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Facility location optimization model for emergency humanitarian logistics

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ABSTRACT

Since the 1950s, the number of natural and man-made disasters has increased exponentially and the facility location problem has become the preferred approach for dealing with emergency humanitarian logistical problems. To deal with this challenge, an exact algorithm and a heuristic algorithm have been combined as the main approach to solving this problem. Owing to the importance that an exact algorithm holds with regard to enhancing emergency humanitarian logistical facility location problems, this paper aims to conduct a survey on the facility location problems that are related to emergency humanitarian logistics based on both data modeling types and problem types and to examine the pre- and post-disaster situations with respect to facility location, such as the location of distribution centers, warehouses, shelters, debris removal sites and medical centers. The survey will examine the four main problems highlighted in the literature review: deterministic facility location problems, dynamic facility location problems, stochastic facility location problems, and robust facility location problems. For each problem, facility location type, data modeling type, disaster type, decisions, objectives, constraints, and solution methods will be evaluated and real-world applications and case studies will then be presented. Finally, research gaps will be identified and be addressed in further research studies to develop more effective disaster relief operations.

1. Introduction

Since the 1950s, both the number and magnitude of disasters have been continuously increasing, with the number of affected people having increased in proportion (about 235 million people per annum on average since the 1990s). In 2014, 324 natural disasters were recorded, with economic damages estimated to be US$ 99.2 billion [1]. According to the International Disaster Database, Asia and the Americas have been the continents most affected by disasters such as floods, earthquakes, storms, and landslides [2]. Disaster is any occurrence that causes damage, destruction, ecological disruption, loss of human life, human suffering, or the deterioration of health and health services on a scale sufficient to warrant an extraordinary response from outside the affected community or area [3]. Such situations may include natural disasters such as drought, earthquakes, floods or storms, and epidemics, or man-made disruptions such as nuclear or chemical explosions [4–6]. According to an increasing number of disasters, many academicians have paid a great deal of attention to “Disaster Management (DM)” for the purposes of helping at-risk persons to avoid or recover from the effects of a disaster [7]. DM activities are conducted across four consecutive stages: mitigation, preparation, response, and recovery. Coppola [8] defined mitigation as reducing the probability of disaster occurrence and decreasing the degree of the hazard; furthermore, he defined preparation as planning activities to be conducted following disaster occurrence that increase chances of survival and minimize financial and other losses. Response was defined as reducing the impact of disasters during their aftermath to prevent additional suffering, financial loss, or other losses. Finally, recovery was defined as restoring the affected area back to a normal situation after the disaster. Disaster situations can be divided into two stages: a pre-disaster or proactive (mitigation and preparation) stage and a post-disaster or reactive (response and recovery) stage. Humanitarian logistics is one of the operations that are involved in following the three stages of the DM activities: preparation, response, and recovery. Humanitarian logistics (HL) is the process of evacuating people from disaster stricken areas to safe places and planning, implementing and controlling the efficient, cost effective flow and storage of goods and materials, while collecting information from the point of origin to the point of consumption for the purposes of relieving the suffering of vulnerable people [9,10].

Because of the increasing severity of recent disasters, research has paid more attention to DM in dealing with humanitarian logistics, with optimization, decision making, and simulation being proposed as the main approaches. Disaster research has tended to employ modeling and optimization to solve emergency humanitarian logistics problems. Labib and Read [11] proposed a hybrid model for learning from

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failures that examined the multifaceted nature of disaster research and the hybrid modeling approaches within this domain and tested a reliability framework and multiple-criteria decision analysis techniques on the 2005 Hurricane Katrina disaster. Verma and Gaukler [12] proposed a deterministic and stochastic model for the pre-positioning of disaster response facilities at safe locations and demonstrated its usefulness with a case study on a Californian earthquake. Scott [13], Kongsomsaksakul et al. [14], Mete and Zabinsky [15], Salman and Yücel [16], Bayram et al. [17], Marcelin et al. [18] and Jabbarzadeh et al. [19] also studied emergency humanitarian logistics' facility location problems.

Recent research has also included surveys on effective DM. Altay and Green [20] reviewed the disaster operation management (DOM) by which this article has employed to focus on the life-cycle phase. Galindo and Batt [21] then extended the article of Altay and Green [20] with new advancements and presented an original evaluation based on the most common assumptions in OR/MS research in DOM. Caunhye et al. [22] reviewed an optimization model for emergency logistics that was classified into three main categories: (1) facility location, (2) relief distribution and casualty transportation and (3) other operations. Each piece of published literature has been analyzed and structured based on relevant goals, constraints, data modeling types, and decisions. Safeer et al. [23] surveyed the modeling parameters for the objective functions and constraints associated with humanitarian logistics distribution that were classified into two groups: casualty transportation and evacuation and relief distribution. Özdamar and Ertem [2] presented a survey that focused on the response and recovery planning phases of the disaster life-cycle. This article examined the vehicle/network representation structures and their functionally. The review structure is based on objectives, constraints, structures of available mathematical models and solution methods. Furthermore, information systems in humanitarian logistics have also been presented. Anaya-Arenas et al. [24] proposed a systematic review of contributions related to the relief distribution networks in response to disasters by categorizing them according to location and network design, transportation, location and transportation, and other important topics. Zheng et al. [25] studied research advances in evolutionary algorithms for disaster relief operations. The research study was classified into five categories (General transportation planning problems, Facility location problems, Routing problems, Roadway repair problems, and Integrated problems) and represents a summary of related papers on evolutionary algorithms for solving specific problems. Habib et al. [9] reviewed the mathematical model in humanitarian logistics by covering all the phases of a disaster, and provided a summary of modeling techniques and solution methodologies.

Facility location models involving the location and selection of distribution centers, warehouses, shelters, medical centers, and other locations are an important approach in DM. Facility location modeling is an approach of strategic planning design for pre- and post-disaster operations and is important for effective and efficient DM planning. In recent research, as has been noted above, emergency humanitarian logistics optimization models have been emphasized as an important element of disaster facility location problems. To overcome these challenges, two approaches can be used to solve this problem; (1) a heuristic algorithm and (2) an exact algorithm. Normally, the emergency humanitarian logistics' facility location problems are NP-hard and most research studies have usually addressed this by using a heuristic algorithm because it requires less time to employ and can solve complicated problems, but the results of this approach are of poor quality when compared with the exact algorithm. Although the first approach can overcome the second approach, the second approach is necessary because it can be used to check the heuristic algorithm, and, moreover, in some real cases, an exact algorithm can also be used to solve the problem. Hence, the use of an exact algorithm is important and unavoidable.

Following on from the previous research studies, a lack of any literature review that has been based on data modeling types and problem types as a basic element of the exact algorithm employed to enhance or develop the emergency humanitarian logistics' facility location problems has been observed. Therefore, we aim to propose a survey of research work on the emergency humanitarian logistical facility location optimization model based on data modeling types and problem types. This will be done not only to conduct this research study, but also to simultaneously present the basic mathematical models associated with this discipline to other individuals to whom they may be of interest. Moreover, each piece of published literature has been analyzed and structured based on the relevant objectives, conditions, disaster types, facility location types, data modeling types, applications, solution methods, categories, and case studies. Finally, any research gaps and future research possibilities will then be identified.

The remainder of this paper is organized as follows: Section 2 presents the scope of the literature review. In Section 3, facility location models are classified into four categories: deterministic, stochastic, dynamic, and robust. Section 4 presents an application and case study. In Section 5 future research that illuminates the research gaps is presented along with a framework analysis. Finally, a conclusion is given in Section 6.

