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RESEARCH ARTICLE

First Cluster Second Route Approach with Collaboration Unmanned Aerial Vehicle in Post-Disaster Humanitarian Logistic

Zeynep Yüksel[1], Dursun Emre Epcim[2], Süleyman Mete[3]

[1](MSc.), Gaziantep University, Faculty of Engineering, Department of Industrial Engineering, Gaziantep, Turkiye
[2](MSc.), Gaziantep University, Faculty of Engineering, Department of Industrial Engineering, Gaziantep, Turkiye
[3](Assoc. Prof. Dr.), Gaziantep University, Faculty of Engineering, Department of Industrial Engineering, Gaziantep, Turkiye

ABSTRACT
It is vital that post-disaster interventions are fast and effective. At this point, the integration of unmanned aerial vehicles in post-disaster logistics, mapping operations, assessment, search and rescue operations has the potential for process optimization. Unmanned aerial vehicles make a significant contribution to these operations by reaching hard-to-reach areas, detecting damage, identifying people trapped under submerged debris, and ensuring the rapid delivery of relief aid, so it is critical to integrate unmanned aerial vehicles in these areas. In this study, a multi-depot vehicle routing model is proposed for application in disaster logistics. Unlike the previous studies in this field, this study contributes to the literature by incorporating unmanned aerial vehicles into logistics vehicles and implementing a first cluster second route approach. This proposed model, which minimizes the time required for humanitarian relief after a disaster, is solved by mixing integer programing with the GAMS/CPLEX solver.

Keywords: Modeling, Cluster, Disaster Logistics, Routing, Unmanned Aerial Vehicle

1. Introduction

According to the AFAD definition, disasters are technological or man-made events that cause physical, economic and social losses to society (Adiguzel, 2019). Minimizing these losses and the harmful effects of disasters is possible through effective disaster management practices. All actions taken to ensure the safety and protection of people and their property from natural or man-made disasters are referred to as disaster management. Despite the fact that these losses or disasters are brought on by disasters cannot be avoided, effective disaster management techniques are capable of reducing their detrimental effects.

Disaster Management (DM) has a cycle which is series of steps. DM includes four main phases: mitigation, preparedness, response and recovery. Mitigation is the identification of hazards and sets of activities designed to reduce the risks of those hazards occurring. Preparedness is a set of actions to reduce the damage of unavoidable disasters. Response is life safety actions that are taken after disasters to reduce fatalities, injuries, and loss. Recovery is the act after the response that is used to help bring people back to what they were pre-disaster (Bravo & Leiras, 2015). Since disasters have stochastic effects and dynamic demands, disaster management is a difficult situation. Therefore, it is important to find efficient solutions in terms of time and cost in disaster management (Kula, Tozanli & Tarakcio, 2012). Considering this importance, creating the most suitable route to the required points is one of the problems that researchers focus on. In this context, vehicle routing problems aim to create the most suitable route according to the distance between the points to be reached in disaster areas, the time available to reach the destination, the number of requirements to be transported and similar criteria. In this way, it becomes possible to provide fast and safe access to disaster areas, to ensure the effective movement of relief teams and emergency supplies, and to meet the urgent needs of disaster victims in a timely manner. Researchers are seeking to improve the process of determining optimal routes by approaching this complex problem with various mathematical models and optimization techniques. Advanced tools such as Geographic Information Systems (GIS) and remote sensing technologies provide important data for detecting damage in disaster areas, monitoring road conditions and establishing routes (Arca, 2012). At the same time, real-time traffic management and intelligent traffic systems continuously update traffic density and road condition information, allowing emergency response teams to change their routes instantaneously.

Unmanned Aerial Vehicles (UAVs) can be used in disaster management phases which are mitigation, preparedness, response

Corresponding Author: Süleyman Mete **E-mail:** smete@gantep.edu.tr
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and recovery (Alsamhi et al., 2022). UAVs can be successfully integrated into disaster relief applications. UAVs have applications in a variety of industries in addition to disaster relief, including the military, commerce, health care, entertainment, sports, safety and security, distribution, emergency response, the agricultural sector, geology, cosmology, meteorology, and the environment. UAV use in these areas contributes considerably (Estrada & Ndoma, 2019). In many crucial stages of DM, UAVs have been used as a key tool. UAVs, for instance, are utilized for mapping disaster affected areas and risk analysis of the relevant areas by virtue of their camera and sensor features. Therefore, UAVs' thermal cameras are also used in search and rescue operations to seek out the location of people buried beneath the wreckage. Thus, UAVs provide search and rescue crews with more time to complete this dangerous mission. Also, UAVs are used as well to deliver emergency supplies to victims. Furthermore, UAVs are also used to evaluate and analyze damage. UAV-provided data of damage assessment is crucial for the planning process of reconstruction.

The first objective in post-disaster relief logistics is to deliver the essential relief supplies to the disaster victims in order to ensure their survival (Eligüzel & Özceylan, 2020). In this context, this paper committed to the delivery of humanitarian relief to victims of a disaster where time is of the essence. We propose a collaboration of truck and UAV distribution model in humanitarian logistics. This collaboration aims to provide fast and efficient relief supplies to disaster victims. Trucks can transport larger quantities of relief supplies than UAVs. However, UAVs can be used in road conditions that can be challenging for trucks. Thus, UAVs can overcome difficult road conditions such as collapsed roads, roadblocks due to the destruction of buildings, etc. and quickly reach areas that are difficult to reach for trucks. Therefore, in this study, a model for a multi-depot vehicle routing problem with a truck-UAV collaboration is proposed. The model first divides the disaster-affected regions into clusters with the P-median method in line with the first cluster second route approach. Once the center points of the clusters are determined, the multi-depot vehicle routing problem is applied with UAV collaboration. This collaboration model aims to deliver emergency aid to disaster areas quickly and effectively.

