A multiobjective mathematical model for a humanitarian logistics multimodal transportation problem

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Abstract

Purpose – The purpose of this paper is to introduce a three-echelon multimodal transportation problem applied to a humanitarian logistic case study that occurred in Mexico.

Design/methodology/approach – This study develops a methodology combining a transshipment problem and an adaptation of the multidepot heterogeneous fleet vehicle routing problem to construct a mathematical model that incorporates the use of land-based vehicles and drones. The model was applied to the case study of the Earthquake on September 19, 2017, in Mexico, using the Gurobi optimization solver.

Findings – The results ratified the relevance of the study, showing an inverse relationship between transportation costs and delivery time; on the flip side, the model performed in a shorter CPU time with medium and small instances than with large instances.

Research limitations/implications – While the size of the instances limits the use of the model for big-scale problems, this approach manages to provide a good representation of a transportation network during a natural disaster using drones in the last-mile deliveries.

Originality/value – The present study contributes to a model that combines a vehicle routing problem with transshipment, multiple depots and a heterogeneous fleet including land-based vehicles and drones. There are multiple models present in the literature for these types of problems that incorporate the use of these transportation modes; however, to the best of the authors' knowledge, there are still no proposals similar to this study.

Keywords Humanitarian logistics, Multiobjective optimization, Multimodal transportation, Mixed-integer linear programming

Paper type Research paper

1. Introduction

The need to respond efficiently to an earthquake with the only aim of minimizing the loss of human lives has led to the development of technologies and strategies capable of helping public and private institutions focused on this task. Researchers around the world have developed a wide number of strategies and mathematical models aimed at improving planning for an effective response. However, not all of them are useful because each region has its own economic, environmental and geographic limitations that prevent their use. In addition to these limitations are added the destructive consequences generated by each natural event. Determining the best response strategy to a catastrophic event in Latin America is a problem that has not yet been studied enough.

Public health emergencies require preparedness and response capacities from the government, public health systems and academic researchers (Lurie *et al.*, 2013). From 2001 to 2013, 4 out of 32 major public global health emergencies were caused by earthquakes, e.g. the Bam earthquake in Iran (2013), the Sichuan

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Data availability: The data used to support the findings of this study are available at https://github.com/marisolroma/MM3E. All figures and tables presented in this article were created by the authors.

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earthquake occurred in 2008, the 2010 earthquake in Haiti and the Japan earthquake occurred in 2011. Earthquake destruction can cause further catastrophes; for example, in March 2011, a powerful earthquake occurred off the northeast coast of Honshu, a main Japan's island, causing significant damage on land and, consequently, a series of large tsunamis devastating several coastal areas of the country producing a major nuclear accident at a power plant along the coast.

Due to earthquakes, road networks are frequently damaged, limiting terrestrial access, emergency shelters are often destroyed and water supplies and urgent medical attention are always required. Therefore, the adequate planning of logistical activities is essential to deliver services and commodities to the affected population Najafi *et al.* (2013). De la Torre *et al.* (2012) define *disaster relief logistics*, commonly known as humanitarian logistics, as the distribution of life-saving commodities to beneficiaries. Thomas and Mizushima (2005) define humanitarian logistics as "the process of planning, implementing, and controlling the efficient, cost-effective flow and storage of goods and materials, as well as related information from point of origin to point of consumption for the purpose of meeting the end beneficiary's requirements." Researchers state that disasters present multiple logistics challenges, including damaged transportation infrastructure and limited communication/coordination of multiple agents. The main differences between humanitarian logistics and business logistics are the existence of unpredictable demand in terms of its location and the large number of products required of a wide variety of supplies, mainly medical and food and the delivery time (Balcik and Beamon, 2008; Kovács and Spens, 2009).

Four stages have been defined in emergency management (EM); these are *mitigation, preparedness, response and recovery* (Altay and Green, 2006; George D. Haddow and Coppola, 2007; McLoughlin, 1985; Thomas and Mizushima, 2005). *Mitigation* consists of reducing the vulnerability of risk areas. The *preparedness* stage educates people to face the disaster. The *response* stage consists of responding efficiently to a situation to minimize the risk of losing human lives. In contrast, the *recovery* stage works to repair the damage caused by a disaster. The International Federation of Red Cross and Red Crescent Societies defines *disaster* as "a sudden, calamitous event that seriously disrupts the functioning of a community or society and causes human, material, and economic or environmental losses that exceed the community's or society's ability to cope using its own resources." Sometimes, in the response stage, relief supplies become excessive because many international donors send them to affected countries; this may seem very good. However, in most cases, the high quantity of supplies limits the proper organization, delaying its timely distribution and increasing its cost.

The delivery time of supplies in a response stage is one of the most important variables in humanitarian logistics because the number of injured people to assist or the loss of human lives after a disaster depends on it. The delivery time depends mainly on the speed of response of the government authorities, the modes of transportation used, the environmental conditions and accessibility to the points of consumption. Two examples are the earthquakes that occurred in Mexico (2017) and Haiti (2010), where road accessibility changed constantly and unpredictably due to the movement of debris and several roadblocks. To counteract the mentioned problems, in recent years, the use of unmanned aerial vehicles (UAVs), commonly called "drones", have been considered as an alternative to traditional road vehicles, motivating the development of many single and multiobjective optimization (MOO) models to deliver medical and food supplies in humanitarian logistics problems (Arenzana *et al.*, 2020). Some of these objectives include the minimization of traveling times, transportation costs, the number and types of vehicles used, the number of storage and transshipment facilities required and the maximization of materials and products transported from the points of origin (depots, collections centers, distribution centers, etc.) to the points of consumption. Escribano *et al.* (2020) show that UAVs can significantly improve response operations during disasters due to infrastructure damage, a key factor in relief distribution.

UAVs are used for many different purposes, including searching for missing people, aerial photography/cartography, fire prevention/control, security/military applications, agriculture, business logistics and EM. For EM, UAVs can distribute different types of essential supplies such as food, water and health care products such as medical toolboxes, medicine, defibrillators, blood samples, oxygen masks, vaccines and insulin injections (Scott and Scott, 2008; Kim *et al.*, 2017), some examples are the use of UAVs in sanitation duties, temperature testing and vaccine delivery during the COVID-19 pandemic in rural medical centers around the world.

The use of UAVs in humanitarian logistics has its origin in 2006 after the devastation caused by Hurricane Katrina, when the Federal Aviation Administration in the USA authorized their use over civil airspace for rescue and disaster relief operations. The main benefits of using UAVs are that they allow for reducing labor costs by minimizing the number of staff needed (Dorling *et al.*, 2017; Thiels *et al.*, 2015); they require much less space to take-off and landing (Haidari *et al.*, 2016); they reduce the carbon emission (Figliozzi, 2017; Goodchild and Toy, 2018; Arenzana *et al.*, 2020); and they avoid road networks, which are vulnerable to disasters and traffic congestion (Dorling *et al.*, 2017; Arenzana *et al.*, 2020; Skorup and Haaland, 2020; Rabta *et al.*, 2018), besides, they are cheaper to maintain than trucks. UAVs can also provide up-to-the-minute updates, which makes them useful for emergency response in fires, oil spills and earthquakes. Nevertheless, UAVs have significant weaknesses; the main one is their transportation capabilities, which are considerably smaller than ground vehicles (Dorling *et al.*, 2017), followed by their limited operations range

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as well as limited flight times due to energy constraints (Rabta et al., 2018). In addition, their efficiency depends on climatic and environmental conditions, which makes them unusable in some disasters such as hurricanes and volcanic eruptions.