2. Scope of literature review

In this paper, emergency humanitarian logistics' facility location optimization models are examined. To develop the literature database, emergency humanitarian logistics' facility location optimization models were searched for in journals, books, and conference proceedings and then classified according to the facility location problem and optimization method categories: deterministic, stochastic, dynamic, and robust. Finally, applications and case studies were reviewed. As the objective of this paper focuses on the exact algorithm or mathematical modeling techniques in emergency humanitarian logistics' facility location optimization problems, only those papers are included which proposed any type of exact algorithm of mathematical technique. Journal search engines such as the transport research board publication database, the IEEE database standard, Science direct, and the Springer journal database were interrogated using "disaster," "facility location," "humanitarian logistics," "optimization model," and "emergency" as the key search strings. Further, the references in each paper, including books and conference proceedings, were scrutinized to reveal any additional relevant papers. Most articles identified in the literature search came from a range of journals: Social-Economic Planning Science, European Journal of Operations Research, Computers & Industrial Engineering, Applied Soft Computing, Expert Systems with Applications, Transportation Research Part B and Part E, Computer & Operation Research, Int. J. Production Economics, Journal of Cleaner Production, the Journal of Risk Research, International Journal of Disaster Risk Reduction and the Journal of the Eastern Asia Society for Transportation Studies.

3. Literature breakdown and analysis

From a general viewpoint, Arabani and Farahani [26] found that facility location problems could be defined across the two elements of space and time, in which space was "a planning area where facilities are located," and time was "the time the location is identified" (developing a new facility or revising an existing facility). Essentially, however, space and time should be analyzed concurrently. Emergency humanitarian logistics' facility location problems included the identification of locations such as fire stations, emergency shelters, distribution centers, warehouses, debris removal sites and medical centers. Potential facilities were identified based on the geography of the respective areas and divided into two: continuing facility location problems (facilities located in the planning areas) and discrete facility location problems (facilities located in candidate locations) [26]. Most facility emergency humanitarian logistics' location optimization models were combined with other logistics problems such as stock pre-positioning, relief distribution, casualty transportation, evacuation planning, resource allocation, commodity flows, and other operations [22]. Facility location optimization models are usually based on mixed integer linear programming (MILP) with binary location variables. Most reviewed models were single level and the least reviewed models were bilevel. Emergency humanitarian logistics' facility location optimization models varied depending on (1) facility location planning objectives, (2) the situation (certainty, uncertainty, and data risk), (3) duration (short term or long term), (4) the number of locations, (5) the service pattern, and (6) the commodity types required.

From the surveyed models, the factors that affected the mathematical model and solution methods were first examined. To expedite this process, the models were separated based on the data modeling types and the problem types: deterministic facility location problems, stochastic facility location problems, dynamic facility location problems, and robust facility location problems.

3.1. Deterministic facility location problems

Deterministic facility location problems are used to select or locate shelters, distribution centers, warehouses, and medical centers by determining the place and input parameters such as the possible number of individuals affected, the location, shelter capacity, transportation costs, and fixed cost, with all parameters being known and constant over time. This problem formed the basis for the dynamic, stochastic, and robust models. Deterministic facility location problems can be separated into four different types.

3.1.1. Minisum facility location problem

This problem selects or locates P facilities (the maximal number of facilities that can be placed) and seeks to minimize the total transport distance (including transport time or transport cost) between the demand points and selected facilities. The formulation for this mathematical model is as follows [27,28]:

Indices and Index sets
I Set of demand nodes; $i \epsilon I$
J Set of facility sites; $j \epsilon J$
Decision variables:
X_j=1 if a facility is located at eligible site j, and 0 otherwise.
Y_{ij}=1 if facility j services demand point i, and 0 otherwise.
Input parameters:
d_{ij} the distance between demand point i and candidate facility j
cap_j the capacity of facility j
P the maximal number of facilities that can be placed
w_i the weight associated to each demand point (demand or number of customers/people)

$$\text{Minimize} \quad \sum_i \sum_j w_i d_{ij} Y_{ij} \tag{1}$$

$$\text{Subject to} \quad \sum_j X_j = P \tag{2}$$

$$\sum_j Y_{ij} = 1 \qquad \forall\, i \tag{3}$$

$$\sum_i w_i Y_{ij} \le cap_j X_j \qquad \forall\, j \tag{4}$$

$$X_j,\ Y_{ij} \in \{0,\ 1\} \qquad \forall\, i, \forall\, j \tag{5}$$

The objective function (Eq. (1)) minimizes the total distance between the demand points and candidate facilities. Eq. (2) states that there are P facilities to be located at site j. Eq. (3) ensures that each demand point i is assigned to facility j. Eq. (4) allows assignment only to sites where facilities are located and ensures that the capacity at each located facility is not exceeded. Eq. (5) sets binary conditions for the model variables. If the capacity at facility j is unlimited, Eq. (4) can be replaced with Eq. (6).

$$Y_{ij} \le X_j \qquad \forall\, i, \forall\, j \tag{6}$$

The distance function is generally identified as rectilinear, Euclidean, or squared Euclidean. However, emergency humanitarian logistics problems consider distance to be the actual distance between the demand points and the facilities. Therefore, d_{ij} is defined as an actual distance and a constant (no distance function). This problem, known as the P-median, was developed by Hakimi [27]. Since that time, it has been widely applied to emergency facility location problems. McCall [29] developed a mathematical model with the prepositioning of assistance pack-up kids during disasters that aims to minimize any associated victim nautical miles and shortages. Verma and Gaukler [12] proposed a deterministic model and a stochastic model that explicitly considered the impact a disaster could have on disaster response facilities and population centers in the surrounding areas. The deterministic model estimated the expected transportation costs over all disaster scenarios and assumed that the costs were linear and depended on the distance to be traveled and the supplies to be shipped. The proposed model was tested using data from a Californian earthquake. According to the relief warehouse, Horner and Downs [30] proposed a warehouse location model for locating relief goods for the affected zones that minimize the cost of the distribution of those relief goods. Other studies focusing on the related relief warehouses had been proposed by Lin et al. [31] and Hong et al. [32]. In order to formulate a multi-objective model or a multi-criteria model, Abounacer et al. [33] proposed a multi-objective location-transportation model for disaster response with the aim of determining the number, position, and mission of the required humanitarian aid distribution centers (HADC) within a disaster region. The identified objectives were to minimize total transportation duration from the distribution centers to the demand points, minimize the number of agents (first-aiders) needed to open and operate the selected distribution centers, and minimize the non-covered demand for all demand points within the affected area. Barzinpour and Esmaeili [34] proposed a multi-objective relief chain location distribution model for urban disaster management. This model was developed for the preparation phase, which considers both humanitarian and cost-based objectives in a goal-programming approach. Similarly, Ransikarbum and Mason [35] presented multiple objectives in an integrated network optimization model developed for making strategic decisions in the supply distribution and network restoration phases during post-disaster management. The proposed model determined fairness/equity based solutions under various constraints of capacity, resource limitations and budget. The objective functions consisted of maximizing equity or fairness, minimizing total unsatisfied demand, and minimizing total network costs. In multi-level optimization, Kongsomsaksakul et al. [14] presented an optimal shelter location model for flood evacuation planning using bilevel programming to minimize total evacuation time (the upper-level problem) and to choose destinations (shelter), and evacuation routes (the lower-level problem). The combined distribution and assignment (CDA) model was adapted to a lower-level problem, with the bilevel programming being solved with a genetic algorithm. Marcelin et al. [18] proposed a p-median based modeling framework linked to a geographic information system for providing people with hurricane disaster relief that aimed to minimize the total demand weighted travel costs between each neighborhood and the nearest relief facility. Moreover, Irohara et al. [36] developed a tri-level programming model for disaster preparedness planning. The facility location and inventory pre-positioning decisions were proposed at the top level of the model while the second level determined the damage inflicted by the disaster and the third level considered response and recovery decisions, respectively. The proposed model was validated by a case study on hurricane preparedness in the southeastern USA by using a dual-ascent approach.

3.1.2. Covering problem

The covering problem has been applied to wide range of emergency humanitarian logistics' facility location problems [37]. The objective of the covering problem is to cover the demand points within distance or time limits. Normally, the use of this problem is suitable for hospitals, fire stations and shelter sites.

