



A Multi-Visit Heterogeneous Drone Routing Model Considering Recharging Decision in Disaster

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Abstract

The complex nature of disasters has required communities and governments to implement plans to reduce the disturbing effects of these disasters. With the breakdown and destruction of road infrastructure in times of disaster, the need to use an Unmanned Aerial Vehicle (UAV) fleet under the concept of humanitarian logistics has become increasingly essential. Therefore, we present a Multi-Visit Drone Routing Problem in this paper. The relief goods are delivered to disaster-affected areas by using heterogeneous drones. We use a linear approximation function to calculate energy consumption. We formulated the proposed bi-objective Mixed Integer Linear Programming (MILP) model by a compromise programming method. To validate the proposed model and to show the model's efficiency, we generate several test problems with the data extracted by experts. The computational results show the satisfactory performance of the model for the delivery of relief items to the damaged nodes by humanitarian drones in the shortest possible time.

Keywords:

Natural Disaster;
Humanitarian Logistics;
Heterogeneous Drones;
Linear Approximation
Function;
Energy Consumption

Introduction

According to the information presented by the Emergency Events Database (EM-DAT), as a Center for Research on the Epidemiology of Disasters (CRED), it has claimed by the end of the second decade of the 21st century that natural disasters have been the reason for 1232000 deaths on Earth. Natural disasters, in addition to high mortality rates, have caused enormous financial losses to nations and governments. Natural catastrophes cause millions of injuries and homelessness each year. In 2004, 2008, 2010, 242765, 235226, and 297140 people lost their lives due to natural disasters, respectively. This data represents the highest death rate due to natural disasters in the last twenty years. For example, the 2004 Indian Ocean earthquake and the 2010 Haiti earthquake are the deadliest natural disasters of the present century [1].

As mentioned earlier, in recent decades, the increase in the population of human societies and the extent of natural disasters has led to a significant increase in casualties and financial losses around the world (Tricoire et al. [2]). To reduce these losses, the need for attention to relief logistics management has increased. The crisis management cycle consists of 4 phases. It includes mitigation, preparedness, response, and recovery or rehabilitation, shown in Fig. 1. Immediate response in the post-disaster can have a significant impact on reducing costs and Casualties (Abounacer et al. [3]). A rapid and effective response is not possible except concerning the management of the flow of relief goods. Goods flow management is possible by applying humanitarian logistics rules Humanitarian logistics means storing, transporting,

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and delivering relief items from the depot to the damaged nodes in the disaster (Rabta et al. [4]).



Fig. 1. Crisis management cycle[†].

In the post-disaster situation, damage to health centers, disruption of the infrastructure of medical networks, and the possibility of water pollution create demand among the people in the disaster-affected areas for urgent medical supplies, water, and medicine (Kouadio et al. [5]). Therefore, the need to pay attention to the humanitarian logistics and quick delivery of relief goods is more important than ever. On the other hand, after crises, governments, and aid organizations face challenges such as the breakdown of roads and transportation infrastructure. For this reason, as well as due to the non-applicability of heavy vehicles to deliver light relief goods such as water and medicine, the use of a humanitarian unmanned aerial vehicle is recommended (Hirschinger [6]).

Using UAVs or drones in commercial businesses became an experiment in the use of drones in disaster. Before using drones in disasters, large companies worldwide have used drones to serve customers and increase their satisfaction by saving time. In 2013, Amazon announced for the first time that it would soon use drones to deliver products to its customers in a short time. Subsequently, in 2017, Amazon announced that the company wants to use a drone delivery system under the Prime Air project (Sudbury and Glaser [7,8]). In the same year, Google, with the awareness of the need to pay attention to disaster logistics, provided a relief delivery system to send water and medicine to the damaged nodes under the Project Wing in disaster (Vincent [9]). Fig. 2 shows an image of the drones used in the Prime Air and Wing projects.

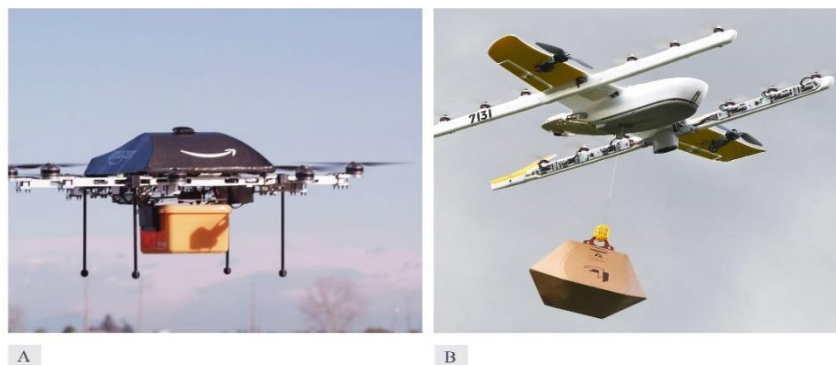


Fig. 2. A) The drone used in Prime Air project[‡], B) The drone used in Wing project[§].

[†] <https://www.bu.edu/emd/emergency-management/emergency-management-principles/>

[‡] <https://www.theverge.com>

[§] <https://www.wsj.com>

According to Agatz et al. [10], several significant features of drones have made them more widely used today in disaster situations. These features include easy application and use, relatively high service speed, and no need for road infrastructure. These characteristics make the use of drones critical in the immediate aftermath of a disaster for the matters such as mapping, photography, and the delivery of relief goods to damaged nodes (Chowdhury et al. [11]). The use of drones in disaster situations reduces road traffic and speeds up the transfer, according to Mishra et al. [12].

In addition to the positive features, drones have limited battery power, limited flight range, and a limit on the amount of carried load. On average, each humanitarian drone, both multi-rotor, and hybrid can hold about 2.5 kg of relief goods (Flamini et al. [13]). For this reason, and limited battery capacity, there is a need for facilities for recharging drones to serve disaster-affected areas by drones, which can be used from existing or pre-built centers to recharge drones in the relief delivery network in the disaster response phase.

To realize the high importance of establishing recharge stations, two similar networks for the delivery of relief goods in the disaster have been shown in Fig. 3. In each network, three humanitarian drones are used to deliver relief goods to the affected areas. In both networks, there are seven damaged nodes and three potential points for establishing a recharge station. Due to the limited flight range of the drone, which is due to the limited energy of the batteries, the drones need to recharge their batteries to create a long trip. Therefore, the routes of drones 1, 2, and 3 without activating the recharge stations in the network (A) have been shown. As observed, the damaged nodes 3 and 4 are deprived of receiving relief goods by the drone. The lack of maximum coverage of damaged nodes in this network is due to the non-activation of recharge stations and little battery power. In the network (B), we can perceive that by activating the recharge stations, the demand of all the damaged nodes will be met by the drones. By comparing both networks, the importance of establishing a recharge station can be understood.

