Review

A Systematic Literature Review on Mathematical Models of Humanitarian Logistics

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Abstract: Humanitarian logistics (HL) is considered one of the most significant issues of disaster operations and management. Thus, HL operation should be viable enough to function well under the uncertain and complex nature of the disaster. Many difficulties in pre-and post-disaster phases bring both human and economic losses. Therefore, it is essential to make sure that the HL operations are designed efficiently. In the last two decades, several publications have emphasized efficient HL operations and proposed several mathematical models and algorithms to increase the efficiency of HL operations and motivated the necessity of a systematic literature review. A systematic literature review is deemed pertinent due to its transparent and detailed article searching procedure. In this study, due to the importance of the mathematical optimization model, we reviewed more than one hundred articles published between 2000 and 2020 to investigate the optimization models in the field of HL. We classified the optimization models into three main problems: facility location problems, relief distribution, and mass evacuation where each of the classified areas includes both deterministic and non-deterministic models.

Keywords: humanitarian logistics; systematic literature review; facility location; relief distribution; mass evacuation

1. Introduction

The exponential increase in the disaster numbers has brought up myriad complications in both human life and the economic sector of a country. The number of affected people is almost proportional to the increase in disaster numbers; on average 224 million people per annum have been affected by disasters since 2006 where the economic damages were USD 154 billion in 2016, 12% above the annual average in 2006–2015 [1]. As the impact is intensifying of disasters on the society and economical sector of a country, the improvement and the reconstruction of humanitarian logistics (HL) has become a great concern nowadays [2].

Since the Asian tsunami occurred in 2004 in the Indian Ocean, humanitarian logistics operations have become an essential area of research for academia. Before the 2004 tsunami, most of the research work considering the disaster management phases. Namely, preparation, relief, recovery, and mitigation, was studied to a smaller extent, and most of the work was in the context of supply chain and logistics. Figure 1 depicts that there were few numbers of published works before 2004 and, after 2004, the number of research work in humanitarian logistics has increased drastically. Owing to a lack of logistical expert, there were limited coordination and collaboration among humanitarian-relief-providing agencies. The lack of proper coordination and collaboration had created a blockage in the airport of the tsunami-affected countries in 2004 [3]. Due to the massive demands during a disaster, sometimes it outstrips the available resources. However, sometimes

relief goods become excessive because many international donors send relief resources to disaster-affected countries and it results in difficulties to sort out the necessary resources and distribute them timely and cost-effectively.
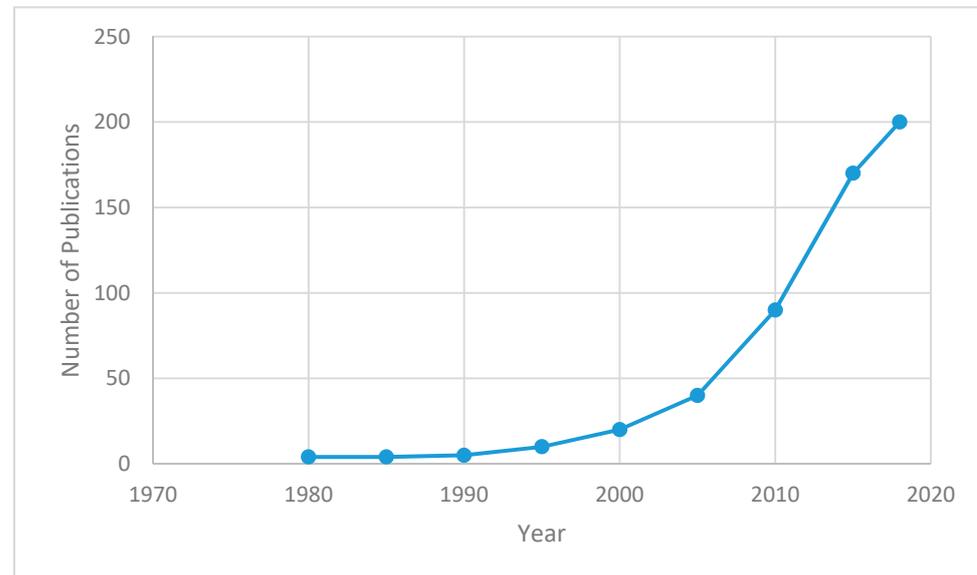

Figure 1. Number of publications by year.

