Multi-Depot Vehicle Routing Problem with Drone Collaboration in Humanitarian Logistics

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

[1] Department of Industrial Engineering, Gaziantep University, Gaziantep 27310
ORCID No: https://orcid.org/0009-0006-8201-372X
[2] Department of Industrial Engineering, Gaziantep University, Gaziantep 27310
ORCID No: https://orcid.org/0009-0005-0082-8750
[3] Department of Industrial Engineering, Gaziantep University, Gaziantep 27310
ORCID No: https://orcid.org/0000-0001-7631-5584

Keywords

Drone-Truck Collaboration, Humanitarian Logistics, Multi-Depot Vehicle Routing Problem, Perishable Commodities

Abstract

Routing problems are used in many areas to obtain the most appropriate results in terms of time and cost. An attempt is made to address the issue by formulating mathematical models that incorporate multiple variables such as capacity, time, cost, and demand, tailored to the specific area of application. Natural disasters are one of these applications. In natural disasters, especially time management is a critical issue. For this reason, routing models play a crucial role in delivering aid to disaster victims and transporting disaster victims to hospitals. In this study, a mathematical model is proposed to be applied in post-disaster humanitarian aid logistics. The model, which aims to minimize the total distribution time, also considers the distribution of perishable commodities. Drones are integrated into this operational framework to facilitate the dissemination of perishable commodities. Thus, a new mathematical model for the multi-depot vehicle routing problem (MDVRP), which includes both truck-drone collaboration and perishable commodities, has been introduced to the literature. The proposed model was solved with a data set in the literature using Python software and the results were tested.

Research Article
Submission Date : 23.12.2023
Accepted Date : 21.07.2024

1. INTRODUCTION

Disasters are tragic events that can cause great losses. Many people around the world lost their lives due to natural disasters in their region. When their effects on people and buildings are examined, earthquakes are among the disasters with the most potential impact (Mavrouli et al., 2023).

[*] Resp author; email: suleyman489@gmail.com

According to EM-DAT (The International data Disaster Database-Center for Research on the Epidemiology of Disaster), 242,000 people lost their lives in the 1976 China earthquake, 222,570 in the 210 Haiti earthquake and 165,708 in the 2004 Indonesia earthquake.
As a result of the tsunami disaster in the Indian Ocean, the number of people who died in the Indonesian earthquake increased to 226,408. Recently, 50,783 people lost their lives as a result of the earthquake that occurred in Turkey on February 6, 2023 (Walika et al., 2023). One of the vital points that increases the magnitude of the effects of disasters such as earthquakes is the distribution of humanitarian aid after the earthquake. Lack of supplies that do not arrive on time may increase the effects of the disaster by causing people to survive the disaster but die afterwards. Therefore, the post-disaster supply chain is very important to reduce post-disaster deaths and prevent the suffering of disaster victims from increasing (Diabat, Jabbarzadeh & Khosrojerdi, 2019). There are many difficulties in carrying out post-disaster humanitarian aid logistics activities. One of these difficulties is that blood and some food materials spoil in a short time. Considering the importance and perishability of these foods, the distribution of such perishable commodities becomes a vital issue (Rashidzadeh et al., 2021)
Routing is one of the most important parts of post-disaster humanitarian logistics. Routing is vital to manage the process and reduce distribution time. For this reason, many academic studies have been conducted on the delivery of supplies to disaster victims as soon as possible, including routing the distance between need points and warehouses. However, when the studies are examined, it is understood that there is a gap in the literature for a situation that includes multi-depot truck-drone collaboration in post-disaster humanitarian relief logistics and also takes perishable commodities into consideration. The aim of this study is to deliver the products to the disaster victims in the most effective way with truck-drone collaboration in vital post-disaster logistics. With a different perspective from the literature, a mathematical model is developed for the multi-depot vehicle routing problem with drones, which includes the safe delivery of perishable products to disaster victims. The mathematical model that had been developed was evaluated on the case study using Python software.
In this study, the following sections, Section 2, contain the literature that has been investigated. In the third section, the problem definition and the mathematical model that has been provided are presented. Testing the model with the illustrated case is covered in Section 4. The limitations of the study are discussed in Section 5, along with a conclusion section that discusses potential research subjects.