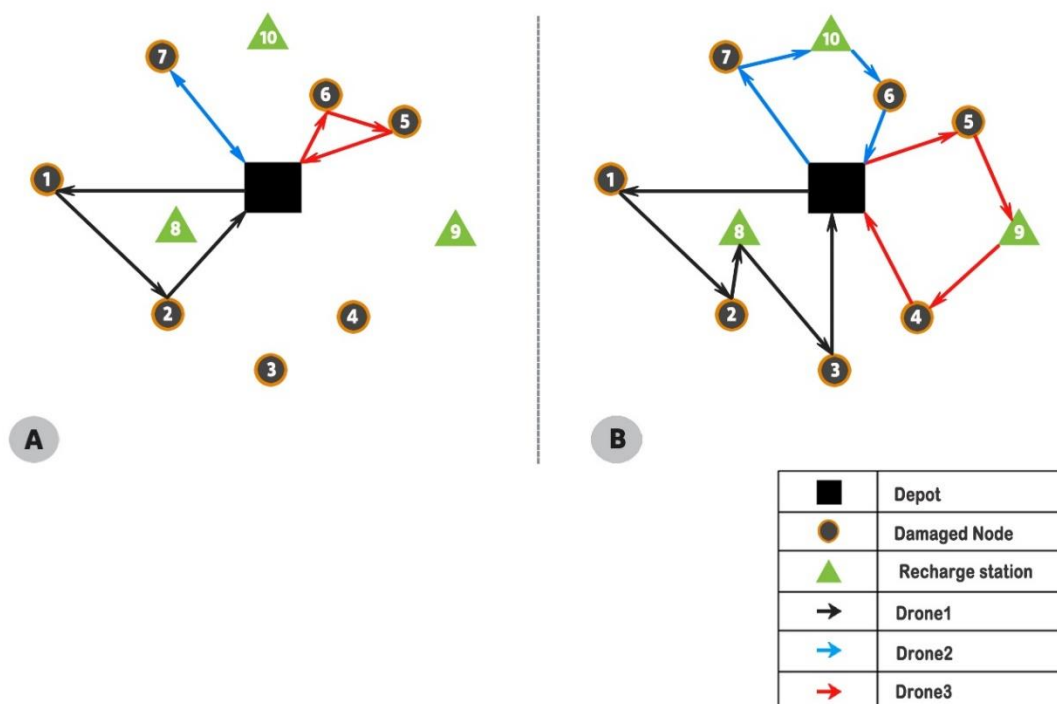


Fig. 3. Relief delivery networks.

It is necessary to use mathematical programming models to locate the recharge stations, and to determine the visit sequence and route of the drones to meet the damaged nodes.

In this research, we consider a drone routing problem to assist in a disaster. In this problem, drones with different characteristics in load carriage rate, battery energy, and speed have been used. Each of these drones starts its trip from the depot and must end this trip in the depot. We develop a mathematical model called Multi-Visit Drone Routing Problem (MVDRP). The multi-visit refers that each drone can meet more than one damaged node in each trip. In this model, the drones' constraints, including battery capacity and the weight of portable relief goods, have been considered. In addition to these constraints, factors such as the arrival time of drones to reach the points, and the requirement to establish facilities for recharging the drones have been considered. It should be noted that the drones considered in this model are of the multi-rotor type with a load-carrying limitation. Given the lack of papers in this field, several test problems have been used to validate the model in the following text.

The rest of this paper is organized as follows. [Section 2](#) reviews relief routing problems and drone routing problems and states the contributions of our developed model. [Section 3](#) describes the MVDRP. [Section 4](#) states the assumptions and introduces the mathematical model. [Section 5](#) presents the solution method. Numerical examples and results of software outputs are presented in [Section 6](#). [Section 7](#) states the sensitivity analysis and its results. The conclusion and recommendations for future researches are declared in [Section 8](#).

Literature Review

In this section, we review the literature of the existing papers under the titles of relief routing problems and drone routing problems.

Relief Routing Problems

The relief routing literature is generally divided into three main categories: 1. Relief distribution, 2. Problems related to evacuation of corpses and injured people, and 3. Problems associated with clearing debris-covered pathways due to disaster (Bayram and Yaman, and Oladi et al. [[14,15](#)]). The purpose of the relief distribution planning is to find a suitable solution to manage the flow of relief goods from depots to the damaged areas so that the time of operations and related costs are minimized (Camacho-Vallejo et al. and Tzeng et al. [[16,17](#)]). In some papers, such as Ozdamar [[18](#)], the problems of combining the evacuation and relief distribution with the air transport fleet have been presented. The clearing of roads and the re-opening of roads to access warehouses, medical centers, and temporary hospitals is done with land vehicles that, Sahin et al. [[19](#)] and Berktas et al. [[20](#)] have addressed this issue in their papers.

In addition to the classic problems of vehicle location and vehicle routing, many studies have used hybrid location-routing problems. For example, Ebrahimnejad et al. [[21](#)], have presented the possible disruptions in the road transport network and a mixed-integer programming model to choose the optimal location of suppliers and the routes of vehicles.

Considering uncertainty is one of the critical points in developing a location-routing model. So that Caunhye et al. [[22](#)] introduced a two-stage location-routing problem for integrating the preparation, and response phase in uncertainty conditions. They made the decisions related to the warehouses' location in the first stage. Decisions associated with the paths leading to the damaged nodes were taken in the second stage. Nedjati et al. [[23](#)] developed a location-routing problem under service time constraints and final destination uncertainty in post-earthquake conditions. Their model objective was to minimize the unmet damaged nodes, which used the

\mathcal{E} -constraint method to solve their linear programming model. They presented a solution method by introducing a genetic algorithm.

Drone routing problems

Drone delivery problems focus on covering the demand of one or more nodes in a network using one or more homogeneous or heterogeneous drones (Macrina et al. [24]). In some researches, such as Choi and Schonfeld [25], they tried to design a homogeneous aerial fleet to serve the demand nodes with the same request. San et al. [26], introduced a delivery system based on heterogeneous drones, in which the UAVs can return to the depot to load new goods to meet the needs of various nodes. The need for reloading is due to the inherent constraints of drones, such as energy and load constraints. Dorling et al. [27] Tried to minimize the delivery costs and the final delivery time of the parcels according to a vehicle routing problem (VRP) by considering the time and financial constraints. In that research, a linear function has been used to estimate the amount of energy consumption, and they have solved their proposed problem using a Simulated Annealing (SA). Troudi et al. [28] designed an air freight delivery system using drones by presenting a multi-objective optimization model considering the time window.