3.1.2.1. Set covering problem. The set covering problem deals with site selection and aims to minimize the total number of facilities or the total fixed cost of open facilities by covering all demand points. The formulation for the set covering problem is as follows [37]:

Input parameters (addition):

c_j fixed cost of facility j
L_i distance limit within which a facility can service demand point i
N_i the set of eligible facility sites located within the distance limit and that are able to service demand point i ($N_i = \{j|d_{ij} \le L_i\}$)

$$\text{Minimize} \quad \sum_j c_j X_j \tag{7}$$

$$\text{Subject to} \quad \sum_{j \in N_i} X_j \ge 1 \quad \forall\, i \tag{8}$$

$$X_j \in \{0, 1\} \qquad \forall\, j. \tag{9}$$

Eq. (7) is the objective for the set covering problem, which is to minimize the total fixed cost of opening facilities or the total number of facilities. Eq. (8) ensures that all demand points are assigned to at least one selected facility within the distance limit. Eq. (9) defines the binary variables in the model.

Toregas et al. [37] first proposed the set covering problem for emergency humanitarian logistics with the aim of minimizing the total number of facilities needed to cover all demand points. Dekle et al. [38] and Ablanedo- Rosas et al. [39] used a set covering problem for an emergency medical center location problem. Hale and Moberg [40] formulated a deterministic set covering problem and a four-step secure site decision process, in which the proposed model secured the site locations presented in step four by identifying the minimum number and possible locations for off-site storage facilities. Similarly, Dekle et al. [38] proposed a set-covering model to cover the demands in a disaster target zone that aims to locate the disaster recovery centers in a pre-disaster context. Hu et al. [41] presented a mathematical model to enhance earthquake shelter location selection along with a process of district-planning for service areas that aimed to minimize the total travel evacuation distance and total costs. The second objective was formulated from the set-covering problem. Finally, they proposed a non-dominated sorting genetic algorithm to be applied to the proposed mathematical model. Aksen and Aras [42] proposed a bilevel fixed-charge location problem, in which the defender (upper level) sought to locate and operate a set of facilities and the attacker (lower level) aimed to maximize the accessibility costs both capacity expansion costs and post-attract demand-weight travelling costs. Abounacer et al. [33] studied a multi-objective emergency location-transportation problem that had three main objectives, one of which was a set covering problem that sought to minimize the total number of agents needed to operate the open HADC.

3.1.2.2. Maximal covering problem. The maximal covering problem designates site selection as P facilities and focuses on maximizing the total number of demand points covered within the distance limitations. The formulation is as follows [43]:

Decision variables (addition):

Z_i=1 if demand point i is covered by a facility within R distance, and 0 otherwise. Note that R indicates distance limit.

$$\text{Maximize} \quad \sum_i w_i Z_i \tag{10}$$

$$\text{Subject to} \quad \sum_{j \in N_i} X_j \ge Z_i \quad \forall\, i \tag{11}$$

$$\sum_{j \in N_i} X_j = P \tag{12}$$

$$X_j, Z_i \in \{0, 1\} \qquad \forall\, i, \forall\, j. \tag{13}$$

The objective is to maximize the total number of demand points covered within the distance limitations (Eq. (10)). Eq. (11) ensures that demand point i is assigned to a selected facility, and also ensures that all facilities assigned to demand point i are located within the given distance limit. Eq. (12) states that there are P facilities to be located in the eligible facility location. Eq. (13) defines the binary variables in the model.

Both the set covering problem and the maximal covering problem are integer linear programming problems. Church and Velle [43] developed constraint (10), which was reformulated as the following Eq. (14), in which the objective function aimed to minimize the number of uncovered demand points within a maximal service distance. Eqs. (14) and (15) were derived by substituting $\overline{Z}_i = 1 - Z_i$ and also by following Eqs. (16) and (17) that represent the same constraints as explained for Eqs. (12) and (13), respectively. The new formulation was utilized in solving this problem using linear programming (LP).

Decision variables (Addition):

$\overline{Z}_i$=1 if demand point i is not covered by a facility within R distance, and 0 otherwise.

$$\text{Minimize} \quad \sum_i w_i \overline{Z}_i \tag{14}$$

$$\text{Subject to} \quad \sum_{j \in N_i} X_j + \overline{Z}_i \ge 1 \qquad \forall\, i \tag{15}$$

$$\sum_{j \in N_i} X_j = P \tag{16}$$

$$X_j, Z_i \in \{0, 1\} \quad \forall\, i, \quad \forall\, j \tag{17}$$

Jia et al. [44] proposed a model and solution approaches for determining the facility locations of medical supplies in response to large-scale emergencies. The problem was formulated as a maximal covering problem with multiple facility quality-of-coverage and quantity-of-coverage requirements. The objective was to maximize demand by ensuring a sufficient quantity of facilities at the stated quality level. A genetic algorithm, a located-allocated heuristic, and a Lagrangian relaxation heuristic were then developed to solve the problem. Murali et al. [45] developed a facility location problem to determine the points in a large city at which medication should be distributed in times of epidemic. Variations in the maximal covering problem were used to maximize the number of people receiving medication. The proposed model selected opened facilities and supplies, with demand being assigned to each location. Santos et al. [46] proposed a maximal covering problem with Lagrange optimization to optimize the number of strategic locations by relaxing constraints to obtain optimal demand coverage for each facility location. The objective was to optimize the number of demand points covered by the optimal number of facility locations. The problem was solved using a locate-allocate heuristic and a large-scale hypothetical anthrax attack emergency in Los Angeles

County was used as a demonstration case study. Abounacer et al. [33] proposed a maximal covering problem with one of the objectives being to minimize the number of uncovered demands. Chanta and Sangsawang [47] studied an optimization model to find appropriate locations for temporary shelters in flood disasters, in which a bi-objective programming model was formulated to minimize total distance and maximize the number of people covered in the affected zones.

3.1.3. Minimax facility location problem

The minimax facility location problem, also known as the “P-center” problem, attempts to minimize the worst system performance within P facilities. The P-center focuses on a demand point being served by the nearest facility and how all demand points can be covered. The P-center problem can be applied to emergency humanitarian logistics' facility location planning for hospitals, fire stations, and other public facilities. The formulation for this problem is as follows [27]:

Decision variables (addition):

D the maximum distance between a selected location and a demand point

$$\text{Minimize} \quad D \tag{18}$$

$$\text{Subject to} \quad \sum_j X_j = P \tag{19}$$

$$\sum_j Y_{ij} = 1 \qquad \forall\, i \tag{20}$$

$$Y_{ij} \le X_j \qquad \forall\, i, \forall\, j \tag{21}$$

$$D \ge \sum_j d_{ij} Y_{ij} \quad \forall\, i \tag{22}$$

$$X_j,\, Y_{ij} \in \{0, 1\} \quad \forall\, i, \forall\, j. \tag{23}$$

The objective function is shown in Eq. (18), which seeks to minimize the maximum distance between a selected location and a demand point. Eqs. (19)–(21) are the same constraints as explained for Eqs. (2), (3), and (6). Eq. (22) forces D to be equal to the maximum distance, and Eq. (23) defines the binary variables in the model.

Talwar [48] studied the location of rescue helicopters in South Tyrol, Italy and utilized the P-center to optimize the locations for three rescue helicopters to serve the growing demand arising from tourist activity accidents. One of the models in this research sought to minimize the maximum or worst response times and heuristics were applied to test this model. Ye et al. [49] presented an emergency warehouse location problem model for a Chinese national emergency warehouse location problem using the P-center problem. The constraints population distribution, economic condition, transportation, and multi-coverage for some vital areas were included in the proposed model and a variable neighborhood search (VNS)-based heuristic algorithm was developed to solve the proposed model.