2. LITERATURE REVIEW

Vehicle routing problem (VRP), one of the most important problems in the field of disaster management, is delivery nodes starting from one or more warehouses (Laporte, 1992). The purpose of VRP in humanitarian logistics is to determine the most appropriate routing considering the constraints such as vehicle capacity, number of vehicles, demand and time. It is anticipated that the integration of drones into traditional VRP in humanitarian logistics will maximize immediate distribution. Hence, multi-depot vehicle routing problems with drone are presented in this section.

Stodola & Kutěj (2024) tackle the MDVRP-D in their study. Drones are paired with vehicles to make deliveries from warehouses to customers. They developed a mathematical model for this problem whose objective is to minimize the duration of the entire logistics operation. In addition, Adaptive Node Clustering Ant Colony Optimization with Node Clustering algorithm, a metaheuristic algorithm based on Ant Colony, is proposed as a solution.

The multi-depot unmanned aerial vehicle (UAV) routing issue was addressed by Li et al. (2021). They suggested a mathematical model that does not impose restrictions on the depot where UAVs launch and land. The proposed model includes multiple objective functions to minimize the time and number of UAVs on the route. Hybrid large neighborhood search was suggested as a potential remedy. Rathinam & Sengupta (2006) paperwork deals with the issue of path selection for a number of UAVs traveling from various depots to particular terminals and locations. Each UAV starts from a depot and travels to at least one location as part of their proposed solution to the issue. For the multi-depot UAV routing problem, the authors additionally provide a 2-approximation approach and a lower bound algorithm. Manyam et al. (2017) focused on the persistent intelligence, surveillance, and reconnaissance routing problem. Their model aims to optimize the data collection and delivery tasks of multiple UAVs. As a solution methodology, they presented complex computational methods as well as heuristic approaches. Habib, Jamal & Khan (2013) studied a real-time optimization problem for UAV path planning in dynamic situations. They considered this problem as a variant of a multi-depot vehicle routing problem (MDVRP) and proposed a mixed integer linear programming (MILP) model for solving this problem. Kim et al., (2017) studied the distribution of drugs and test kits by drones for patients with chronic diseases who need to go to clinics for routine health examinations in rural areas. They proposed two models for this situation. In the first of these models, they used the closure approach to find the optimal number of drone centers. In the second model, they proposed a MDVRP model that minimizes the operating costs of drones. Haller (2021) worked on two models to optimize the US Marine Corps' use of UAVs. In the first model, the author aimed to find the optimal depot locations for the charging and supply of UAVs. In the second model, author proposed a model for the MDVRP for UAVs by improving a single depot model in the literature. Hamid, Nasiri & Rabbani (2023) worked on optimizing the homemade food delivery process. They used drones and crowdsourcing as two novel approaches for this process. To solve this problem, they developed a multi-warehouse vehicle routing model using transport costs, freshness of the delivered food and delivery date satisfaction as objective functions. Due to the complexity of the problem, they proposed a self-regulating hyper-heuristic method to obtain a solution. This method is based on genetic algorithm and modified particle swarm optimization and includes new selection and mutation mechanisms. Calamoneri, Corò & Mancini (2022) pointed out that autonomous operation of unmanned aerial vehicles (UAVs) is an effective method to identify people in need of assistance in natural disasters. They encourage the use of an interface between computer science, especially sensor networks and Operations Research. In their research, they modelled their topic as a graph theoretic problem called Multi-Depot Multi-Path Vehicle Routing Problem with Total Completion Time minimisation (MDMT-VRP-TCT). They proposed a mixed integer linear programming (MILP) formulation for small instances and developed a heuristic for large instances. Lu et al. (2024) conducted research on an issue aimed at reducing human contact during epidemics and minimizing the involvement of drones in the diagnosis and treatment procedures. The authors of the research utilized a heuristic that combines the single link (S-LINK) algorithm, greedy randomised adaptive search process (GRASP), and genetic algorithm (GA). The authors introduce a novel vehicle routing problem (VRP-mD_ER) that incorporates the usage of drones to minimize collision in specific scenarios. Liu et al. (2024) tackled the difficulties associated with last mile delivery by employing a diverse fleet of drones to transport big packages. Within this system, the primary drone is responsible for transporting heavy and sizable packages, whereas lesser drones are assigned to deliver lightweight and compact products. A two-stage optimization strategy was employed to address this problem.