Humanitarian logistics is one of the most complex logistics operations because it takes place in an environment of severe disaster. A wrong decision can cause an increase in deaths. Even though there exists research on transshipment problems in this domain as well as on routing problems (*milk runs* problems) to deliver medical and food supplies that propose an interaction between UAVs and ground vehicles, MOO models that combine these two configurations of transportation have not been widely studied.

This work addresses the study of a three-echelon humanitarian logistics problem related to the response stage after an earthquake. A bi-objective optimization model for a transportation system that combines a full-truck-load transshipment problem [based on the transshipment model proposed by Olivares-Benitez et al. (2013)] with a heterogeneous fleet capacitated vehicle routing problem (an adapted version of Arenas Vasco (2018) is proposed . To evaluate the performance of the proposed model, this is applied to the case study of the earthquake that occurred in Mexico on September 19, 2017, in which approximately 370 people died and more than 3,000 were injured. The first objective of the model minimizes the total transportation costs among echelons and the cost associated with opening facilities; the second objective minimizes the delivery time of supplies. These two objectives are used because many countries, including Mexico, have budget constraints to respond to an emergency. To solve the model, the ϵ-constraint method is used. This method allows to build a set of nondominated solutions commonly called Pareto-Front. A Pareto-Front is useful for decision-makers because it shows the strategic balance between the objectives of the model in different scenarios (Yv et al., 1971; Caramia and Dell'Olmo, 2008).

The contribution of this paper is twofold. First, a mathematical model for a multiobjective three-echelon transportation problem, which considers the use of a heterogeneous fleet composed of drones and land vehicles, is proposed. Second, an extensive computational experience, considering a case study on humanitarian logistics, is provided to show the performance of the proposed method.

The paper is structured as follows. Section 2 discusses previous studies related to the problem. In Section 3, the methodology of the study is developed. Section 4 describes the case study used to evaluate the proposed model. In Section 5, the results of the computational experience are presented and discussed. Finally, in Section 6, some conclusions and suggestions for further research are outlined.

2. Literature review

Over the years, many strategies and mathematical models have been developed with the aim of minimizing the loss of human lives in the response stage of a natural disaster. The literature review suggests that, in general terms, these models fall into two categories: facility locations and relief distribution (Caunhye et al., 2012; Habib et al., 2016; Nolz et al., 2011). Most of these models consider only one or two echelons. Other categories include evacuation and casualty transportation. Most of the facility location models in humanitarian logistics integrate the operations of location (building new facilities or choosing among existing ones), evacuation or relief distribution (Caunhye et al., 2012). These models are mainly based on mixed-integer programs using binary variables to identify the facilities (shelters, warehouses, collection centers, depots, distribution centers, etc.), routes and several transportation modes to be used. Their main objectives are to minimize delivery times and operating costs. In addition, they consider budget constraints, facility expansion, damage and injury to emergency equipment and personnel. Models focused on relief distribution consist of bringing relief (medical supplies, shelters, manpower, sanitation and other resources) to the affected zones (Caunhye et al., 2012). Most of the research available in the literature focuses exclusively on relief distribution; in addition, these models have been developed mainly to solve problems for a single objective because they are easier to solve. Both facility location and relief distribution models generally contemplate the use of land vehicles for their operations. Some of the most representative studies regarding the use of drones in the health-care system are described below.

Scott and Scott (2017) developed two models concerned with the design of a drone-based health-care-delivery network that facilitates time and cost-effective delivery. Escribano et al. (2020) share a stochastic vehicle routing problem that coordinates UAVs with land vehicles and demonstrates the benefits of their use in terms of costs. Arenzana et al. (2020) proposed an optimization model to design UAV-based hospital-delivery networks, which minimizes drone-traveling time, battery-consumption levels, CO_2-emission levels, vehicle investment and infrastructure costs. Arenzana et al. (2020) considered UAVs during humanitarian crises. They developed a mathematical model for a stochastic vehicle routing problem, which uses UAVs to reveal road damage conditions and trucks to subsequently deliver commodities during a relief distribution operation. Numerous benefits were obtained in the selection of truck routes compared with deterministic methods; in this work, UAVs limitations were highlighted. Skorup and Haaland (2020) identified the potential benefits of UAVs in reducing social interaction in daily tasks and slowing down the spread of COVID-19. Other authors (Chang et al., 2007; Duran et al., 2011; Iakovou et al., 1997; McCall, 2006; Psaraftis et al., 1986; Wilhelm and Srinivasa, 1996) have developed models that combine the location of facilities, the relief distribution for single-echelon and single-objective humanitarian logistics problems, which suggest the use of only land vehicles. However, other researchers (Mete and Zabinsky, 2010; Rawls and Turnquist, 2010) have developed two-echelon models with one and two objectives to meet the needs in the response stage of a disaster, and these models also were focused on the use of land vehicles. The model proposed in this document differs from previous works by offering a study of a three-echelon bi-objective problem, which considers UAVs as one mode of transport in the third echelon. Table 1 summarizes the literature found for emergency logistics models used in facility locations with relief distribution in the response stage of a disaster.

3. Methodology

3.1 Problem definition

The problem studied in this work is a multiobjective multimodal 3-echelon problem (MM3E). Given a network $G = (N, A, K^v)$

Table 1 Literature about facility locations models with relief distribution

Author	Echelons	Objectives Cost	Time	Capacity	Constraints Requirements and bounds	Transport modes
Chang *et al.* (2007)	Single	Transportation, facility opening, equipment rental, penalties, shipping distance of rescue equipment	–	Facility	–	Ground and aquatic vehicles
Iakovou *et al.* (1997)	Single	Facility opening, operations, transportation	–	Facility	Critical time to meet demand	Ground vehicles
McCall (2006)	Single	Transportation, shortages	–	Facility	Number of kits to pre-position, budget	Ground vehicles
Mete and Zabinsky (2010)	Double	Warehouse operations	Traveling	Vehicle	Inventory shortage upper bound threshold	Ground vehicles
Psaraftis *et al.* (1986)	Single	Facility opening, stock acquisition, transportation, operations, unmet demand, delay	–	–	–	Ground, aerial, aquatic vehicles
Rawls and Turnquist (2010)	Double	Facility opening, transportation, unmet demand, holding	–	Facility	–	Ground vehicles
Scott and Scott (2017)	Single	–	Traveling	Vehicle	Budget, distance	UAVs
Wilhelm and Srinivasa (1996)	Single	Facility opening and expansion, stock acquisition, operations	–	Facility	Time-phased cleanup requirement	Ground and aquatic vehicles