Until the last decade, it was considered that natural disasters are low frequency, but in the last decade, it has been seen that the United States, China, India, the Philippines, and Indonesia are most frequently structured by natural disasters [1]. Among various natural disasters, hurricanes are one which most frequently hit the Caribbean and Central Africa. On the other hand, because of the movement and collisions of lithospheric plates, which result in "the ring of fire"—90% of the world's earthquakes occur along the ring of fire. Japan, the Philippines, Indonesia, and Papua New Guinea have a long history of earthquakes because of their presence in the "Ring of Fire" region [4].

Numerous studies have been published by different authors in the last decade with a different title but with the same purpose of lowering the sufferings of people in disaster-stricken regions. The number of publications per year from 1980 to 2019 is depicted in Figure 1. It is discussed in the earlier paragraph that there are four stages in humanitarian operations; these are mitigation, preparedness, response, and recovery [5]. Mitigation includes the steps to reduce the vulnerability of disaster-stricken areas such as reduce the loss of life, property, and others, while the preparedness stage educates people on how to better prepare themselves to confront the disaster. Not only the people but also the preparedness stage helps the government to take proactive approaches to have a robust structure in the time of disaster. The response and recovery stages are the post-disaster phases. The response stage works to respond efficiently to minimize the loss of economic and human life while the recovery stage works to resort to the damages caused by the disaster.

In the field of HL, there are a few literature review articles published already that follow the different procedures and structures. Focusing on the disaster operation life cycle, Altay and Green [6] published a review article where they explained the required activities of the stages of the disaster. Natarajarathinam, Capar, and Narayanan [7] studied the current practices and research trends to manage the supply chain in times of crisis. Simpson and Hancock [8] reviewed the operations research technique applied in the emergency responses for the last 50 years. Caunhye, Nie, and Pokharel [9] reviewed the optimization models for emergency logistics. They have broken down the literature into three parts: facility locations, relief distribution, and causality transportation. Leiras and Adriana [10] studied the trend of HL literature by applying the systematic literature review

process. However, the optimization model was not studied properly. On the other hand, Habib, Lee, and Memon [3] reviewed the mathematical models of the supply chain for crisis management. The authors divided the literature into three parts: facility location, network restoration, and evacuation. Bealt and Mansouri [2] discussed the literature review in the view of a collaborative aid network. They tried to find out the literature focusing on community involvement, coordination, and collaboration between different stakeholders. Boonmee, Arimura, and Asada [11] reviewed the facility location problem in HL. In their study, facility location problem is divided into four categories; one is the deterministic facility location problem, and another is the non-deterministic, which includes the stochastic and robust facility location problem and, lastly, the dynamic facility location problem. On the other hand, Ruiz [12] reviewed the literature only focusing on the relief distribution network of emergency management.

A very interesting survey on the public health system was performed by Burkle, Bradt, and Ryan [13]. The authors studied the overlooked opportunities of the public health information system and explored the current trend of it. Finally, they proposed a model for a population-based management system by a global public health database. Goldschmidt and Kumar [14] provided a literature review on the disaster management life cycle where authors covered three domains, namely, supply chain management, economics, and disaster management.

As of now the published literature review on HL focuses on a certain stage of a disaster life cycle and some modeling techniques. The literature review only focusing on mathematical modeling for the deterministic and non-deterministic models are not studied for all the four stages of the disaster. None of these published works cover the three main domains of HL and their approaches are not holistic in terms of modeling technique and solution methodologies. Therefore, this review article aims to provide a detailed study covering both the deterministic and non-deterministic models of the HL.