Normally, this problem is used as a risk guarantee for the longest distance between a demand point and a selected facility. The minimax facility location problem is quite different from the minisum facility location problem and the covering problem. The minisum facility location problem considers the locations of general facilities such as distribution centers and inventory, and the covering problem is similar to the minimax facility location problem as it concentrates on optimizing overall system performance within particular distance or time limits. However, the minimax facility location problem attempts to minimize the worst performance of the system by minimizing the longest distance or time between demand points and the selected facility within P facilities.

3.1.4. Obnoxious facility location problem

In contrast to Sections 3.1.1–3.1.3, which focused on optimizing the distance between a demand point and a selected location (the nearer the better), the obnoxious facility location problem seeks to have demand points far from facilities but try to have it as close as possible such as chemical plants, nuclear reactors, garbage dumps, or waste-water treatment plants [36]. The objective function, therefore, is opposite to those outlined in Sections 3.1.1–3.1.3, as follows:

- Maxisum facility location problems aim to select facility locations and maximize the total distance between a demand point and a selected location [50].
- Minimum covering problems aim to select facility locations and minimize the number of demand points covered [51].
- Maximin facility location problems aim to select facility locations and maximize the minimum distance between a demand point and a selected location [52].

In the field of emergency humanitarian logistics, the use of this problem represents an opportunity to overcome this challenge. According to the recovery stage in the post-disaster phase, some facility locations need to be located far from the affected area even though it is advantageous to have them as close as possible to that area. These facility locations can include those associated with debris (waste) management or recycling sites. The advantage of accounting for this problem can help in safely overseeing the post-disaster phase so as to avoid causing harm to the health of human beings and to avoid polluting the environment after the actual occurrence of the disaster. A number of obnoxious facility location problems have been studied to improve emergency humanitarian logistics. Fetter and Rakes [53] developed a facility location model to help locate temporary disposal and storage reduction (TDSR) facilities in support of disaster debris cleanup operations. The proposed model aims to minimize the total fixed and variable costs of debris collection that are involved with the opening and closing costs of the TDSRs, the fixed costs of making RSR (reduction, separation, and recycling) technology available at the TDSR locations, managing the operation costs of removing debris, along with the variable costs of applying RSR technology, and the revenue received from selling recycled materials. Hu and Sheu [54] proposed a reverse logistics system for post-disaster debris management so as to minimize economic, risk-induced and psychological costs. The multi-objective linear programming system was formulated and applied in Wenchuan Country, China. Other post-disaster debris operations have been proposed by Lorca et al. [55], Pramudita et al. [56], and Sahin et al. [57].

3.2. Dynamic facility location problem

The first discussion examined deterministic emergency humanitarian logistics' facility location problems by deciding on a period of time (single-period model) in which the parameters were constant. However, generally, in real-world problems, the facility location problem is a decision that has long-term effects, so the parameters of the system such as the demand points, operating costs, distribution costs, and environmental factors may vary over time and facility additions can occur at different times (multi-period model). That is, not only where but also when to build a facility becomes a critical decision. Ballou [58] first proposed the dynamic facility location problem, after which Scott [13] proposed an efficient approach using dynamic programming.

There are two main factors in the dynamic facility location problem that affect the decision to select an appropriate location for the facility: cost and time. Cost is a trade-off between incurring expenditure to establish the new facility or modify a current facility, the opening and closing times for which are determined over the course of the planning time horizon [25]. This deterministic model can be reformulated as a dynamic deterministic model, in which there are T time periods ($t \in T$). The model formulation is as follows [59]:

$$\text{Minimize} \quad \sum_{t=1}^{T} \sum_{j=1}^{m_T} f_{ij}(x_t, y_t) + \sum_{t=2}^{T} r_t z_t \tag{24}$$

$$\text{Subject to} \quad z_t = \begin{cases} 0 \text{ if } d_{t-1,t} = 0, & (\text{for } t = 2, \dots, T) \\ 1 \text{ else if } d_{t-1,t} > 0 \end{cases} \tag{25}$$

In Eq. (24), there are m_t candidate destinations (candidate sites) in period t. The first term in Eq. (24) is the transport cost between a facility located at (x_t, y_t) and destination j. Note that (x_t, y_t) is coordinates at period t. The second term in Eq. (24) is the relocation cost, r_t which defines the relocation cost in period t, with $d_{t-1,t}$ is the distance by which the facility is relocated in period t. Eq. (25) is affected by this distance.

Moeini et al. [60] proposed a dynamic facility location model for locating and relocating a fleet of ambulances. The proposed model controlled the movements and locations of ambulances to provide better coverage of the demand points. The objective focused on minimizing both the demand points covered and the costs related to relocating the vehicle. Afshar and Haghani [61] presented a mathematical model that controlled the flow of several relief commodities from the source to the receiver by considering vehicle routing, pick-up or delivery schedules, the optimal location for several layers of temporary facilities, several capacity constraints for each facility, and the transportation system. Similarly, Khayal et al. [62] proposed a network flow model for the selection of temporary distribution facilities and the allocation of resources for emergency response planning. The objective function sought to minimize the logistics and deprivation costs of the relief distribution and consisted of the fixed costs, transportation and distribution costs, and the delay penalty costs. A case study was conducted using sample data from 15 cities in South Carolina, USA.

3.3. Stochastic facility location problem

For optimization under uncertainty, there have been two approaches, one of which is stochastic optimization, in which the uncertain parameters are allocated to a probability distribution. The stochastic facility location problem has been examined across a wide range of professional and academic fields, as it can respond well to real-world problems. The stochastic model can develop from deterministic model, in which the uncertain parameters can add in objective or constrain. For example, Salman and Yücel [16] formulated a stochastic integer programming model that determined the location of emergency response facilities (ERFs), with an objective to maximize the expected total demand within a predetermined distance parameter over all possible networks (Eq. (26)). The proposed model is as follows:

Indices and index sets (Addition);

S Set of periods; $s \in S$

Decision variables (Addition):

O_{ij}^s=1 if demand point i is covered by a facility at location j in scenario s, and 0 otherwise.

E_i^s=1 if demand point i is covered in scenario s, and 0 otherwise.

Input parameters (Addition):

$P(s)$ the occurrence probability of scenario s

g_{ij}^s=1 if demand point i is covered by a facility at location j in scenario s, and 0 otherwise.

$$\text{Maximize} \quad \sum_i \sum_s P(s) w_i E_i^s \tag{26}$$

$$\text{Subject to} \quad \sum_j X_j \le P \tag{27}$$

$$E_i^s \le \sum_j O_{ij}^s \qquad \forall\, i, \forall\, s \tag{28}$$

$$O_{ij}^s \le g_{ij}^s X_j \qquad \forall\, i, \forall\, j, \forall\, s \tag{29}$$

$$O_{ij}^s, X_j, E_i^s \in \{0, 1\} \qquad \forall\, i, \forall\, j, \forall\, s \tag{30}$$

Eq. (27) allows at most P open ERFs. Eq. (28) enforces that demand point i is covered in scenario s only if it is covered by at least one open facility. Eq. (29) ensures that demand point i is covered by facility j in scenario s only if there is a surviving path shorter than the coverage distance limit R between demand point i and facility j in scenario s. Not that R indicates distance limit. Eq. (30) defines the binary variables in the model. The proposed model is a maximal covering problem. A Tabu search algorithm was proposed to solve Istanbul earthquake preparedness problems.

