions such as seasonal conditions and weather pose serious problems for flight safety, which limits relief material transportation operations. As a result, operational tasks with transport aircraft and helicopters responsible for logistics become more difficult. With groundbreaking developments in unmanned aerial vehicles (UAV) technology today, flight costs have significantly decreased. The use of UAV's for post-disaster material delivery is considered a significant development in emergency logistics because UAV's can easily perform various tasks in disaster areas due to their different load-carrying capacities. UAV's that can operate in a coordinated manner with unmanned ground vehicles (UGV's) and can be coordinated by a disaster coordination center can significantly increase delivery efficiency.

2.2. Increased Natural Disasters and Challenges

As the threat of weather-related catastrophes, pandemics, climate change, extreme weather conditions, depletion of natural resources, and the expansion of urban areas in disaster-prone regions continues to grow, emergency and humanitarian efforts have significantly risen. Over the past two decades, more than 7,000 natural disasters have been documented globally. The number of global disaster events between 2000 and 2022 is shown in Fig. 1 [7].

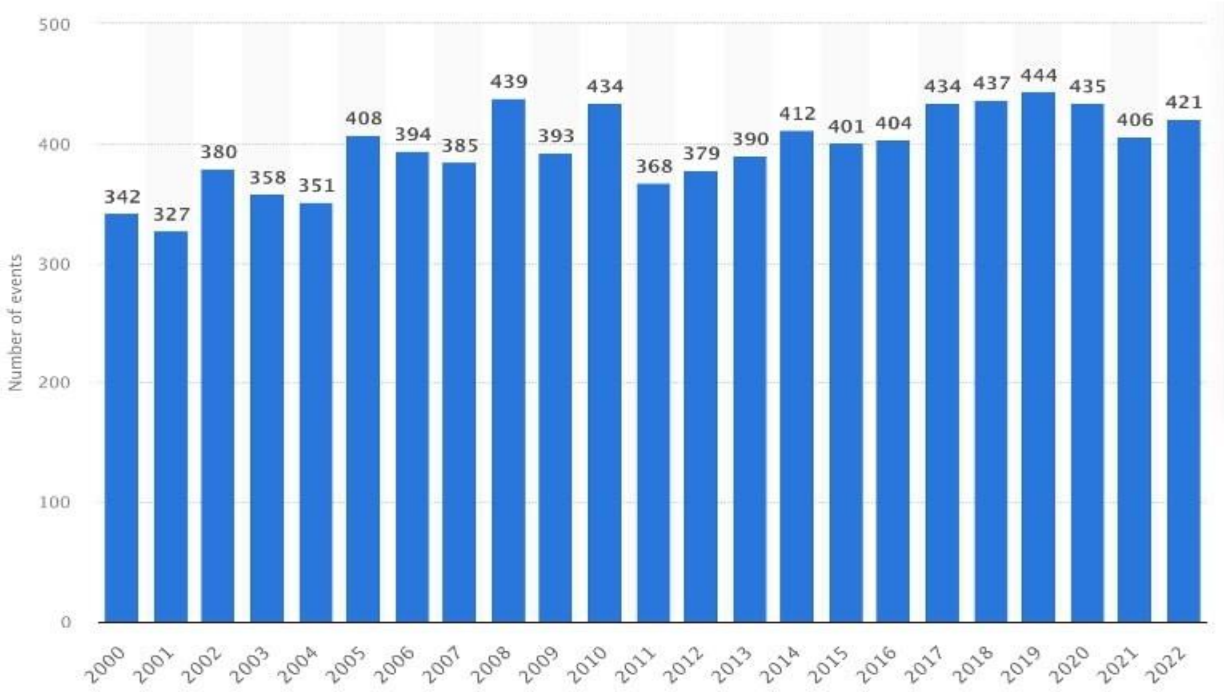


Figure 1. Global number of natural disasters events 2000–2022.

Natural disasters of significant magnitude, such as 2005 Hurricane Katrina in the USA [8], 2012 Japanese tsunami [9], 2015 Nepal earthquake [10], and 2023 Maraş earthquake in Türkiye [11], often result in emergency logistics challenges. These challenges can limit the effective management of emergency resources in affected areas. For instance, 2023 Maraş earthquake in Türkiye caused severe damage to infrastructure, which led to fatal delays in search and rescue operations and relief supplies distributions. In some cases, inefficient emergency logistics management in the affected area results in fatalities [4]. Highlighting the increasing frequency and impact of natural disasters underscores the necessity for innovative logistics solutions, such as the integration of UAVs and UGVs to improve disaster response efficiency.

The COVID-19 pandemic has also highlighted the critical role of emergency logistics and supply chain management in responding to disasters. As a result, there is growing interest among academic researchers and humanitarian logistics practitioners in emergency logistics management to ensure adequate provision of emergency and humanitarian assistance during and after a disaster [12].

Effective emergency logistics management is critical to the survival of affected individuals and the effective management of emergency and humanitarian aid. Logistics plays a crucial role in providing relief supplies and transporting beneficiaries to relief centers, such as hospitals. A recent study estimates that 73% of spending during humanitarian operations goes into logistics [13]. Therefore, logistics-centric disaster risk reduction strategies are vital to vulnerable communities. Emergency logistics differs from business logistics in terms of the end goal, dynamics, and variability of the problem. Emergency logistics practitioners must deal with highly dynamic and stochastic demand in both volumes and location. Unlike business logistics, where downstream members focus on cost and profit, in emergency logistics, they focus on survival and immediate medical attention. The lead times in emergency logistics are very short and require an efficient logistics and transportation network to support the most crucial at stake, i.e., human lives.

2.3. Role of UAVs in Disaster Management

The most important thing to pay attention to in disaster situations is to protect the lives of the disaster victims. In this context, the first 72 hours after the disaster are critically important, which means that Search and Rescue (SAR)-logistics operations must be carried out quickly and efficiently. According to Erdelj [14], UAV's perform their duties in three stages in disaster management as listed below:

- Pre-disaster readiness: operations including surveys conducted before the disaster, threshold sensing, and Early Warning Systems (EWS) [15],
- Disaster assessment stage: real-time situational awareness during the disaster and completion of damage studies for logistical planning [16],
- Post-disaster operations: including search and rescue missions, emergency material deliveries, and similar operations [17].

After the first two stages mentioned above, according to the information obtained from the disaster coordination centre, urgent delivery of materials to emergency assembly points is of critical importance in disaster response stage. Since the delivery will be done against time, it needs to be organized as quickly as possible. There are few studies on logistic planning specifically related to medical supplies using autonomous unmanned ground and air vehicles. The ability of UAVs to perform a wide range of tasks in disaster scenarios makes them ideal for integration into disaster logistics systems, enhancing overall response capabilities.