The rest of the paper is organized as follows: the research methodology is explained in Section 2. Section 3 provides an explanation of the published literature for the last two decades. Section 3 is further divided into subsections according to the deterministic and nondeterministic nature of the model. Finally, future directions are added in Section 4 while the conclusions are explained in Section 5.

2. Research Methodology

A systematic review process differentiates itself from other existing review processes by its organized and categorical approach. A systematic literature review process aims to bring out the zest from the existing published studies by following a procedure of searching, collecting, and analyzing the available resources. There are four steps for systematic review methodology; these are planning, searching, screening, and reporting [15].

Planning: The planning stage of the systematic literature helps to frame the question on which the review process starts. Normally, research questions are framed in such a way that helps to answer the current research status of a particular area and the research gap of that area. The planning stage helps to avoid the ambiguity of the review result.

Searching: The searching stage depends on the research questions addressed in the planning stage. In this literature review, we tried to collect the papers from 2000 to 2020. While searching for the papers some keywords have been used and these keywords are: "humanitarian logistics", "disaster management", "relief operations", "humanitarian relief operations", "facility locations in disaster management", "location and routing problem in HL", "commodity distribution", "relief logistics", "relief distribution and evacuation", "stochastic programming", "robust optimization", "uncertainty in disaster management", "emergency response". This searching procedure was performed with the following databases mentioned in the following Table 1. The paper collected and depicted in Figure 1 only states the optimization of HL. Only papers collected from 1980 to 2019 were considered, though we mainly concentrated on the articles that were published after

2000. On the other hand, a few articles published in 2020 were also studied to see the recent approach to this field.

Table 1. The database search for the articles.

Database	Website
Google Scholar	https://www.scholar.google.com
Science Direct	https://www.sciencedirect.com
Scopus	https://www.scopus.com/freelookup/form/author.uri
	https://www.elsevier.com/search-results?query=
	humanitarian%20logistics&labels=journals
Emerald Insight	https://www.emeraldinsight.com

Screening: An unbiased screening process is very important for a good literature review. In this study, an intensive screening process is carried out where the inclusion and exclusion criteria are considered. This study focuses on the mathematical modeling technique in the field of HL. Thus, only those papers are included that follow the mathematical modeling technique. We did not include conference papers but peer-reviewed journal articles. Articles written from the perspective of commercial supply chain management are out of the scope of this literature review.

Reporting: In this stage, papers are divided according to the classification of HL operations. Every classified area of HL is discussed according to the nature of the model (i.e., deterministic and non-deterministic models). Finally, the current trend and the research gap are analyzed.

3. Research in Humanitarian Logistics

3.1. Facility Location Problems

In disaster management (DM), the identification of the appropriate location of shelters, medical centers, warehouses, distribution centers, debris removal sites, and others is very important to mitigate human suffering. To find the prior mentioned centers, the study of facility location problems (FLPs) in DM plays a vital role. According to Boloori Arabani and Farahani [16], FLPs can be defined depending upon two questions—which area should be selected to locate the facilities, and when should new facilities be established, or existing facilities modified? Caunhye, Nie, and Pokharel [9] reviewed most of the optimization models related to facility location problems in humanitarian logistics. The articles they reviewed include the decision of selecting new facility locations or choosing the locations among existing facilities for relief distribution, evacuation of people, and stocking the relief items before the disaster. Jia, Ordóñez, and Dessouky [17,18] surveyed research articles that only include facility location models. The main challenge of the facility location problems is to find out the optimum location for facilities to minimize people's sufferings by satisfying the demand of people while keeping the associated cost minimum.

It has been found from the review of FLPs in DM that most of the articles are based on a single objective, and few papers are based on multi-objectives. From the surveyed articles, FLPs are divided into the deterministic and non-deterministic models. Deterministic and non-deterministic models of facility location problems are described in Tables 2 and 3, respectively, where the objective of each problem, constraints, decisions, stage of the disaster, solution method, and problem type are mentioned.

Table 2. Deterministic models of the facility location problem.