The remainder of this paper is organized as follows. A review of the literature is included in section 2. The problem formulation is described in Section 3, and it contains the mathematical models with p-median clustering and multi-depot vehicle routing with UAVs in subsection 3. Section 4 presents the analysis of the illustrative scenarios using the GAMS/CPLEX solver for the developed mathematical model. In section 5, a real case from the literature is considered and analyzed with different clustering numbers. Section 6 contains the conclusions and future studies suggestions.

2. Literature Review

At the stage of indisputable disasters, there exist numerous fields of study related to disaster management. Disaster studies have concentrated on search and rescue (SAR), assessment, and monitoring in alongside humanitarian logistics. These studies in the literature aim to manage processes effectively and efficiently in disaster situations, accelerate emergency aid services and facilitate the coordination of emergency response processes. This section includes research on vehicle routing problems with UAVs in the disaster area and this literature analysis is presented in Table 1.

It is very important to deliver resources when disaster strikes. Yin et al. (2023) conducted a routing study to provide this distribution in their study. In the course of the research, there is truck and drone cooperation. They developed a branch-and price-and-cut algorithm and tested it by applying it to a real case in China in 2008.

Faiz, Vogiatzis & Noor-E-Alam (2023) developed 2ECVRP to be applied in humanitarian logistics. The first stage involves trucks, and the second stage involves drones. In the model they developed, drones first determine the demand of the regions to eliminate the uncertain demands part. Then, the delivery takes place upon the determined demand. They solved the models with a heuristic approach. In addition, the results were tested with its applicability after Hurricane Maria in Portugal. Redi et al. (2021) implemented routing to evaluate damage after a disaster. There are 2 model proposals in this study which are the Two-Echelon Vehicle Routing Problem combined with Assignment (2EVRPA) and the Two-Echelon Collaborative Vehicle Routing Problem (2ECoVRP). In real events, they used both exact solution and tabu search methods to solve the models they developed. They drew the conclusion that the 2ECoVRP model performs better than the 2EVRPA model in light of their findings.

In Martins, Hirsch &Juan (2021) study, the model was developed by using the pick up-and-deliver routing type for the delivery of aid to the affected areas in emergency situations such as disasters. Thanks to the sensors, the images of the affected area are provided to the authorities. In this way, these areas with known demand are provided by drones. They proposed a heuristic approach solution to the model they developed.

Liperda et al. (2020) used a 2ECVRP approach with a combination of trucks and drones for a mapping operation in a flood disaster. The model they developed was solved with the exact solution method and annealing, which is one of the metaheuristic approaches. With the results they obtained, they determined that a difference of 4.8% occurred.

A routing analysis for post-disaster damage assessment procedures was carried out by (Adsanver, Coban & Balcik 2021). In their study, they used just drones alone instead of cooperation with ground vehicles. In addition to the exact solution, they proposed a heuristic algorithm to reach faster solutions for more complicated problems.

Rabta, Wankmüller, Reiner (2018) developed a distribution model with drones in order to overcome the transport problems in a disaster. In this way, it is aimed to deliver urgent needs (such as vaccines, water augmentation requests) to the regions by air cargo. They solved the model as a mixed integer linear program and analyzed it with different scenarios.

Calamoneri, Corò & Mancini (2022) created the Multi-Depot Multi-Trip Vehicle Routing Problem with Total Completion Times minimization (MDMT-VRP-TCT) model, which provides assistance to the rescue team in post-disaster search and rescue operations. They devised a model that minimizes time. They proposed a metaheuristic approach for the solution of the model.

Han et al. (2020) conducted a study by integrating drones into the routing problem for challenging situations where roads are destroyed. They worked on a problem definition in which drones deliver materials to customer locations while vehicles transport the materials. For the solution, they considered a VRPTW model with the objectives of minimizing the number of vehicles and energy consumption. They also used an artificial bee colony algorithm and compared it with other algorithms. Research was carried out by Grogan et al. (2022) to evaluate drone damage and to locate search teams. In their investigation, they examined Oklahoma tornado data. They strengthened the system by including warehouse failure and made use of multi-station vehicle routing models and coverage clusters as well. They came to the conclusion that more stations and staff were required as warehouse failure grew.

Ribeiro et al. (2021) studied the use of unmanned aerial vehicles (UAVs) in search and rescue operations for post-disaster situations. They proposed a new VRP called VRPSN which includes UAVs and charging stations of UAVs. They developed a mixed integer linear program model for solving the proposed VRPSN. They also used a heuristic method for solving the model when the data size is large. Lu, Yang & Yang (2022) proposed a multi-objective humanitarian shopping and delivery vehicle routing problem for humanitarian logistics consisting of two subproblems involving drone and truck cooperation. The two subproblems in the proposed problem are co-operative routing and the allocation of relief supplies, respectively. They developed a PDVRPD model as MILP to solve these problems. This model has two objectives: to simultaneously minimize the maximum cooperative route time and to maximize the minimum satisfaction rate of demand nodes. They also developed and compared two heuristic methods for solving this model.

