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An optimization model for network design in disaster relief planning

Modelo de optimización para el diseño de redes de asistencia en catástrofe

Authors: Double-blind review

KEYWORDS:
Operations research; MILP; humanitarian supply chain

Investigación de operaciones, modelos de programación lineal entera mixta, cadena de suministro humanitario

ABSTRACT: A model was created to optimize aid relief efforts by identifying the best location to set up shelters. This model, which was developed using a mixed-integer linear program - MILP, considers the availability of resources and the cost of different locations, as well as constraints that must be met to ensure timely aid delivery. A solution involving the use of branch-and-cut algorithm with the help of GeoJSON API and Python code was proposed. Additionally, a study was conducted to assess the impact of the model by analyzing the water supply during a natural disaster in Mocoa, Colombia in 2017. The results of the study showed that the model had a positive impact on reducing the distance resources had to travel, increasing the satisfaction of shelter needs, and decreasing the costs of implementation.

RESUMEN: Se ha creado un modelo para optimizar las operaciones de ayudas humanitarias identificando la mejor ubicación para instalar los refugios. Este modelo, desarrollado mediante modelos de programación lineal entera mixta, tiene en cuenta la disponibilidad de recursos y el coste de las distintas ubicaciones, así como las restricciones que deben cumplirse para garantizar la entrega puntual del recurso. Se propuso una solución que implicaba el uso de un algoritmo de ramificación y corte, con la ayuda del API GeoJSON y Python. Además, se realizó un estudio para evaluar el impacto del modelo analizando el suministro de agua durante un desastre natural en Mocoa, Colombia, en 2017. Los resultados del estudio mostraron que el modelo tuvo un impacto positivo en la reducción de la distancia que debían recorrer los recursos, el aumento de la satisfacción de las necesidades de refugio y la disminución de los costes de implementación.

1. Introduction

The global demand for humanitarian aid, including requests for assistance from national governments, continues to increase. This is because natural disasters are becoming more severe, conflict is rising, and populations worldwide are being impacted by the global financial crisis, high food prices, energy and water shortages, population growth, and urbanization [1]. Humanitarian aid responds to situations where the security, rights, and well-being of specific communities, groups, or collectives are at risk. This aid can take many forms, including economic, social, logistical, or moral [2]. In addition, natural disasters and humanitarian emergencies are expected to affect the less prepared countries [3]. According to the June 2018 biannual report of the UN Office for the Coordination of Humanitarian Affairs (OCHA), so far this year, 40 countries have been affected, and 134.1 million people required some form of humanitarian assistance [4].

Therefore, it is appropriate to propose new initiatives to contribute to the preparation and rapid response to such events. Humanitarian logistics is the process of planning, implementing, and controlling the flow and storage of goods, materials, and information, from the origin to the end of consumption, to alleviate the suffering of vulnerable people in a disaster situation. Indeed, humanitarian logistics are required to support the planning and implementation of response networks to ensure a successful operation. The mobilization of personnel, the distribution of resources, the evacuation of the wounded, and the resettlement of affected people require a logistical system to maximize effectiveness [5]. Also, humanitarian logistics presents a series of challenges that differ from conventional operations logistics. For instance, although it may be known that certain events will undeniably occur, the uncertainty of variables such as time or location is much more significant. Similarly, the provision of aid to the vulnerable population, together with the devastation of a greater or lesser extent of the area surrounding the disaster, translates into greater difficulty in carrying out logistical operations [6].

Given these observations, it is reasonable that the study of humanitarian logistics has attracted the scientific community's attention. In addition, the location of humanitarian aid facilities is one of the most challenging aspects of humanitarian relief programs because aid agencies must respond rapidly to disasters to mitigate their negative impacts. The evolution of research on this subject has been chiefly directed toward formulating analytical models. These may include a variety of proposals that make up contributions to the research direction they provide and their findings [7–10]. This is explored in more depth in the literature review section. Although there are multiple methodologies to carry out this practice, none can guarantee a fast and integrated scheme that facilitates a reliable and applicable solution in the shortest time. When addressing the problem of locating facilities for humanitarian attention after a disaster, operational needs change on the fly as the emergency develops and multiple organizations open and close facilities in short time frames, considering dynamic needs and resource levels [5].

Effective facility location is the linchpin of a responsive humanitarian aid logistics network. Inefficiently placed facilities can drastically impede both accessibility to essential resources and the equality of their distribution. While these challenges exist in many logistical frameworks, they are amplified in the realm of humanitarian response due to the unpredictable nature of crises and the vast scale of operations.

To address these challenges, the proposed model underscores three pivotal factors that have been underrepresented in existing studies:

- **Weighted Average Distance**: Instead of merely considering raw distances between supply and demand nodes, the model takes a more nuanced approach. By incorporating the demand volumes of distant facilities, it recognizes the critical importance of remote areas that serve large populations. This method ensures that the model does not indiscriminately favor closer facilities, but instead provides a balanced perspective where demand volumes significantly influence resource allocation decisions.

- **Demand Proximity Considerations:** A unique constraint ensures that a substantial portion of the demand, such as 80% in a given scenario, is met by suppliers within a specified distance, like 50 miles. This is not an arbitrary decision; in humanitarian contexts, time is often critical. Ensuring that a large percentage of demand is met by nearby facilities allows essential supplies to reach those in need more quickly, making the aid response more agile and timely.