In recent years, papers have been published on drone delivery systems, taking into account environmental considerations about reducing carbon dioxide emissions. Figliozzi [29] has studied the effect of using drones on reducing carbon dioxide emissions and has compared the aerial fleet with the fleets of delivery of goods using diesel vehicles in terms of environmental impact.

Researches have been done with more emphasis on energy models. For example, Liu et al. [30] developed a model to examine the energy consumption of multi-rotor drones and tested their studies in practical terms, and published the results. Zhang et al. [31] provided a valuable review of drone delivery models emphasizing energy consumption calculation.

Drone systems are used for monitoring, object detection, motion tracking, and support operation (Chmaj and Selvaraj [32]). Garapati et al. [33] examined the timing of a surveillance operation by a drone fleet. In this research, game theory has been used to plan drones' allocation to the desired points. Alfeo et al. [34] presented a model for planning search operations by drones without having information on target points and reported the optimal response by a meta-heuristic solution method. Zema et al. [35] proposed a method for preparing architectural plans using the ability to photography drones.

Most of the researches and models proposed for drones are for regular service and commercial use. The use of drone fleets for non-commercial purposes, especially in the post-disaster situation, seems critical. For this reason, researches have been conducted in recent years on the use of capacitated drone in the aftermath of natural and unnatural crises. For example, Molina et al. [36] considered drones to plan the search and rescue operation for the missing. Scott and Scott [37] have introduced a mathematical model to optimize the visit of damaged nodes by drones in a healthcare system. Many papers emphasize the importance of product delivery at all stages of the crisis management cycle, including the response phase. Focusing on a routing problem, Huang et al. [38] emphasized the use of drones in crisis management. They point to the ability to remotely control drones without users' physical presence at the demand point.

Choi et al. [39] described and examined how humans used drones for civilian and humanitarian purposes from 2009 to 2015. Rabta et al. and Mosterman et al. [4,40] investigated the use of humanitarian drones in disaster and disruption situations to reduce the impact of damage to medical and health infrastructure. They presented two models to deliver light relief packages to affected areas to minimize costs and the final delivery time. Chowdhury [41]

developed a mixed-integer programming model to inspect disaster-affected points and used two heuristic algorithms to solve their problem. Rottondi et al. [42], in a new study, they have introduced a multi-objective programming model for multitasking missions and reported results for their large-scale problem by presenting two heuristic solution methods.

According to the literature review, several papers in the field of drone routing problems were selected due to their similarity to the present study and are classified and presented in Table 1 based on significant features.

Table 1. Summary of researches on drone routing problem.

Researches	Objective function	Multiple/single drone	Multiple-visit	Drone recharge	Drone energy
Dorling et al. (2017)	total time and operation costs	multiple	yes	no	yes
Yadav and Narasimhamurthy [43], (2017)	completion time	multiple	yes	no	yes
Choi and Schonfeld, (2018)	operation costs	multiple	yes	yes	no
Chowdhury, (2020)	energy costs	multiple	yes	yes	yes
Agatz et al. (2018)	operations costs	Single	no	no	no
Troudi et al. (2018)	distance and number of drones	multiple	yes	no	yes
Liu [44], (2019)	ensure safety and efficiency	multiple	yes	no	no
Poikonen and Golden [45], (2020)	weightdelivery time	multiple	yes	no	yes
This study	delivery time and total costs	multiple	yes	yes	yes

By studying various researches, it was found that no research has been done on the relief delivery by drone considering all the following features.

These features, which in a way indicate research gaps, are:

- Use of heterogeneous drones
- Use of batteries with various capacities to supply drone power
- Considering the service time to the damaged nodes and the recharge time
- Establishing recharge stations
- Optimization of drone flight speed
- Calculation of the energy and approximation of the energy consumption

We observed a model with a number of the above features in the Chowdhury [41]. This paper is produced outside the delivery literature to inspect the damaged areas after the disaster. We used a linear approximation function is introduced by Dorling et al. [27] for calculating the energy consumption of a multi-rotor drone based on the drone's weight. The main contributions of this paper are as follows:

- In our model, the drone battery energy level, drone load weight, and drone arrival time of reaching any point are considered decision variables.

- In this model, unlike most papers where the load of the drone used consists of only one package, we considered drones with the ability to carry several relief packages to reach the affected areas. This means that each drone can meet more than one demand point, which indicates that the model is Multi-Visit one.

- Our model provides two significant possibilities for drone users in disaster situations, as follows:

A) Using various speed levels for flying drones

B) Considering the batteries with various drones' capacities.

Given that limited researches have been done in the field of relief logistics considering integrated decisions. In this paper, we presented a novel model for drone delivery by considering the basic features of the vehicle routing problem (such as visit each point only once, the need not to form the sub-tour, etc.).

Problem Description

The objective of this paper is to develop a mixed-integer linear programming model for a location-routing problem called MVDRP. The multi-rotor drones are used in delivery operations after a natural disaster under the relief logistics literature. The transportation network studied in this paper includes the mentioned components: 1) a depot where the drones are located and storage of relief goods, 2) damaged nodes affected by natural disasters, and 3) drone recharge stations. In this model, by activating some potential recharge stations located in the available or prefabricated locations, it is possible to determine the drones' route from the depot to the damaged points and then return the drones from the damaged points or recharge station to the depot point. The major decisions to be made in the mathematical model are: 1) first to establish the recharge stations 2) to make decisions about the determination of the drones' route. Next, 3) the decision about the weight of the drone to be assigned to the injured people by the drone at each damaged node, 4) decision about the drone's battery energy level, 5) arrival time for the drone to reach each point, and 6) decision about the speed level and type of the selected battery are made.

In the post-disaster immediate response, government and non-governmental aid organizations and local agents send a team of assessment experts to the affected areas shortly after the disaster. They provide valuable information about the extent and level of the catastrophe and notify relief centers, by receiving the information about the demand for various relief goods in the affected areas. At this stage, to meet the demand of the affected areas, light relief items such as medicine and water, are sent by drones from the depot to the damaged nodes. The humanitarian drones in our model are heterogeneous multi-rotor drones so that the battery of each drone has its unique energy capacity. The drones can also fly at different speed levels. In the proposed mathematical model, details such as the amount of energy consumption of drones and the time required for each drone to serve the points of demand and recharging have been considered. Before deciding on the drone's trajectory, our model first established points among potential recharge stations. It should be noted that each drone must return to the depot after delivering relief packages to one or more damaged points without creating a sub-tour. In determining the delivery quantities, it is necessary to pay attention to capacity and energy constraints. All relief goods delivered by a drone cannot exceed the capacity of the drone.