Zhang et al. (2021) studied truck-drone collaboration for information gathering in natural disaster situations. They formulated a bi-objective mixed integer linear programming (MILP) model for a scenario in which a drone with a camera exits the truck, collects information and then returns to the truck to recharge. After decomposing the proposed problem into two sub-problems consisting of truck and drone paths, they obtained a general solution by using a column generation based heuristic algorithm. Redi et al. (2020) studied the co-operation of ground vehicles and drones for mapping operations after a disaster. In their study, they propose a model of the two-level vehicle routing problem 2EVRP-MOD. They tested their work with real data of small size and obtained exact results. Chowdhury et al. (2021) studied unmanned aerial vehicles due to their potential to serve and monitor a disaster-affected area. In their study, a mixed integer linear programming model (MILP) is proposed to minimize the cost of post-disaster monitoring by taking into account various drone characteristics, such as battery charging costs, service costs, hovering, turning, acceleration, cruise and deceleration costs of the drone. In addition, two heuristic methods, the adaptive large neighborhood search (ALNS) algorithm and the modified backtracking adaptive threshold acceptance (MBATA) algorithm, are proposed to solve large-scale problems.

Hachiya, Mas & Koshimura (2022) emphasized the necessity of unmanned aerial vehicles after major disasters such as earthquakes and tsunamis compared to existing vehicles such as trucks and helicopters. A multi-UAV vehicle routing model (UAVRP) was proposed for the use of UAVs in humanitarian aid logistics, which considers three different objectives: the speed of distribution, the urgency of the material and even distribution to shelters. Furthermore, the proposed model is optimized by Q-learning (QL), one of the reinforcement learning methods. The QL algorithm is compared with other heuristic algorithms and the results are presented.

Zhang et al. (2022) investigated the multi-day time-dependent vehicle routing problem with split deliveries by unmanned aerial vehicles (UAVs) (MTTDVRP-SD). A vehicle routing model is proposed for the scenario where UAVs are allowed to make multiple trips and the demands of delivery points can be split. The proposed model is solved by a meta-heuristic algorithm based on the simulation annealing (SA) framework and compared with different solution algorithms. Shadlou, Ranjbar & Salari (2023) analyzed the situation after natural disasters where some areas are isolated due to the destruction of roads. To prevent the disaster from increasing the destruction of isolated areas, an integer linear mathematical model was developed in which drones are used to survey the situation and carry a limited number of materials until the roads are repaired. Due to the complexity of the model, a logic-based Benders decomposition algorithm was developed to solve the model.

Zhang et al. (2023) emphasized the importance of rapid assessment of the damage and situations that occur as a result of natural disasters. It was stated that the use of drones for these stops has significant potential in terms of the speed of the evaluator. For the use of drones in post-disaster assessment, a drone arc routing problem in which road segments are selectively evaluated in order to maximize the arc informative profits collected within a predefined time limit is considered. In the study, the RTOARPM model is proposed, which allows drones to go outside the road network to shorten the travelling time. The proposed model is solved with different algorithms and performance evaluations are performed. Yan et al. (2023) emphasized that drone and truck cooperation can be used in various situations such as military surveillance, reconnaissance, logistics delivery, disaster search or rescue. A vehicle routing model is proposed for a drone-truck co-operation scenario where multiple drones can be used to reduce the probability of mission failure in the case of various attacks. The proposed model is solved with different heuristic algorithms and their performances are compared.

Table 1. Overview of Vehicle Routing Problem with UAV in Disaster

	Application				**Routing**									**Objective Function**					**Application**		**Solution Method**	
References	**Logistic**	**Assessment**	**Mapping Op.**	**Search/Rescue**	**2ECVRP**	**2ECoVRP**	**UAVR**	**VRPTW**	**PDVRP**	**VRP**	**VRPSN**	**MDVRP**	**RTOARPM**	**Time**	**Cost**	**Multi**	**Profit**	**Total priority scores**	**Collaboration**	**Only UAV**	**Exact**	**Heuristic/Metaheuristic**
Yin et al. (2023)	✓									✓					✓				✓		✓	✓
Faiz, Vogiatzis & Noor-E-Alam (2023)	✓				✓										✓				✓		✓	✓
Redi et al. (2021)		✓			✓	✓								✓					✓		✓	✓
Martins, Hirsch &Juan (2021)	✓				✓				✓					✓						✓		✓
Liperda et al. (2020)			✓		✓									✓					✓		✓	✓
Adsanver, Coban & Balcik (2021)		✓					✓											✓		✓	✓	✓
Rabta, Wankmüller, Reiner (2018)	✓						✓								✓					✓	✓	
Calamoneri, Corò & Mancini (2022)				✓								✓		✓					✓			✓
Han et al. (2020)	✓							✓								✓			✓			✓
Grogan et al. (2022)		✓										✓								✓		✓
Ribeiro et al. (2021)				✓							✓				✓				✓			✓
Lu, Yang & Yang (2022)	✓								✓							✓			✓			✓
Zhang et al. (2021)	✓									✓							✓		✓			✓
Redi et al. (2020)			✓		✓									✓					✓		✓	
Chowdhury et al. (2021)		✓					✓								✓					✓		✓
Hachiya, Mas & Koshimura (2022)	✓						✓									✓				✓		✓
Zhang et al. (2022)	✓						✓										✓			✓		✓
Shadlou, Ranjbar & Salari (2023)		✓					✓							✓						✓		✓
Zhang et. al. (2023)		✓											✓				✓			✓		✓
Yan et. al. (2023)	✓									✓					✓				✓			✓
Proposed Model	✓											✓		✓					✓		✓	

There are very few studies on the multi-depot vehicle routing problem with truck-UAV collaboration. According to the research, there is no similar study on the application of this vehicle routing variant in post-disaster humanitarian relief distribution with UAV collaboration. In addition, it differs from the studies in the field of post-disaster logistics with its first cluster second route approach. Thus, this study contributes to the literature by proposing a model for the MDVRP-D problem with truck-UAV collaboration in post-disaster humanitarian logistics.