Authors	Objective Function	Constraints	Decisions	Stage of the Disaster	Solution Method	Problem Type
Dekel et al., (2005)	Minimize facilities for each area with a given distance and maximize the probability of using facilities	Identify the location of the facility for each area	Location identification	Recovery	Pick-the-farthest algorithm	Set covering model
McCall (2006)	Minimize (victim nautical miles, shortage)	FC, BC	Location selection, unmet demand,	Preparation	GAMS/CPLEX	P-median problem
Kongsomsaksakul et al., (2005)	Minimize total evacuation time and evacuee travel time	FC, LC, DC, TT, VC	Shelter location selection, route and destination selection,	Response	GA	Location-allocation model
Jia et al., (2007)	Maximize the demand with sufficient quantity of facility and quality level	FC, FA, DC, FA	Facility location selection, number of serviced facility	Response	CPLEX	Maximal covering, p-median, p-center
Balcik et al., (2008)	Maximize demand coverage by distribution centers	IL, FC, BC, DC	Number and location of the distribution center, amount of relief supplies	Preparation and response	GAMS/CPLEX	Maximal covering location model
Rath et al., (2011)	Minimize (depot opening cost, transportation cost), maximize the covered demand	FC, VC, VTT, BC, DC	Depot identification, quantity of relief item, maximum operative budget, arc selection for vehicle	Response	AECA, The constraint pool heuristic, CPLEX	Set covering and vehicle routing model
Lin et al., (2012)	Minimize the operational cost	VC, FC, IL, FA	Depot location selection, number of vehicles, demand point selection	Response	A two-phase heuristic approach is coded in C language and interfaced with ILOG CPLEX	Minimum facility location
Abounacer et al., (2014)	Minimize the transportation duration, number of agents (first-aiders) and total uncovered demand	FC, VC, LC, WT	Location selection, amount of commodity to deliver	Response	Epsilon constraint method, Exact Pareto front, CPLEX	Minimum set covering, maximal covering
Barzinpour et al., (2014)	Maximize the cumulative coverage of the population in pixels of the region, minimize the setup cost and transportation cost	MCC, CTC, FC, IL, DC	Location of shelter, allocation of people, amount of commodity to be transferred or stored	Preparation	LINGO	Maximal covering
Hu et al., (2014)	Minimize (total cost of shelter, total evacuation distance)	FC, CC, ACS	Location selection, shortest distance, assignment of the community to shelter, construction cost	Preparation	Genetic algorithm	Set covering
Ye et al., (2015)	Minimize the number of warehouses	NWSE, LD, DSOW	Warehouse location selection, selection of open warehouse for emergency operation	Preparation	VNS algorithm, CPLEX	p-center problem

Table 2. *Cont.*

Authors	Objective Function	Constraints	Decisions	Stage of the Disaster	Solution Method	Problem Type
Khayal et al., (2015)	Minimize logistics cost and penalty cost	FC, SC, CF, DS, TT, FA	Location of demand and supply point, resource allocation and transfer, coverage, back ordered demand	Response	CPLEX	Dynamic facility location
Xu et al., (2016)	Minimize the total distance, maximize the coverage of all shelters, maximize the shelter coverage for people	FC, DPC, SRS	Evacuation shelter site selection	Response	Lagrangian heuristic algorithm and GIS	p-median and set covering
Chen et al., (2016)	Minimize the assignment cost of facilities	FC, DS, MAF	Temporary EMS location selection	Preparation	Reduced LR and greedy algorithm, K-medoids algorithm	Capacitated facility location
Perez-Galarce et al., (2017)	Minimization of total traveled distance by the victim	CR, AM	Number of the victim, location of the refugee center	Preparation	CPLEX	Uncapacitated facility location model
M. Akbari et al., (2017)	Minimize total cost before and after interdiction	FC, BC, CAF	Customer assignment, location of facility	Response	Tabu search, Rainfall optimization, Random greedy search	A tri-level facility location r-interdiction median model;
Cotes and Cantillo et al., (2019)	Minimize the sum of private cost (transportation, inventory, fixed) and deprivation cost	ADC, FC, FLC, DT, TT	Amount of prepositioned product	Preparation	GAMS/CPLEX	capacitated facility location
Das Rubel (2018)	Maximize the coverage	NW, CLW, TOC	Location selection of local warehouse (LW) and regional warehouse, coverage of LW	Response	Open source python package solver GLPK and PULP	Maximal covering problem
Tabana et al., (2017)	Minimize the total cost of procurement and preparation, minimize the total relief operational cost, minimize the total operational relief time	FC, IL, DC, VC, BC, SP	Location selection, amount of unused product, shortage of product, inventory level	Preparation and response	NSGA-II and RPBNSGA-II	Facility location, vehicle routing, and inventory management
Wapee Manopiniwes et al., (2020)	Minimize the amount of unsatisfied demand	SC, VC, DS, NV	Amount of vehicle, amount of supplies, location selection	Response	Gurobi optimizer	Location and routing