2.4. Traveling Salesman Problem (TSP) and Vehicle Routing Problem (VRP)

The Traveling Salesman Problem (TSP) and Vehicle Routing Problem (VRP) to address last-mile delivery problems are widely studied in the literature [18], [19], [20], [21], with various variants being considered to account for different operational aspects. The increase in online shopping has made fast delivery an important issue, and researchers are working to improve last-mile logistics and reduce negative externalities.

While trucks have a high capacity and long working range, they are costly and generate negative externalities such as noise and CO2 emissions [22]. Drones, on the other hand, have several advantages, such as high travel speed and low operational costs, but they have limited payload capacity and a short operating range due to limited energy. Therefore, using drones in tandem with trucks could be an efficient way to serve customers. This logistic system can also be used for planned deliveries by autonomous ground and air vehicles in case of possible disasters in urban areas with density populations [23].

According to Raj and Murray [24], there has been increased interest towards last-mile delivery which includes the use of combinations of unmanned aerial vehicles (UAV) and unmanned ground vehicles (UGV), for instance, the flying sidekick traveling salesman problem (FSTSP) and the traveling salesman problem with drone (TSP-D). There are several versions of these problems, some with multiple trucks or drones and different objectives such as reducing time or cost.

One common assumption in the literature [25], [26], [27], [28], [29], [30] about the hybrid UAV/UGV delivery model is that UAVs have constant endurance or flight range, independent of their speed or payload. Such an assumption leads to the conclusion that increasing or decreasing UAV speed reduces the total delivery time or has no effect. In this study, we showed that difference UAV speed difference can affect cluster number and total flight time. These studies provide a foundation for understanding how to optimize the coordination between UAVs and UGVs, a core component of this research.

2.5. Real-World Applications and Case Studies

Ferrandez [31] conducted a study to evaluate the efficacy of incorporating unmanned aerial vehicles in delivery networks. The study compared the efficiency of a truck-drone network with a standalone delivery system in terms of overall delivery time and energy consumption. The findings indicated that

the in- tandem delivery system was more effective than the standalone system, and using multiple drones per truck was even more optimal in terms of energy and time savings.
Major companies like Amazon Prime Air, UPS and DHL are using drone delivery services, and they have received permission from the Federal Aviation Administration for commercial drone deliveries [32]. Now, Matternet has the Swiss aviation authority's approval to conduct complete logistics operations in different cities using their drones. These drones have the capability of transporting loads of up to 2 kilograms and 4 liters over a distance of 20 kilometers [33].
A study was conducted by Safaei et al. [5] to create a relief distribution system, and the way resources flow is illustrated in Fig 2. This system consists of four layers: suppliers, a central warehouse, a Red Crescent (RC) center, transfer depots, and affected areas. The suppliers are responsible for providing the relief items that are needed, making them a crucial part of the relief chain. The RC center has an initial inventory in their ware- house, and the transfer depots act as a link between the supply and distribution points in the network. They receive commodities and plan their distribution to the disaster victims. The real-world use cases confirm the advantages of combining aerial vehicles (UAVs) and unmanned ground vehicles (UGVs) supporting the viability of our suggested logistics approach.

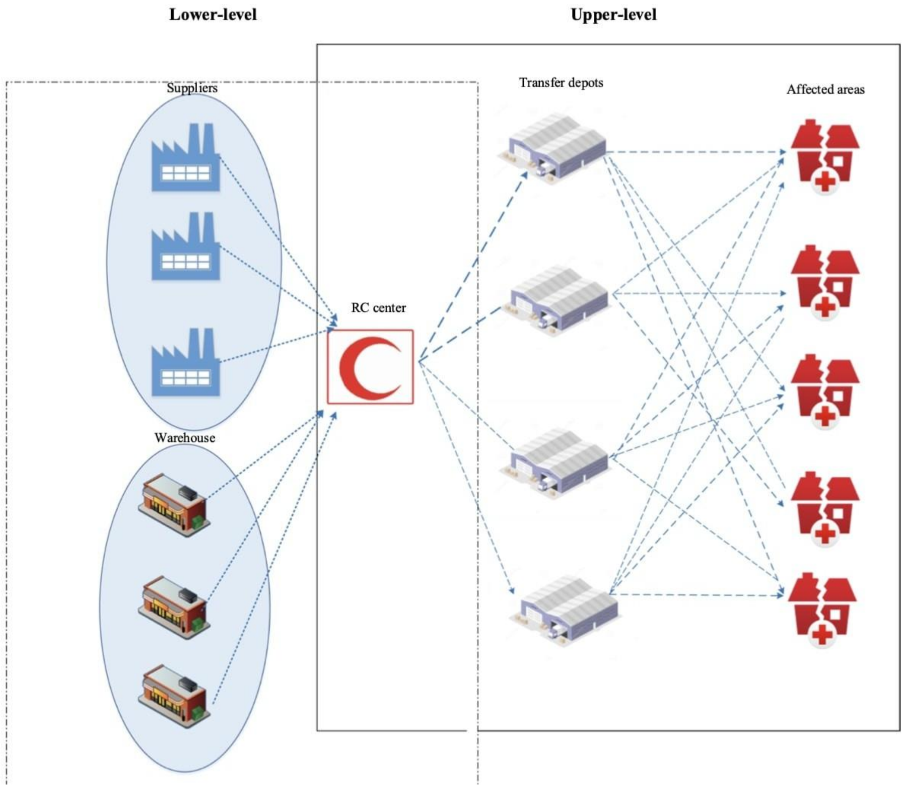


Figure 2. Structure of disaster logistic operation.
In this study, aid requests received by the disaster coordination center were collected, and the delivery of medical kits to emergency assembly points was attempted as quickly as possible using UAV/UGV from a transfer depot. In the next section, the details of the routing problem are explained.