- **Attention Flow Restrictions:** The efficiency of a humanitarian response hinges not only on the number of people a facility can serve, but also on the speed at which it can do so. Our model incorporates the rate at which facilities can meet demands, acknowledging that raw capacity alone can be misleading. A center capable of serving hundreds may still be inefficient if it takes too long to attend to each individual. By considering the rate of service, the model emphasizes the importance of both capacity planning and operational speed, which are crucial in emergency situations.

Given these tailored constraints and considerations, it is clear that this model offers more than a basic approach to the problem. Understanding the complexities of humanitarian logistics necessitates considering social costs in post-disaster relief modeling. However, it's important to recognize the broader context in which these models are applied. While the social costs model is comprehensive, it adds complexity. In high-pressure situations with limited resources and time, models focused on distance provide clear and straightforward solutions. By focusing solely on reducing deprivation costs, there is a risk of inadvertently causing unequal outcomes.

Therefore, the purpose of this article was to design a model for facility location in disaster relief operations, providing a realistic and practical solution for the design of a supply network. The model was developed using an integrated approach that combines a Mixed Integer Linear Programming (MILP) framework solved with a branch-and-cut algorithm and input data obtained from the Google Maps web mapping service for distance calculations. To validate the model, a case study was conducted to evaluate its performance in the water supply operation during the natural disaster that occurred in 2017 in the municipality of Mocoa, Colombia. The validation results demonstrated the advantages of implementing the proposed model for facility location in disaster relief operations. The methodology incorporates a predefined list of candidate facilities identified through a preliminary analysis of the affected area. Furthermore, the model includes constraints focused on minimizing the distance between supply and demand nodes while ensuring a high percentage of demand satisfaction. Additionally, it integrates a system that synergizes with precise GIS data to accurately capture distance information.

2. Literature review

The location of facilities for humanitarian logistics operations has attracted the attention of researchers for many years. This section explores the most recent contributions to this topic. Initially, various authors have addressed location problems using operations research approaches, such as the center of gravity method, to identify the optimal placement of temporary or fixed facilities within specific geographic areas. For instance, some researchers sought to determine the best site for quick relief center operations by minimizing the total transportation cost, using the center of gravity approach to locate a facility that balances distances and demand volume in a network of customer locations [11].

Building on these efforts, regional cooperation-based models have also been explored. One such model was constructed to optimize relief warehouse locations by minimizing the maximum expected cost across regions, emphasizing the principle of territorial priority [12]. Additionally, another study focused on determining the optimal number and locations of warehouses in Nepal for a humanitarian relief chain designed to respond to sudden-onset disasters. This problem was tackled using a simplex algorithm with a branch-and-bound method applied to the relaxed integer problem [13]. Furthermore, a facility location model explicitly incorporating deprivation costs in the objective function was developed for pre-positioning supplies during disasters, further advancing the field [14].

In addition, some research is based on stochastic programming. For example, two location models were provided that explicitly consider the impact a disaster can have on response facilities and population centers. The first was a deterministic model that includes distance-dependent damages to disaster response facilities and population centers, while the second was a stochastic programming model that extended the first by directly considering damage intensity as a random variable [15]. Similarly, multi-criteria modeling frameworks were investigated for discrete stochastic facility location problems with single sourcing, assuming that demand was stochastic and imposing a service level[16].

Other authors have employed goal programming approaches; for instance, a multiple-objective decision model was proposed to simultaneously locate central and local distribution centers, aiming to minimize distances among demand points, local and main distribution centers, and to minimize the number of regional distribution centers and central warehouses [17]. Along the same lines, a bi-objective bilevel optimization model was proposed to locate relief distribution centers in humanitarian logistics [18]. In related work, a multi-objective programming model was developed for locating relief goods distribution centers and health centers, distributing relief goods, and transferring casualties to health centers pre/post-disaster [19]. Later, a bi-objective optimization model was created to determine the optimal temporary medical service locations and allocation plan by maximizing the number of expected survivors and minimizing total operational costs using ambulances and helicopters [20].

Furthermore, several key contributions involve Mixed Integer Linear Programming (MILP) models. For instance, a stochastic linear programming model was proposed for the optimal placement of shelters in small Colombian cities [21]. Similarly, a stochastic model was developed to determine the location and capacities of distribution centers for emergency stockpiles, and this study also introduced an evolutionary heuristic, supported by a MILP model, that generates high-quality solutions efficiently in terms of time [22]. Also, aggregate scenarios were defined to forecast demand using past disaster data and future trends, with orders for relief items based on these scenarios then fed to a MILP model to improve current supply networks [23]. In the same way, a method was introduced to quantify the impact on accessibility and equity in locating post-disaster healthcare service facilities, including a robust MILP to choose facility locations that optimize accessibility while ensuring equity [24]. Another study proposed a MILP model to minimize economic effects by assessing the fixed, variable, and penalty costs associated with the adverse environmental and human impact of post-disaster scenarios [25]. Later, a Mixed Integer Nonlinear Programming (MINLP) model was developed to determine the location of distribution points and inventory assignment, minimizing the number of installations and deprivation costs (a cost imposed on survivors for lack of access to critical supplies) [26]. In other studies, researchers have developed simulation models for humanitarian logistics; for example, a simulation-based approach was proposed to determine the demands of relief supplies until governmental and central humanitarian organizations reach the affected area, followed by the development of a plan to allocate temporary disaster response (TDR) facilities and distribute relief supplies [27].