During the initial step, the process of task allocation involves the creation of multi-task allocation schemes. In the subsequent stage, known as single drone route planning, the routes for the drones are selected. The initial phase involves the introduction of a simulated annealing (SA) algorithm, which is subsequently followed by a variable neighborhood descent (VND) algorithm for the routing of the primary drone, and dynamic programming (DP) for the routing of the smaller drones. Tan et al. (2024) conducted research to enhance the efficiency of urban drone delivery operations with a focus on sustainability. This research highlighted the significance of noise optimization in sustainability methods within this domain. Within this particular scenario, a hybrid cost function was formulated by considering both the impact of noise and the length of the path. They suggested a three-stage heuristic technique to optimize this routing strategy. Lichau et al. (2024) conducted a study on the two-stage vehicle routing issue with drones (2E-VRP-D) and introduced a novel cluster partitioning model. This model efficiently enumerates partial routes that correspond to drone movements using a dynamic programming approach. The model was solved using a precise branch-and-cut-and-price approach and a labeling technique. Furthermore, they suggested modifying the well-recognized rounded capacity cuts for the specific problem and use preprocessing techniques to decrease the complexity of the challenge. Bhuiyan et al. (2024) emphasized the capacity of aerial drones to decrease delivery time and energy usage in the transportation of time-sensitive and small items. They examined the issue of optimizing drone deployment for the direct delivery of time-sensitive products. The researchers introduced a novel mixed integer programming model, along with fresh valid inequalities, a new greedy heuristic algorithm, and a Genetic algorithm. These tools aim to assist business owners in efficiently planning and managing their drone fleets by minimizing the fleet size, the need for additional batteries, and the overall energy consumption.

As a result of the research, there are very few studies of the multi-depot vehicle routing problem involving drone collaboration in disaster logistics. In this context, the consideration of the distribution of perishable commodities in drone collaborative studies of the multi-depot vehicle routing problem differs from other studies. Thus, the problem definition and mathematical model proposal of this study contribute to the literature.

3. PROBLEM DEFINITION and FORMULATION

There are numerous obstacles associated with humanitarian logistics following a disaster. The state of roads, uncertainty of demand, spoilage of products, and inaccessible areas for vehicles are among the challenges. Distribution in post-disaster humanitarian logistics is the issue that this study addresses. There is an emphasis on the most rapid and effective delivery of relief supplies, including perishable product, to disaster-affected regions. Transportation is particularly challenging due to road conditions, particularly for perishable product deliveries that require prompt delivery. Currently, drones are the favored method for the distribution of perishable commodities due to their superior speed and immunity to road conditions when compared to trucks.

Figure 1. Problem definitin

In this paper, we suggest a mathematical model that accounts for the timely delivery of perishable products to demand points. The problem is regarded as an open form of the multi-depot vehicle routing problem (MDVRP), as illustrated in Figure 1. The classical vehicle routing problem is enhanced by the integration of a drone in the proposed model, which facilitates the cooperation between trucks and drones. The materials to be distributed are divided into 2 groups: other necessities (Type 1) and perishable commodities (Type 2). Type 1 materials include needs such as clothes, blankets, non-perishable products, while type 2 includes needs with the risk of spoilage. The model is designed to guarantee the safe delivery of perishable products and the rapid delivery of all supplies. The assumptions of the problem, which deals with post-disaster humanitarian aid in MDVRP open form for two different product types, are as follows.

- There are sufficient numbers of logistics vehicles and relief supplies in warehouses.
- Distribution points and demands are known.
- Only one product type is in demand at each distribution point.
- Perishable product demands for a single point cannot exceed the maximum drone capacity.
- The fleet of logistics vehicles used in distribution is homogeneous.

3.1 Mathematical Model

In this study, MDVRP-D model is proposed to be implemented in post-disaster humanitarian aid logistics. The notations of the proposed model are as shown in Table 1.