Mathematical Programming Model

A new mathematical model has been presented in this paper to formulate the MVDRP. This model has been developed for the delivery of post-disaster relief items by a fleet of heterogeneous drones. The energy source of these drones is a battery that can be recharged in the drones' route. This represents a well-integrated MILP model introduced to minimize total delivery time. By studying the literature in the previous section, it was found that despite the rich research in commercial goods delivery systems, we face a severe shortage of papers on drone delivery problems in the disaster.

Before formulating the model, in this section, we state the following assumptions that have been considered in the problem:

1. Only one depot has been intended for the drone delivery network.
2. Drones leave depots and recharge stations with a full charge.
3. Each damaged point is serviced with only one drone.
4. It is not possible to reuse the drones after returning to the depot.
5. Each drone can deliver relief items to more than one damaged point.
6. The maximum number of damaged nodes is equal to the number of drones in the depot.
7. For each drone, there is exactly one direct route from the depot to a recharge station and a return route from a recharge station to the depot.
8. To create a route, a drone cannot travel directly from one recharge station to another recharge station.

In the following tables, sets, indices, parameters, and variables used in mathematical modeling are defined in the form of tables. Then a MILP mathematical model is presented for the proposed problem.

Table 2. Sets and indices.

Symbol	Description
V_D	damaged nodes indexed by i and j
V_R	potential drone recharging stations indexed by i and j
V_o	Depot
V	all nodes including: depot, damaged nodes, and potential drone recharging stations: $V_o \cup V_R \cup V_D$
K	drones indexed by k
S	drone speed levels indexed by s
B	drone battery levels indexed by b

Table 3. Parameters.

Symbol	Description
φ_{ik}	drone $k \in K$ service time at node $i \in V_D$ / recharge time at node $i \in V_R$
$\bar{\tau}$	average time for UAV to take off
wei_b	weight of battery type $b \in B$ in kg
cap_b	drone energy capacity with battery type $b \in B$ in J
M	A great number
$D_i, i \in V_D$	amount of customer demand in demand node
F	cost of using a drone
$CR_r, r \in V_D$	cost of establishing a recharge station
$d_{ij}, i, j \in V$	time distance between node i and j
α	energy consumed per kg in $Watt / kg$
β	energy required to keep the multi-rotor drone in the air in J / s
\bar{V}_{ks}	average drone $k \in K$ speed under speed level $s \in S$

Table 4. Decision variables.

Symbol	Description
U_j	1: if the recharge station $j \in V_R$ is established 0: o.w
X_{ijk}	1: if the path between i and $j \in V$ traversed by drone $k \in K$ 0: o.w
W_{ijk}	the payload weight carried by drone $k \in K$ in the path between i and $j \in V$
E_k	1: if drone $k \in K$ is selected 0: o.w
Z_{ijks}	1: if drone $k \in K$ travels through the path i to $j \in V$ under $s \in S$ speed level 0: o.w
Q_{bk}	1: if drone $k \in K$ with a battery $b \in B$ is selected 0: o.w
Y_{jk}	drone $k \in K$ battery energy level at arrival time on node $i \in V$
T_{ik}	arrival time of drone $k \in K$ at node $i \in V$
T_{ilk}	arrival time of drone $k \in K$ at node $l \in V_o \cup V_R$ after leaving node $i \in V$
m_{ijk}	total weight of drone $k \in K$ travels from node i to node j
$p(m_{ijk})$	linear function of energy consumption in term of drone $k \in K$ weight

According to the assumptions, indices, parameters, and variables defined, the mathematical model of optimization of the two proposed objectives for the design of the humanitarian distribution network of relief goods is presented as follows:

$$Minz_1 = \sum_k F_k E_k + \sum_i \sum_j \sum_k c_k d_{ij} X_{ijk} + \sum_{r \in V_R} CR_r U_r \quad i$$

$$Minz_2 = \sum_{j \in V_D} \sum_k T_{jk} \quad ii$$

Subject to:

$$\sum_k \sum_{i \in V} X_{ijk} = 1 \quad \forall j \in V_D \quad (1)$$

$$\sum_{i \in V, i \neq j} X_{ijk} = \sum_{i \in V, i \neq j} X_{jik} \quad \forall j \in V, \forall k \quad (2)$$

$$\sum_{i \in V} \sum_k X_{ijk} \leq M \cdot U_j \quad \forall j \in V_R \quad (3)$$

$$\sum_{j \in V} \sum_k X_{ijk} \leq M \cdot U_i \quad \forall i \in V_R \quad (4)$$

$$\sum_s Z_{ijks} = X_{ijk} \quad \forall i, \forall j \in V, \forall k \quad (5)$$

$$T_{jk} \geq T_{ik} + \varphi_{ik} + \sum_s d_{ij} \frac{Z_{ijks}}{V_{ks}} + \bar{\tau} - M(1 - X_{ijk}) - M(1 - E_k) \quad \forall j \in V, \forall k, \forall i \in V_R \cup V_D \quad (6)$$

$$T_{jk} \geq \varphi_{ik} + \sum_s d_{ij} \frac{Z_{ijks}}{V_{ks}} + \bar{\tau} - M(1 - X_{ijk}) - M(1 - E_k) \quad \forall j \in V, \forall k, \forall i \in V_O \quad (7)$$

$$\sum_{i \in V} X_{ijk} \leq 1 \quad \forall j \in V_R, \forall k \quad (8)$$

$$\sum_{j \in V} X_{ijk} = E_k \quad \forall i \in V_o, \forall k \quad (9)$$

$$X_{ijk} \leq E_k \quad \forall i, \forall j \in V, \forall k \quad (10)$$

$$m_{ijk} = \sum_b wei_b Q_{bk} + w_{ijk} \quad \forall i, \forall j \in V, \forall k \quad (11)$$

$$\sum_b Q_{bk} = 1 \quad \forall k \quad (12)$$

$$Y_{jk} \leq Y_{ik} - (\alpha \cdot m_{ijk} + \beta) \left(\sum_s d_{ij} \frac{Z_{ijks}}{V_{ks}} + \bar{\tau} \right) + M(1 - X_{ijk}) \quad \forall i \in V, \forall j \in V_D, \forall k \quad (13)$$