There are many significant and successful contributions in the literature to treat emergencies in humanitarian logistics using other approaches. For instance, a multi-objective stochastic programming model was proposed for developing an earthquake response plan, followed by the creation of a new multi-objective particle swarm optimization algorithm to solve this model [28]. Another study examined relief distribution to non-evacuating populations in a post-disaster setting, comparing the accessibility to relief of the aging and other people using P-median-based modeling linked to a geographic information system (GIS) [29]. Additionally, a user-friendly decision support tool was designed to optimize Urban Emergency Rescue Facility Locations (UERFLs) in large-scale urban areas, describing the design, architecture, and implementation of the tool [30]. A mathematical model was presented, combining locational decisions with the max-flow problem to select safe destinations that maximize the number of people assisted [31]. Finally, a procedure was developed for structuring an aid distribution network in disaster response operations, incorporating UAV (Unmanned Aerial Vehicle) technologies and geographic information systems (GIS), and applied to a real-life situation [32].

3. Methodology

In this section, the main guidelines of the proposed model are presented. The problem of designing a facilities network to support humanitarian logistics operations was analyzed considering a list of candidate locations to avoid the unrealistic scenario of selecting these locations within a continuous surface by traditional methods such as the Center of Gravity or Weber's method. These methods may make specific locations unsuitable for settling facilities during humanitarian operations. Thus, the list of sites should respond to methods that go hand in hand with a thorough inspection of the affected area. A network can be defined as a collection of nodes and arcs, where a node is a point within the network, and an arc is a union between two nodes [33]. With these considerations in mind, this model was designed as an allocation model in which a finite number of demand nodes for humanitarian assistance could be satisfied by several supply nodes. The goal was to optimize a network of humanitarian aid facilities to meet the demand across the designated area. While the concepts may appear straightforward, solving an optimization problem for real case studies is inherently complex. To address this, an integrated solution scheme was proposed, centered on the design of a Mixed Integer Linear Programming (MILP) model to achieve the desired objectives.

Additionally, the model was optimized utilizing a branch-and-cut algorithm. The mathematical framework of the MILP model was implemented in Python 3.10 and solved with the Gurobi Optimizer 9.5.2 to enhance problem-solving efficiency. The Google Maps API was employed to retrieve geospatial data. This data was presented in the GeoJSON format, a widely recognized standard for encoding diverse geographic data structures. Utilizing this format ensured effortless integration and analysis within various GIS tools and platforms. This algorithm was based on the possibility of accessing public cartography and accurate road network data for specific study problems and then exporting these data remotely to a database. Users can easily access the application from any computer connected to the Internet using a standard browser and an API Key. API keys are generated in the Google Cloud console and are unique identifiers that authenticate calls to Google Maps Platform.

3.1 MILP model

In the Mixed Integer Linear Programming (MILP) model developed, two primary indexes were introduced to represent the nodes in our supply-demand network. Index i designates a specific supply node, while index j corresponds to a particular demand node. For the facilitation of flow between these nodes, the notation x_{ij} was defined. Here, x_{ij} represents the arc or the connection from supply node i to demand node j. In the context of this model, there are n supply nodes and m demand nodes in total. Furthermore, the central goal of this network is captured by the objective function denoted as z. This function, which serves as the measure of optimization, is detailed in Equation 1. Next, the two most essential components in deciding to open new facilities were considered: a fixed cost (C_i) incurred by locating or "opening" a supply node (B_i) and a variable cost c_{ij} depending on the flow through the arc. Then, this function assumes, for all possible arcs, a particular cost multiplied by the flow through x_{ij}:

$$\text{Min z} = \sum_{i=1}^{n}\sum_{j=1}^{m} c_{ij}x_{ij} + \sum_{i=1}^{n} C_i B_i \tag{1}$$

Equally important, B_i is a binary variable. It can only take two values, either 0 or 1. The model uses this variable to indicate whether to open or not a facility, and this is for all the i nodes in the supply set. This variable was added to the objective function, multiplied by the fixed cost for opening an i supply node. This could be for flow over a week, a month, a year, etc., then this fixed cost (C_i) is the cost of opening this facility for that period. A supply constraint was also required (Equation 2). That is making sure that everything from the supply nodes does not exceed what is available there for all the i nodes within the supply set (S_i):

$$\sum_{j=1}^{m} x_{ij} \leq S_i \qquad \forall i \epsilon S \tag{2}$$

In the same way, Equation 3 is the demand constraint. It makes sure that all the flows coming into a specific j node must exceed or be equal to the demand at each one of those (D_j):

$$\sum_{i=1}^{n} x_{ij} \geq D_j \qquad \forall j \epsilon D \tag{3}$$

Similarly, two constraints were introduced in the model; these limit the number of facilities open. One sets a minimum value, F_{min}, and the other an upper bound, F_{max}. These values are the number of facilities that could be opened:

$$\sum_{i=1}^{n} B_i \leq F_{max}; \quad \sum_{i=1}^{n} B_i \geq F_{min} \tag{4}$$

In addition, link constraints were considered. It is not possible to supply from a supply node unless it is open. In Equation 5, W is a big number and the binary variable B_i can take two values, either 0 or 1. Considering the options and choosing these W's, it is not recommended to make it excessively big, because it slows down some of the solution time. It was proposed to set it equal to the sum of all the demand because the flow on each individual arc can never be greater than the total demand required. The particular value of W can at times compromise the stability of the solver. As attentive readers may have noted, there might be no need for this constraint if we multiply the right-hand side of equation 2 by B_i. However, the inclusion of this restriction has been left at the discretion of the reader.

$$x_{ij} - WB_i \leq 0 \tag{5}$$

Facility location models are crucial at the strategic level of supply chain decision-making [34]. While economic concerns may not be the primary focus in humanitarian logistics, their significance cannot be overlooked. The goal of any supply chain design is to balance cost-efficiency with the quality of services provided. In this context, the essence of service is closely linked to rapid response times. Humanitarian aid organizations aim to serve affected populations promptly, striving to mitigate the impacts of disasters as effectively as possible. Therefore, the challenge lies in the design of this logistical network. Thus, in general terms, the goal of this model was to find the scenario that implies the lowest costs and, at the same time, considers timely humanitarian assistance.