Table 1. Notations of MDVRP-D model

Indices	
i, j	Tasks and depots
v	Fleet of trucks
u	Fleet of drones
d	Depots
p	Product type
QV	Capacity of truck
QU	Capacity of drone
Takeoff	Time for the takeoff of the drone

Landing	Time for the landing of the drone
MF	Maximum flight time
Parameter	
R_{jp}	Demand for product p at point j $(j \in j-d)$
TU_{ij}	The time of reaching from point i to point j by drone
TV_{ij}	The time of reaching from point i to point j by truck
Variables	
S_{iv}	Arbitrary numbers
S_{iu}	Arbitrary numbers
Binary Variables	
X_{ijv}	1, if truck v arrives at point j after leaving point i (I≠j); otherwise, 0
Y_{iju}	1, if drone u arrives at point j after leaving point i (I≠j); otherwise, 0

Objective function (1) minimizes the time it takes logistics vehicles to deliver relief supplies.

$$Min \quad \sum_{i}\sum_{j}\sum_{v}\left(TV_{ij} * X_{ijv}\right) + \sum_{i}\sum_{j}\sum_{u}\left(TU_{ij} * Y_{iju}\right) \tag{1}$$

Constraint (2-3) ensures the same number of trucks and drones leaving and returning to the depot.

$$\sum_{i\in i-d}\sum_{j\in j\cap d} X_{jiv} = \sum_{i\in i-d}\sum_{j\in j\cap d} X_{ijv} \qquad \forall v \tag{2}$$

$$\sum_{i\in i-d}\sum_{j\in j\cap d} Y_{jiu} = \sum_{i\in i-d}\sum_{j\in j\cap d} Y_{iju} \qquad \forall u \tag{3}$$

Constraints (4-5) allow the same truck or drone to leave the depot only once.

$$\sum_{j\in j-d}\sum_{i\in i\cap d} X_{ijv} \leq 1 \qquad \forall v \tag{4}$$

$$\sum_{j\in j-d}\sum_{i\in i\cap d} Y_{iju} \leq 1 \qquad \forall u \tag{5}$$

Constraint (6-7) ensures that there is only one entry into a task by a drone or a truck.

$$\sum_{i}\sum_{v} X_{ijv} + \sum_{i}\sum_{u} Y_{iju} = 1 \qquad \forall j \in j-d, i \neq j \tag{6}$$

$$\sum_{j}\sum_{v} X_{ijv} + \sum_{j}\sum_{u} Y_{iju} = 1 \qquad \forall i \in i-d, i \neq j \tag{7}$$

Constraint (8-9) ensures that the truck or drone entering the same point leaves that node.

$$\sum_{j} X_{ijv} = \sum_{j} X_{jiv} \qquad \forall v, i \in i-d\,, i \neq j \quad (8)$$

$$\sum_{j} Y_{iju} = \sum_{j} Y_{jiu} \qquad \forall u, i \in i-d\,, i \neq j \quad (9)$$

Constraint (10-11) provides that the payload carried by each truck and each drone along its route does not exceed its capacity.

$$\sum_{p} \sum_{j \in j-d} \sum_{i} R_{jp} * X_{ijv} \leq QV \qquad \forall v \qquad (10)$$

$$\sum_{p} \sum_{j \in j-d} \sum_{i} R_{jp} * Y_{iju} \leq QU \qquad \forall u \qquad (11)$$

Constraint (12) ensures that perishable commodities can only be delivered by drones.

$$\sum_{i} \sum_{u} Y_{iju} = 1 \qquad \forall j \in j-d, i \neq j: eğer\ R_{j2} \neq 0 \quad (12)$$

Constraint (13) ensures that the time required by each drone along its route, including landing and takeoff time, does not exceed the maximum flight time.

$$\sum_{j \in j-d} \sum_{i \in i \cap d} Y_{iju} * \left(TU_{ij} + takeoff\right) + \sum_{j \in j-d} \sum_{i \in i-d} Y_{iju} * \left(TU_{ij} + take-off + landing\right)$$
$$+ \sum_{i \in i-d} \sum_{j \in j \cap d} Y_{iju} * \left(TU_{ij} + landing\right) \leq MF \qquad \forall u \qquad (13)$$

Constraint (14-15) prevents routes that do not start and end at the depot.