Similarly, Akgün et al. [7] studied DM risk for a demand point, so the proposed model sought to minimize the risks and select locations such that a reliable facility network to support the demand points could be constructed. The risk at a demand point was determined as the multiplication of the (probability of the) threat, the vulnerability of the demand point (the probability that it is not supported by the facilities), and the consequence (value or possible loss at the demand point due to threat). Balcik and Beamon [63] proposed a maximal covering location model that integrates the facility location problem and the inventory decision problem for the humanitarian relief chain under uncertain scenarios. The proposed model considers multiple item types and captures budgetary constraints along with capacity constraints. Another maximal covering problem has been proposed by Murali et al. [45] that presented a maximal covering location problem with chance constraints to determine the points in a large city where medication should be distributed to the population, with the aim of maximizing the number of people serviced under both uncertain and limited time/resource conditions, and a hypothetical anthrax attack in Los Angeles County was solved using a locate-allocate heuristic. Duran [64] developed an inventory location model, which determined a set of typical demand instances given a specified upfront inventory and finds the configuration of the supply network that minimizes the average response time over all the demand instances. This article obtained the typical demand instances from historical data. The supply network consisted of the number and location of the warehouses and the quantity and type of items held in inventory in each warehouse. Klibi et al. [65] studied the strategic problem of designing an emergency supply network to support disaster relief over a planning horizon. The proposed approach involved three phases: scenario generation, design generation, and design evaluation; a two-stage stochastic programming formulation was proposed using a sample average approximation method to solve the problem. The approach was assessed using a case study inspired from real-world data provided by the Northern Carolina emergency management division. Similarly, Rawls and Turnquist [66] proposed an emergency response-planning tool that considers the location and quantities of various types of emergency supplies to be pre-positioned under uncertain conditions. The proposed mathematical model provides an emergency response pre-positioning strategy for hurricanes or other threats that determines the uncertainty of demand and any uncertainties with regard to transportation network availability after an event has occurred. This study was tested using a real case scenario in the Gulf Coast area of the US by using the Lagrangian L-shaped method to address the problem. Other stochastic programming techniques involved with emergency humanitarian logistics' facility location problems were proposed by Manopiniwes and Irohara [67], Psaraftis et al. [68], Wilhelm and Srinivasa [69], Chang et al. [70], Rawls and Turnquist [71] and Mete and Zabinsky [72].

3.4. Robust facility location problem

The second of the two optimization approaches under uncertainty is robust optimization. For this problem, the probabilities are unknown, so the uncertain parameters are identified using discrete scenarios or continuous ranges. Robust optimization differs from stochastic optimization and sensitivity analysis in that robust optimization includes slack in the solution [73]. A few papers have addressed uncertainty parameters in the objective function, which is also known as a "penalty function," under varying scenarios [22]. Bertsimas et al. [74] addressed the general robust optimization as follows:

$$\text{Minimize} \quad f_i(x) \tag{31}$$

$$\text{Subject to} \quad f_i(x, u_i) < = 0, \quad \forall\, u_i \in U_i,\ i = 1, \dots, m$$
$$x \in R^n, \ \ U_i \subseteq R^k \tag{32}$$

where x is a vector for the decision variables, f_0 and f_i are as before, u_i indicates uncertain parameters (disturbance parameters), and U_i indicates the uncertainty sets, which, for this model, will always be closed. The objective of Eq. (31) is to determine minimum cost solutions x^* from all the feasible solutions for all realizations of the disturbances u_i within U_i. If the set of U_i is a singleton, the corresponding constraint has no uncertainty or certainty. Originally, this problem offered some measure of feasibility protection for optimization problems containing parameters that were not exactly known. There have been many formulas developed to tackle this challenge such as the extended Bertsimas-Sim (delta) Formulation and the extended chance constrained formula. For further insight, see Bertsimas et al. [74] for a review of the theory and applications of robust optimization.

Mulvey et al. [75] first proposed robust optimization, and since that time, it has been seen as an effective approach for the optimal design and management of supply chains operating in uncertain environments. Robust optimization has been used across many professional or academic fields, but its use in emergency humanitarian logistics is not widespread. Paul and Hariharan [76] proposed stockpile location and allocation planning for effective disaster mitigation, within which robust optimization and scenario planning were conducted to determine the final solution. Bozorgi-Amiri et al. [77] presented a multi-objective robust stochastic programming approach for disaster relief logistics under uncertainty that focused on demand, supplies, and the cost of procurement and transportation. The proposed model sought to locate the appropriate node for opening relief distribution centers so that the objective function minimized total cost and maximized demand coverage in the affected zone. Jabbarzadeh et al. [19] proposed a robust network design model for the supply of blood during and after disasters. The proposed model aimed to determine supply chain design decisions under a set of scenarios. The objective of the proposed model was to minimize the total supply chain costs for locating permanent facilities and moving temporary facilities, operational costs, inventory costs, and blood transportation costs. To transform the nonlinear model to an LP model, it was based on Mulvey et al. [75] and Yu and Li [78]. Similarly, Das and Hanaoka [79] presented a robust network design with supply and demand uncertainties in humanitarian logistics that aims to minimize the total costs of the network as well as the variance of the total costs. This proposed model attempts to seek the location of the relief distribution centers (RDC), the inventory level in each RDC and the distribution of relief to different locations along with the procurement of that relief. Finally, a case study on the earthquake in Bangladesh was used for validation of the proposed model.

From the examination of the deterministic, stochastic, dynamic, and robust facility location problems, the objectives, constraints, and solution methods associated with the emergency humanitarian logistics' facility location problem optimization model were summarized (Table 1). As can be seen, most of the identified objectives consist of risk, covered/uncovered demand, satisfied/unsatisfied demand, the number of selected facilities, evacuation time, transport time, transport distance, transport cost, the fixed cost at the selected facility, operating costs at the selected facility, and the number of demand points. Weight was also commonly applied to the objective function. Several constraints were added to facility selection such as facility capacity requirements and bounds. Constraints can be applied to other problems such as traffic assignment [17], commodity flows [33], and inventory [65]. For optimum solutions, exact algorithms have been commonly used. However, for large-scale data, exact algorithms can take a long time to solve, so advanced algorithms such as genetic algorithms [14], Tabu searches [16], clustering algorithms [76], and locate-allocate heuristics [44] are essential. For simplification, many techniques have been proposed to modify the models, especially for the stochastic and robust optimization models, such as the epsilon-constraint method and the sample average approximation method. Problem type, data modeling type, and facility location type are shown in Table 2, which presents a classification of the facility location problems and models identified from previous research. Most facility location problems were found to be minisum, set covering, maximal covering, and minimax facility location problems. Obnoxious facility location problems were the least proposed problems. As the deterministic model is the basis for the stochastic, dynamic, and robust facility location models, it has been used extensively in more complex facility location stochastic models such as Akgün et al. [7], Verma and Gaukler [12], and Salman and Yücel [16]. Dynamic and robust facility location problem models are not as widely spread as expected, and most tend to focus on shelters, distribution centers, warehouses, and medical centers. Some research has studied sub-facilities such as temporary distribution centers [61,62] and temporary shelters [80].

4. Application and case studies

Facility location problems have been applied to a wide range of problems such as evacuation, vehicle movements, transportation routes, relief distribution logistics, stock pre-positioning, casualty transportation, resource allocation, commodity flows, traffic control, and warehouse locations. Abounacer et al. [33] studied a facility location problem with a transportation problem for disaster response. Afshar and Haghani [61] proposed a mathematical model that integrated a relief commodity flow problem, a facility location problem, a vehicle routing problem, and a transportation problem. Bayram et al. [17] developed a model that optimally located shelters and assigned evacuees to the nearest shelter site. Similarly, Kongsomsaksakul et al. [14] proposed a shelter location-allocation model for flood evacuation planning. The proposed model was formulated from a facility location problem and a CDA problem. Khayal et al. [62] presented a network flow model for dynamic selection of temporary distribution facilities and resource allocation for emergency response planning, in which a facility location problem, an allocation problem, a community flow problem, and a supply assignment problem were included in the formulation model. Feng and Wen [81] proposed a model that was formulated as a multi-commodity, two-model network flow problem (private vehicle flow and emergency vehicle) based on a bilevel programming problem and network optimization theory. Moeini et al. [60] proposed a dynamic location model for the locating and relocating of a fleet of ambulances. Kilci et al. [80] proposed MILP to select the location of a temporary shelter site, in which a facility location problem, an assignment problem, and a modified pairwise analysis were included. Following on from previous research studies, some case studies can generate results through the use of an exact algorithm because they can formulate a real case by using a few variables and a few parameters. Moreover, some models have used certain techniques to reduce the number of variables, parameters, and constraints such as those proposed by Das and Hanaoka [79], Irohara et al. [36], and Bozorgi-Amiri et al. [77]. Presently, there are many advanced software companies who have overcome this challenge through exact algorithm efficiency. However, a heuristic algorithm is still necessary to solve the larger problem.