In understanding the complexities of humanitarian logistics, we highly value Holguín-Veras's recommendation to incorporate the concept of social costs into post-disaster relief modeling [35]. This metric, which combines both logistic and deprivation costs, offers a nuanced perspective on disaster response. However, it is essential to appreciate the broader context in which these models are employed. While the social costs model is comprehensive, it also introduces additional complexity. In high-stress situations with limited resources and time constraints, models based on distance provide a clarity that is both predictable and easy to execute. Gutjahr's observation further supports our approach by focusing solely on minimizing deprivation costs risks unintentionally creating inequitable outcomes [36]. Emphasizing distance can lead to a more balanced distribution of resources, preventing inadvertent prioritization of certain groups. Operational realities also play a pivotal role in our decision-making. On-the-ground situations, such as challenging terrains, damaged infrastructure, and accessibility issues, mean that the shortest distance might not always translate to the quickest delivery. Despite these challenges, distance remains a tangible and easily quantifiable metric. This makes distance an optimal starting point, especially when complemented with real-time situational data.

Adopting distance as the foundational metric does not preclude incorporating aspects of the social costs approach. As the model evolves and more data accumulates, there is potential to develop a hybrid approach that amalgamates the strengths of both methodologies. In summary, the commitment to distance-based modeling is rooted in practicality, the urgency of response, and the necessity for a framework that remains consistent in the tumultuous setting of disasters. Navigating the landscape of humanitarian assistance requires a willingness to adapt strategies to best serve affected populations. Thus, the model includes the following two constraints:

A constraint for the maximum allowed average distance was included (Equation 6). Each x_{ij} is multiplied by its distance d_{ij}, which corresponds to the distance from a node i to a node j. This operation involves the calculation of a weighted distance. Also, this value is divided by the sum of the total demand (D_j) to calculate the percentage represented. The constraint sums all arcs x_{ij} and obtains a weighted average distance. By setting a limit on this average, the model ensures that resources are not overly concentrated in nearby or easily accessible regions at the expense of those further away. This puts a cap on how "unfair" the distribution can be in terms of distance, compelling the logistics model to find a solution that distributes resources more equitably across different regions regardless of their proximity to supply points.

$$\sum_{ij}\left(\frac{d_{ij}x_{ij}}{\sum_j D_j}\right) \leq \phi \qquad (6)$$

In addition, Equation 7 involves another distance constraint. The right side of this constraint is an input value φ, this value is defined as the minimum percentage of demand that must be met within a minimum distance value; the left side of this constraint includes an x_{ij} arc multiplied by a new input data, a constant a_{ij}. This value is equal to 1 if a demand node j served by a supply node i is within a given distance value, and it is equal to 0 otherwise. For example, consider a logistic network with collection centers and shelters, where the former are the supply nodes and the latter are the demand nodes. A value of 50 miles is considered to determine a_{ij}. The value of φ is 80%. Then, if a collection center i supplies a shelter j, a_{ij} will have the value of 1, if the distance between i and j is less than or equal to 50 miles; otherwise, it will be 0. The constraint will only consider those combinations within 50 miles and divide that value by the total demand. Therefore, the percentage of total demand within 50 miles must be greater than or equal to a minimum percentage value φ, which in this case is 80%. In other words, 80% of the demand supplied must be at a distance less than or equal to 50 miles. This constraint is crucial to ensure a short distance on humanitarian supply trajectories.

$$\sum_{ij}\left(\frac{a_{ij}x_{ij}}{\sum_j D_j}\right) \geq \varphi \qquad (7)$$

Furthermore, it was necessary to have a restriction that limits the attention in the facilities (Equation 8). While a facility may have enough capacity, this feature may not be conducive to providing prompt attention. For instance, if a humanitarian attention facility is responsible for several shelters, the waiting rate for attention may increase considerably per person. Similarly, storage systems depend on the volume of people sheltered and the frequency with which demand is supplied to this community. An example of this can be illustrated if a person requires 15 liters of water per day for basic needs and has a water supply tank with a capacity of 10,000 liters, but with a current base of 7.5 liters per minute. Thus, this tank could supply water to over 650 people, but it would take more than 21 hours, which is counterproductive. Therefore, it is recommended to establish a value to limit the maximum flow of attention (δ). It is essential to mention that this constraint may not be indispensable for some case studies, and the user can run the model without it.

$$x_{ij} \leq \delta \qquad \forall ij \qquad (8)$$

Finally, there are non-negativity constraints for the flows:

$$x_{ij} \geq 0 \qquad \forall ij \qquad (9)$$

3.2 Geospatial Data Extraction

Computing the distance between combinations of supply and demand nodes is an input required by the model. In addition, a network structure defined on maps and routing optimization algorithms is needed. However, the availability of this data and the price of good mapping can be challenging. Therefore, a Python code was developed and integrated with the GeoJSON API to overcome these limitations. With this code, it is possible to collect real distance data from the road network for any case study and record this information in a database. In this case, the API distance matrix created by Google is a service that provides the distance and travel time for a matrix of origins and destinations according to the recommended route between the start and endpoints. Anyone can access the API through an HTTP interface, with requests built as a URL string, using sources and destinations, along with an API key [37]. Algorithm 1 below shows an example response.