$$S_{iv} - S_{jv} + QV * X_{ijv} \leq QV - \sum_{p} R_{jp} \qquad \forall i \in i-d, j \in j-d, v, i \neq j \quad (14)$$

$$S_{iu} - S_{ju} + QU * Y_{iju} \leq QU - \sum_{p} R_{jp} \qquad \forall i \in i-d, j \in j-d\,, u, \neq j,$$
$$: if\ R_{j1} \leq QU\,, R_{j2} \leq QU \qquad (15)$$

Constraints (16-17) provide upper and lower bounds for logistic vehicles.

$$\sum_{p} R_{ip} \leq S_{iv} \leq QV \qquad \forall i, v \qquad (16)$$

$$\sum_{p} R_{ip} \leq S_{iu} \leq QU \qquad \forall i, u: if\ R_{j1} \leq QU\ and\ R_{j2} \leq QU \quad (17)$$

3.1 Implementation of Case

The proposed model was tested by applying the mathematical model to the case in the article by Song & Ko (2016). As stated in Table 3 from the data with 50 demand points, the data set was made suitable for the developed model by determining temporary warehouses with the p-median method, increasing the amount of demand in the data by 150 times and randomizing the product types at the demand points.

Initially, the p-median approach was employed to identify temporary warehouse locations based on 50 demand points. Subsequently, the model's solution is evaluated using the logistics tools whose features are given in Table 2 and the data set provided in the case study. The results demonstrate the model's efficacy in a comprehensive case study with 50 demand points, since it consistently produces achievable outcomes within the specified time limit. Nevertheless, the approach necessitates the use of a heuristic algorithm to achieve optimal outcomes within a limited timeframe and to generate quicker and more effective solutions when dealing with larger datasets.

Table 2. Features of logistic vehicles

	Capacity (kg)	Max. Flight time (min)	Velocity (km/h)
Truck	800	-	60
Drone	200	30	80

Table 3. Data set taken and organized from the literature

Customer Index	X	Y	Demand (kg)	Product Type	Customer Index	X	Y	Demand (kg)	Product Type
1	1109	1490	60	2	26	3403	1368	225	1
2	2765	2179	75	2	27	2042	699	270	1
3	975	2998	135	1	28	1598	2151	105	1
4	90	842	240	1	29	933	58	15	2
5	938	1208	255	1	30	2792	811	105	1
6	3908	1005	135	1	31	3378	1073	15	2
7	1223	1590	60	2	32	4980	3935	90	1
8	4654	3092	210	1	33	161	1906	75	2
9	2930	208	270	1	34	3293	2871	60	2
10	1675	2458	180	1	35	2763	3169	255	1
11	425	2213	135	1	36	3366	1493	120	1
12	1947	3108	60	2	37	2839	4964	60	2
13	4307	1275	165	1	38	2870	4650	90	1
14	3627	4873	165	1	39	4583	2600	135	1
15	1666	4325	135	1	40	1436	4002	240	1
16	2021	1984	165	1	41	4782	1486	270	1
17	1235	466	225	1	42	23	3866	180	1
18	3437	2020	120	1	43	3030	1489	255	1
19	2480	2877	105	1	44	4092	4156	15	2
20	1898	3563	120	1	45	4020	2598	165	1
21	1126	199	210	1	46	942	691	75	2
22	112	4397	75	2	47	1647	4798	105	2
23	362	1860	90	1	48	4812	1674	210	1
24	1137	2712	150	1	49	4332	3428	270	1
25	1203	1789	240	1	50	4952	2609	240	1

The results obtained from the proposed mathematical model for the multi-depot vehicle routing problem with drone collaboration in post-disaster humanitarian aid logistics demonstrate the applicability of the concept in minimizing the overall distribution time. Table 4 indicates the achievable outcome obtained within a time frame of 10800 seconds utilizing the dataset mentioned in the literature. The routes were established with a combined fleet of 16 logistics vehicles, consisting of 7 trucks and 9 drones. The distribution of humanitarian aid supplies to the designated locations was successfully completed within 377 minutes through the collaborative efforts of trucks and drones. Trucks were mostly employed for delivering large quantities of supplies to demand points, while drones were utilized for swift delivery of perishable commodities to demand points. This collaborative strategy aims to enhance the efficiency of the post-disaster humanitarian aid logistics process by using the benefits of various logistics vehicles.