Materials and Methods

In this section we discuss a problem related to routing for UAV/UGV operations, in emergency logistics. This model involves ground vehicles (UGVs) and unmanned aerial vehicles (UAVs) working together to streamline delivery tasks during situations. Specifically, it focuses on enhancing the efficiency of delivering kits to emergency gathering points by considering factors like UAV flight range, delivery order and operational capabilities of both UAVs and UGVs. The subsequent conversation delves into

the assumptions that guide our model, which are based on post disaster operational scenarios. It also delves into how these assumptions shape the problem-solving approach we take.
Assumptions:
Our model is built on assumptions that reflect real world challenges in post disaster logistics;

- Central Depot: There is a designated depot where all medical supplies and vehicles are located, acting as the starting and ending point for delivery routes.
- UGV Capacity: Each UGV has the capability to carry up to four UAVs, aligning with the capacity of sized ground vehicles.
- UAV Capacity: Each UAV can transport one kit due to current limitations in drone payload capacities.
- Visits: Each assembly point is attended by either a UAV or a UGV, preventing redundancy in service provision and optimizing resource utilization.
- Predefined Assembly Points: Emergency assembly points are already set, making it easier to plan the routes for both drones and ground vehicles.
- UAV Return Process: UAVs can come back to the ground vehicle at stops for recharging or reloading, making operations more flexible.
- Multiple Deployments at Once: To minimize total flight time, multiple UAVs can be dispatched from a single UGV stop simultaneously.
- Repeated Takeoffs: UAVs may be launched multiple times from the same point if necessary, maximizing their usage and efficiency.
- Operational Constraints: The range of flights and battery life limit how long UAVs can operate based on their battery capacity, reflecting world limits.
- Vehicle Speeds Consideration: The speeds of both ground vehicles (S_{UGV}) and drones (S_{UAV}) affect delivery times, recognizing their impact on efficiency.
- Load Capacities Acknowledged: The plan takes into account the carrying capacities of both ground vehicles (C_{UGV}) and drones (C_{UAV}) for distributing loads effectively.

These assumptions play a role in shaping the framework of our hybrid UAV/UGV routing challenge, where the primary objective is to plan routes that minimize overall delivery time while considering vehicle capacities, technological constraints, and the urgent nature of emergency logistics.

3.1. Defining the Problem

Based on these assumptions the hybrid UAV/UGV routing challenge aims to optimize the coordination between UAVs and UGVs for delivering emergency kits. The main depot serves as a hub for all delivery operations with UAVs and UGVs working to follow pre- determined routes efficiently reaching emergency assembly points. The aim is to reduce delivery time by addressing the operational limitations of UAVs (such as battery life and payload capacity) and UGVs (such as vehicle capacity and speed). The model utilizes integer linear programming (MILP) to determine the set of routes taking into ac- count how UAV flight capabilities interact with UGV routing while meeting the pressing demand for medical supplies in disaster affected areas.
The following sections provide a representation of this challenge outlining indices, parameters and decision variables that capture the intricacies of emergency logistics, in urban settings.

Table 1. Indices, Parameters, and Decision Variables

Indices	Description
P	Emergency assembly point indices, where $P = \{1, 2, . . . , p_{max}\}$ and p_{max} is the total number o assembly points in the urban area.
Q	Stop indices, where $Q = \{1, 2, . . . , q_{max}\}$ and q_{max} is the total number of stops in the urban are
R	UAV indices, where $R = \{1, 2, . . . , r_{max}\}$ and r_{max} is the total number of UAVs on the UGV.
W	UAV battery swapping indices, where $W = \{1, 2, . . . , w_{max}\}$ and w_{max} is the total number of battery swaps allowed for each UAV.

Parameters	Description
$N_{(p,q)}$	A matrix that indicates whether an emergency assembly point *p* should be delivered from st *q*, with values "1" for yes and "0" for no.
$D_{(p,q)}$	The distance from each emergency assembly point *p* to the stops *q* in minutes.
S_{UGV}	Speed of the UGV in meters per minute.
S_{UAV}	Speed of the UAV in meters per minute.
C_{UGV}	Maximum carrying capacity of medical kits for the UGV.
C_{UAV}	Maximum carrying capacity of medical kits for the UAV.
RR_{UAV}	Recharging rate of the UAV battery in minutes per percentage of charge.

Decision Variables	Description
$M_{(p,q,r)}$	A binary decision variable indicating whether UAV *r* delivers a medical kit to assembly point from stop *q*.
$B_{(q,r,w)}$	A binary decision variable indicating whether UAV *r* swaps its battery at stop *q* for the *w*-th time.
$SD_{(q,r)}$	A real-valued variable representing the total time in minutes that UAV *r* spends delivering ar charging at stop *q*.
$SDM_{(q)}$	A real-valued variable representing the maximum time spent at stop *q* by any UAV, derived from the UAV with the longest delivery and charging time.
$SE_{(p,q,r)}$	A real-valued variable representing the charging time in minutes for UAV *r* after delivering t emergency assembly point *p* from stop *q*.

3.2. Problem Formulation

In this section, we explained the proposed objective function and constraints in the model related to the problem.

Constraints:

• Equation (1) ensures that each medical kit will be delivered by any UAV at any stop.

$$\sum_{p=1}^{p_{\max}} \sum_{r=1}^{r_{\max}} M_{(p,q,r)} = 1, \quad \forall p \in P \tag{1}$$

• Equation (2) ensures that UAVs only deliver to emergency assembly points within their range at each stop. Since the UAV carries a medical kit on the way to delivery, it consumes 150% (60/40) of its charging time. Therefore, the distance from the emergency collection point to the stop in terms of time must be less than 2.5 times the total flight time of 60 minutes. Since the UAV returns empty on the delivery return, it consumes as much charge as it spends time.

$$2{,}5N_{(p,q)}D_{(p,q)}M_{(p,q,r)} \leq 60, \forall p \in P, q \in Q, r \in R \tag{2}$$

• Equation (3) is used to obtain the charging time in minutes for UAV r to deliver to emergency assembly point p from stop q within the model, as obtained from equation (2).

$$2.5N_{(p,q)}D_{(p,q)}M_{(p,q,r)} = SE_{(p,q,r)}, \qquad \forall p \in P, q \in Q, r \in R \tag{3}$$

• Equation (4) finds the total time in minutes that UAV r spends on delivering and charging from stop q.

$$\sum_{p=1}^{p_{\max}} (2N_{(p,q)} D_{(p,q)} M_{(p,q,r)} + SE_{(p,q,r)}) = SD_{(q,r)}, \quad \forall q \in Q, r \in R \tag{4}$$

• Equation (5) is used to obtain the total time in minutes that UAVs spend on delivering and charging from stop q, where the UAV with the longest charging time is considered.

$$SD_{(q,r)} \leq SDM_{(q)}, \qquad \forall q \in Q, r \in R \tag{5}$$

• Equation (6) ensures that each UAV carries no more medical kits than its capacity.

$$\sum_{p=1}^{p_{\max}} M_{(p,q,r)} \leq C_{\text{UAV}}, \quad \forall r \in R, q \in Q \tag{6}$$

• Equation (7) ensures that the UGV carries no more medical kits than its capacity.