Primarily, these distance values are extracted by iterative calls to Google Maps API, which provides accurate traveling distances between each pair of locations. By default, distances are calculated for driving mode using the road network. Also, distance values may be subject to certain restrictions. Restrictions are indicated by choosing what Google should avoid when calculating the travel time (tolls, highways, ferries, indoor, or default: null). No restrictions were included in this code. In addition, units specify either metric or imperial units when displaying distances in the results. If units are not specified, the origin country of the query determines the units to use. The Python code is shown in Algorithm 2.

3.3 Executable model

The MILP model was implemented in Python and solved using a Branch-and-Cut algorithm. This algorithm combines the Branch-and-Bound ($B\&B$) method with cutting planes to efficiently solve

Algorithm 1 API Distance Matrix: Sample request and response

Requirement: The following example requests the distance matrix data between Washington, DC and New York City, NY, in JSON (JavaScript Object Notation) format. Mode: driving.

Response:


```
{ "destination_addresses" : [ "New York, NY, USA" ],
"origin_addresses" : [ "Washington, DC, USA" ],
"rows" : [
  {
   "elements" : [
     {
        "distance" : {
        "text" : "225 mi",
        "value" : 361715
     },
        "duration" : {
        "text" : "3 hours 49 mins",
        "value" : 13725
     },
     "status" : "OK"
    }
    ]
   }
  ],
"status" : "OK" }
```


Algorithm 2 Google Distance Matrix API in Python

```
import googlemaps
import pandas as pd
gmaps = googlemaps.Client(key= "Insert your API key here")
supplyP = pd.read_csv("supply.csv" )
shelters = pd.read_csv("shelters.csv")
data = [ "ID_SUPPLY_POINT", "SUPPLY _POINT" ]
data += point
matrix = pd.DataFrame(columns=data)
for index, point in supplyP.iterrows():
    distance = [ ]
    for index, shelter in shelters.iterrows():
        try:
            Cdistance = gmaps.distance_matrix(point["LOCATION"], shelter["LOCATION"])
            d = (Cdistance["rows"][0]["elements"][0]["distance"]["value"]/1000)
        except:
            d = " "
        distance.append(d)
    temp = [supply_point["ID"], supply_point["LOCATION"]]
    temp.extend(distance)
    temp = pd.DataFrame([temp], columns=data)
    matrix = matrix.append(temp, ignore_index=True)
Nfile = pd.ExcelWriter("distance.xlsx")
Nmatrix.to_excel(Nfile, "DATA", index=False)
Nfile.save()
```

Mixed-Integer Optimization Problems [38]. While the *B&B* algorithm provides a foundational approach, Branch-and-Cut extends it by incorporating additional cuts to eliminate infeasible regions of the search space and improve solution quality.

For our implementation, we utilized the Gurobi solver, which is well-suited for handling complex optimization problems efficiently. The Branch-and-Cut approach used in Gurobi follows these key steps:

Step 1. Initialization: Preprocess the MILP formulation and solve its LP relaxation. If the LP relaxation is infeasible, the problem itself is infeasible, and the algorithm terminates. If the LP solution satisfies the MILP constraints, then the problem is solved, and the algorithm terminates. Otherwise, initialize bounds and prepare for branching.

Step 2. Node Selection: Choose a subproblem from the active list of nodes. Solve the LP relaxation of this subproblem. If the relaxation is infeasible, discard the node. If feasible, proceed to the next step.

Step 3. Generating Cuts: Generate and add cuts to the LP relaxation to further refine the feasible region. If no useful cuts can be added, proceed to the next step.

Step 4. Pruning and Updating Bounds: If the LP solution of a subproblem meets or improves upon the current best solution, update the lower bound and incumbent solution. Prune nodes that cannot yield a better solution.

Step 5. Branching: If necessary, branch on the current subproblem to create additional subproblems. Add these subproblems to the active list and continue the process.

4. A Complete Example

The model was implemented within the context of the natural disaster in Mocoa, Colombia. This event occurred on the night of March 31, 2017, due to the sudden overflow of the Mocoa, Sangoyaco, and Mulato rivers, and the Taruca, Taruquilla, and La Mision streams. This was followed by an avalanche that seriously impacted this municipality, leaving reports of the dead, injured, and missing people in its wake and a suspension of basic services [39, 40]. The situation report, prepared by OCHA (United Nations Office for the Coordination of Humanitarian Affairs) in collaboration with UMAIC (Colombia Information Management and Analysis Unit) [40, 41] was studied.

During this emergency, water services were suspended, and demand was met with the help of water tanks. In this case, the proposed model was implemented to find the optimal location of the water supply tanks (supply nodes) to meet the demand of the shelters enabled (demand nodes), as it was possible to access accurate data of this operation. During the humanitarian operation, these tanks were located at different points in the affected areas [42].