$$Y_{ik} \geq \left[\sum_s d_{ij} \frac{Z_{ijks}}{V_{ks}} + \bar{\tau} \right] (\alpha \cdot m_{ijk} + \beta) - M(1 - X_{ijk}) \quad \forall i \in V, \forall j \in V, \forall k \quad (14)$$

$$Y_{ik} = \sum_b cap_b Q_{bk} \quad \forall i \in V_o \cup V_R, \forall k \quad (15)$$

$$w_{ijk} \leq M \cdot X_{ijk} \quad \forall i, j \in V, \forall k \quad (16)$$

$$\sum_{i \in V(i \neq j)} w_{ijk} = \sum_{i \in V(i \neq j)} w_{jik} + D_j \sum_{i \in V(i \neq j)} X_{ijk} \quad \forall j \in V_D, \forall k \quad (17)$$

$$\sum_{i \in V(i \neq j)} w_{ijk} = \sum_{i \in V(i \neq j)} w_{jik} \quad \forall j \in V_R, \forall k \quad (18)$$

$$\sum_{i \in V_D} w_{ijk} = 0 \quad \forall k, j \in V_o \quad (19)$$

$$X_{ijk} \leq 1 \quad \forall k, \forall i, j \in V_o \cup V_R / i \neq j \quad (20)$$

$$\sum_{j \in V_o} X_{ijk} = 0 \quad \forall k, \forall i \in V_o \quad (21)$$

$$\sum_{j \in V_R} X_{ijk} = 0 \quad \forall k, \forall i \in V_R \quad (22)$$

The first objective function (i) attempts to minimize the operation costs such as the cost of using drones, the cost of transporting drones over the network, and the cost of using recharge stations. The second objective function (ii) has been introduced to minimize the delivery time of service operations to the damaged points.

Constraint (1) states that each damaged node is serviced by only one drone. Constraint (2) is known as a flow constraint, which ensures that at each node of a complete directed path, an incoming arc of a drone must be followed by an outgoing arc of that drone. Constraints (3) and (4) control the entry and exit of each drone in the recharge stations and the need of establishing a recharge station. Constraint (5) has been considered to determine the speed level of each drone in the considered path. Constraints (6) and (7) determine the arrival time for each drone to reach the points along the route. Constraint (8) ensures that each drone meets a recharge station once.

Constraint (9) states that each drone has exactly one exit route from the depot. Constraint (10) controls that a path is established between two points only when a drone is assigned to it. Constraint (11) calculates the total weight of the drone, including battery and load, in each path. Constraint (12) ensures that each drone uses only one type of battery. Constraint (13) calculates the energy level of the drone $k \in K$ when it reaches each node. Constraint (14) ensures that the drone k has enough energy to reach the next point. Constraint (15) states that the drone energy is full before leaving the depot, and the recharge station. Constraint (16) States that the movement of load by drone in an arc is possible if the arc is active. Constraint (17) examine that if the drone moves from i to j , the difference between the load (at arrival and departure) is equal to the demand at location i . Constraint (18) ensures that the weight of the drone load when leaving the recharge station does not change from the moment the drone enters that station. Constraint (19) states that each drone returns to the depot without load. Constraint (20) is defined to create logical solutions. It states that each drone is allowed to travel from the depot to a recharge station only once and vice versa. Constraints (21) and (22) ensure that each drone is not allowed to travel from the depot to depot and from the recharge station to another recharge station.

To linearize our model, we define a new variable as follows:

$$MZ_{ijks} = m_{ijk} \cdot Z_{ijks} \quad \forall i, j \in V, \forall k, \forall s$$

In this case, nonlinear constraints (14) and (15) are replaced by linear constraints (23) and (24):

$$y_{jk} \leq y_{ik} - \alpha \sum_s \frac{d_{ij}}{V_{ks}} MZ_{ijks} - \alpha m_{ijk} \bar{\tau} - \beta \left[\sum_s d_{ij} \frac{Z_{ijks}}{V_{ks}} + \bar{\tau} \right] + M(1 - X_{ijk}) \quad \forall i \in V, \forall j \in V_D, \forall k \quad (23)$$

$$y_{ik} \geq \left[\alpha \sum_s \frac{d_{ij}}{V_{ks}} MZ_{ijks} \right] + \alpha m_{ijk} \bar{\tau} + \beta \left[\sum_s \frac{d_{ij}}{V_{ks}} Z_{ijks} + \bar{\tau} \right] - M(1 - X_{ijk}) \quad \forall i \in V_D, \forall j \in V, \forall k \quad (24)$$

Also, constraints (25) to (28) are additional constraints for linearization:

$$MZ_{ijks} \leq M \cdot Z_{ijks} \quad \forall i, j \in V, \forall k, \forall s \quad (25)$$

$$MZ_{ijks} \leq m_{ijk} \quad \forall i, j \in V, \forall k, \forall s \quad (26)$$

$$MZ_{ijks} \geq m_{ijk} - M(1 - Z_{ijks}) \quad \forall i, j \in V, \forall k, \forall s \quad (27)$$

$$MZ_{ijks} \geq 0 \quad \forall i, j \in V, \forall k, \forall s \quad (28)$$

Solution Method

The model presented in this paper is a bi-objective model that has been solved using one of the conventional methods of solving multi-objective models. In this research, a compromise programming approach has been used to solve this problem. In some papers, this method is referred to as the weighted sum method. The weighted sum method puts the available objective functions in the range $[0, 1]$, which is possible by normalizing the functions.

To solve the model, we first scale the two available objective functions. The formed objective function consists of two criteria. To normalize the obtained objective function, we proceed according to the following equation:

$$\text{Min}Z = w_1 \left(\frac{z_1 - z_1^+}{z_1^- - z_1^+} \right) + w_2 \left(\frac{z_2 - z_2^+}{z_2^- - z_2^+} \right) \quad (29)$$

Where, w_1 and w_2 are the weights intended for the objectives z_1 and z_2 . Experts have been consulted to obtain the mentioned weights, and we set w_1 equal to 0.2 and w_2 equal to 0.8. The presented term, z^- represents the worst value of the objective function and z^+ denotes the best value of the objective function for the criterion.

Numerical examples and results

To solve the MVDRP problem in this paper, we needed to solve the MILP model using the exact solution method of GAMS (General Algebraic Modeling System) software. To generate several test problems to solve the proposed mathematical model, we generated the value of parameters based on the uniform distribution function in logical intervals. Table 5 shows the range of generated data.