$$\sum_{p=1}^{p_{\max}} \sum_{r=1}^{r_{\max}} M_{(p,q,r)} \leq C_{\text{UGV}}, \quad \forall q \in Q \tag{7}$$

• Equation (8) ensures that the number of battery swaps for each UAV does not exceed the maximum allowed number of swaps $w_{\max}$.

$$\sum_{q=1}^{q_{\max}} \sum_{w=1}^{w_{\max}} B_{(q,r,w)} \leq w_{\max}, \quad \forall r \in R \tag{8}$$

• Equation (9) ensures that the flying range of each UAV does not exceed its maximum flying range after a battery swap.

$$(2{,}5\ N_{(p,q)}\ D_{(p,q)}\ M_{(p,q,r)}) + (2{,}5\ N_{(p,q+1)}\ D_{(p,q+1)}\ M_{(p,q+1,r)}) \leq 60\ (1 + B_{(q,r,1)}),$$

$$\forall p \in P, q \in Q, r \in R, q < q_{\max} \tag{9}$$

• Equation (10) ensures that the total flying time of each UAV, including the time spent on deliveries and battery swaps, does not exceed the maximum allowed flying time $t_{\max}$.

$$\sum_{q=1}^{q_{\max}} \left(SDM_{(q)} \cdot M_{(p,q,r)} + \sum_{w=1}^{w_{\max}} B_{(q,r,w)} \cdot RR_{UAV} \right) \leq t_{\max}, \quad \forall r \in R, p \in P \tag{10}$$

• Equation (11) ensures that the UAVs can only fly from stops visited by the UGV. V_{UGV} is a binary variable that takes the value "1" if the UGV visits stop q and "0" othervise. This ensures that UAVs can only fly from stops visited by the UGV.

$$M(p,q,r) \leq V_{UGV}(q), \forall p \in P, q \in Q, r \in R \tag{11}$$

• Objective Function:

The UGV and UAV collaborative logistics path optimization model aims to minimize the total distribution cost. The objective function is shown in Equation (12), which min- imizes the total time spent by the UAV with the longest delivery to emergency assembly point and charging time at each stop in minutes.

$$Z_{\min} = \sum_{q=1}^{q_{\max}} SDM_{(q)} \tag{12}$$

3.3. Solution Methodology

In this section, we explain the approach we used in our model outlining how we applied clustering, routing and optimization algorithms in sequence to create a hybrid UAV/UGV routing plan, for emergency logistics.

Our research hypothesizes that by combining drones (UAVs) and ground vehicles (UGVs) in emergency logistics and applying K Means Clustering, TSP and MILP techniques we can enhance delivery speed and efficiency during disasters. Specifically, we propose that using the K Means Clustering method can help organize emergency assembly points into groups reducing travel distances for drones. The TSP algorithm aims to optimize routes for ground vehicles ensuring they take the paths to reach all cluster centers efficiently. Additionally, MILP is expected to assign delivery tasks to drones in a manner that maximizes their capabilities and flying range while minimizing delivery time. We believe this hybrid strategy will surpass single vehicle approaches – such as using drones or only ground vehicles – in terms of speed and resource management. This is because the combined system leverages on the strengths of both vehicle types; the agility of drones and the capacity/range of ground vehicles. Ultimately this integrated approach offers a more effective solution for emergency logistics, in disaster scenarios.

3.3.1. Clustering

In the first step of our solution strategy, we divide the area into clusters to optimize how UAVs are deployed from UGVs. We utilize the K Means Clustering algorithm because of its effectiveness, in grouping data points (such as emergency assembly points) into a number of clusters denoted as *k*, based on their proximity. This stage is crucial for simplifying operations by segmenting delivery points which helps minimize UAV travel distances and ensures coverage within their limits.

Reasoning Behind the Algorithm Choice; We opt for K Means due to its straightforwardness and efficiency in creating groupings that support the routing phase by assigning cluster centers as stops for UGVs we can strategically position them to launch UAVs thus improving delivery efficiency.

Operational Process; Following the methodology proposed by Ferrandez et al. [31], the K Means algorithm assigns emergency assembly points to the cluster center and updates these centers until convergence is achieved. This iterative process plays a role, in pinpointing optimal UAV launch sites that fall within flight ranges.

3.3.2. Routing

After we define the cluster centers, we figure out how to guide the UGVs to these centers by using the Traveling Salesman Problem (TSP). This known optimization challenge aims to find the route that visits each location once and then returns to the starting point, which is perfect, for planning out UGV paths between cluster centers.

Reason for Choice; We opt for TSP because it directly helps optimize routes ensuring that UGVs take the path through planned stops. This way we can minimize travel times. Contribute to reducing delivery times effectively.

3.3.3. Optimization

The last stage of our approach involves utilizing Mixed Integer Linear Programming (MILP) to outline the delivery tasks assigned to UAVs from each UGV location. MILP enables the representation of decision variables, like which UAV's responsible for delivering to each assembly point within a set of linear constraints (e.g., UAV capacity, flight range).

Implementation Detail: This phase determines the distribution of delivery assignments to UAVs stationed on a UGV considering factors such as battery life and payload capacity. The goal is to ensure that every emergency assembly point receives service in the time while considering the operational limitations of the UAVs.

Integration Insight: MILP complements the clustering and routing stages by offering a optimized allocation of delivery tasks effectively connecting strategic planning with tactical execution, in the hybrid UAV/UGV routing framework.

3.3.4. Combined Methodology

Our methodology combines the advantages of K Means clustering, TSP routing and MILP optimization to tackle the logistics involved in emergency deliveries. This integrated strategy not simplifies procedures but also guarantees that deliveries are carried out within the boundaries and capabilities of the hybrid UAV/UGV system ultimately aiming to reduce total delivery time and enhance responsiveness during emergencies.

3.3.5. Flowchart

To explain how our hybrid UAV/UGV routing solution, Fig. 3. shows the process where a UGV and four UAVs start from a depot to deliver goods to emergency assembly points from six UGV stops landing on the UGV at the stop.

The flowchart in Fig. 3 shows the steps involved in our approach for emergency logistics using UAV/UGV routing. The process begins with generating coordinates for assembly points. Then applying the K Means Clustering Algorithm to divide the area into clusters for optimizing UAV deployments from UGVs. This clustering method helps simplify operations and reduce travel distances for UAVs.

Afterward we establish routes for UGVs using the Traveling Salesman Problem (TSP) to find the paths between cluster centers. This ensures that UGVs follow routes, saving time on travel. Following route planning we use Mixed Integer Linear Programming (MILP) to optimize delivery assignments for UAVs by assigning tasks based on constraints, like UAV capacity and flight range.