Emergency humanitarian logistics' facility location problem structures depend on the research goals. The most prevalent disaster

Table 1
Objectives, constraints, and solution methods for emergency humanitarian logistics' facility location problem optimization models.

Authors	Objective	Constraints			Solution method
		Capacity	Requirements and bounds	Other	
Abounacer et al. [33]	Transportation distance, the number of agent need to operate the opened HADCs, Uncovered demand	Facility, vehicle, link	Number of agent, number of trip performed (Vehicle), Daily work time for a vehicle, time limit	Transportation problem	Epsilon-constraint method, Exact Pareto front
Afshar and Haghani [61]	Unsatisfied demand	Facility, vehicle, Supply	Number of facility	Commodity flow, vehicle flow, transportation network design, linkage between vehicle and commodity	Exact algorithm
Akgün et al. [7]	Risk	–	Number of facility	–	Exact algorithm
Aksen and Aras [42]	Cost incurred before and after the interdiction attempt	Facility	Number of facility	–	Tabu search, Sequential solution method
Balcik and Beamon [63]	Total expected demand covered by the established distribution centers	Facility	Budget	Inventory problem	Exact algorithm
Barzinpour and Esmaeili [34]	Cumulative coverage of population, setup costs, transportation costs, equipment holding costs, shortage costs	Facility, transportation	–	Demand and supply	Exact algorithm (Goal programming)
Bayram et al. [17]	Evacuation time	Facility	Number of facility	Traffic assignment, balance flow, evacuation management	Second order cone programmingtechniques
Bozorgi-Amiri et al. [77]	The expected value and the variance of the total cost of the relief chain, satisfaction levels, shortages in the affected areas	Facility	–	Commodity flow, inventory	Exact algorithm (Lingo)
Chang et al. [70]	Transportation, facility opening, equipment rental, penalties, shipping distance of rescue equipment	Facility	–	Prioritized facility allocation	Sample average approximation
Chanta and Sangsawang [47]	Number of demand zones, Weight distance	Facility	Number of facility, distance limit	–	Epsilon-constraint approach, Exact algorithm
Chen et al. [84]	Distance	Facility	Number of assignment	Financial problem	Exact algorithm
Dar and Hanaoka [79]	Cumulative cost of pre- and post-disaster circumstances	Facility	Delivery capacity of supplier	–	Exact algorithm
Dekle et al. [38]	Facilities for each area with a given distance	–	Identify the location of the facility for each area	–	Pick-the-Farthest (PTF) Algorithm
Dessouky et al. [82]	Demand-weighted distance	Facility	Number of facility, distance limit	–	Exact algorithm
Duran et al. [64]	Average response time	Facility	Number of facility, total inventory allowed	Inventory problem	Exact algorithm
Feng and Wen [81]	Travel time, Number of private vehicle	Link	Traffic demand	Traffic control	Genetic algorithm
Fetter and Rakes [53]	Fixed cost and variable cost of facility, making technology, operation, transportation, and revenue	Facility	Number of facility, the ability to characterize the debris from specific regions	–	Exact algorithm
Hale and Moberg [40]	Number of opened felicities	Facility	Minimum and maximum distance	–	Exact algorithm
Hong et al. [32]	Total logistic cost	–	Distance between warehouse and facility, number of facility, demand	–	Exact algorithm
Horner and Downs [30]	Cost of distributing relief goods	Facility	Number of facilities	Demand fulfilment constraint	Exact algorithm
Hu et al. [41]	Cost of opening, travel evacuation distance	Facility	–	–	Genetic algorithm
Irohara et al. [36]	Costs of establishing the centers, cost of maintaining the pre-positioned inventories, the recovery costs post-disaster	Facility	Distance, number of evacuation centers	Assignment of communities	Dual Ascent Solution
Jabbarzadeh et al. [19]	Fixed cost and variable cost of facility, operational cost, transportation cost, inventory cost	Facility (permanent and temporary)	The number of blood supply of donor group, storage capacity	–	Exact algorithm (Branch and bound: Lingo)
Jia et al. [44]	Covered demand	Facility	Number of facility	Quality level	Genetic algorithm, Locate-allocate heuristic, Lagrangean relaxation heuristic, Exact algorithm
Kedchaikulrat and Lohatepanont [83]	Cost structure and AHP score	Facility, vehicle	Size of the facility	–	Exact algorithm (Pareto dominance)
Khayal et al. [62]	Fixed cost, transportation cost of resource	Facility, supply	–	Commodity flow, supply assignment,	Exact algorithm

(continued on next page)

Table 1 (continued)

Authors	Objective	Constraints			Solution method
		Capacity	Requirements and bounds	Other	
	allocation, distribution cost, delay penalty cost			resource transfer, demand satisfaction	
Kilci et al. [80]	Weight of operating candidate shelter	Facility	–	Pairwise utilization difference	Exact algorithm
Klibi et al. [65]	Transportation and procurement cost, Penalty associated to satisfying point of distribution demands	Facility, quantities of items	Budget, vendor supply quantities	Inventory level, risk level	Two-stage stochastic programming, Sample average approximation method, Monte-Carlo procedure, multi-criteria decision-making method
Kongsomsaksakul et al. [14]	Evacuation time	Facility, link	Link	Combined distribution, assignment problem	Genetic algorithm
Lin et al. [31]	Shortage penalty cost, delay delivery penalty cost, shipping cost, unfairness of service cost	Facility	Number of depots, trucks, travel time, delivery items quantity	–	Two-phase heuristic approach
Manopiniwes and Irohara [67]	Cost of opening, shipping cost, response time	Facility, Vehicle	Number of vehicles, Number of distribution centers, available response time	–	Exact algorithm (Goal Programming)
Marcelin et al. [18]	Total demand weighted travel cost	Facility	Number of facility	–	Exact algorithm
McCall [29]	Victim nautical miles, shortage	Facility	Budget, delivery limit, the number of stockpile, the number of community	Unsatisfied demands	Exact algorithm
Mete and Zabinsky [72]	Warehouse operation, transportation time	Vehicle	Inventory shortage upper bound threshold	–	Exact algorithm
Moeini et al. [60]	Cost of Relocation of the vehicle, Covered demand	–	Number of ambulances, time	Relocation problem	Exact algorithm
Murali et al. [45]	Number of demand points	Facility	Number of facility, supply available during emergency	–	Locate-allocate heuristic
Paul and Hariharan [76]	Fatality cost, the cost of maintaining a stockpile	Facility	Budget	Senility, type of medical condition, unique nature of each type of disaster	Disaster event simulation-HAZUS-MH, Clustering Algorithm, Patient grouping algorithm, Exact algorithm
Psaraftis et al. [68]	Facility opening, stock acquisition, transportation, operations, unmet demand, delay	–	–	–	Exact algorithm
Ransikarbum and Mason [35]	Fairness/equity, unmet demand, network cost	Facility, road	Number of disrupted nodes and disrupted arcs, Budget	Flow conservation	Exact algorithm (Goal Programming)
Rawls and Tumquist [71]	Costs of commodityacquisition, stocking decision, transportation, shortage, holding	Facility, link	Demand, number of facilities, inventory level	Resource allocation	Exact algorithm
Rawls and Turnquist [66]	Facility opening, transportation, unmet demand, holding	Facility, link	Number of facility	–	Lagrangian L-shaped method
Salman and Yücel [16]	Covered demand	–	Number of facility	All-pairs shortest path problem	Tabu search
Santos et al. [46]	Number of demand points	Facility	Number of facility, distance limit	–	Exact algorithm
Talwar [48]	Weight distance, Un-weight distance	Facility	Number of facility	–	Weiszfeld algorithm, Two-point and three-point search heuristics
Verma and Gaukler [12]	Transportation cost	Facility	Number of facility	Supplier	Exact algorithm, Modified L-shaped, Sample average approximation method, Master problem heuristic
Wilhelm and Srinivasa [69]	Facility opening and expansion, stock acquisition, operations	Facility	Time-phased cleanup requirement	–	Heuristics based on linear programming
Ye et al. [49]	Number of warehouses	–	Number of warehouses, distance limit	–	Variable neighborhood search, Exact algorithm

Table 2
Problem types, data modeling types, and facility location types for emergency humanitarian logistics' facility location problems.