In the study, four distinct types of supply tanks were utilized, each differentiated by their volumetric capacity in liters. These tanks were categorized as follows: 250 L, 5,000 L, 10,000 L, and 20,000 L. Using this classification, a comprehensive assessment was conducted on 35 potential sites as candidate locations for tank establishment. Given the flexibility for each site to accommodate any of the four tank types, a cumulative total of 140 different site-tank combinations were evaluated. Notably, the model was specifically tailored to replicate the exact scenario observed during the real-world humanitarian operation. Also, the guidelines for this type of operation were analyzed to include the shelter's demand for water. According to the National Shelter Management Manual of the Colombian Red Cross Society [43], the community must be guaranteed a minimum of 15 liters of water per inhabitant per day to carry out basic activities. This is detailed in Table 1.

As of the date of the report, 12 shelters had been opened serving nearly 726 families, for a total of approximately 2462 people. Table 2 presents the demand per shelter. Regarding the objective function, fixed costs were determined by the unit value of establishing a specific capacity water supply tank. The variable cost corresponded to the transportation cost incurred in the supply operation; the value was calculated according to the liters of water transported. For example, transporting 1000 gallons would cost approximately 16.38 USD [44, 45]. Since the problem included 12 shelters and 140 possible tank locations, the API was applied to calculate these 1680 distance combinations using Google Maps. The exact geographical coordinates of the nodes were considered in the model to achieve a realistic solution. Concerning the entry data of constraints related to short response time (Equations 6 and 7), the maximum allowed distance was set at 0.5 km, then the weighted average distance was less than this value. Similarly, the minimum permissible demand within this distance was required to be greater than or equal to 85%. This was based on the guidelines of the National Manual for Shelter Management of the Colombian Red Cross Society, which states that the distance between any shelter and the nearest place of supply must not exceed 500 meters. Also, for the attention limit constraint (Equation 8), the manual indicated a maximum of 250

Table 1 Basic water needs per person

Basic water needs	Influence factor	Liters Required
For drinking and use with food	Depends on individual climate and physiology	2.5 - 3L
Basic hygiene practices	Depends on social and cultural norms	2 - 6 L
For cooking	Depends on type of food, social and cultural norms	3 - 6 L
Approximate amount of water required:		7.5 - 15 L

Table 2 Enabled shelters

N°	Shelter	Demand (L)	People	Families	Boys	Girls	Adults
1	Instituto Tecnológico del Putumayo	5970	398	112	84	81	233
2	Shelter A2	5715	381	119	69	51	261
3	Shelter A3	3765	251	88	35	38	178
4	Shelter A4	3030	202	61	34	22	146
5	Shelter A5	3630	242	75	38	53	151
6	Shelter A6	1530	102	26	24	26	52
7	Shelter A7	3675	245	83	38	40	167
8	Shelter A8	3000	200	55	12	19	169
9	Shelter A9	1515	101	27	20	23	58
10	Shelter A10	750	50	10	4	8	38
11	Shelter A11	1650	110	32	10	18	82
12	Shelter A12	2700	180	38	32	30	118
		36930	2462	726	400	409	1653

Table 3 Optimal Solution (summary)

Objective Sense:	Minimization	Algorithm	Branch and Cut
Objective Function:	Total Cost	Solution Status	Optimal
Objective Type:	Lineal	Objective Value	10533
Number of Variables:	1820	Iterations	1466
Number of Constraints:	3516	Pre-solve Time (s)	0.22
Solver:	MILP	Solution Time (s)	0.64

Table 4 Optimal Solution (results)

Enabled supply nodes	12	Distance $\leq 0,1$ km	22.4%
Total Cost (USD)	$10,533	0.1 km $\leq$ Distance $\leq$ 0.25 km	58.8%
Average distance (km)	0.56	0.25 km $\leq$ Distance $\leq$ 0.50 km	6.0%
Weighted average distance (km)	0.50	0.50 km $\leq$ Distance $\leq$ 0.75 km	1.4%
Maximum recorded distance (km)	5.63	0.75 km $\leq$ Distance $\leq$ 1 km	0.0%
		1 km $\leq$ Distance	11.4%

people per water source, which is equivalent to a supply limit of 3750 liters. Thus, people do not have to wait too long to fill their containers [43].

4.1 Overall Performance

First, the problem was solved without varying the established input parameters. Therefore, the model tried to find the optimal values in this first run. Tables 3 and 4 show characteristics of the model, along with the total cost and the calculation of a set of metrics: the average distance, the weighted average distance associated with the distance by the amount of volume supplied, and the maximum distance (representing which shelter is farthest from any supply tank). Also, the percentage demand within different distance intervals is presented by computing what percentage of the demand is supplied within 0.1 km; 0.1 km to 0.25 km; 0.25 km to 0.50 km; 0.50 km to 0.75 km; 0.75 km to 1.0 km; and more than 1 km of distance.

In the conducted operation, the total expenditure amounted to approximately 10,533 USD. This was facilitated by the deployment of 12 tanks, which adequately supplied 12 shelters. The outcomes of the operation were notably positive for several reasons. Firstly, an optimal solution was achieved that fully satisfied the constraints outlined earlier. Additionally, a significant 81.2% of the demand was met from locations within a radius of 0.5 km or less. This proximity in supply not only underscores the efficiency of the operation, but also ensures that the response in humanitarian contexts is swift and impactful.The optimal distribution of the network is presented in Table 5.

4.2 Comparative analysis

Subsequently, several scenarios were tested where the minimum requirements of the weighted average distance were modified. It is essential to mention that there was no other change in the model except for the variation of this value. Remember that according to the guidelines of the Colombian Red Cross Society [43], the distance between any family space and the nearest place of supply should not exceed 500 meters (0.5 km). Therefore, minor modifications to this distance were made to study its variation and the sensitivity of the model.