3. Problem Definition

Access to victims can be hampered by factors such as traffic, debris blocking roads and road collapses caused by natural disasters. This situation is one of the main difficulties encountered in post-disaster humanitarian aid logistics. At this point, the integration of UAVs into routing is critical because UAVs are not affected by these factors compared to trucks and can provide faster transportation. Therefore, in this study, firstly, the points to be distributed are limited by using the p-median method in the regions where such factors prevent or delay the needs from reaching the victims. Then, as shown in Figure 1, the relief supplies and UAVs to be distributed from the depots are transported by trucks to the central point of the clusters.

The logistics vehicles used are a homogeneous fleet. After the trucks reach the central point, the demands of the regions affected by the natural disaster are covered by the UAVs. The batteries of the UAVs that are ready for redistribution are replaced and maintained when they return to the central point. Thus, the arrival time of each UAV leaving the center points is reset to zero. After completing the distribution in the regions, the UAVs return to the trucks at the central point and then to the warehouses with the trucks. In this study, a MILP for the MDVRP-UAV problem is proposed for use in post-disaster relief logistics. The proposed model aims to minimize the distribution time.

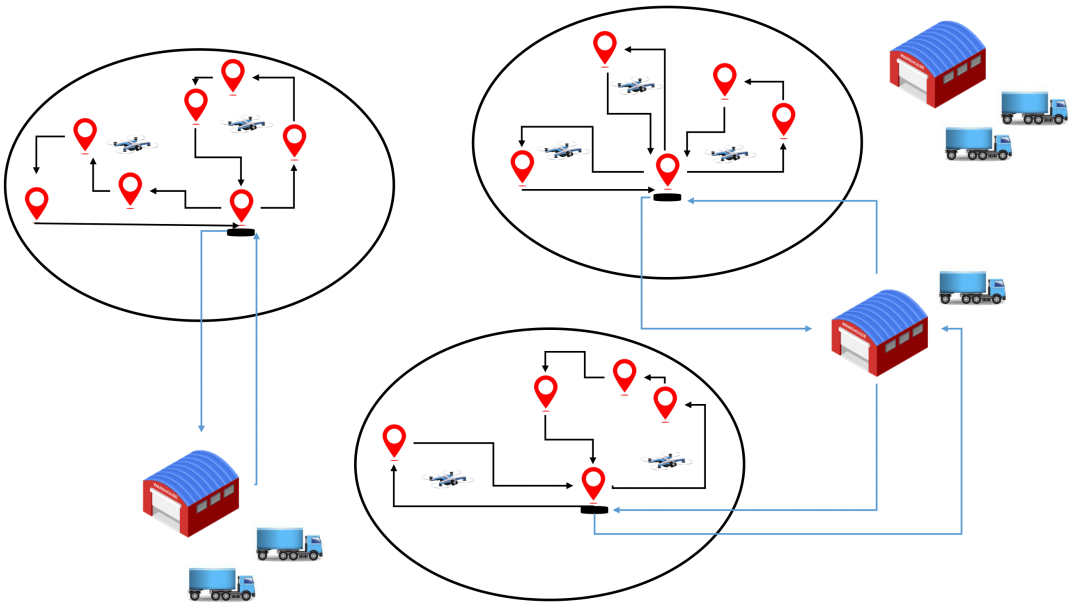


Figure 1. Multi Depot Vehicle Routing Problem with UAV Collaboration

The model assumptions are given as follows:

- Depots and demand nodes are known.
- Demand quantities of nodes are known.
- Trucks have enough capacity for UAVs and relief supplies.
- When a UAV turns back to the center point, the flight time of the UAV resets.
- Since the trucks departing from the warehouse carry the materials to the center point, the demand at that point is accepted as 0.
- The velocities of logistics vehicles are known.
- The capacity, maximum flight and service time of unmanned aerial vehicles are known.
- The UAV maintenance and battery replacement time at the center point is ignored.

3.1. The Proposed Mathematical Models

The mathematical model is developed implementing first cluster second route approach. This section is divided into two parts: clustering and routing. Initially, a clustering model was used to classify all the requirements points into a desired number of clusters according to the distance between them. The p-median problem clustering model proposed by (ReVelle & Swain, 1970) is utilized, and the MDVRP-UAV model is proposed. The model was developed by utilizing the papers of (Li et al., 2021) and (Han et al., 2019).

3.1.1 Cluster Model

The aim of the p-median method is to minimize the sum of distances between temporary depots and demand points (Eligüzel & Özceylan, 2021). This problem is addressed by using a clustering model to create a desired number of clusters based on point-to-point distances. The notations of the p-median method used as a clustering model in this study are given in Table 2 below.