Author	Classification of facility location problems					Classification of data modeling				Facility location type
	Minisum	Set covering	Miximal covering	Minimax	Obnoxious	Deterministic	Stochastic	Dynamic	Robust	
Abounacer et al. [33]	×	×	×			×				Distribution centers (HADC)
Afshar and Haghani [61]	×							×		Temporary distribution centers
Akgün et al. [7]				×			×			Pre-positioning
Aksen and Aras [42]		×				×				Shelters
Balcik and Beamon [63]		×					×			Distribution centers
Barzinpour and Esmaeili [34]	×	×	×			×				Distribution centers
Bayram et al. [17]	×					×				Shelters
Bozorgi-Amiri et al. [77]	×						×		×	Relief distribution centers
Chang et al. [70]	×						×			Rescue resource storehouses
Chanta and Sangsawang [47]	×			×		×				Shelter
Chen et al. [84]	×					×				Shelter
Dar and Hanaoka [79]	×								×	Relief distribution centers
Dekle et al. [38]		×				×				Disaster recovery centers
Dessouky et al. [82]	×					×				Warehouse (Medical supplies)
Duran et al. [64]	×						×			Warehouse
Feng and Wen [81]	×					×				Shelter
Fetter and Rakes [53]					×	×				Debris removal site
Hale and Moberg [40]		×				×				Storage facilities
Hong et al. [32]	×					×			×	Distribution warehouses and break of bulk points
Horner and Downs [30]	×					×				Distribution centers
Hu et al. [41]	×	×				×				Shelters
Irohara et al. [36]	×					×				Evacuation cemters
Jabbarzadeh et al. [19]	×	×					×		×	Blood facilities, blood centers and blood donors
Jia et al. [44]			×			×				Medical supply distribution centers
Kedchaikulrat and Lohatepanont [83]	×					×				Warehouses
Khayal et al. [62]	×	×						×		Temporary Distribution centers
Kilci et al. [80]		×				×				Temporary shelters
Klibi et al. [65]	×						×			Distribution centers
Kongsomsaksakul et al. [14]	×					×				Shelters
Lin et al. [31]	×					×				Temporary depots
Manopiniwes and Irohara [67]	×						×			Relief distribution centers
Marcelin et al. [18]	×					×				Distribution facilities
McCall [29]	×					×				Stockpiles
Mete and Zabinsky [72]	×						×			Warehouses
Moeini et al. [60]			×					×		Ambulances
Murali et al. [45]			×			×	×			Point of disbursement
Paul and Hariharan [76]		×		×					×	Warehouse
Psaraftis et al. [68]	×						×			Equipment stockpiling facilities
Ransikarbum and Mason [35]	×					×				Relief warehouse
Rawls and Tumquist [71]	×							×		Storage facilities
Rawls and Turnquist [66]	×						×			Pre-positioning of supplies
Salman and Yücel [16]			×				×			Shelters
Santos et al. [46]			×			×				Shelters
Talwar [48]	×			×		×				Location of rescue helicopters
Verma and Gaukler [12]	×					×	×			Disaster response facilities and population centers
Wilhelm and Srinivasa [69]	×						×			Storage locations
Ye et al. [49]				×		×				Warehouses

Table 3
Disaster types and case studies for emergency humanitarian logistics' facility location problems.

Authors	Disaster type	Case study
Abounacer et al. [33]	General	Numerical experiments
Afshar and Haghani [61]	General	Numerical experiments
Akgün et al. [7]	Earthquakes	Turkey
Aksen and Aras [42]	General	Numerical experiments
Balcik and Beamon [63]	Earthquake	National Geophysical Data Center
Barzinpour and Esmaeili [34]	Earthquake	Tehran
Bayram et al. [17]	General	Transportation network test problem, OR library, Istanbul road network
Bozorgi-Amiri et al. [77]	Earthquakes	Iran
Chang et al. [70]	Flood	Taipei City
Chanta and Sangsawang [47]	Flood	Bangkruai, Thailand
Chen et al. [84]	Earthquake	Beijing. China
Dar and Hanaoka [79]	Earthquake	Bangladesh
Dekle et al. [38]	General	Florida county
Dessouky et al. [82]	Epidemic	Anthrax disaster, Los Angeles
Duran et al. [64]	General	CARE International
Feng and Wen [81]	Earthquakes	Taiwan
Fetter and Rakes [53]	Hurricane	Chesapeake
Hale and Moberg [40]	General	Seven city example in the northeast
Hong et al. [32]	General	South Carolina
Horner and Downs [30]	General	Leon County, Florida
Hu et al. [41]	Earthquake	Chaoyang District of Beijing
Irohara et al. [36]	Hurricane	southeast USA
Jabbarzadeh et al. [19]	Earthquakes	Iran (IBTO)
Jia et al. [44]	Epidemic	Anthrax disaster, Los Angeles
Kedchaikulrat and Lohatepanont [83]	General	Thai Red Cross
Khayal et al. [62]	General	South Carolina, USA
Kilci et al. [80]	Earthquakes	Kartal, Istanbul, Turkey
Klibi et al. [65]	General	North Carolina
Kongsomsaksakul et al. [14]	Inundation of dam and reservoir	Longan network in Utah
Lin et al. [31]	Earthquake	Angeles County
Manopiniwes and Irohara [67]	Flood	Chiang Mai, Thailand
Marcelin et al. [18]	Hurricane	Leon country, Florida
McCall [29]	General	Australia
Mete and Zabinsky [72]	Earthquake	Seattle
Moeini et al. [60]	General	Val-de-Marene, France
Murali et al. [45]	Epidemic	Anthrax attack, Angeles
Paul and Hariharan [76]	Earthquakes, Hurricane	Northridge, Kartina
Psaraftis et al. [68]	Oil spills	New England
Ransikarbum and Mason [35]	Hurricane	South Carolina
Rawls and Tumquist [71]	Hurricane	North Carolina
Rawls and Turnquist [66]	Hurricane	Gulf Coast area of the US
Salman and Yücel [16]	Earthquakes	Istanbul
Santos et al. [46]	Flood	Marikina City, Philippines
Talwar [48]	General	South Tyrol, Northern Italy
Verma and Gaukler [12]	Earthquakes	California
Wilhelm and Srinivasa [69]	Oil spills	Galveston Bay Area
Ye et al. [49]	General	China

investigations were found to be earthquakes, hurricanes, floods, dam inundations, and epidemics, and some papers proposed optimization models for general disaster scenarios. Numerical examples and real case studies were developed and illustrated to validate the mathematical models shown in Table 3.

5. Future research direction

In future research, facility location problems could be applied to many techniques such as decision making and simulation. To further the already valuable work, optimization models could also be used for dynamic or robust emergency humanitarian logistics' facility location models, which would allow for the incorporation of uncertain time periods, uncertain environments, facility location risks, the possibility of facility locations, uncertain demand, disruption events, different fluctuation patterns, and facility expansion.