Finally, the methodology concludes by examining the outcomes and performance measurements assessing how quickly deliveries are made and the overall efficiency to guarantee that the suggested logistics solution works well. This thorough method is designed to cut down on delivery time and improve responsiveness, in situations.

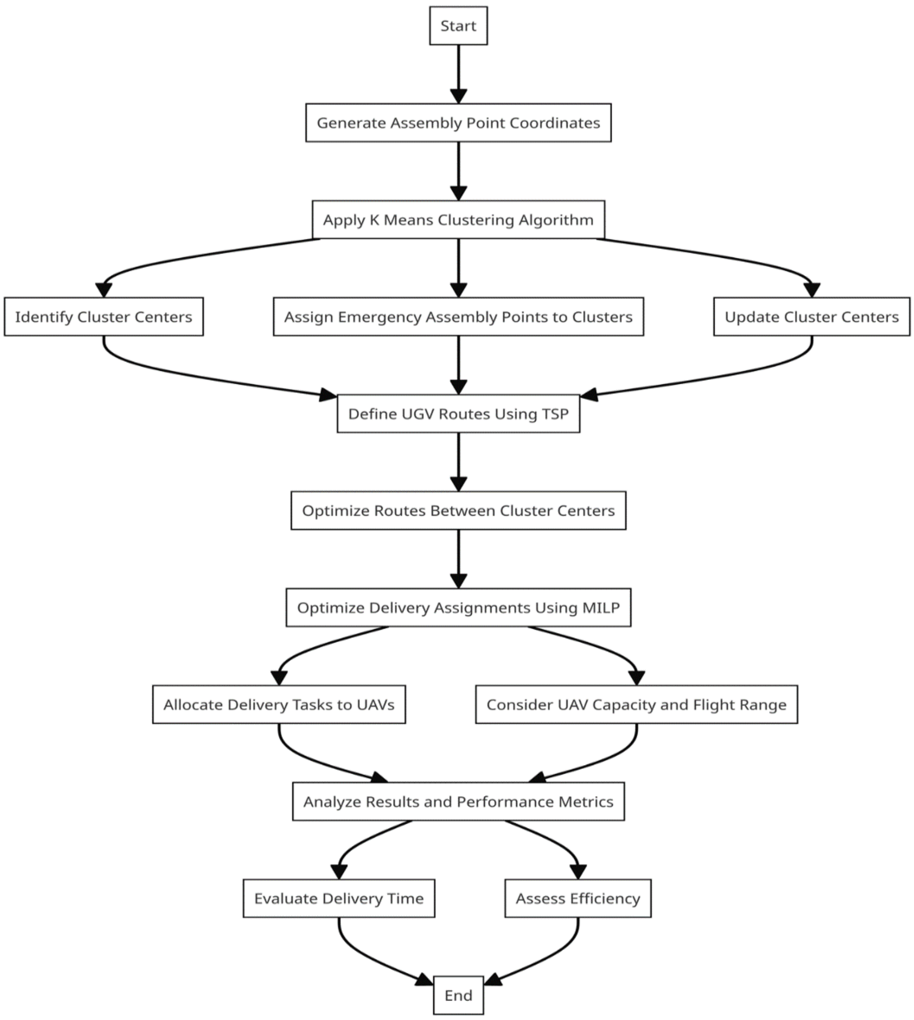


Figure 3. Flowchart of hybrid UAV/UGV routing solution.

In order to describe our hybrid UAV/UGV routing solution approach, in Fig. 4, UGV and four UAVs that left from a central depot deliver to emergency assembly points from six UGV stops, and land on the UGV at the next stop.

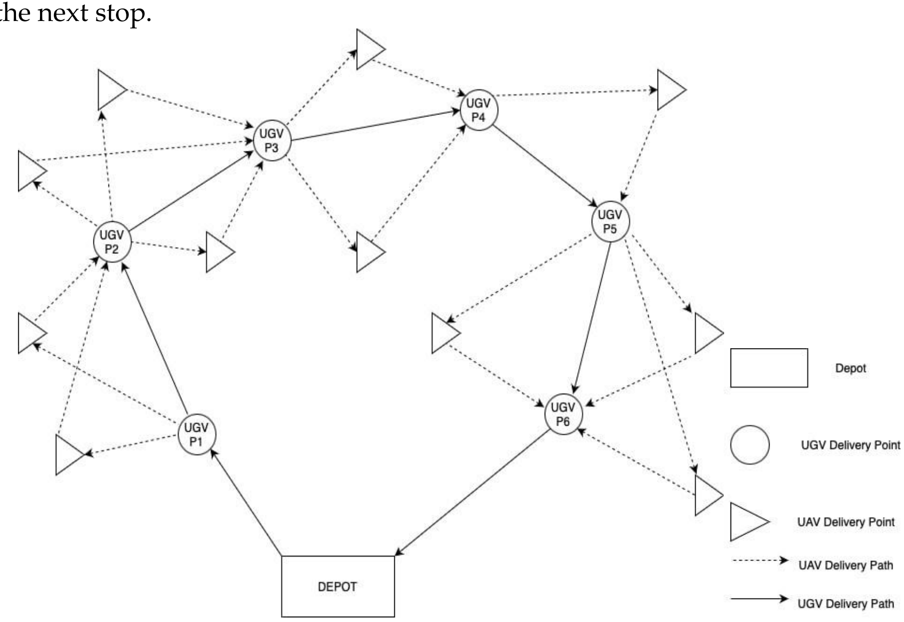


Figure 4. A sample of hybrid UAV/UGV routing solution.