Table 2. Notations of Cluster Model

i,j	Task points
p	Number of clusters
X_{ij}	1, i points assigned to point j; otherwise,0
d_{ij}	The distance between i and j points

Objective function (1) minimizes the distance between points assigned to the cluster.

$$Min \sum_{i} \sum_{j} d_{ij} * X_{ij} \tag{1}$$

Constraint (2) ensures that each task is assigned to a cluster.

$$\sum_{j} X_{ij} \quad \forall i \tag{2}$$

Constraint (3) determines the number of clusters.

$$\sum_{j} X_{jj} = p \tag{3}$$

Constraint (4) ensures that no task is assigned to a point that is not designated as the center point.

$$X_{ij} \leq X_{jj} \quad \forall i, j \tag{4}$$

3.1.2 Routing Model

After a disaster, it becomes difficult to reach the points of demand due to road disturbances. To overcome this challenge and minimize the time to deliver vital aid, a new MDVRP-UAV model is proposed by integrating UAVs into MDVRP. This model, which aims to minimize the total routing time, also takes into account the capacity of UAVs and the maximum flight time of UAVs. In Table 3, the notations of the proposed routing model and the related symbols used are explained.

Table 3. Notations of Routing Model

Indices	
i,j	Tasks and depots
v	Fleet of trucks
d	Fleet of UAVs
Sets	
S_d	Set of depots
S_t	Set of tasks
S_c	Set of center points
S_{dc}	$S_d \cup S_c$
Parameters	
T_{ijd}	The time of reaching from point i to point j by UAV d
$T2_{ijv}$	The time of reaching from point i to point j by truck v
L_j	Demand of point j
Scalar	
F	Maximum flight time of UAV
service	Total time of loading, take-off and unloading at the point where the UAV routing
K_d	Capacity of UAV
Z	Small number
M	Large number
Positive Variables	
AT_{id}	Arrival time to point i by UAV d
FAT_{jd}	Variable for regulation
u_{id}	Real numbers
Binary Variables	
Y_{ijv}	1, if truck v arrives at point j after leaving point i (i≠j); otherwise, 0
X_{ijd}	1, if UAV d arrives at point j after leaving point i (i≠j); otherwise, 0

Objective function (5) minimizes the transportation time of trucks to center points and the distribution time of UAVs in satisfying the demand points in clusters. In addition, arrival times (AT) are controlled with FAT added to the objective function. This ensures that the AT value takes the smallest value it can take.

$$Min \sum_{j \in S_{dc}} \sum_{i \in S_{dc}} \sum_{v} Y_{ijv} * T2_{ijv} + \sum_{j \in S_t} \sum_{i \in S_t} \sum_{d} X_{ijd} * T_{ijd} + FAT_{jd} \tag{5}$$

Constraint (6) provides the truck departing from the depot to return to the same depot again from the center point it travels to.

$$Y_{ijv} - Y_{jiv} = 0 \quad \forall i \in S_d, j \in S_c, v \tag{6}$$

Constraint (7) enables all UAVs to be cycled.

$$\sum_{j \in S_t} X_{ijd} = \sum_{j \in S_t} X_{ijd} \qquad \forall d, i \in S_t \tag{7}$$

Constraint (8) allows just one entrance from any point by any UAV to each point except the center point.

$$\sum_{i \in S_t} \sum_{d} X_{ijd} = 1 \qquad \forall j \in S_t, j \notin S_c, i \neq j \tag{8}$$

Constraint (9) permits a single UAV exit to all points, with the exception of the center point, from any point.

$$\sum_{j \in S_t} \sum_{d} X_{ijd} = 1 \qquad \forall i \in S_t, i \notin S_c, i \neq j \tag{9}$$

Constraint (10) ensures that one truck from any depot is assigned to each center point.

$$\sum_{i \in S_d} \sum_{v} Y_{ijv} = 1 \qquad \forall j \in S_c \tag{10}$$

Constraint (11) prevents the same truck from departing from more than one depot and traveling to more than one center point.

$$\sum_{i \in S_d} \sum_{j \in S_c} Y_{ijv} \leq 1 \forall v \tag{11}$$

Constraint (12) guarantees that the total amount of demand on the UAVs route does not exceed the UAVs capacity.

$$K_d \geq \sum_{i \in S_t} \sum_{j \in S_t} L_j * X_{ijd} \forall d, i \neq j \tag{12}$$

Constraint (13) assures that the arrival time of each UAV is reset at the center point.

$$AT_{id} = 0 \qquad \forall d, i \in S_c \tag{13}$$

Constraint (14) provides the UAVs to calculate the arrival time.

$$AT_{jd} \geq AT_{id} + T_{ijd} + service - M * (1 - X_{ijd}) \;\; \forall i, j \in S_t, j \notin S_c, \forall d, i \neq j \tag{14}$$

Constraint (15) prevents the time the UAV spends along the route until it returns to the center point from exceeding the UAV's maximum arrival time.

$$AT_{id} + T_{ijd} + service \leq F \;\; \forall d, i \in S_t, j \in S_c \tag{15}$$

Constraint (16) ensures sub-round elimination, which eliminates UAV routes that do not start and end at the center point.

$$u_{id} - u_{jd} + K_d * X_{ijd} \leq K_d - L_j \;\; \forall d, i, j \in S_t, i, j \notin S_c, i \neq j \tag{16}$$

Constraint (17) satisfies the restriction of the variable u.