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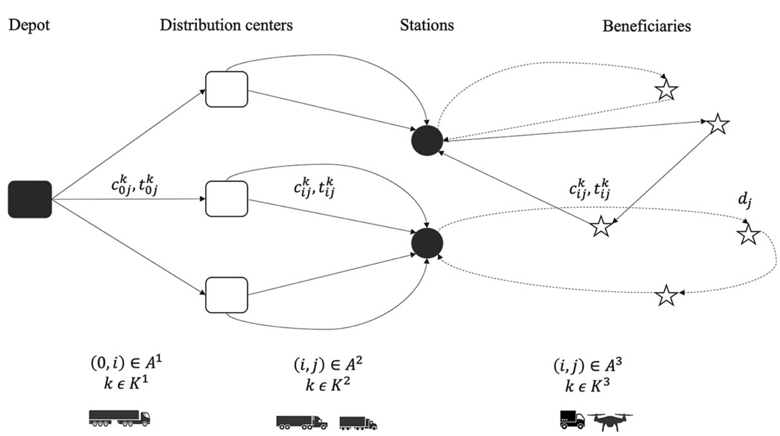
(Figure. 1), where $N = \{\{0\} \cup N_{dc} \cup N_s \cup N_c\}$ is the set of nodes that corresponds to the depot, distribution centers, stations and final beneficiaries, respectively; $A = \{A^1 \cup A^2 \cup A^3\}$ ($A^1 = \{(0,j): j \in N_{dc}\}, A^2 = \{(i,j): i \in N_{dc}, j \in N_s\}, A^3 = \{(i,j): i \in N_s, j \in N_c\}$) is the set of possible arcs among the nodes corresponding to N and K^e is the set of vehicles used at each echelon $e \in E = \{1, 2, 3\}$. In the first echelon, a set of homogeneous vehicles K^1 departs from the depot $\{0\} \in N$, which has a limited capacity V_0^1, to the distribution centers N_{dc} with limited capacity V_i^1. Then, in the second echelon, items are transported from these centers to the set of stations N_s, each with capacity V_j^2, $j \in N_s$, using a set of heterogeneous land vehicles K^2. Finally, in the third echelon, products located at each station are distributed to the final beneficiaries N_c using a heterogeneous fleet vehicle, K^3 (composed by land vehicles and drones). There exists a transportation cost c_{ij}^k and a delivery time t_{ij}^k for each $(i,j) \in A$ and vehicle $k \in K^e$ at each echelon $e \in E$. Some other assumptions must be considered:

Figure 1 Representation of the MM3E network



Notes: The vehicles at the bottom of each echelon represent the type of vehicles used in each of them. The vehicles in the first echelon depart from the depot, the vehicles used in the second echelon depart from the distribution centers and the vehicles used in the third echelon depart from the stations.
Source: Created by authors

- There are enough vehicles and products to satisfy the demand, and no vehicle return is considered in the first two echelons.
- Distribution centers must be served by only one vehicle from the depot, and a station must be served only by one distribution center.
- Open a distribution center incurs in an extra cost F_i.
- All stations are available to receive products from open distribution centers.
- There is a limited and capacitated fleet of vehicles available in the third echelon.
- In the third echelon, vehicles can serve one or more final beneficiaries and then must return to the stations; all beneficiaries in N_c must be visited.
- The fleet of vehicles in the third echelon (drones and land vehicles) departs from a fixed station established close enough to the affected areas.
- All vehicles of the system (drones and land vehicles) can travel unlimited distances.

The aim of the MM3E is to find the best design of routes that departs from the depot to the final beneficiaries to attend their demand such that the trade-off between the total transportation cost, the cost of opening distribution centers and the total traveling time is minimized satisfying operational constraints.

Given the definition of the problem provided above, the mathematical formulation for the MM3E is as follows.

Parameters:

- t_{ij}^k: Delivery time of an arc $(i, j) \in A^e$ traversed by vehicle $k \in K^e$, $e \in E$.
- c_{ij}^k: Transportation cost of an arc $(i, j) \in A^e$ traversed by vehicle $k \in K^e$, $e \in E$.
- F_i: Fixed costs of opening a distribution center $i \in N_{dc}$.
- V_i^e: Capacity of $i \in N \backslash N_c$, $e \in E$.
- d_i: Demand of beneficiaries $i \in N_c$.
- Q_k: Capacity of vehicle $k \in K^e$, $e \in E$.
- R_k: Number of available vehicles of type $k \in K^e$, $e \in E$.
- The maximum time allowed to complete the deliveries from the depot to the final beneficiaries.

Decision variables:

- $x_{ij}^k = 1$ if arc $(i, j) \in A^e$ is traversed by vehicle $k \in K^e$, $e \in E$; otherwise, 0.
- $z_i = 1$ if a distribution center $i \in N_{dc}$ is open; otherwise, 0.
- $q_{ij}^k =$ Accumulated load of vehicles of type $k \in K^e$ that traverse an arc $(i, j) \in A^e$ of echelon $e \in E$.
- $w_{ks} = 1$ if a vehicle type $k \in K^3$ departs from station $s \in N_s$; otherwise, 0.
- $u_i \geq 0$ auxiliary variables to avoid subtours.

3.2 Mathematical model

In this section the formulation of the mathematical model is shown, as well as the description of each equation. The ϵ-constraint method was used to model the MM3E problem due to its potential to achieve efficient points in a nonconvex Pareto Front. The objective selected to be the objective function is the one related to costs (f_1) and the objective related to delivery time (f_2) is handled as a series of constraints which are explained below as well:

$$\begin{aligned} \min \quad & (f_1, f_2) \\ & f_1 = \sum_{e \in E} \sum_{k \in K^e} \sum_{i,j \in A} c_{ij}^k x_{ij}^k + \sum_{i \in N_{dc}} F_i z_i \\ & f_2 = T \end{aligned} \tag{1}$$

$s.t.$

$$t_{0i}^a x_{0i}^a + t_{ij}^b x_{ij}^b + \sum_{(j,k) \in A^3} t_{jk}^c x_{jk}^c \leq T \qquad a \in K^1, b \in K^2, c \in K^3, (i,j) \in A^2 \tag{2}$$

$$\sum_{k \in K^1} q_{0i}^k = \sum_{j \in N_s} \sum_{k \in K^2} q_{ij}^k \quad i \in N_{dc} \tag{3}$$

$$\sum_{i \in N_{dc}} \sum_{k \in K^1} q_{0i}^k \leq V_0 \tag{4}$$

$$\sum_{j \in N_s} \sum_{k \in K^2} q_{ij}^k \leq V_i^1 z_i \quad i \in N_{dc} \tag{5}$$

$$\sum_{j \in N_c} \sum_{k \in K^3} q_{ij}^k \leq V_i^2 \quad i \in N_s \tag{6}$$

$$q_{0i}^k \leq Q_k x_{0i}^k \quad i \in N_{dc}, k \in K^1 \tag{7}$$

$$q_{ij}^k \leq Q_k x_{ij}^k \quad (i,j) \in A^2, k \in K^2 \tag{8}$$

$$\sum_{i \in N_c} \sum_{j \in \{N_s \cup N_c\}} d_i x_{ij}^k \leq Q_k \quad k \in K^3 \tag{9}$$

$$\sum_{i \in N_{dc}} z_i \geq 1 \tag{10}$$

$$\sum_{(i,j) \in A^e} x_{ij}^k \leq R_k z_i \quad k \in K^e, e \in E \backslash \{3\} \tag{11}$$

$$\sum_{k \in K^1} x_{0i}^k \geq z_i \quad i \in N_{dc} \tag{12}$$

$$\sum_{k \in K^3} \sum_{j \in \{N_c \cup N_s\}} x_{ij}^k = 1 \quad i \in N_c \tag{13}$$

$$\sum_{j \in \{N_c \cup N_s\}} x_{ij}^k = w_{ki} \quad i \in N_s, k \in K^3 \tag{14}$$