Table 3. Non- deterministic models of the facility location problem.

Authors	Objective Function	First Stage Decisions	Second Stage Decisions	Uncertain Components	Stage of Disaster	Solution Approach/Technique	Model Type
Chang et al., (2007)	Minimize the expected shipping distance	Location of rescue storehouse	The number of resources to be stored	Demand	Preparation	LINGO	Two-stage stochastic programming
G. Rawls et al., (2010)	Minimize the total expected cost	Location selection, amount of pre-positioned commodity	Distribution of available supplies	Demand and transportation network availability	Preparation	LLSM algorithm, CPLEX	Two-stage stochastic programming
G. Rawls et al., (2012)	Minimize the expected cost	Stocking quantity, location selection	–	Demand	Preparation and response	CPLEX	Stochastic programming
Murali et al., (2012)	Maximize the number of people taking medication	Facility location selection, supply to be assigned to the facility, allocated supplies to demand point	–	Demand	Response	Locate–allocate heuristic	Probabilistic model (CCM)
Rennemo et al., (2014)	Maximize the utility (in terms of demand satisfaction and monetary budget)	Location selection, Number of vehicle type, Amount of commodity type	Level of the residual budget, amount of commodity type, number of vehicle type	Demand, the size of the vehicle fleet, available medical personnel and state of infrastructure	Response	Xpress-IVE	Three-stage stochastic programming
Hong et al., (2015)	Minimize the cost of opening facilities and purchasing the relief supplies (1st stage) and expected total cost (2nd stage)	Size and location of the facility	Amount of commodity to be shipped, amount of shortage and surplus, the inventory level of relief supplies	Demand and transportation capacities	Preparation	Preprocessing algorithm, combinatorial patterns, MATLAB, AMPL, CPLEX	Two-stage stochastic programming
Renkli et al., (2015)	Minimize the total weighted distance between affected areas and their assigned disaster response facilities	Location selection of warehouse, amount of relief item to be sent		Amount of relief item	Preparation	CPLEX	Probabilistic model (CCM)
Amiri et al., (2016)	Minimize the maximum amount of shortage, total travel time, pre- and post-disaster cost	Location of the facility, amount of commodity to transfer, amount of commodity to procure, inventory level, tour selection	–	Procurement cost, transportation cost, demand, amount of stocked commodity	Preparation and response	ϵ-constraint method, GAMS/CPLEX	Stochastic programming
An et al., (2015)	Minimize the total expected system cost	Location of facility, service allocation	–	Disaster location	Preparation	Lagrangian relaxation	Stochastic programming
Golabi et al., (2017)	Minimize the aggregated travel time of both people and the UAVs	Location selection, the flight time, required numbers of reload	–	Demand, shortest path length	Preparation	GA, MA	Stochastic programming