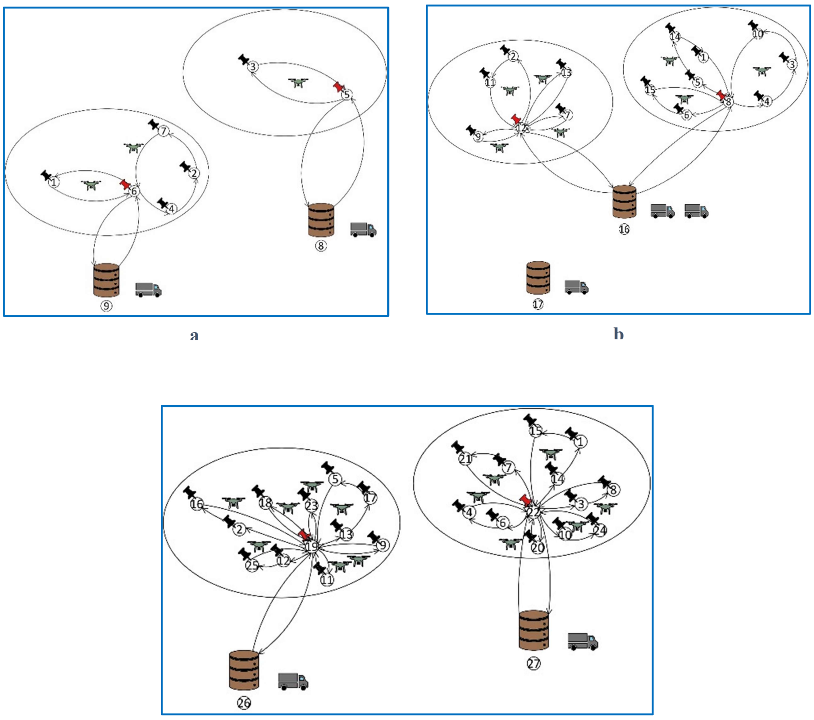
$$L_i \leq u_{id} \leq K_d \forall i, d \tag{17}$$

Constraint (18) allows adjustment of the AT variable.

$$FAT_{jd} = Z * AT_{jd} \;\; \forall j, d \tag{18}$$

4. Illustrative Example

A scenario-based study was conducted to test the proposed model. It was solved for scenarios A, B and C respectively, containing 7-15-25 demand points. For each case, first cluster second route approach is implemented. In cases, UAVs cover a distance of 1 unit in 3.75 units of time. In addition, the maximum flight time of the UAVs is 500 units and the payload capacity is 200 units. The results of these illustrated scenarios are given in Table 4.



a b

c

Figure 2. The Scenarios for the Case with 7, 15, and 25 Demands Nodes

The data in the scenarios of the case study are independent of each other. In Figure 2, in scenarios A and C, trucks are assigned to the center points from different depots, while in scenario B, trucks are assigned from the same depot. In addition, the number of routes increased with the increase in demand points in the scenarios, and therefore the number of logistic vehicles used also increased. The truck-UAV collaboration model used in the proposed routing and multi-depot vehicle routing runs smoothly in every scenario in the illustrative example and achieves optimum results.

Table 4. Results of Illustrative Example

Problem	Number of Point	P-Center Points	Routes of Trucks	Routes of UAVs	Objective Function
Scenario 1	7	5,6	9-6-9; 8-5-8	5-3-5;6-1-6;6-4-2-7-6	299.4065
Scenario 2	15	8,12	16-12-16; 16-8-16	8-6-15-8;8-5-14-1-8;8-4-3-10-8;12-7-12;12-9-12;12-13-12;12-2-11-12	603.0635
Scenario 3	25	19,22	26-19-26; 27-22-27	22-20-22;22-10-24-22;22-3-8-22;22-14-1-15-22;22-7-21-22;22-6-4-22;19-11-19;19-9-19;19-13-17-5-19;19-23-19;19-18-19;19-2-16-19;19-12-25-19	757.1346

The model demonstrated effective performance across diverse contexts, encompassing a modest-scale instance comprising 7 tasks, as well as a relatively large scenario involving 25 tasks. The acquired findings unequivocally affirm the aptitude and reliability of the proposed models.

5. Real Case

Table 5. Real Case Data

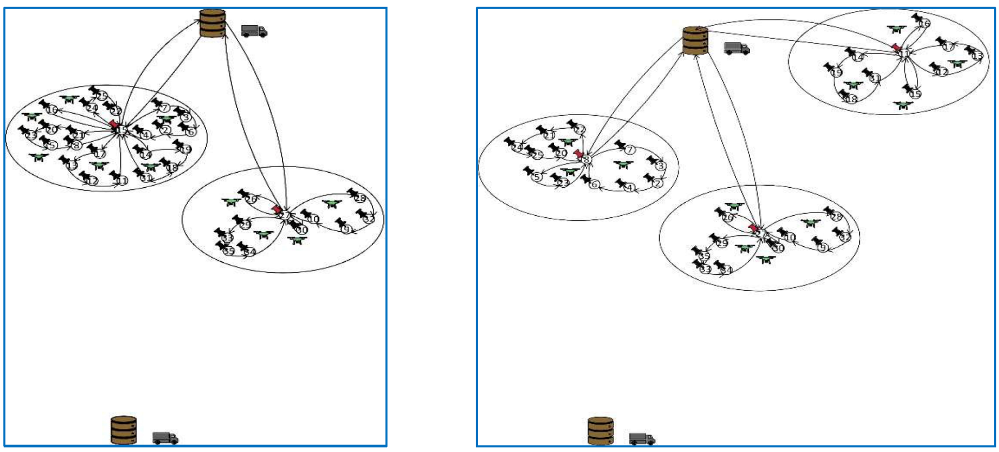
Node	Destination	Coord_X (km)	Coord_Y (km)	Demand (kg)
1	Pamplona (Depot)	83	115	0
2	Tudela I	87	27	14.2
3	Tudela II	87	26	8
4	Tudela III	86	27	98.8
5	Tudela IV	86	25	56.4
6	Tudela V	86	26	23.3
7	Tudela VI	87	25	44.3
8	Tudela VII	86	24	6.7
9	Castejon I	78	54	45.6
10	Castejon II	79	53	6.7
11	Corella I	70	31	7.6
12	Corella II	70	32	2.4
13	Corella III	70	33	23.3
14	Corella IV	69	30	6.5
15	Corella V	71	29	123.4
16	Corella VI	71	30	125.4
17	Corella VII	72	31	115.7
18	Cintuenigo I	68	27	65.4
19	Cintuenigo II	66	26	6.7
20	Cascante I	79	17	5.6
21	Cascante II	80	16	2.3
22	Cascante III	81	18	34.5
23	Cascante IV	79	18	64.4
24	Cascante V	79	16	44.4
25	Cascante VI	78	16	107.8
26	Peralta I	69	58	186.8
27	Peralta II	70	58	7.8
28	Peralta III	70	57	8.7
29	Peralta IV	69	58	67.5
30	Peralta V	70	58	6.5
31	Peralta VI	70	28	12.3
32	Marcilla	74	56	65.4
33	Villatuerta I	52	96	5.6
34	Villatuerta II	53	98	45.6
35	Villatuerta III	52	96	56.4
36	Depot 2	75	41	0