$$\sum_{j \in \{N_c \cup N_s\}} x_{ji}^k = w_{ki} \quad i \in N_s, k \in K^3 \tag{15}$$

$$\sum_{j \in \{N_c \cup N_s\}} d_i x_{ij}^k = \sum_{j \in \{N_c \cup N_s\}} d_i x_{ji}^k \quad i \in N_c, k \in K^3 \tag{16}$$

$$u_i = 1 \quad i \in N_s \tag{17}$$

$$u_j \geq u_i + 1 - (|N_c \cup N_s|)\left(1 - \sum_{k \in K^3} x_{ij}^k\right) \quad (i,j) \in A^3 \tag{18}$$

$$2 \leq u_i \leq |N_c \cup N_s| \quad i \in N_c \tag{19}$$

$$q_{ab}^k \geq 0, x_{ij}^k \in \{0,1\} \quad (i,j) \in A, k \in K^e, e \in E \tag{20}$$

$$w_{ks} \in \{0,1\} \quad s \in \{N_s, N_c\}, k \in K^e, e \in E \tag{21}$$

$$z_i \in \{0,1\} \quad i \in N_{dc} \tag{22}$$

The objective functions (1) minimize the total transportation costs plus the cost associated with opening distribution centers, and the total delivery time from the depot to the beneficiaries, respectively. Constraints (3) ensure that traveling times do not exceed the maximum time can take a delivery from the depot to the final beneficiaries. Constraints (4) establish that the quantity delivered from the depot to the distribution centers must be equal to the quantity delivered from the distribution centers to the stations. Constraints (5)–(7) avoid that the quantity delivered from the depot/distribution center/station does not exceed their corresponding capacity, respectively. Constraints (8)–(10) avoid to exceed vehicle capacities. Constraints (11) establish that at least one distribution center must be open. Constraints (12) ensure that the number of vehicles used at each echelon does not exceed the maximum number available. Constraints (13) force to send product to open distribution centers. Constraints (14) establish that each beneficiary must be served for only one vehicle. Constraints (15)–(16) determine that if a vehicle departs from a station $i \in N_s$, then there must be an arc that exits and enters to that station. Constraints (17) are flow conservation constraints. Constraints (18)–(20) avoid are Miller–Tucker–Zemlin constraint to avoid subtours. Constraints (21)–(23) represent the variable domain.

4. Case study

The proposed model was implemented for a case a study occurred in Mexico on September 19, 2017, where a Mw 7.1 earthquake occurred with an epicenter at 55 km (34 mi) from the south of the city of Puebla that lasted for approximately 20 s (Working Group of the National Seismological Service and UNAM, 2017). The earthquake caused damage in Guerrero, Mexico City, Morelos, Oaxaca and Puebla. A total of 369 people died, and more than 7,000 people were injured (Criales and Mota, 2019).

In Mexico, immediately after a natural disaster, an extraordinary emergency declaration is established and resources of the Fund for Emergency Attention (FONDEN) are immediately distributed to address the primary needs of the affected population (food, shelter and health).

Fuerza México is a digital platform that contains data from the Ministry of Finance and Public Credit of different agencies and entities involved in the reconstruction tasks from the earthquakes occurred on September 7 and 19, 2017. This platform does not provide information, documentary support on donations or actions carried out by the private sector. According to the general rules of FONDEN, entities must follow four main steps after a natural disaster:

1. Request emergency support to meet the immediate needs of the population.
2. Request immediate partial supports (charged to FONDEN) to obtain resources for the execution of emerging actions, the restoration of communications, basic services and the removal of debris from the affected area to avoid further damage and protect the population.
3. Once immediate partial supports have been received, a damage evaluation committee is installed to evaluate and quantify the damages in different sectors. Entities may request resources to cover expenses derived from the damage assessment work carried out from the natural event.
4. The necessary works and actions for the reconstruction are determined.

4.1 Data

The proposed mathematical model is developed around a three-echelon system consisting of a depot, distribution centers, stations, demand nodes (beneficiaries) and different transportation modes per echelon. Table 2 lists the case study elements, and Figure 2 illustrates them in the context of Mexico.

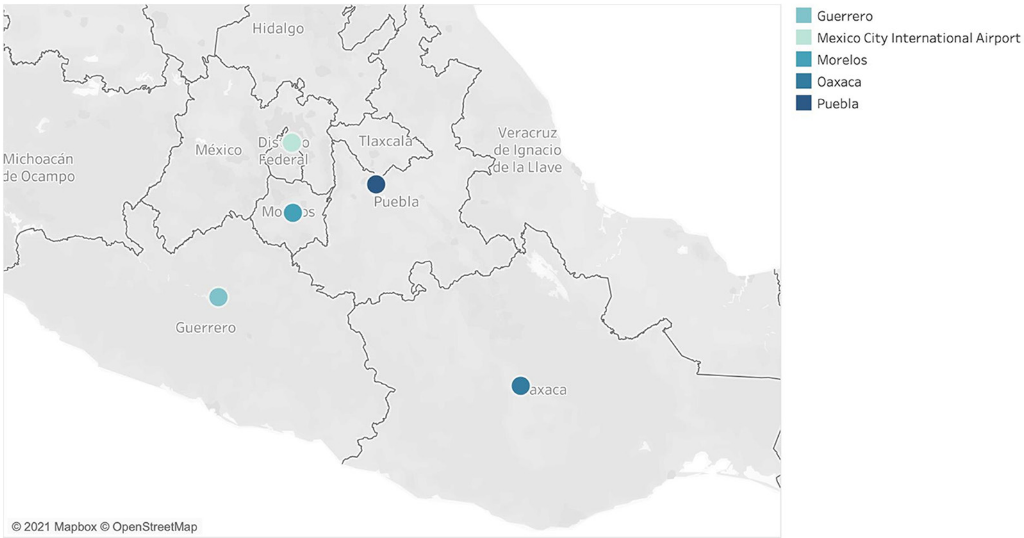
It is important to consider that, for the adoption of drones in response to natural disasters where roads are damaged, the entities in charge of distributing products must have access to infrastructure to use drones, consider the climate conditions of the area, and be aware of UAVs management policies in the region where the vehicles will be used. In Mexico, these policies include the following: UAVs can only be operated during the day in areas not classified as prohibited, restricted or dangerous; they must be at least 9.2 km from controlled airports, 3.7 km from uncontrolled aerodromes and 900 m from heliports; and they must not drop objects that could cause damage to people or property. Moreover, for drones that weigh more than 2 kg, authorization from the Dirección General de Aeronáutica Civil is required, and the drone operator must have a pilot license (Secretary of Communications and Transportation, 2019).

Table 2 Case study elements

Element	Case study representation and characteristics
Depot	Mexico City International Airport
Distribution centers	The center of the most affected states
Stations	The most affected municipalities of each state
Demand nodes	The most affected communities of each affected municipality
Transportation modes in the first echelon	Truck (artic type): Loading capacity of 24,500 kg at a velocity of 40 km/h
Transportation modes in the second echelon	Truck (18 ton): loading capacity of 9,500 kg at a velocity of 55 km/h
	Truck (7.5 ton): loading capacity of 3,000 kg at a velocity of 60 km/h
Transportation modes in the third echelon	Large van: Loading capacity of 1,000 kg at a velocity of 65 km/h
	Drones: Loading capacity of 180 kg at a velocity of 50 km/h

Source: Created by authors

Figure 2 Geographical representation of the states in the Mexican Republic



Note: The states and their respective percentage of the total demand are Guerrero (57%), Morelos (15%), Oaxaca (22%) and Puebla (6%)
Source: Created by authors

Indeed, these policies must be considered to help address future natural disasters in Mexico.