The analysis of Table 6 showed that the maximum distance to supply a shelter was between 5.63 and 6.28 km, then there was no significant variation in this aspect. In addition, the percentage of demand met that exceeded one kilometer of distance did not substantially participate in the total value in any scenario, concentrating between 11.4% and 13.6%. Correspondingly, no value was recorded greater than 0.75 km and less than 1 km. As expected, the scenario that established 0.49 km as the maximum value of weighted average distance presented the best result, with 86.5% of demand met at a distance less than or equal to 0.25 km. In contrast, the last scenario that set 0.61 km as the maximum value of weighted average distance presented 62.7% in this same distance range. Overall, it is possible to mention that the proposed objectives of designing a model that prioritizes timely attention in humanitarian operations were adequately accomplished.

Regarding the total cost as a function of the maximum values of weighted average distance, it was observed that costs increase as more supply nodes are set up close to the demand nodes, which means that costs will increase by preferring to use several nodes because of the proximity they represent, rather than setting up a single node that supplies several points from a more distant location. The solution to the 0.61 km scenario had the lowest cost (7,756 USD). The 0.49 km scenario had very different closeness values; however, it was much more expensive (12,843 USD). Finally, when comparing the number of supply nodes enabled in each scenario, it should be noted that there is no marked trend in this case. The scenarios of 0.49 km, 0.50 km, and 0.51 km require 11, 12, and 12 facilities, respectively. This value decreases in the 0.53 km, 0.55 km, and 0.57 km scenarios, which require only 9, 8, and 8 facilities, respectively. This is supported by the need to open more supply nodes to meet the distance requirements set out in the model. However, it was observed that these values increased in the last two scenarios, with 18 and 15 facilities, although the total cost decreased (see Table 6).

At first, one might assume that as distance increases, the number of facilities would either increase or decrease in a predictable manner. However, several factors could contribute to the results not fitting this simple trend. The spatial distribution of demand is a significant factor. Depending on where the demand is concentrated, some facilities might be better positioned to serve a larger number of people even if they are farther away. Additionally, there might be capacity constraints on the supply nodes. In scenarios where these nodes have a maximum capacity, it could be more optimal to have multiple facilities closer to the demand than having fewer overburdened facilities. The observation that the number of supply nodes doesn't decrease, even when the weighted average distance is relaxed, is particularly interesting. The

Table 5 Optimal selected locations and covered demand points

Demand node (Shelters)	Demand (Liters of water)	Selected supply node	Flow (Liters of water)	Distance (km)
Shelters A1	5970	Node 08	250	0.16
		Node 43	3750	0.16
		Node 44	1970	0.32
Shelter A2	5715	Node 51	1965	0.13
		Node 53	3750	0.11
Shelter A3	3765	Node 52	3750	0.11
		Node 53	15	0.14
Shelter A4	3030	Node 66	3030	0.16
Shelter A5	3630	Node 70	3630	0.03
Shelter A6	1530	Node 51	35	0.13
		Node 52	760	0.16
		Node 53	735	0.16
Shelter A7	3675	Node 42	3675	0.16
Shelter A8	3000	Node 51	3000	0.02
Shelter A9	1515	Node 66	1515	5.63
Shelter A10	750	Node 06	250	0.32
		Node 53	500	0.64
Shelter A11	1650	Node 63	1650	0.02
Shelter A12	2700	Node 60	2700	2.09

Table 6 Comparing scenario results

	Maximum weighted average distance (km)							
Scenarios:	0.49 km	0.50 km	0.51 km	0.53 km	0.55 km	0.57 km	0.59 km	0.61 km
Enabled supply nodes	11	12	12	9	8	8	18	15
Total Cost (USD)	$12,843	$10,533	$9,551.8	$9,397.2	$8,367.3	$8,367.3	$7,908	$7,756.5
Average distance (km)	0.57	0.56	0.54	0.61	0.62	0.62	0.94	0.95
Weighted average distance (km)	0.490	0.499	0.509	0.514	0.546	0.546	0.586	0.610
Maximum recorded distance (km)	5.63	5.63	5.63	5.63	5.63	5.63	6.28	6.28
Percent satisfied demand within distance brackets:								
Distance $\leq$ 0.1 km	22.4%	22.4%	19.3%	22.4%	22.4%	22.4%	13.9%	13.9%
0.1 km $\leq$ Distance $\leq$ 0.25 km	64.1%	58.8%	58.1%	58.1%	48.2%	48.2%	48.8%	48.8%
0.25 km $\leq$ Distance $\leq$ 0.50 km	2.0%	6.0%	9.8%	6.0%	16.0%	16.0%	22.2%	22.2%
0.50 km $\leq$ Distance $\leq$ 0.75 km	0.0%	1.4%	1.4%	2.0%	2.0%	2.0%	3.5%	1.4%
0.75 km $\leq$ Distance $\leq$ 1 km	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
1 km $\leq$ Distance	11.4%	11.4%	11.4%	11.4%	11.4%	11.4%	11.5%	13.6%

locations and demands could also dictate that even with a more generous distance allowance, more nodes are still necessary to serve efficiently. Lastly, the abrupt change in trend in the last two scenarios needs attention. The significant increase in the number of facilities, coupled with a decrease in total cost, indicates a major shift in the model's optimization. It could be that after a certain distance, the model optimizes to open many more facilities to counteract other rising costs.