The real data from a delivery company that Faulin et al. (2011) utilized in their study to solve a capacity-constrained vehicle routing problem were altered and used in accordance with the model in the solution of the model that was developed in the study. The Cartesian coordinates of the delivery and depot and the demands of the delivery points were taken from these real data. The demands were reduced by 10% to be suitable for the model. Since the model developed for the study is a multi-depot vehicle routing model, a new depot location is included in the real situation. The coordinates of the new depot location, which were determined using the center of gravity method with the demand points, were added to the case data, as shown in Table 5. Table 6 also provides data on the logistics vehicles used in this real case.

In line with the first cluster - second route approach, the demand points were first analyzed in this real case with 2, 3, 4 and 5 clusters. Subsequently, the routing model was solved independently for the four situations. The results of the implementation of MDVRP-UAV modeling are given in Table 7.

Table 6. Logistic Vehicles Data

Velocity of truck	Velocity of UAV	Maximum flight time of UAV	Service time of UAV	Capacity of UAV
90 km/h	120 km/h	8 h	0.2 h	200 kg

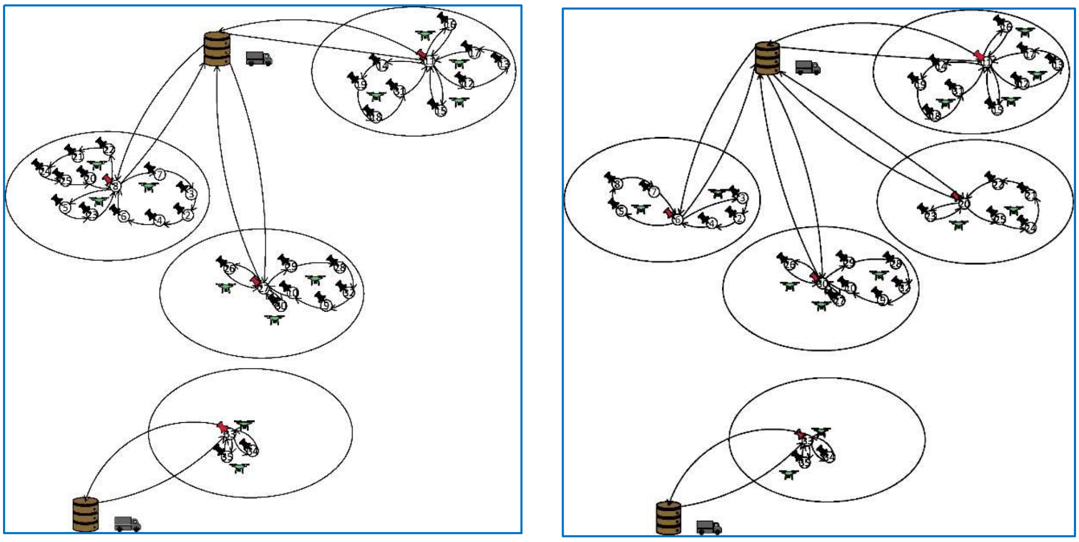


Scenario 1 **Scenario 2**

Figure 3. Routes for Real Case with 2 and 3 Clusters

In Figure 3, the 34 demand points in the real case are analyzed in 2 and 3 clusters. The center points of the clusters were determined as 15-27 and 8-11-27 respectively. For 2 different clusters, the trucks that will carry the relief supplies and UAVs to these center points are assigned from the same depot. The main reason for this assignment is to obtain a better depot location than the existing depot since the center of gravity method is used when selecting a new depot. In addition, the demand points in the cluster with center point 27 are the same for both scenarios. However, there is a change in one route due to the displacement of demand points 33 and 35 in this cluster with center point 27. A total of 10 UAVs and 2 trucks were used in scenario 1 and 11 UAVs and 3 trucks were used in scenario 2.

As shown in Figure 4, in scenarios 3 and 4, the real data reflects the routes when solved with the proposed MDVRP-UAV model. Unlike the cases in Figure 3, both depots are used. In scenario 2 and scenario 3, the center points are similar. The difference between these scenarios is that since there are 4 clusters in scenario 3, demand points 33, 34 and 35 in the cluster of 27 center points in scenario 2 are separated to form a new cluster with 33 center points. In addition, the fact that the vehicle arrives at this new cluster center from the different depot also differentiates these two scenarios. In addition, in scenarios 3 and 4, while the clusters with 11 center points are the same, only the center points have changed due to the fact that the 27 and 30 center points are located at the same coordinates, and no change is observed in the routes. In scenario 3, a total of 12 separate UAV routes were formed, while in scenario 4, 13 UAV routes were formed.