Table 4. Result of data set

Logistics Vehicles	Routes	Objective Function
Truck	10-24-3-42-40-15; 5-17-21-4-5; 5-23-11-25-28-16-10; 26-48-41-13-6-26; 49-8-50-39-45-49; 26-30-9-27-5; 10-19-35-18-43-26	377 min
Drone	5-33-7-1-5; 26-31-2-34-49; 5-29-46-5;15-20-12-10;49-14-44-49; 15-22-47-15;15-37-38-15; 26-36-26; 49-32-49	

4. CONCLUSION

Over the past few years, the significance of humanitarian logistics in mitigating the consequences of post-disaster situations has become increasingly apparent in the aftermath of natural calamities. Scientists have carried out several investigations to enhance and streamline this process. This work presents a novel model (MDVRP) for the open-form multi-point vehicle routing problem, specifically addressing the distribution of perishable items. This effort adds to the existing body of knowledge in the field of humanitarian logistics. An exceptional feature of this study is the integration of truck-drone collaboration. Although trucks have the advantage of more capacity, drones are more favorable in terms of efficiency and accessibility to challenging locations, which is particularly crucial for perishable commodities. The model findings clearly demonstrate that the combination of these two logistical methods has produced successful outcomes for solving vehicle routing difficulties in humanitarian logistics.

Given its NP-hard complexity, the mathematical model that was created underwent testing using a case study from the literature consisting of 50 data points. It was determined that the ideal outcome could not be achieved within a time frame of 10800 seconds. This constraint of the model implies that the utilization of heuristic methods will be a focus of future research. Furthermore, a potential avenue for future research involves enhancing the model through the utilization of diverse logistics vehicles. In addition, demand uncertainty of distribution points and weather conditions may be future studies that add value to the literature by dynamizing the model.

Conflict of Interest

The authors declare no potential conflicts of interest with respect to the research, authorship, and/or publication of this paper.

Contribution of Authors

[1st Author Zeynep Yuksel]: Editing the introduction, general design, preparation of visuals and tables, arrangement of data, literature review, mathematical model development, coding and solution of the model, discussion and improvement of the results, revision of the manuscript according to the requests of the advisor and editor.

[2nd Author Dursun Emre Epcim]: Literature review, developed a mathematical model, coded and solved the model, discussed and enhanced the results, and revised the work based on the feedback from the adviser and editor.

[3rd Author Suleyman Mete]: The study supervisor is responsible for designing the study framework, assessing its suitability, establishing the study's boundaries and main areas of focus, and reviewing and editing the paper.

REFERENCES

Bhuiyan, T. H., Walker, V., Roni, M., & Ahmed, I. (2024). Aerial drone fleet deployment optimization with endogenous battery replacements for direct delivery of time-sensitive products. *Expert Systems with Applications*, *252*, 124172. https://doi.org/10.1016/j.eswa.2024.124172

Calamoneri, T., Corò, F., & Mancini, S. (2022). *Multi-Depot Multi-Trip Vehicle Routing with Total Completion Time Minimization* (arXiv:2207.06155). arXiv. http://arxiv.org/abs/2207.06155

Diabat, A., Jabbarzadeh, A., & Khosrojerdi, A. (2019). A perishable product supply chain network design problem with reliability and disruption considerations. *International Journal of Production Economics*, *212*, 125-138. https://doi.org/10.1016/j.ijpe.2018.09.018

Habib, D., Jamal, H., & Khan, S. A. (2013). Employing Multiple Unmanned Aerial Vehicles for Co-Operative Path Planning. International Journal of Advanced Robotic S*ystems*, *10*(5), 235https://doi.org/10.5772/56286

Haller, J. R. (t.y.). *Expanding Optimization of Energy Efficient UAV Routing in Support of Marine Corps Expeditionary Advanced Base Operations with Multiple Supply Depots*.