5. Computational experience

The mathematical model was programmed with Python using Anaconda Navigator – Spyder 4.0.1 on a MacBook Pro with a 2.7 GHz Intel Core i5 and an 8-GB 1867 MHzDDR3 with Gurobi solver version 9 implemented.

5.1 Testing plan

For the purposes of this research, the Fuerza Mexico platform was used as a data source for the delivery of emergency support during the earthquake in question. The data includes demand of emergency medical products, such as medicine, water and supplies for doctors by the state. The proposed model was tested for the case study main instance (Data 1-1) and the instances derived from it (Data 1-2, Data 2-1, Data 3-1 and Data 4-1). Subsequently, it was tested with instances of different sizes and randomly generated parameter values to analyze the capability of the model to process problems of different sizes. Specifically, for the DataV1, DataV2, DataV3, DataV4 and DataV5 instances, the demand and cost values were generated with a uniform distribution between the maximum and minimum values of each parameter. The number of distribution centers, stations and demand nodes were arbitrarily selected so that the number of total nodes in the network was less than that of the main instance and its derivatives. To perceive the effect of the number of vehicles available in the third echelon in the central processing unit (CPU) time, the number of vehicles available for the first and second echelon was assigned a very large value, and the third echelon was given a smaller number of vehicles available. Vehicle and facility capacities remained the same. Tables 3 and 4 show the general characteristics of the instances used for this

Table 3 General characteristics of the main case study instances

	Instances characteristics						Transportation modes					
							E1		*E2*		*E3*	
Name	n	N_0	N_{dc}	N_s	N_c	N_c (%)	Mode	Res	Mode	Res	Mode	Res
Data 1–1	50	1	4	10	35	100	1	4	2	16	2	20
Data 1–2	50	1	4	10	35	100	1	4	2	16	2	12
Data 2–1	20	1	2	5	12	79	1	4	2	16	2	16
Data 3–1	11	1	1	2	7	57	1	4	2	16	2	14
Data 4–1	31	1	2	5	23	21	1	4	2	16	2	16

Notes: *n* denotes the number of nodes, N_0 the number of depots, N_{dc} the distribution centers, N_s the stations, N_c the demand nodes, N_c (%) the percentage of covered demand, *E1* the first echelon, *E2* the second echelon, *E3* the third echelon, *Mode* denotes the transportation modes available and *Res* is the number of vehicles of each *mode* that can be used
Source: Created by authors

Table 4 General characteristics of the generated instances

Instances characteristics						Transportation modes					
						E1		*E2*		*E3*	
Name	*n*	N_0	N_{dc}	N_s	N_c	Mode	Res	Mode	Res	Mode	Res
DataV1	15	1	2	2	10	1	32	2	80	2	6
DataV2	18	1	2	3	12	1	32	2	80	2	10
DataV3	16	1	3	2	10	1	32	2	80	2	7
DataV4	25	1	2	2	20	1	32	2	80	2	6
DataV5	19	1	3	3	12	1	32	2	80	2	10

Notes: *n* denotes the number of nodes; N_0 the number of depots; N_{dc} the distribution centers; N_s the stations; N_c the demand nodes; *E1* the first echelon; *E2* the second echelon; *E3* the third echelon; *Mode* denotes the transportation modes available and *Res* is the number of vehicles of each *mode* that can be used
Source: Created by authors

project. For the instances that yielded results in a short CPU time, a Pareto front is presented, and for the instances with a high CPU time, the GAP performance is analyzed.

5.2 Computational results

From Table 5, it is evident that, due to a lack of memory, the largest instance for the case study (Data1-1) was not optimally solved; moreover, there is no noticeable reduction in the optimality GAP while running the program with the same delivery time for 1 h vs 8.5 days (Figure 3). Also, despite the time established to make the deliveries in the last mile, only land transportation was used; however, the cost value decreased as the delivery time increased. For the instance Data 1-2, still covering 100% of the demand, with almost half fleet available and with a maximum routing time of 12.2 h, no optimal solution was found, but with 400 h for the time value, it was possible to generate a dominated solution with a GAP of 0.36% (Figure 4). Optimal solutions were found for Data 2-1 in less than 12 min covering 79% of the demand, and for Data 3-1 in less than 2 s covering 57% of the demand. Ultimately, dominated solutions were yielded for Data 4-1, which covers 21% of the demand. No significant difference can be observed in the GAP value regarding delivery time. With an epsilon time restriction of 12.2 h, a significant decrement in the GAP value can be observed in the first minute, but thereafter, it improves slightly (Figure 5). Alternatively, when the delivery time is 400 h, the GAP does not change.

Considering that the instance size is given by the number of total nodes in the network and the number of vehicles available for use in the third echelon, the generated instances are smaller than those of the case study, and therefore, an optimal solution was found for all of them, and a Pareto front was built for each (Table 6). The CPU time required to identify optimal solutions for DataV1 was below 14 s, whereas that for DataV2 ranged from 7 to 5,501 s. For DataV3, the CPU time < 72 s, and though DtataV4 is the largest generated instance, the CPU was < 11 s. For DataV5, the CPU time was between 8 and 491 s.

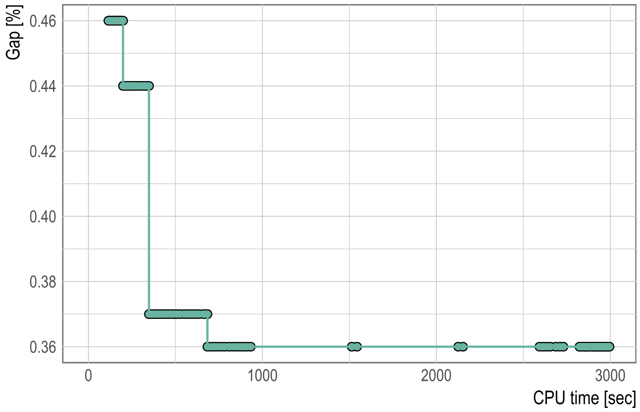
Generally, in the first and second echelons, the decisions made in the model are about what distribution centers to open and what vehicles to use depending on their capacity; the differences in delivery time and costs when using different resources are notorious but not extreme. On the other hand, the most critical decisions of the model are those of the third echelon related to the last-mile decisions because the delivery time and the costs depend on the vehicles to be used (as they differ in costs and capacities) and the routes to perform, which

Table 5 Solutions of the case study principal instance and its derivatives

Instance	Time	Cost [US$]	Solution N_c (%)	Solution type	CPU time [s]	GAP (%)
Data 1-1	12.2	40,185.40	100	D	3,600.00	0.36
	400	40,111.60			3,648.44	0.18
	400	40,083.18			748,088.34	0.09
Data 1-2	12.2	–	100	NS	3,600.00	–
	400	37,429.80		D	3,600.00	0.65
Data 2-1	12.2	20,134.50	79	ND	679.32	0.01
	400	20,134.50			474.66	0.01
Data 3-1	2.16	20,030.80	57	ND	0.74	0.00
	2.2	20,030.80			0.11	0.00
	2.3	20,030.80			0.31	0.00
	2.4	20,030.80			0.06	0.00
	2.5	20,030.80			0.72	0.00
	2.6	20,030.80			0.01	0.00
	2.7	20,030.80			0.39	0.00
	2.8	20,030.80			2.03	0.00
	3	20,030.80			0.47	0.00
Data 4-1	12.2	20,063.80	21	D	3,670.54	0.26
	400	20,058.30			3,600.08	0.24