The model present in this study is tested on a computer equipped with an Apple M2 Pro processor and 16 GB RAM. The Julia programming language was used for the calculations, and the Python programming language was used for the 3D visualization of the results.
For Julia calculations:

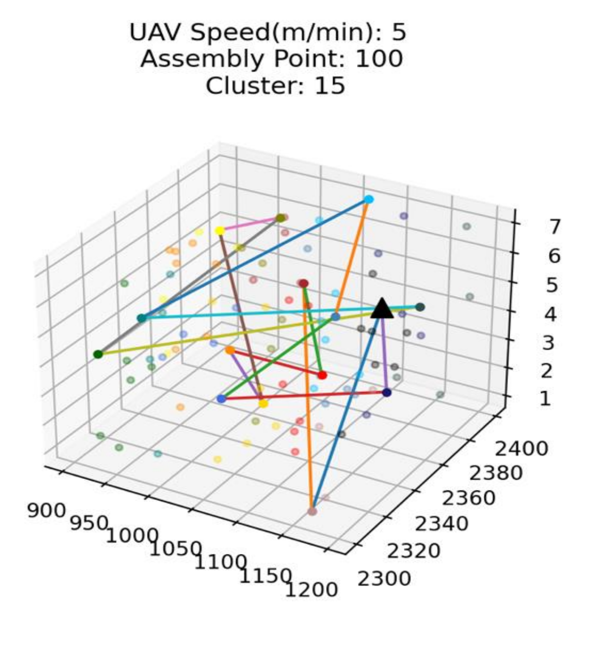
- The number of emergency assembly points is defined as 100 and 200, and the coordinates of assembly points are generated using the JuliaLang/Random.jl rand function package [34].
- The K-means clustering algorithm is used to cluster the assembly points [35]. The maximum number of iterations is set to 200. The emergency assembly points are assigned to each cluster based on their distance to the centre of each cluster.
- The time (in minutes) it takes for each assembly point to reach its assigned cluster's centroid is calculated via JuliaStats/Distances.jl distance package [36].
- For each cluster, LinearAlgebra package [34] is used to deter- mine the optimal assembly points to be delivered by each UAV.
- The heuristic traveling salesman [37] package is used for the UGV route.
- The model is solved using the HiGHS optimizer [38]. The objective function is to minimize the total time taken to deliver to all emergency assembly points.

For Python 3D Visualization:

- matplotlib.pyplot [39] package is used to create the 3D scatter plots and lines,
- pandas [40] package is used to read in and manipulate the data from the Excel files,
- glob package is used to get a list of all Excel files in the current working directory.

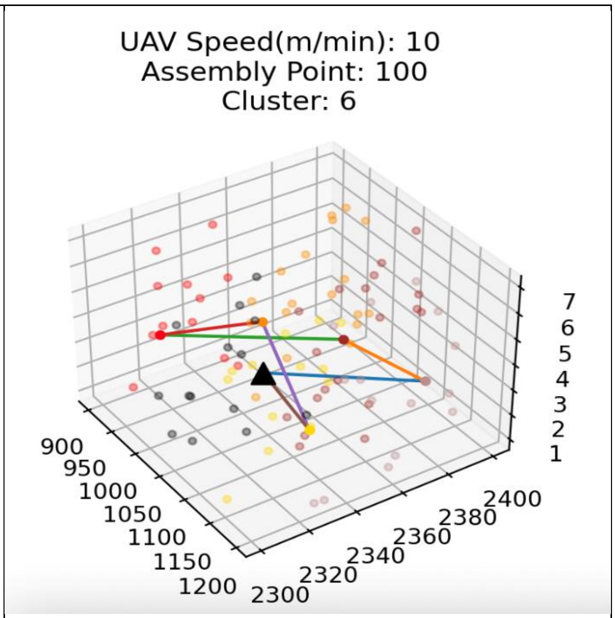
4. Results

In the application, unmanned ground vehicle (UGV) is defined as one, and unmanned aerial vehicle (UAV) is defined as four on the UGV. The battery capacity is determined as 40 minutes with the UAV payload and 60 minutes without the payload. The flight time is defined as 10 m/min when the UAV is loaded and 15 m/min when it is empty. We tested the assembly point parameter at 100 and 200. For both scenarios, we changed the UAV speed parameter to 5 m/min, 10 m/min, and 15 m/min, conducting a total of 6 different scenarios to analyze their effects on total flight time and cluster number.



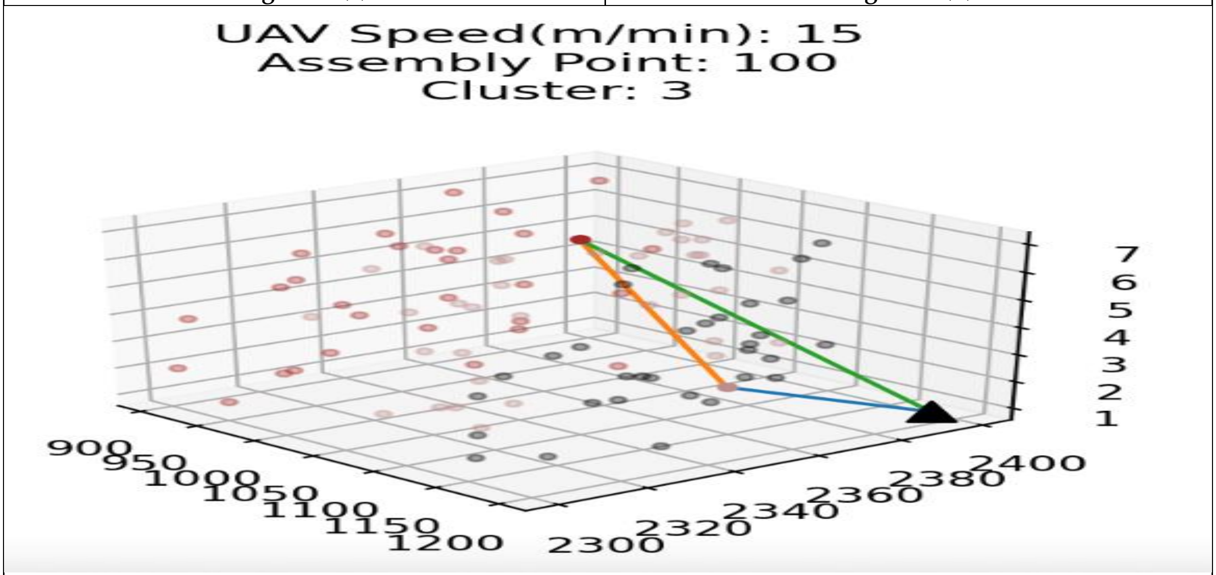
Total flight time (m/min): 531,34

Figure 5. (a)



Total flight time (m/min): 353,8

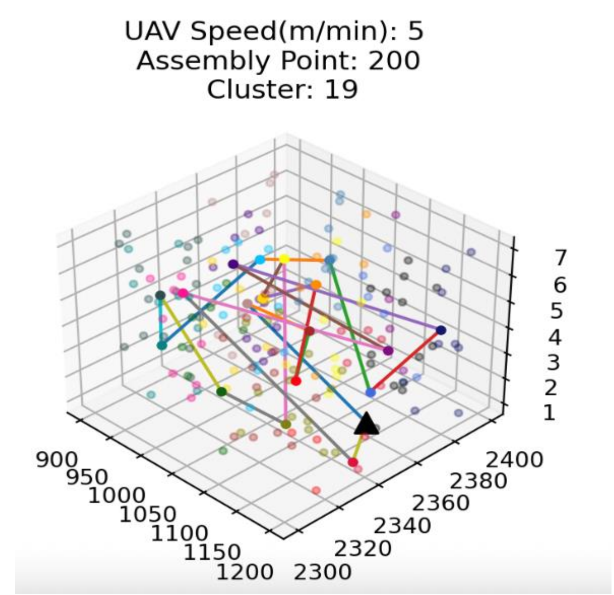
Figure 5. (b)