Table 5. Generated data.

Symbol	Description	Value
φ_{ik}	drone k service time / recharge time at node $i \in V_D \cup V_R$	Uniform (300, 360)
$\bar{\tau}$	average time for UAV to take off	Uniform (100, 300)
wei_b	weight of battery type b in kg	Uniform (1.5, 2.5)
cap_b	drone energy capacity with battery type b in joule	Uniform (300000, 400000)
M	A great number	100000
$D_i, i \in V_D$	amount of demand in damaged nodes	Uniform (2, 4)
F_k	cost of using a drone	Uniform (100000, 200000)
$CR_r, r \in V_D$	cost of establishing a recharge station	Uniform (10000, 15000)
$d_{ij}, i, j \in V$	time distance between node i and j	Uniform (8000, 13000)
α	energy consumed per kg	Uniform (40, 50)
β	energy required to keep the rotor-drone in the air	Uniform (20, 30)
\bar{V}_{ks}	average drone k speed under speed level s	Uniform (100,300)

We solved the existing model according to the generated data and using GAMS software version 24.1.2 on a personal computer with a 2.8 GHz CPU and 16 GB of RAM. To validate the model and to receive logical solutions from the software, we generated seven numerical examples in various problem sizes. According to the model's assumptions, the number of depots in all generated instances is considered one. The information of the generated test problems is shown in Table 6.

Table 6. Generated test problems.

Test problem number	V	V_o	V_R	V_D	K	S	B
1	4	1	1	2	2	2	1
2	6	1	2	3	3	3	3
3	7	1	2	4	3	3	3
4	8	1	2	5	3	3	3
5	9	1	2	6	3	3	3
6	10	1	2	7	3	3	3
7	11	1	3	7	4	4	3

We solved the existing model using the generated data in GAMS software, the general results of which can be seen in [Table 7](#). GAMS software provided feasible solutions for the test problems 1 to 5 in the run time shown. However, for test problems 5 and 6, the software could not find a feasible solution during 4 hours of code execution, which indicates the need to find an efficient solution method to solve the problem on a large scale.

Table 7. Result of solving the test problems 1.

Solution with GAMS		
Test problem number	Objective function value	CPU time (s)
1	2552.3	0.22
2	4121.7	1.42
3	6334.5	20.4
4	9591.4	106
5	12148.7	750.5
6	-	14400
7	-	14400

We now examine the output of the problem in test problems 3 and 5. According to [Fig. 4](#), in test problem 3, among the existing drones k1, k2, and k3, all drones were activated for service, and of the two potential recharge stations 2 and 3, both were recharged. From b1, b2, b3 batteries with various energy capacities, the b3 battery has been selected for all three drones. The visit sequence of the damaged nodes by heterogeneous drones is evident in the [Fig. 4](#). [Table 8](#) has presented the other important software output that is the arrival time for each drone to reach the nodes.

Table 8. Test problem 3 drones' routes information.

Drone arrival time	Node						
	2	3	4	5	6	7	Depot
K1 arrival time(s)		1730	865.8		2524		3617
K2 arrival time(s)				912.1			1733
K3 arrival time(s)						838.2	1816.4

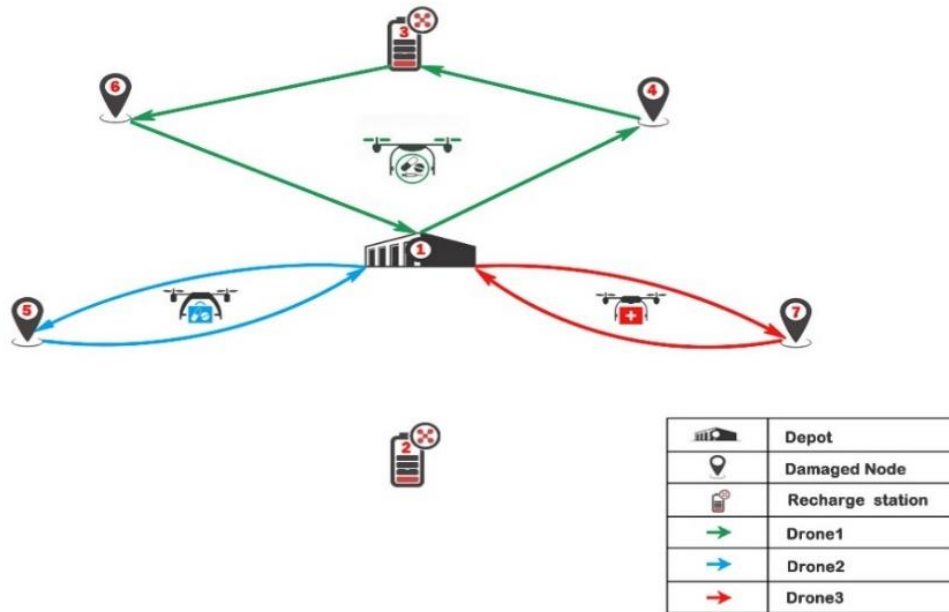


Fig. 4. Test problem 3 network.

As shown in Fig. 5, in test problem 5, drones k1, k2 and, k3 have been activated for service. Among the two potential recharge stations 2 and 3, both recharge stations have been established. Among batteries b1, b2, b3 with various energy capacities, b3 battery has been activated for k1 and k2 drones and b2 battery for k3 drone. The visit sequence of the nodes damaged by heterogeneous drones is evident in Fig. 5. Table 9 presents the other important software output that is the arrival time for each drone to reach the nodes.