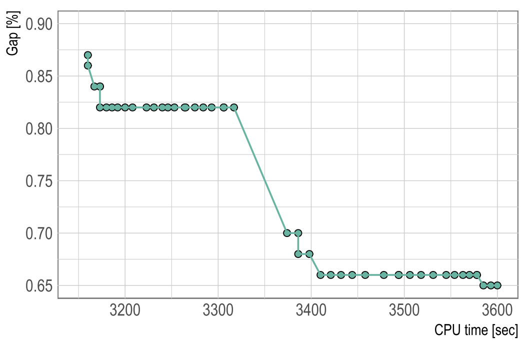
Notes: "Time" denotes delivery time; "cost" denotes objective value; "N_c (%)" denotes the percentage of the total demand that is satisfied in the indicated instance; *D* denotes the dominated solution; *ND* denotes the nondominated solution; *NS* denotes no solution
Source: Created by authors

Figure 3 Evolution of Gurobi solutions (Data 1-1)



Note: To obtain the solutions presented in the graph, the algorithm was run with a total time limit (ε-constraint) of 400 h for 3,600 s (CPU time)
Source: Created by authors

Figure 4 Evolution of Gurobi solutions (Data 1-2)



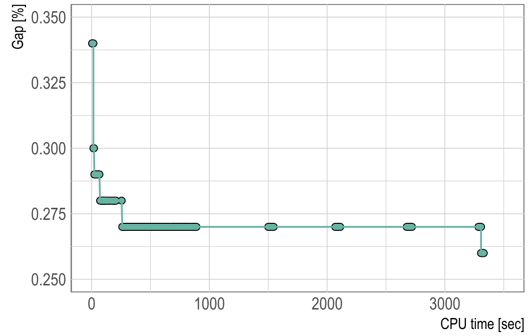
Note: To obtain the solutions presented in the graph, the algorithm was run with a total time limit (ε-constraint) of 400 h for 3,600 s (CPU time)
Source: Created by authors

may require significant computational resources when the size of the instances increases.

Table 7 shows the dominated solution obtained, for instance, Data 1-1, which has a minimum delivery time of 12.2 h, CPU time of 1 s and GAP of 0.36%. Indeed, two out of the four distribution centers were opened, and only six out of the 10 stations available were used. In the second echelon, only one of the two transportation modes was used, i.e. the one with the lowest load capacity. In the third echelon, only land transportation was used, and 10 routes were constructed to satisfy the 35 demand nodes.

In general, the solutions for the generated instances were similar. When the epsilon constraint on the delivery time was large, cheaper and larger capacity vehicle modes were used. On the contrary, when time was more restricted, faster transportation modes were selected despite their capacity, leading to an increase of transportation costs due to the use of drones (Figures 12 and 13). Accordingly, when the delivery

Figure 5 Evolution of Gurobi solutions (Data 4-1)



Note: To obtain the solutions presented in the graph, the algorithm was run with a total time limit (ε-constraint) of 12.2 h for 3,600 s (CPU time)
Source: Created by authors

time is larger, fewer routes are constructed in the third echelon, and the total cost is reduced (Figures 7–11). Moreover, it was found that the size of the instances involves more complexity to the problem. As the number of nodes increases, the CPU time increases as well. Also, if the number of vehicles available in the third echelon increases, the computational time increases significantly. Therefore, nondominated solutions were found for all the instances generated because they are considerably smaller than the case study instance and because they consider less vehicles available for delivery in the last mile.

5.3 Discussion

The previous information reflects that with the application of a model such as the one proposed in this research, more conscious decisions can be made. For Data 2-1, the optimal solutions do not suggest using drones in the last mile, and there is no improvement in cost value, even when the value assigned to delivery time increases dramatically, which contradicts what other studies have stated about the minimization of costs with the use of drones; therefore, it is worth it to check the parameters with which the costs are measured in other studies to guarantee a fair comparison. Likewise, in the optimal solutions for Data 3-1, last-mile deliveries were not assigned to drones regardless of delivery time, so drones keep being the last option to use in the last mile. Nevertheless, a minimal improvement in costs was detected (Figure 6). Finally, though no optimal solutions were found for Data 4-1, the dominated results show a significant decrease in the cost value when increasing the delivery time. In this case, drones were used regardless of delivery time, not leaving clear the situation in which the mathematical model uses drones to deliver the products.

The proposed model is effective to solve small to medium-sized humanitarian logistics supply-chain problems that use drones as a transportation mode in the third echelon of the network. Nevertheless, for big-size problems, we encourage the use of approximated methods. One of the key factors that affect the performance of the model is the number of available drones for use; the greater the number, the more

Table 6 Solutions of the generated instances

	Solution Model I				
Instance	**Time [h]**	**Cost [US$]**	**Solution type**	**CPU time [s]**	**GAP (%)**
DataV1	1,130	3,230	ND	7.37	0.00
	1,142	3,230		13.23	0.00
	1,154	3,155		3.12	0.00
	1,166	3,155		6.1	0.00
	1,178	3,104		3.76	0.00
	1,190	3,104		3.62	0.00
	1,202	3,068		2.86	0.00
	1,214	3,062		5.01	0.00
DataV2	1,215	3,448	ND	52.26	0.00
	1,250	3,215		5,500.41	0.00
	1,285	3,073		2.83	0.00
	1,355	3,069		5.98	0.00
	1,390	3,059		7.65	0.00
	1,565	3,049		12.38	0.00
DataV3	765	4,110	ND	72.25	0.00
	800	4,030		22.25	0.00
	835	3,966		1.02	0.00
	870	3,157		2.17	0.00
	940	3,101		2.07	0.00
	1,045	3,091		2.95	0.00
	1,185	3,077		5.25	0.00
	1,465	3,064		0.95	0.00
	1,815	3,055		0.85	0.00
DataV4	705	3,136	ND	9.59	0.00
	730	3,119		10.95	0.00
	755	3,099		6.42	0.00
	780	3,088		3.07	0.00
	830	3,083		2.22	0.00
	855	3,078		2.6	0.00
	905	3,076		1.47	0.00
	955	3,071		2.71	0.00
DataV5	745	4,022	ND	490,36	0.00
	765	3,902		114.22	0.00
	790	3,872		10.05	0.00
	815	3,866		8.36	0.00
	840	3,858		8.88	0.00
	865	3,858		13.96	0.00

Source: Created by authors

combinations, therefore, the higher CPU time. Because of the above, we encourage the demodulation of the model as well.

To deal with large-scale humanitarian logistics problems, some meta-heuristics like genetic algorithm (GA) or neighborhood search can be used, as well as a fix-and-optimize approach where the value of the binary variables are defined by a meta-heuristic and the rest of the variables' values are obtained from the optimization of the model. The above is to reduce the computation time because these problems must be solved in seconds to expedite aid operations.