Total flight time (m/min): 307,13

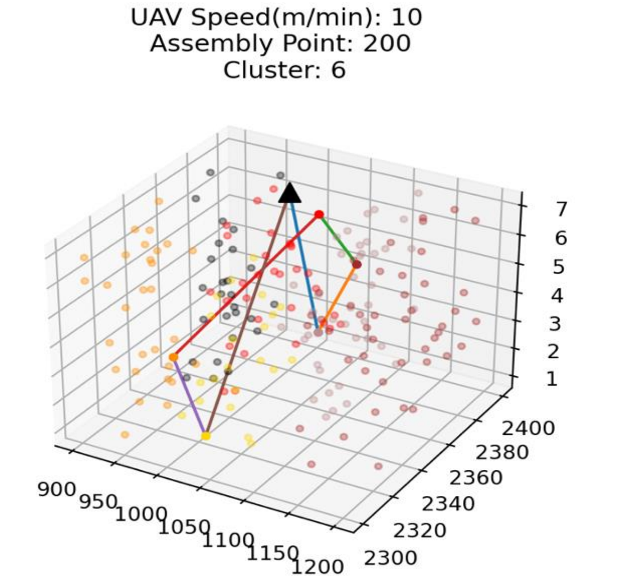
Figure 5. (c)

The results show that in Figure 5. (a), (b), (c), the total delivery time decreases significantly from 531 to 307 as UAV speed increases from 5 m/min to 15 m/min and cluster number and UGV stops decrease. This is an expected result since the UAV can cover more distance in a shorter time with higher speed than UGV. So, UAVs can deliver the medical kits to emergency assembly points faster.



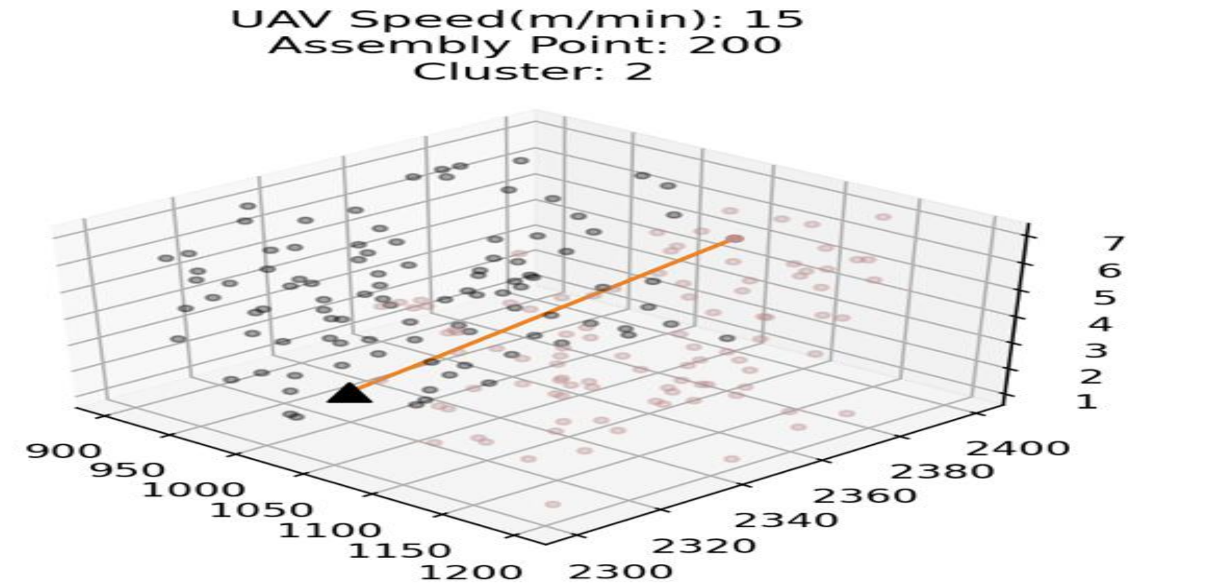
Total flight time (m/min): 820,81

Figure 6. (a)



Total flight time (m/min): 649,22

Figure 6. (b)



Total flight time (m/min): 773,9

Figure 6. (c)

In Figure 6. (a), (b), (c), however, the pattern is not as straightforward. Although the total delivery time still decreases as UAV speed increases from 5 to 10 in figure 6 (a) and (b), it increases again when the drone speed is set to 15 in figure 6 (c). Like figure 5, the number of clusters decreases as the UAV speed increases. The model clearly shows us that there is an optimal balance between assembly point number, UAV speed and number of clusters. In figure 6. (b) result shows that minimal total time depends on not only UAV speed, but also cluster and assembly point numbers.

Table 2. Results of testing scenarios

Scenario	Point Number	UAV Speed	Cluster Number	Total Flight Time
1	100	5 m/min	15	531 m/min
2	100	10 m/min	6	353 m/min
3	100	15 m/min	3	307 m/min
4	200	5 m/min	19	820 m/min
5	200	10 m/min	6	649 m/min
6	200	15 m/min	2	773 m/min

We summarize the model parameters and results for six scenarios in Table 2. In the first three scenarios, we defined assembly point number 100. As you can see, increasing the UAV speed from 5 m/min to 10 m/min resulted in a significant reduction in cluster number and total flight time, while increasing the UAV speed further to 15 m/min resulted in a smaller decrease in cluster number and total flight times.
In the last three scenarios, we defined assembly point number 200. Increasing the UAV speed from 5 m/min to 10 m/min resulted in a significant reduction in cluster number from 19 to 6, and also a decrease in the total flight time from 820 m/min to 649 m/min. This suggests that increasing the UAV speed has a large impact on the system's performance. However, increasing the UAV speed from 10 m/min to 15 m/min did not result in as large of a reduction in cluster number or total flight time, as the cluster number only decreased from 6 to 2, and the total flight time increased slightly from 649 m/min to 773 m/min. This suggests that increasing the UAV speed beyond a certain point may result in diminishing returns in terms of improving the system's performance.
Overall, the results show that the UAV speed parameter is a critical factor in the system's performance and should be carefully considered when optimizing the system. We must consider other parameters for achieving overall system optimization.
In scenario 5, we obtained the best solution. The total emergency assembly points located at the stops, the farthest assembly point from any stop, the total time spent at the stops, the time spent by the ground vehicle and the total time is presented in Table 3. The coordinates of the emergency assembly point and the assignments of the UAVs for delivery are presented in Table 5.