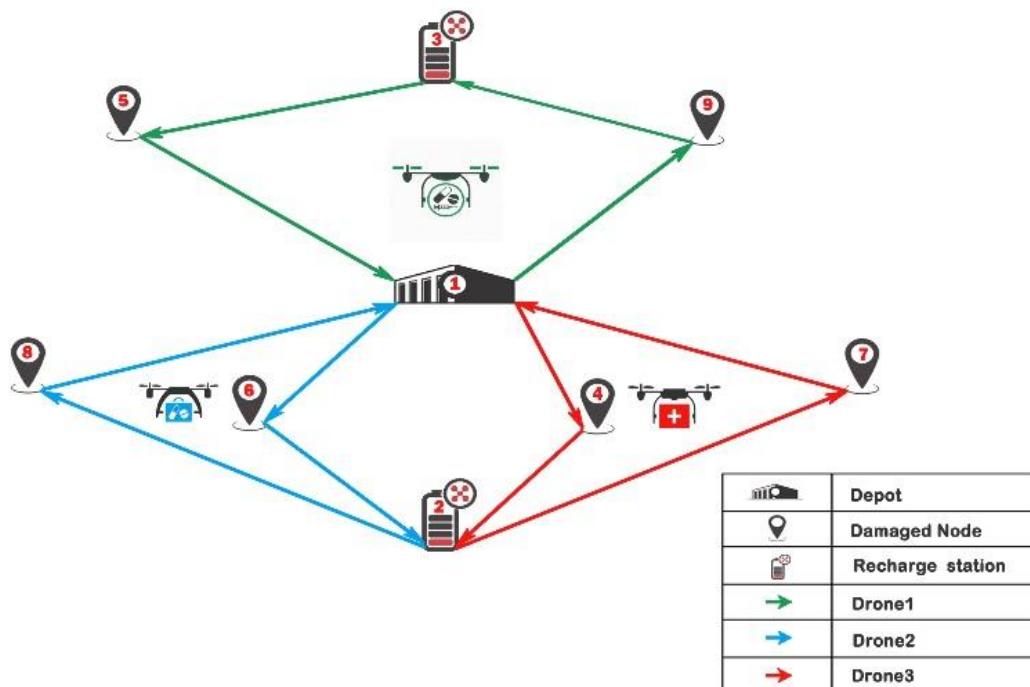


Fig. 5. Test problem 5 network.

Table 9. Test problem 5 drones' routes information.

Drone arrival time	node								
	2	3	4	5	6	7	8	9	Depot
K1 arrival time(s)		1750		2672.5				868.6	3663.57
K2 arrival time(s)	1797.3				902		2776.5		3664.3
K3 arrival time(s)	1723.8		894.2			2622.6			3591.89

As previously discussed in the model output, the use of recharge stations and the activation of sufficient drones in operation, save time. To find the effect of having a recharge station, we can look at the process from the point of view of an observer at the depot point. If there were no recharge stations, more drones would probably have been used to service the nodes, and the weight delivery time would have increased dramatically. However, we face a limited number of drones and time in natural conditions. We can prove the presented claim by looking at Fig. 6, which is taken from test problem 5. It is observed that by establishing sufficient recharge stations, while sending humanitarian drones and covering all damaged nodes simultaneously, drones 2, 1 and, 3 returned to the depot almost simultaneously and with time intervals in a relatively short time after completing the operation.

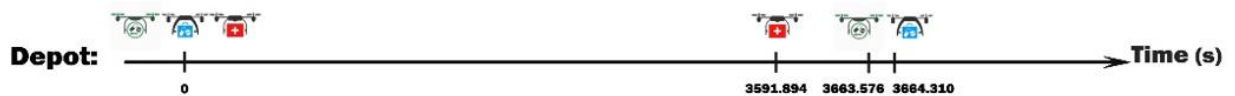


Fig. 6. Depot, from the point of view of an observer.

Sensitivity analysis

To analyze the problem and find the effect of changing the parameters' values on the model's output, we applied changes to the amount of data in test problem 4. The results of this analysis can be observed in Tables 11 and 12.

Table 10. The sensitivity of the objective function to the drone speed.

Drone speed	20	25	30	35	40
Objective function value	10110	9212	8586	8180	6141

Table 11. The sensitivity of the objective function to (α).

(α) Energy consumed per kg	20	30	40	50	60
Objective function value	7044	8561	9591	10321	10892

According to Fig. 7 and sensitivity analysis, the higher the speed level of the humanitarian drone, the lower the value of the objective function. This means that increasing the speed of drones and using newer multi-rotor drones providing a higher level of speed to the users can save time and decrease costs.

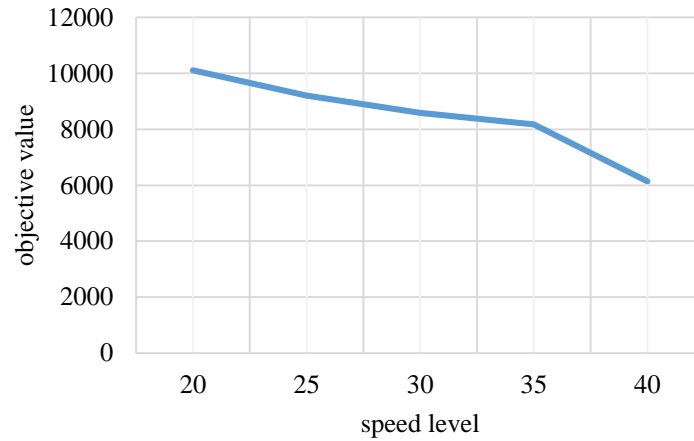


Fig. 7. Diagram of the sensitivity of the objective function to the drone speed.

According to Fig. 8 and the sensitivity analysis performed, the higher the α value, which confirms the drone energy consumption per kilogram, the higher the value of the objective function. This means that increasing the weight delivery time weight delivery time and operation costs are directly related to expanding the α value.

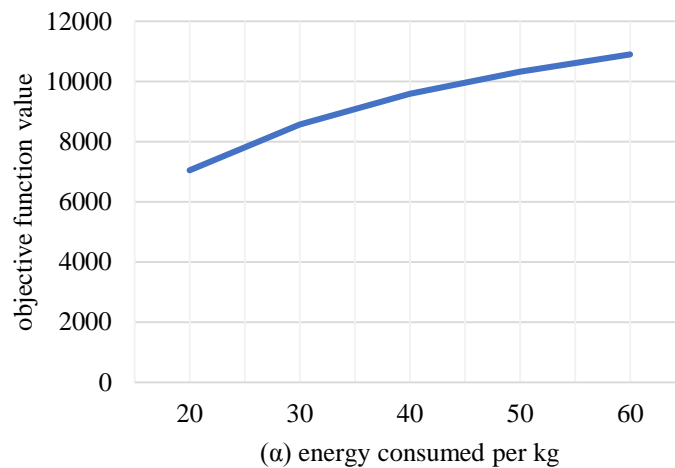


Fig. 8. Diagram of the sensitivity of the objective function to (α).

In this section, we intend to examine the performance of the MVDRP model using test problem 4 and making changes to influential parameters value. For this purpose, we first introduce the key parameters and indices of the problem. The four critical parameters of the model for sensitivity analysis include: 1) V , representing the number of damaged points and somehow determining the problem size, 2) cap_b representing the energy capacity of the drone battery, 3) d_{ij} determines the time interval between damaged nodes, and 3) F_k determines the cost of using a drone in a disaster logistics network.