Table 3. *Cont.*

Authors	Objective Function	First Stage Decisions	Second Stage Decisions	Uncertain Components	Stage of Disaster	Solution Approach/Technique	Model Type
Moreno et al., (2018)	Minimize logistics cost and deprivation cost	Location, procured number of vehicles	Procured number of vehicle in 2nd stage, amount of commodity to ship, inventory of commodity, unmet demand	Demand, incoming supply, available routes	Response	CPLEX, FXO, TSH, and TSH+FXO	Two-stage Stochastic programming
Kinay et al., (2018)	Maximize minimum weight of facilities	Location selection of facilities, allocation of demand points to the open facilities	–	Demand	Preparation	CPLEX	Max–min probabilistic model (CCM)
Rezaei-Malek et al., (2016)	Minimize total cost, weighted response time	Warehouse location selection, amount of commodity to transfer, shortage of commodity, stock level	–	Disruption, demand, transportation time	Preparation and response	GAMS/CPLEX	Robust stochastic optimization
Muggy et al., (2017)	Maximize the cumulative weighted demand	Location of facility	–	Supply, demand	Response	CPLEX	Robust stochastic optimization
Ni et al., (2018)	Minimize 1st stage cost (facility cost and commodity holding cost) and 2nd stage cost (transportation cost, penalty cost)	Location of facility, pre-positioned inventory amount	–	Demand, proportion of usable inventories, road link capacity	Preparation and response	CPLEX	Min–max robust optimization
Yahyaei et al., (2018)	Minimize total cost (transportation, facility opening cost)	Location selection of facility (UDC, SDC), amount of shipped relief item	–	Number of affected people	Preparation and response	GAMS/CPLEX	Robust optimization
Oksuz et al., (2020)	Minimize the setup cost of TMC and expected transportation cost	Medical center location selection	Assignment of causalities, medical center assignment for a specific patient	Capacity of hospital, number of causalities, distance of road	Response	CPLEX	Two-stage stochastic programming
Julia Monzon et al., (2020)	Minimize the expected unsatisfied demand	Selection of arc, decision of inventory	Flow of goods, supply quantity	Demand and state of transportation network	Preparation	GAMS/CPLEX	Two-stage stochastic programming
S. Mohammadi et al., (2020)	Minimize the total logistics cost, minimize the total time of relief operation	Supplier selection, distribution center selection, dispatching of injured people		Demand, capacity of facility, time, cost	Response	GAMS	Robust optimization
Phillip R. Jenkins et al., (2020)	Maximize the demand coverage, minimize the maximum number of located facilities and reallocation	Location selection, reallocation, aeromedical helicopter deployment		Aeromedical helicopter	Response	CPLEX	Robust optimization

The abbreviations used in Table 3 are as follows: LLSM: Lagrangian L-shaped method, CCM: chance constraint method, SMSP: Stochastic Multi-Scenarios Program, AHP: analytical hierarchy process, FXO: fix and optimized heuristic, TSH: two-step heuristic, MSDCs: medical supplies distribution centers, UAV: unmanned aerial vehicle, GA: genetic algorithm, MA: memetic algorithm, UDC: unreliable distribution center, SDC: safe distribution center.

3.1.1. Deterministic Models

In the deterministic facility location problem, input parameters are known and constant over time. Input parameters such as transportation cost, facility establishment cost, fixed cost, the capacity of the shelter, number of affected people, and location are used in the deterministic facility location problem to select or locate safe places for affected people. Temporary or existing distribution centers for commodity distribution, warehouses for stock pre-positioning, medical centers for the treatment of wounded people, and debris removal points are also used in deterministic models.

In most cases, demand is considered at the node, not in the link of deterministic FLPs. That is why the deterministic FLPs in HL can be called network facility location problems. However, some research has been carried out in some cases in which demands arise on links and nodes [19]. Deterministic models of the network facility location problem in HL can be classified into some categories: median problems, center problems, and covering problems.