Table 3. Test results of scenario 5

Stops	Assembly Points at Stop	Farthest Point at Stop	Total Time at Stop
1	28	4.3944	75.4291
2	41	5.8527	116.0542
3	47	5.3240	164.7108
4	32	4.3709	94.1934
5	30	4.3418	82.6783
6	22	4.9514	56.8706
	Time spent by UGV between stops (min):	59.2853	
	Total time spent by UAV/UGV (min):	649.2217	

In Table 5., the first column shows the number of the stop, followed by the number of assembly points located at each stop. The third column provides information about the farthest assembly point from the stop, measured in minutes. The fourth column presents the total time spent at each stop, measured in minutes. The next row provides information about the time spent by the ground vehicle between stops, which is measured at 59.28 minutes. Finally, the last row of the table shows the total time spent by both the UAV and the ground vehicle, which is measured at 649.22 minutes. We have six stops with varying numbers of assembly points. Stop 3 has the highest number of assembly points at 47, while stop 6 has the lowest at 22. The farthest assembly point at each stop ranges from
4.34 minutes to 5.85 minutes. The total time spent at each stop ranges from 56.87 minutes to 164.71 minutes. Additionally, the table provides information on the time spent by the UGV between stops, which is 59.29 minutes, and the total time of UAV/UGV operation, which is 649.22 minutes.

The coordinates of the emergency assembly points and the clusters they are assigned to are presented in Table 4. As there are a total of 200 assembly points, information on the first 10 and last 10 assembly points is provided.

Table 4. The coordinates of the emergency assembly points and the assignments of the UAVs.

AP no	X-axis	Y-axis	Altitude	Cluster	AP no	X-axis	Y-axis	Altitude	Cluster
1	1044	2301	2	6	–	–	–	–	–
2	960	2326	3	5	–	–	–	–	–
3	1145	2340	7	3	191	945	2367	6	1
4	1022	2388	6	4	192	998	2382	5	4
5	1176	2384	7	3	193	974	2389	7	1
6	1081	2307	2	6	194	914	2383	3	1
7	1200	2381	3	3	195	1193	2351	2	3
8	968	2399	6	1	196	925	2306	6	5
9	1142	2319	6	3	197	1059	2310	7	6
10	930	2329	5	5	198	928	2383	5	1
–	–	–	–	–	199	1097	2349	1	2
–	–	–	–	–	200	985	2337	5	4

5. Discussion

5.1 Comparison with Literature

Our research shows that combining UAVs and UGVs in routing can speed up deliveries by optimizing routes and tasks. This finding is consistent, with the research of Ferrandez et al. [31] who also highlighted the efficiency improvements of systems. In contrast to Raj and Murray [24] who concentrated on UAVs only our strategy harnesses the strengths of both UAVs and UGVs leading to a rounded and flexible system. A notable advantage of our approach is the use of MILP for task distribution an element in managing logistical scenarios as noted by Agatz et al. [25]. However it's worth noting that our reliance, on linear models may not entirely capture the nature of real world emergencies.

5.2 Dynamic Process and Future Research

Acknowledging the nature of disaster situations it is suggested that upcoming studies integrate factors to create scenarios effectively. For example, using random variables to model uncertain demand and supply conditions could provide deeper insights into system performance under stress. Furthermore leveraging data, from disaster responses to enhance our models and create stronger formulas could be beneficial. This strategy may aid in connecting frameworks, with real world implementations enhancing the systems ability to handle obstacles effectively.

5.3 Research Limitations

Although our research offers a method, for managing disaster logistics it does have some drawbacks. The primary constraint is the linearization of a dynamic and chaotic process.Real world disasters include variables that our existing model doesn't fully consider. Additionally assuming a speed and capacity, for UAVs as highlighted in research [25][26] may not always be accurate. It's essential to tackle these limitations in studies to create a thorough and adaptable logistics framework.

Our study highlights the benefits of using UAV/UGV systems to enhance disaster relief logistics. Through the integration of K Means Clustering, TSP and MILP techniques we have shown improvements, in efficiency. It is crucial to recognize the changing nature of disasters and the constraints of our methodology. Moving forward it is important to consider incorporating factors and actual field data to strengthen the systems resilience and effectiveness across disaster situations.

6. Conclusion

In this study, we suggested a collaborative UAV/UGV routing model with the objective function of total cost minimization, which uses multiple drones on a truck to deliver medical kits to emergency assembly points. The main goal of using the cost function is to minimize people's waiting time for medical kits in affected areas.

The affected area is divided into sub sections by using K-means clustering method and each cluster center is defined as UGV stop. Deliveries are made from UGV stops to assembly points via UAVs. UAVs can launch multiple times from truck to deliver packages as long as its battery capability for flight range. To show how the objective function works in our proposed model, some scenarios are tested, and their results are compared with each other.

Experimental results show that the total delivery time decreases significantly when UAV speed increases and cluster number and UGV stops also decrease. This is an expected result since the UAV can cover more distance in a shorter time with higher speed than UGV. So, UAVs can deliver the medical kits to emergency assembly points faster. However, the pattern is not as straightforward. Although the total delivery time still de- creases as UAV speed increases in some scenarios, it increases again when the drone speed exceeds a certain speed. The model clearly shows us that there is an optimal balance be- tween assembly point number, UAV speed and number of clusters. The results show that minimal total time depends on not only UAV speed, but also cluster and assembly point numbers. This suggests that increasing the UAV speed beyond a certain point may result in diminishing returns in terms of improving the system's performance.

Overall, the results show that the UAV speed parameter is a critical factor in the system's performance and should be carefully considered when optimizing the system. We must consider other parameters for achieving overall system optimization.

Future research suggestions are listed here:

- To enable faster deliveries, autonomous battery replacement station for UAV's on the UGV's,
- Time window and experimental analysis of model,
- Dynamic take-off and landing on ground vehicle by UAV's,
- Delivery scenarios using multiple UAVs and UGVs,
- Testing scenarios where time minimization is not prioritized by assigning mission- criticality factors to flights,
- Dynamically determining the UAV speed according to the region and flight conditions,
- Real-time autonomous logistics management system operating in coordination with the disaster coordination center.

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