To test the performance of the mathematical model, and to find the sensitivity of the objective functions to the key parameters introduced, we used the generated test problems to produce many scenarios. For each of the key parameters, we set 2 specific high and low values, which can be observed in Table 12. There are 16 scenarios are resulting from 4 key parameters. To get the value of the first objective function, which is a cost function, the second objective function, which is a time function, and the total objective function, which is the result of a single objective mathematical model, we needed to run the software 48 times (3×16) to execute the

problem code. A summary of the generated scenarios with the parameters' values and objective functions has been reported in Table 13.

Table 12. The value of key parameters.

Parameters and indices	Name	Level	Value
Number of damaged nodes	V	2	3, 5
Drone battery energy capacity	cap_b	2	300000, 500000
Time distance between nodes	d_{ij}	2	U (8000, 12000) U (13000, 17000)
Cost of using a drone	F_k	2	100000, 200000

Table 13. The value objective functions for 16 scenarios.

Scenario	V	cap_b	d_{ij}	F_k	z1 (total cost)	z2 (delivery time)	Z
1	3	300000	u(8000,12000)	100000	608504.1	2842.7	3451.2
2	3	300000	u(8000,12000)	200000	908504.1	2842.7	3751.2
3	3	300000	u(13000,17000)	100000	766985.8	3473.9	4240.8
4	3	300000	u(13000,17000)	200000	1066985.8	3473.9	4540.8
5	3	500000	u(8000,12000)	100000	608504.1	2842.7	3451.2
6	3	500000	u(8000,12000)	200000	908504.1	2842.7	3751.2
7	3	500000	u(13000,17000)	100000	766985.8	3473.9	4240.8
8	3	500000	u(13000,17000)	200000	1066985.8	3473.9	4540.8
9	5	300000	u(8000,12000)	100000	838361.9	8024.715	8863
10	5	300000	u(8000,12000)	200000	1126551.5	8055.9	9182.5
11	5	300000	u(13000,17000)	100000	1110781.5	9787.4	10898.2
12	5	300000	u(13000,17000)	200000	1410781.5	9787.4	11198.2
13	5	500000	u(8000,12000)	100000	831142.3	7979.9	8811.1
14	5	500000	u(8000,12000)	200000	1131142.2	7979.9	9111
15	5	500000	u(13000,17000)	100000	1103561.9	9742.6	10846.1
16	5	500000	u(13000,17000)	200000	1403561.9	9742.57	11146.1

This sensitivity analysis, with the help of generating multiple scenarios and simultaneous change of several parameters' value together, is much more efficient than conventional methods of sensitivity analysis. In the following, according to Table 13, we will analyze the effect of parameters' value changes on the model output.

• Damaged points

It is clear that increasing the number of damaged nodes increases the problem's size and leads to an increase in the amount of cost and weight delivery time of the operation. But as shown in Table 13, when the rise in the number of demand nodes is accompanied by the rise in the distance between points and the cost of using the drone and reducing the battery capacity of the drone, a significant increase is observed in the financial and time costs for delivering relief goods in disaster. For example, by comparing two scenarios 2 and 9 where the value of d_{ij} ,

cap_b and F_k are unchanged in both, by increasing the number of nodes from 3 to 5, the total objective function value increases by 155.3%. As you can see, in scenario 9, by selecting another level of all parameter's value, the total objective value increases by 224.5% compared to scenario 1. This argument confirms the claim.

• Battery capacity

Increasing the capacity of the selected battery for drones will facilitate service operations and reduce costs. However, in some scenarios, with a fixed number of damaged nodes and the value of other parameters, despite the increase in the selected battery capacity, there is no significant change in the value of the total objective function value. Comparing the two scenarios 1 and 5 in Table 13, in which all parameters' values are fixed except the cap_b value changes from 300,000 to 500,000, the objective function value remains unchanged.

• Distance between nodes

Increasing the distance between damaged points prolongs the weight delivery time of the operation. However, in the scenarios discussed in Table 13, increasing the number of demand nodes has a more significant effect than increasing the range of points' distance on the value of the total objective function. For example, by comparing two scenarios 1 and 9 in which the size of the problem increases from 3 to 5 by changing the value of V , the total objective function value increases 156.8%. While by comparing two scenarios 1 and 3, only the range of distances increases, the total objective function value increases 22.8%. Of course, by an excessive growth in the range of distances between nodes, the problem may provide a feasible solution. By an excessive increase in the number of damaged nodes, we should make the operation possible by increasing the number of available drones.

• The cost of using a drone

The higher the cost of using the drone, the higher the value of our objective function, and vice versa. But the cost of using a drone, when combined with changes in other parameters, has a more significant effect on the output of the model. Considering the greater weight for the cost objective function, we will see a more significant impact of changes in cost-related parameters on the value of the final objective function.

Conclusions and future researches

In this research, we developed a new MILP model for solving an aerial relief delivery problem called Multi-Visit Drone Routing Problem (MVDRP). This model was developed to deliver light relief goods such as water and medicine in the disaster response phase by a heterogeneous drone fleet. The energy source for the drones is the battery, which made the drones to be recharged during the trip. The aim of the presented multi-objective model is to minimize service delivery time and minimizing operation costs. The major contributions of the model were to describe the energy level of the drones, the arrival time of the drones to damaged points, and the weight of the drones at the damaged nodes as decision variables. The multi-visit nature of each drone was one of the important points considered in the model. Providing two significant possibilities for using different speed levels for flying, and considering batteries with various drones' capacities were presented in this paper. Besides, we used a linear approximation function to calculate the energy consumption of the multi-rotor drone based on its weight. The model intended to locate recharge stations at the candidate points and determine the sequence of visit damaged nodes by drones, and servicing them in the shortest possible time with a cost-saving approach. Furthermore, the energy constraints, drone flight range, and load limitation

have been considered. The time of taking off the drones and the time of their service to the damaged nodes were considered. To show the efficiency of the model, we generated several test problems under the extracted value of parameters from the point of view of experts. We solved these test problems under the exact solution method using GAMS software. According to the sensitivity analysis performed, the model is much more sensitive to increasing the number of damaged nodes, and the distance between them. This is due to the essential consideration of the time factor throughout the modeling process. Providing a dynamic model for such a problem in a disaster situation where information changes dynamically over time can be an interesting proposition for future research. Besides, the application of inventory control issues and considering uncertainties in the demands, and providing appropriate approaches to dealing with uncertainties such as fuzzy, robust programming, etc., can be other recommendations for future research. Also, we can pay attention to the multitasking feature of the air delivery operations by humanitarian drones in the new problems.

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