Scenario 3 Scenario 4

Figure 4. Routes for Real Case with 4 and 5 Clusters

Table 7. Results of Real

Number of Clusters	P-Center Points	Routes of Trucks	Routes of UAVs	Execution Time	Objective Function
2	15,27	36-15-36; 36-27-36	27-26-27;27-30-27;27-29-33-35-34-27;27-28-32-9-10-27;15-16-15;15-14-19-18-31-15;15-21-20-23-5-8-15;15-17-13-12-11-15;15-7-3-6-2-4-15;15-24-25-22-15	15: 3600 sec 27: 21.359 sec	2.7773 h
3	8,11,27	36-8-36; 36-11-36; 36-27-36;	27-26-27;27-30-27;27-29-33-35-34-27;27-28-32-9-10-27;8-7-3-2-4-6-8;8-22-21-24-25-20-8;8-5-23-8;11-12-13-17-11;11-15-11;11-16-16;11-14-19-18-31-11	8: 96.703 sec 11: 29.953 sec 27: 19.843 sec	2.646 h
4	8,11,27,33	1-33-1; 36-8-36; 36;11-36; 36-27-36	8-5-23-8;8-7-3-2-4-6-8;8-22-21-21-25-20-8;11-14-19-18-31-11;11-16-11;11-12-13-17-11;11-15-11;27-26-27;27-30-27;27-29-28-32-9-10-27;33-34-33;33-35-33	8: 105.281 sec 11: 29.734 sec 27: 0.391 sec 33: 0.218 sec	2.755 h
5	6,11,20,30, 33	1-33-1; 36-6-36; 36-11-36; 36-20-36; 36-30-36	6-5-8-7-6;6-3-2-4-6;11-14-19-18-31-11;11-12-13-17-11;11-16-11;11-15-11;20-25-24-21-22-20;20-23-20;30-36-30;30-27-30;30-29-28-32-9-10-30;33-34-33;33-35-33	6: 1.328 sec 11: 22.906 sec 20: 0.453 sec 30: 0.422 sec 33: 0.282 sec	3.03 h

In the 2-3-4 and 5-cluster scenarios applied on real data, the cluster centers are usually assigned to trucks from the depot generated with the center of gravity method to deliver relief supplies and UAVs to the center points. When the number of UAVs to move from the center points was examined, it was found that there were 10, 11, 12 and 13 UAVs, respectively, and the total number of routes created for the clusters were 12, 14, 16 and 18.

The results obtained in scenarios 3-4 and 5 are optimal. However, in the 2-cluster scenario, due to the high number of demand points in the cluster where the center point number 15 is located, a time constraint of 3600 was restricted while solving. Since the optimal result could not be achieved within this time, the feasible result was obtained. When the obtained objective function results are compared, it is seen that the optimal number of clusters for this case is 3. Therefore, the case with 3 clusters is the fastest and most efficient scenario for truck-UAV collaboration deployment in this real case.

6. Conclusion

Natural disasters that might result in a loss of life and property are unavoidable. Thus, it is necessary to minimize their effects as much as possible. In this context, this study introduces a new perspective to the vital disaster logistics by providing UAV integration to the multi depot vehicle routing problem in order to deliver the aid to the disaster victims as fast as possible. In addition, the model developed with the first cluster and second route approach to the MDVRP-UAV problem has contributed to the literature. This approach formed the basis of the model and provided a more efficient routing of logistics vehicles. In addition, this study has shown that the integration of UAVs provides fast access convenience even in harsh post-disaster conditions.

The obtained mathematical model was first solved with a GAMS/CPLEX solver for 3 different illustrative cases with 7, 15, 25 points respectively. Then, it was solved for 4 different cluster numbers using the data of a real delivery problem found in the literature. Thus, this study tests the applicability of the proposed MDVRP-UAV model in post-disaster humanitarian aid logistics. The findings reveal the critical importance of the integration of unmanned aerial vehicles into the vehicle routing problem in the post-disaster area.

The findings of this study and the MDVRP-UAV model it contributes to the literature will also shed light on future studies. It is expected to bring valuable findings to the literature by expanding the MDVRP-UAV model developed in this study in the following scopes. For instance, clustering analysis can be performed by implementing different clustering methods. In addition, the model can bring a different approach to the literature by including multiple product types and providing priority distribution according to the emergency situation. In furthermore, the model can be developed by considering the distribution of perishable products in post-disaster distribution. Moreover, the model can be improved by integrating the unmanned aerial vehicle according to dynamic weather conditions. Also, the model can be considered to be dynamicized according to uncertain demand quantities. Furthermore, since the model is very limited, the solution may not be obtained in larger cases. At this point, the development of heuristic methods is among the possible studies.

The model contributes to the literature with the integration of unmanned aerial vehicles into a multi-depot vehicle routing model to be used in post-disaster humanitarian relief logistics. Thus, it increases the potential of future studies in this field. In addition, the findings of this study are of great importance, especially in terms of the devastating effects of disasters.

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ORCID IDs of the authors

Zeynep Yüksel 0009-0006-8201-372X
Dursun Emre Epcim 0009-0005-0082-8750
Süleyman Mete 0000-0001-7631-5584

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