On the other hand, as we have seen in other research works and case studies, the use of drones expedites the delivery of different products in a matter of time and accessibility; however, their use in real-life situations implies some limitations. On the economic side, the use of drones requires strong economic investments for their purchase and for their infrastructure, making their use unattractive for governments that do not have the resources, which is why it is important to carry out these types of studies to show the benefits of their long-term use. Socially speaking, the use of drones implies considering different risk situations to face. For example, in dangerous areas, there may be loss of equipment or product, so it is important to consider it both at the budget level and at the tactical level in operations. Finally, the commercial implications include the providers of said drones, as well as the necessary resources for their operation. To regulate the above, including the economic and social implications as well, it is necessary to generate special policies for the use of drones in disaster situations and aid distribution in such a way that these minimize conflicts that may arise between the different sectors.

Moreover, it is important to consider that using drones can cause ethical and legal implications. If a drone brings help to people in a private property, it can lead to property invasion problems. If the drones are used to explore areas in any type of risk through cameras, it can be considered a violation of privacy. In the worst case, if a drone presents a technical failure or is handled incorrectly, it can cause an attack on the integrity of people or property, as well as on the drone itself. Therefore, insurance services must be provided for drones that bring aid during disasters, and regulations must be developed for the use of drones during these specific situations in which the integrity of people and property is put at stake.

Finally, this model can be adapted to address other logistical challenges in natural disaster and pandemics such as COVID-19; nevertheless, the greatest challenge is in responding to limited-access areas; therefore, major changes must be made in the last-mile deliveries, data of these regions can be obtained with the Google API routes including the traveling distance and time between places for land and air vehicles.

6. Conclusions and recommendations for future research

Historically, the use of UAVs in logistics activities has great benefits, and their flexibility makes them excellent modes of transportation. However, in practice, their economic, political and social limitations should always be considered. This makes regulating the use of UAVs a priority issue to avoid violating the privacy and rights of citizens when they are used.

In this research, a mathematical model for a humanitarian logistics supply-chain problem using UAVs as an additional transportation mode is developed. The model has been applied to the case study of the Earthquake on September 19, 2017, in Mexico.

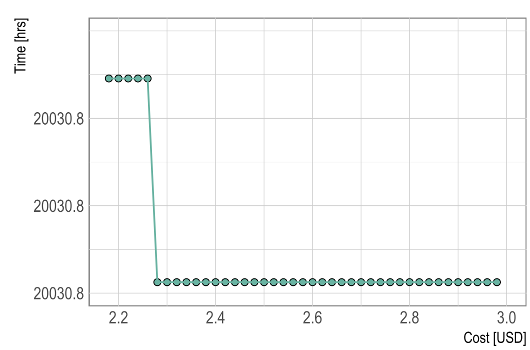
The results of the study suggest that when the delivery time is restricted, the transportation costs increase, and in the last echelon, an increased number of routes are assigned to the UAVs (because there is less response time to deal with the emergency). When a larger delivery time is considered, transportation costs decrease, and routes are assigned to transportation modes with larger capacity, regardless of their

Table 7 Solution of the case study full instance (data 1-1)

Data 1-1	**Instance characteristics**	**Time [h]**	**12.20**
		Cost [US$]	40,185.40
		CPU time [s]	3,701.33
		GAP [%]	0.36%
First echelon			
Depot	*Distribution center*	*Product* (kg)	*Transportation mode*
Airport	Morelos	3,835	Trucks 0
Airport	Guerrero	2,131	Trucks 0
Second echelon			
Distribution center	*Station*	*Product* (kg)	*Transportation mode*
Morelos	Ticuman	203	Trucks 2
Morelos	Parque 19 de Febrero	633	Trucks 2
Morelos	Club Paraíso	1,039	Trucks 2
Morelos	Atenango del Río	1,960	Trucks 2
Guerrero	Jojutla	203	Trucks 2
Guerrero	Colegio Bach	1,928	Trucks 2
Third echelon			
Station of origin	*Route*	*Product (kg)*	*Transportation mode*
Atenang del Río	Atenango del Río > Ciudad Ixtepec > Atenango centro > Copalillo > Juitepec > Huajuapan León > Atenango del Río	965	Truck
	Atenango del Río > Tepecoacuilco > Istmo Tehuantepec > Iguala > Taxco > San José Ayuquila > Atenango del Río	995	Truck
Club Paraíso	Club Paraíso > Yecapixtla > Club Paraíso	203	Truck
	Club Paraíso > Ocuituco > Jantetelco > Tetela Volcán > Palacio Municipal > EC San Gabriel	836	Truck
Colegio Bach	Colegio Bach > CEmiliano Zapata > Santuario Virgen > Zacatepec > BUAPP > Colegio Bach	454	Truck
	Colegio Bach >Tlayacapan > ExconventoXVI > Axochiapan > Colegio Bach	609	Truck
	Colegio Bach > Huitzuco > Palacio Cortés > Buenavista Cuellar > TeotitlánFM > Templo Santiago A > Escuela Héroes R > Colegio Bach	865	Truck
Jojutla	Jojutla > Xochitepec > Jojutla	203	Truck
Parque 19 de Febrero	Parque 19 de Febrero > Cuautla > Ayala > Iglesia San Juan B > Iglesia Santa Cruz > Parque 19 de Febrero	633	Truck
Ticuman	Ticuman > Yautepec > Ticuman	203	Truck