The relationship between facility location types and disaster stages is shown in Fig. 1. Disasters can be divided into the pre-disaster (mitigation and preparation) and post-disaster (response and recovery) stages. In the mitigation stage, future research could seek to treat hazards by relocating inhabitants farther from the risk area (arc (1)). As safety area planning is a long-term plan, dynamic and robust models could be adapted into mathematical models. In the preparation stage, research could investigate optimum planning and preparation for facility locations such as warehouses, shelters, permanent distribution centers, and permanent medical centers so as to increase the chances of survival and minimize financial and other losses.

Stochastic, dynamic, and robust facility planning models can be used to respond to real situations. For example, as distribution warehouses should be located near disaster sites but still place in safety area because they are the reception points for commodities and donations (domestic and international), suppliers, and NGOs, research could focus on when to transfer goods. Ye et al. [49] and Paul and Hariharan [76] developed a deterministic and robust model for emergency humanitarian logistic warehouses, but did not include a stochastic or dynamic model (arc (2)). For the response stage, emergency decision makers will have to play a major role in this stage in managing the available resources while the disaster is still in progress. This phase is referred to as the "Disaster in progress" phase. At this time, emergency decision makers are involved but they merely make emergency decisions for unexpected events or for when emergency cases occur. In this stage, the most important considerations are shelters and medical centers that can respond to demand and ensure the wounded are transferred to medical centers. When permanent medical centers are located in the risk areas, the medical center needs to be able to evacuate patients to shelters as quickly as possible. Therefore, permanent medical centers should be located in safe areas, so further research could examine where to locate or relocate permanent medical centers. Immediately following the disaster, temporary shelters need to be rapidly identified, so emergency decision makers need to be able to identify suitable evacuation shelters as quickly as possible (arc (3)). Finally, in the recovery stage, research could investigate optimum locations for temporary distribution centers (sub-distribution centers) to ensure efficient commodity distribution, and also to determine the optimum placement of temporary medical centers to ensure that the wounded are treated rapidly. Dynamic temporary distribution center and medical center selection methods have been proposed, but none have included robust models. In addition, obnoxious facility location problems have not been widely employed in DM research, so while optimum facility locations as close as possible to the disaster areas have been investigated, considerations regarding facilities far from potential epidemic zones, such as centers for disease control and prevention (an epidemic may occur following a disaster) and garbage dumps for debris removal have not been fully studied (arc (4)). The relationships in this stage need to be further investigated as warehouses send commodities (food, medicine, clothes, etc.) to shelters and medical centers (medicines, medical equipment). Likewise, when an epidemic breaks out, both permanent and temporary medical centers send patients with illnesses or infections to centers for disease control and prevention.

Facility location problems can be supported or developed to combine aspects such as routing problems, evacuation problems, relief distribution problems, casualty transportation problems, inventory problems, resource allocation problems, traffic control problems, debris management problems, and community flow problems as elucidated in Zheng et al. [25]. In some situations, two disasters may occur, such as an earthquake followed by a tsunami. Therefore, more

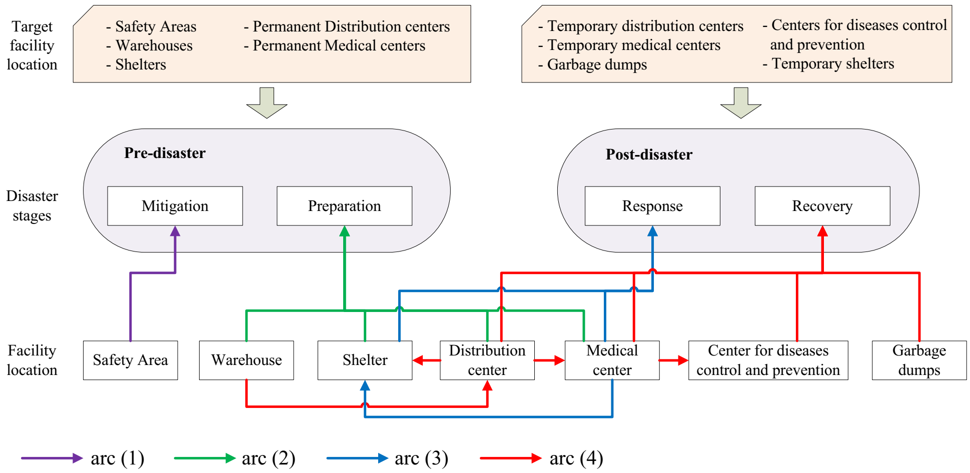

Fig. 1. Relationship model between disaster stages and facility location types.

research is needed that considers multi-disaster scenarios. Moreover, integrated disaster stage management is also important in the decision-making process in emergency humanitarian logistics' facility location problems. Normally, researchers have always focused on each stage and a few research studies have concentrated on integration disaster stage management. Consequently, integrated disaster stage management is recognized as a major gap that should be considered going forward.

The objective function model could also be designed differently to create a single-objective or multi-objective model that could be single level or bilevel. Most objectives have focused on minimum time, minimum cost, minimum distance, minimum number of located facilities, and coverage by a maximum number of demand points. New objective functions could be developed by integrating the facility location problem with the other above-mentioned problems. Further, new objectives focused on environmental effect, reliability, risk, and ease of access could be developed. Constraints could also be added, such as an assessment of evacuee behavior (demand) and age of population (old age and childhood). For a more realistic approach, researchers should determine what the uncertain factors are such as demand, supply and time. Moreover, quantitative and qualitative measurements could be added to the parameters so as to include quality measurements in considering facility location problems such as availability, accessibility, functional ability and risk. According to the informed judgement of experts, this represents one element that we should emphasize and bring forward to be applied in the mathematical model. However, the key question is not only “How can we optimize the facility location in emergency humanitarian logistic problems” but also “How can we seek a suitable facility location in the emergency humanitarian logistic problems that we can commandeer and use” as well.

Current emergency humanitarian logistics' optimization models have some limitations due to the large-scale data, so it can be complex to calculate and finding the optimum can take an excessive amount of time and computing power. Therefore, the development of advanced algorithms that can be applied to emergency humanitarian logistics is necessary to add to the present stable of genetic algorithms, tabu searches, locate-allocate heuristics, Lagrangian relaxation heuristics, particle swarm optimization, ant colony optimization, biogeography-based optimization, artificial immune systems, and hybrid algorithms. See Zheng et al. [25] for a review of the research advances in evolutionary algorithms (EAs) applied to disaster relief operations.

6. Conclusions

This paper reviewed optimization models for emergency humanitarian logistics' facility location problems based on data modeling types and problem types and to examine the pre- and post-disaster situations with respect to facility location. Four main models were investigated: deterministic, stochastic, dynamic, and robust. The deterministic facility location problem addressed facility location problems for minisum problems, covering problems, minimax problems, and obnoxious problems. This review attempted to survey the objectives, conditions, case studies, applications, disaster types, facility location types, solution methods, and emergency humanitarian logistics' facility location problem categories. The literature's main objective was found to be focused on responsiveness, risk, and cost-efficiency. In emergency humanitarian logistics problems, responsiveness and risk are the major criteria, with most models aiming to minimize response time, evacuation time and/or distance, transportation costs (distance and time), the number of open facilities, facility fixed costs or operating costs, uncovered demand, unsatisfied demand, and risk, along with maximizing the demand points covered. Depending on the problem type, the literature showed that the problem types could be merged with other problems and that the facility location problem could be applied along with other techniques such as decision theory, queuing theory, and fuzzy methods. Owing to the prevalence of earthquakes, hurricanes, floods, and epidemics in the world, these were the main focus of emergency humanitarian logistics research. An exact solution was found to be one efficiency technique, but advanced algorithms were found to be most effective for large-scale problems. Finally, research gaps and future research were identified as assisting in developing future disaster operations. This review has highlighted the extensive range of emergency humanitarian logistics' facility location optimization models that have been developed since the 1950s.

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