5. Conclusion

It was possible to design a model using Mixed Integer Linear Programming (MILP) to solve facility selection problems in humanitarian assistance operations proposing a methodology that considers viable location options resulting from an analysis of an affected area in a disaster situation. Also, not only was the allocation model designed to minimize costs but also constraints were considered focusing on the distance between supply and demand nodes and the percentage of this demand to be satisfied as a priority. Furthermore, the solution scheme to collect distance information using Google Maps and a branch-and-cut algorithm worked synergistically. This branch-and-cut algorithm was coded in Python, and computational experiments showed the procedure was effective. For this model, timely humanitarian attention is the top priority for the location of facilities. The model generally seeks to set up an optimal network based on the shortest response time according to factors such as the maximum allowable average distance, the minimum percentage of demand that must be met within a minimum distance value, and the capacity limit in facilities. Thus, considering that the research focused on a strategic design to support humanitarian logistics operations, the model uses distance as the most appropriate variable to achieve the proposed objectives.

In the case study, several scenarios were tested where the maximum weighted average distance was modified, and the percentage of the demand satisfied within 0.1 km; 0.1 km to 0.25 km; 0.25 km to 0.50 km; 0.50 km to 0.75 km; 0.75 km to 1.0 km; and more than 1 km of distance, was calculated. Overall, the results of the validation presented positive benefits. This is based on the proximity between a supply node, and a demand node is one of the best ways to ensure rapid response time and comprehensive care. First, the most significant percentage of satisfied demand was generated when locating the supply nodes at a distance greater than 0.1 km and less than or equal to 0.25 km, reaching values between 48.2% and 64.1% in the different scenarios analyzed. Additionally, the following most significant percentages were recorded when locating supply nodes at a distance of fewer than 0.1 km. Thus, the rates of demand satisfied at this distance reached values between 13.9% and 22.4% in the different scenarios. In contrast, the lowest percentages of satisfied demand were found by locating supply nodes at distances greater than 0.75 km away. Finally, regarding the total cost, we noted that the total cost increased as the maximum weighted average distance and the maximum recorded distance were reduced. This is important because the results showed that the model allows allocating humanitarian funding in proportion to costs and aligning the constraints according to local priorities in different contexts.

In addition to these inferences, depending on the institutions or bodies involved, it is possible to present other ways of using this model in practice. For example, regarding the case study, it would be possible to go back and establish that 85% of the demand should not be within 0.5 km of the supply nodes; perhaps another value could be set. As the complexity of the problem increases, it is possible to alter these numbers and analyze how much these changes cost and the level of humanitarian attention. In the case study, the solution of having 12 supply nodes within the established distance conditions can be slightly more expensive compared to other scenarios. Indeed, implementing such an optimal solution at a lower cost may not be entirely appropriate. Additional constraints may also be imposed, which is an advantage of the model, as it can be adapted to many hypothetical scenarios.

Notably, the model helps analyze that the variable cost of supply will decrease if the supply nodes are closer to the demand nodes. This is logical, as aid agencies commonly open response facilities closer to affected areas. In this way, they can reduce costs and, in fact, also improve their response time. But, as you have more of these facilities, the cost of supplying the points of origin that supply these response facilities increases. One of the most significant considerations is the cost associated with establishing and maintaining multiple facilities. These expenses include land acquisition or rent, infrastructure setup, facility upkeep, utilities, and the establishment of essential communication lines. Labor costs also rise with the addition of more facilities. As the number of nodes in the supply chain increases, so does the complexity of the entire operation. While managing a single, centralized facility might be straightforward, adding more facilities requires advanced management systems and potentially the recruitment of specialized staff.

Another crucial factor is the impact on the supply chain's points of origin when stocking an increasing number of response facilities. As the number of facilities grows, ensuring consistent stock levels across all locations becomes a significant logistical challenge. This often requires smaller, more frequent shipments, leading to higher per-unit costs compared to larger, consolidated shipments. Furthermore, economies of scale may be lost when operations are spread across multiple smaller facilities rather than centralized in a single, expansive one. This could increase overall operational costs, particularly in terms of procurement and distribution efficiency. Future research should further investigate these dynamics, especially in more complex distribution networks where points of origin, as well as supply and demand nodes, are considered. Additionally, while this study focused on the supply of a single good, future research should address the simultaneous demand for multiple products or services, which may reveal different operational challenges. Analyzing the model's approach to fairness is also crucial, as the current measure may allow some demand points to be poorly served, especially at greater distances (as shown in Table 6). Exploring alternative fairness measures, such as those suggested in prior revisions, could provide more equitable outcomes. Moreover, a deeper analysis is needed to explain the increase in the number of tanks when the average distance constraint is relaxed. While the result is described, understanding the underlying reason could offer valuable insights into the model's behavior. Considering these aspects and incorporating stochastic demand and additional cost factors into the model would enhance its practical application and provide a more comprehensive analysis.

6. Declaration of competing interest

We declare that we have no significant competing interests, including financial or non-financial, professional, or personal interests interfering with the complete and objective presentation of the work described in this manuscript.

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8. Author contributions

All authors contributed to the design of the study. K.P. was responsible for google API and python integration, and data analysis; D.G was responsible for data extraction and preparation; C.B. provided important insight and supervised the analysis.

9. Data availability statement

The authors confirm that the data supporting the findings of this study are available within the article.

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