Median Problem

The focus of the median problem is on minimizing the distance between facilities and the demand node where weight is considered for demand points. According to C.S. ReVelle, Eiselt, and Daskin [20], in median problems, the nearest open facilities serve the demand of people, although the furthest facilities can serve the demand of people depending on facilities' capacity, economies of scale, or other cost structures. P-median problems are an important part of the median problem because p-median problems select or locate the maximum number of facilities that serve each demand point. The formulation of the p-median problem by Charles S. ReVelle and Swain [21] is as follows:

Indexes and Set:	
I	Set of demand points indexed by $i \in I$;
J	Set of facilities indexed by $j \in J$.
Input Parameters:	
d_{ij}	The distance between each demand point i and candidate facility j;
w_i	The weight associated with each demand point i;
p	Maximum number of facilities to be located.
Decision Variables:	
x_j	1 if a facility is located at candidate node j and 0 otherwise;
y_{ij}	1 if demand point i is assigned to the facility at candidate node j and 0 otherwise.

$$Minimize\ Z = \sum_{j \in J} \sum_{i \in I} w_i d_{ij} y_{ij} \tag{1}$$

$$Subject\ to\ \sum_{j \in J} y_{ij} = 1\ \ \forall i \in I, \tag{2}$$

$$y_{ij} - x_j \leq 0\ \ \forall i \in I,\ \forall j \in J, \tag{3}$$

$$\sum_{j \in J} x_j = p, \tag{4}$$

$$x_j,\ y_{ij} \in \{0,1\}\ \ \forall i \in I,\ \forall j \in J. \tag{5}$$

The objective Function (1) minimizes the weighted total distance between demand points and candidate facilities. Constraint (2) ensures that each demand node i is assigned to a candidate facility j. Constraint (3) ensures that only the open facility will be used for demand assignment. While Constraint (4) stipulates that p facilities be opened or located at the facility j. Constraint (5) denotes the decision variables which decide binary form.

McCall [22] proposed a model for the pre-disaster scenario where the author emphasized the prepositioning operation of assistance pack-up kits. This study is concerned with minimizing the shortage of relief kits and distance between affected people's location and shelter. The main decisions of this model are to locate the different types of kits at different sources, deliver kits to satisfy the demand, and whether to open stockpile or not. Lin [23] proposed a mathematical model to find out the location of temporary depots around the disaster-affected area. One of their objectives is to minimize the travel distance of the vehicle between the demand node and central depot, which is the drawback of the previous research article published by Flanigan [24]. The objective of their model is to minimize the penalty cost and transportation cost. This model is for the post-disaster scenario (response stage) while considering the constraints of the facility (depot) capacity, vehicle capacity, and the relationship between depots and demand points that ensures the assignment of demand points only to the selected depot. To deal with the multi-objective or multi-criteria model, considering the median problem, Abounacer, Rekik, and Renaud [25] proposed a multi-objective to determine the location of relief distribution centers and a transportation plan for distributing the relief. As a solution method, the author used the epsilon-constraint method due to the multi-objective model. For flood evacuation planning, a multi-level optimization model is presented in [26]. The authors divided their problem into an upper-level problem and a lower level problem. In the upper-level problem, minimization of total evacuation time is addressed, and choosing the shelter and the route for evacuee is addressed in the lower level problem. The lower level problem is focused on two issues—distribution and assignment simultaneously—where the evacuee's decision to choose the evacuation route is given preference. The main decisions of this model were to select the shelter locations and the routes.

Covering Problem

In covering problems, according to Boloori Arabani and Farahani [16], a coverage distance is followed between each demand node and the facility where each demand node will be served by each facility. Normally covering problems are suitable for the facility location problems where it is necessary to find out the location of hospitals, fire stations, and shelter sites. Covering problems can be classified into the set covering and maximal covering problems.

a.　　Set Covering Problem

The objective of the set covering problem is to minimize the total number of facilities while satisfying all the demand points. It also deals with location selection and minimization of the fixed cost of open facilities. The formulation of the set covering the problem proposed by Toregas [27] is as follows:

Input Parameters:	
c_j	Fixed cost of facility j;
S_i	Maximum distance for a facility to service demand node i.
Decision variables:	
x_j	1 if a facility is located at candidate node j and 0 otherwise.

$$Minimize\ Z = \sum_j c_j x_j \tag{6}$$

$$Subject\ to\ \sum_{j \in N_i} x_j \geq 1 \ \ \forall i, \tag{7}$$

$$x_j \in \{0,1\} \ \ \forall j. \tag{8}$$

The objective function of the set covering problem (Equation (6)) minimizes the required number of facilities to fulfill the customers' order or total fixed cost of opening facilities. Constraint (7) ensures that the number of candidate facility locations within the distance limit cannot be lower than 1 and the binary variable of this model is defined by Constraint (8).