Hamid, M., Nasiri, M. M., & Rabbani, M. (2023). A mixed closed-open multi-depot routing and scheduling problem for homemade meal delivery incorporating drone and crowd-sourced fleet: A self-adaptive hyper-heuristic approach. *Engineering Applications of Artificial Intelligence*, *120*, 105876. https://doi.org/10.1016/j.engappai.2023.105876

Kim, S. J., Lim, G. J., Cho, J., & Côté, M. J. (2017). Drone-Aided Healthcare Services for Patients with Chronic Diseases in Rural Areas. *Journal of Intelligent & Robotic Systems*, *88*(1), 163-180. https://doi.org/10.1007/s10846-017-0548-z

Laporte, G. (1992). The vehicle routing problem: An overview of exact and approximate algorithms. *European Journal of Operational Research*, *59*(3), 345-358. https://doi.org/10.1016/0377-2217(92)90192-C

Li, X., Li, P., Zhao, Y., Zhang, L., & Dong, Y. (2021). A Hybrid Large Neighborhood Search Algorithm for Solving the Multi Depot UAV Swarm Routing Problem. *IEEE Access*, *9*, 104115-104126. https://doi.org/10.1109/ACCESS.2021.3098863

Lichau, S., Sadykov, R., François, J., & Dupas, R. (2024). *A Branch-Cut-And-Price Approach for the Two-Echelon Vehicle Routing Problem with Drones*. https://doi.org/10.2139/ssrn.4865970

Liu, H., Wu, G., Yuan, Y., Wang, D., Zheng, L., & Zhou, W. (2024). An iterative two-phase optimization method for heterogeneous multi-drone routing problem considering differentiated demands. *Complex & Intelligent Systems*. https://doi.org/10.1007/s40747-024-01472-6

Lu, S.-H., Benaglia, M. F., Nguyen, A.-T., Rivera, E. R., & Cheng, J.-W. (2024). Vehicle routing problem with drones as an aid for epidemic relief. *International Journal of Shipping and Transport Logistics*. https://www.inderscienceonline.com/doi/10.1504/IJSTL.2024.139062

Manyam, S. G., Rasmussen, S., Casbeer, D. W., Kalyanam, K., & Manickam, S. (2017). Multi-UAV routing for persistent intelligence surveillance & reconnaissance missions. *2017 International Conference on Unmanned Aircraft Systems (ICUAS)*, 573-580. https://doi.org/10.1109/ICUAS.2017.7991314

Mavrouli, M., Mavroulis, S., Lekkas, E., & Tsakris, A. (2023). The Impact of Earthquakes on Public Health: A Narrative Review of Infectious Diseases in the Post-Disaster Period Aiming to Disaster Risk Reduction. *Microorganisms*, *11*(2), 419. https://doi.org/10.3390/microorganisms11020419

Rashidzadeh, E., Hadji Molana, S. M., Soltani, R., & Hafezalkotob, A. (2021). Assessing the sustainability of using drone technology for last-mile delivery in a blood supply chain. *Journal of Modelling in Management*, *16*(4), 1376-1402. https://doi.org/10.1108/JM2-09-2020-0241

Rathinam, S., & Sengupta, R. (2006). Lower and Upper Bounds for a Multiple Depot UAV Routing Problem. *Proceedings of the 45th IEEE Conference on Decision and Control*, 5287-5292. https://doi.org/10.1109/CDC.2006.377732

Song, B. D., & Ko, Y. D. (2016). A vehicle routing problem of both refrigerated- and general-type vehicles for perishable food products delivery. *Journal of Food Engineering*, *169*, 61-71. https://doi.org/10.1016/j.jfoodeng.2015.08.027

Stodola, P., & Kutěj, L. (2024). Multi-Depot Vehicle Routing Problem with Drones: Mathematical formulation, solution algorithm and experiments. *Expert Systems with Applications*, *241*, 122483. https://doi.org/10.1016/j.eswa.2023.122483

Tan, Q., Zhong, S., Qu, R., Li, Y., Zhou, P., Lo, H. K., & Zhang, X. (2024). Low-Noise Flight Path Planning of Drones Based on a Virtual Flight Noise Simulator: A Vehicle Routing Problem. *IEEE Intelligent Transportation Systems Magazine*, 2-17. https://doi.org/10.1109/MITS.2024.3396430

Walika, M., Moitinho De Almeida, M., Castro Delgado, R., & Arcos González, P. (2023). Outbreaks Following Natural Disasters: A Review of the Literature. *Disaster Medicine and Public Health Preparedness*, *17*, e444. https://doi.org/10.1017/dmp.2023.96