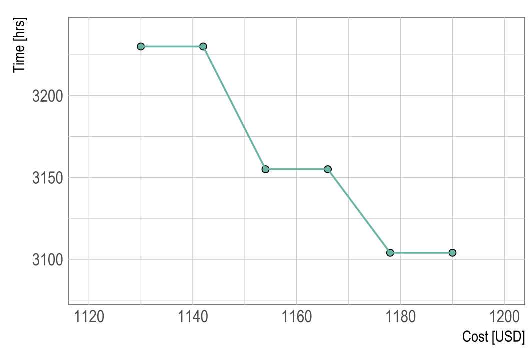
Source: Created by authors

Figure 6 Pareto front (Data 3-1): total cost vs total delivery time



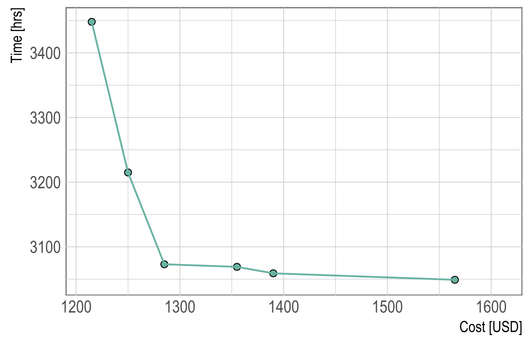
Source: Created by authors

Figure 7 Pareto front (DataV1): total cost vs total delivery time



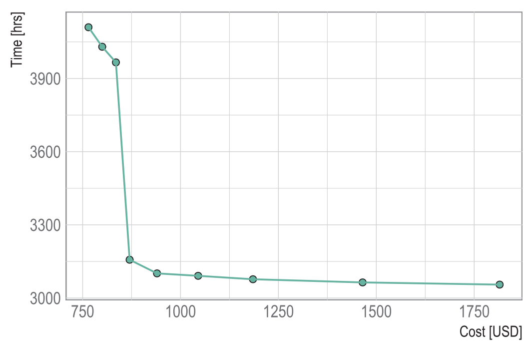
Source: Created by authors

Figure 8 Pareto front (DataV2): total cost vs total delivery time



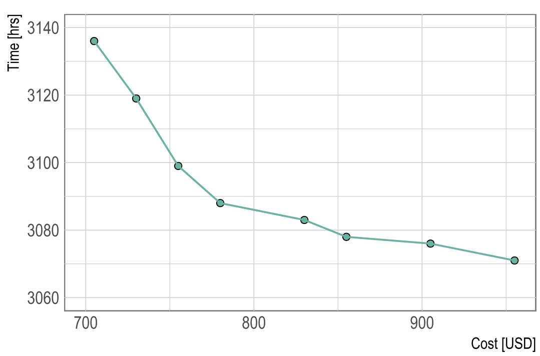
Source: Created by authors

Figure 9 Pareto front (DataV3): total cost vs total delivery time



Source: Created by authors

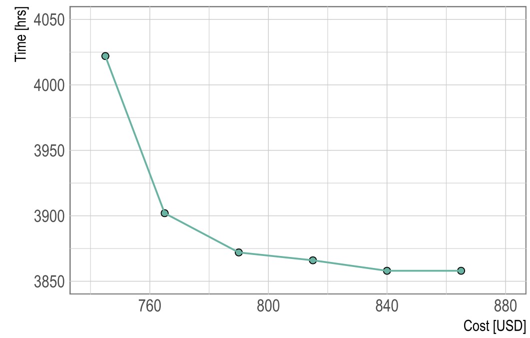
Figure 10 Pareto front (DataV4): total cost vs total delivery time



Source: Created by authors

speed. Although the proposed model is limited to large-scale applications, it provides a good representation of a transportation network that can be designed and optimized to increase the performance of the given response during a natural disaster, extending it to consider the potential use of UAVs to address this problem, which is one of the major contribution of this research.

Figure 11 Pareto front (DataV5): total cost vs total delivery time



Source: Created by authors

Alternatively, UAVs can be used to decrease delivery time in the last mile to regions with limited access. Although some researchers highlight the low maintenance cost of UAVs, their implementation can result in high costs because it is a relatively new technology, and therefore, implementing them is more feasible with a large emergency budget. Furthermore, the model can be adapted to problems that have arisen from the COVID-19 pandemic. For example, they can be used to respond to the high demand for oxygen tanks and distribute them in areas that have difficult access, as well as for the distribution of vaccines through cold chains. For problems where demand is greater than UAVs' capacity, modifications should be made to the proposed model so that final users can receive their products in more exhibitions, or it could be considered not to use drones at all as a transportation mode.

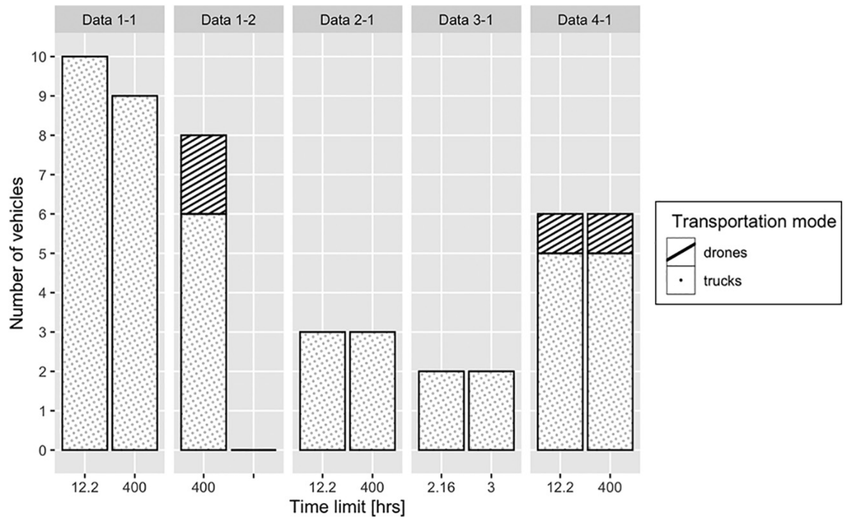
This research has different implications in real-life situations. Although the model can be adapted to any system anywhere in the world for problems beyond humanitarian logistics, its application may be limited by the economic, geographical and social situation (security and crime rates) where it is implemented, as well as regulations and policies for the use of UAVs.

The economic impact of this research can be visualized in both the short and long term. In the short term, investment in UAVs is large, whereas, in the long term, as explained in the literature review, their use can have a positive impact on associated costs as well as on CO_2 emissions. These economic implications are consistent with the results obtained in this research, as the more routes assigned to UAVs, the cost is higher.

The use of UAVs during natural disasters can have a positive and negative social impact. A positive impact can be achieved if UAVs are seen as reliable vehicles that can help during any emergency in the shortest possible time. However, a negative impact is associated with privacy violations and vehicle damage due to the crime rate in the area. Thus, regulations should be made to address these problems and UAVs insurance services. Regarding their economic impact, currently, UAVs are relatively high-cost vehicles. However, with its continued development, it is expected that the viability of its use will increase in a few years.

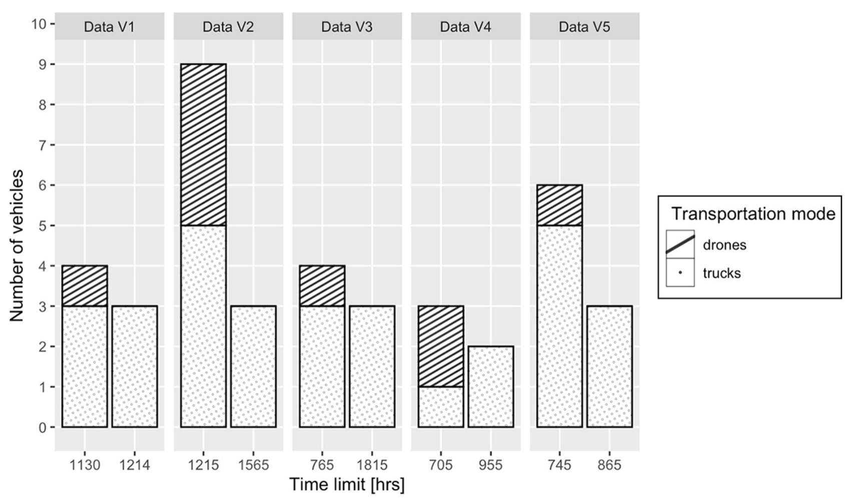
For future research, the model can be adapted to allow vehicles to make additional routes doing an adequacy of the

Figure 12 Number of drones and trucks used in the solutions to perform the routes in the third echelon



Note: The solutions correspond to the study-case full instance and the instances derived from it
Source: Created by author

Figure 13 Number of drones and trucks used in the solutions to perform the routes in the third echelon



Note: The solutions correspond to the generated instances
Source: Created by author

vehicle routing problem with multiple routes in the last echelon. To expand the model, more parameters should be considered, such as vehicle–distance ratio and the number of times a demand node can be visited by a vehicle. Furthermore, because for larger scale instances, the proposed model, solved by using a general-purpose solver, was not able to obtain optimal (even feasible) solutions in a reasonable computing time, it is recommended to explore the design and the development of metaheuristics to obtain good quality solutions efficiently. Some of the most used meta-heuristics for multiobjective problems are GA-based solution methods, which can be a good starting point for future research lines.

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