In humanitarian logistics, the first model on the set covering problem to minimize the total number of facilities needed to cover all demand points is presented in [27]. For the medical center location problem, Dekle [28] proposed a set covering model to minimize the facilities for each area with a given distance. The authors used the covering location model to identify the potential location of disaster recovery centers (DRCs) with a two-stage approach, where the stage-1 approach gave three idealized DRC locations requiring each residence in the county to be within 20 miles of the closest DRC, and the stage-2 approach was used to refine the approximate solution from stage-1. The main decision was to identify the location of the facility for each area and, as a solution method, the authors used the pick-the-farthest (PTF) algorithm. For the warehouse location and routing problem, a multi-objective optimization model was adopted by Rath and Gutjahr [29] that had three objectives, one of which is a set covering problem that tried to minimize the facility opening cost. Apart from this objective function, other objective functions are related to minimizing transportation costs and maximizing demand coverage. The model decides to select open depot, shipped quantity from the plant to the depot, maximum operative budget, and selecting the arc to use on a tour of a vehicle. Two solution methods were proposed in this problem. The first approach is an exact method to solve the small instances and the second one is a math-heuristic technique, which is named as constraint pool heuristic. Both in the exact and the heuristic method, the authors used the adaptive epsilon-constraint algorithm (AECA). On the other hand, Hu, Yang, and Xu [30] proposed a multi-objective optimization model for the selection of the shelter location after an earthquake that is aimed to minimize the total evacuation travel distance and total cost of the facility. Between two objectives, the second objective is the set covering problem where the facility (shelter) capacity and safety service area contiguity constraint satisfaction (separation of the service area into several parts should be avoided to decrease the chaos among evacuees) are considered. Finally, the authors proposed a non-dominated sorting genetic algorithm as one of the multi-objective evolutionary algorithms to solve their model.

According to Xu [31], the existing studies of facility location problems are not suitable enough for the response stage of the HL, particularly for an earthquake due to avoiding the perspective of urban planning. To overcome this overlooked problem of the facility location model, the authors studied seven principles for locating earthquake evacuation shelters, and, following these principles, they proposed a multi-criteria constraint location model. The model is derived from a *p*-median model and a location set covering model where objectives are to minimize the total distance, maximize the coverage of all shelters, and maximize the shelter coverage of people. The second objective is related to the set covering problem where the authors tried to optimize the number of shelters to save government investment. The main decision of this model is to select the evacuation shelter location, and the model is solved by the Lagrangian heuristic algorithm.

b.　Maximal Covering Problem

According to R. Church and ReVelle [32], the maximal covering problem search for *p* facilities that can serve the maximum population within a stated service distance or time given a limited number of facilities. The mathematical formulation of this problem is stated as follows:

Decision Variables:	
z_i	1 if demand node *i* is covered by a facility within distance *S*, otherwise 0. Note that *S* indicates the distance limit.

$$\textit{Minimize } Z = \sum_i w_i z_i \tag{9}$$

$$\textit{Subject to } z_i - \sum_{j \in N_i} x_j \leq 0 \;\; \forall i, \tag{10}$$

$$\sum_{j \in N_i} x_j = p \tag{11}$$

$$x_j, z_j \in \{0, 1\} \quad \forall j. \tag{12}$$

The objective is to maximize the number of covered demand nodes within the distance limitations. Constraint (10) ensures that if there is no facility at one of the candidate locations serving the node, demand node i can not be covered while Constraint (11) states that in the eligible facility location there can be p facilities and Constraint (12) is the binary variable of this model.

Jia, Ordóñez, and Dessouky [17] analyzed the large-scale emergencies and proposed facility location model and their model can be used as a maximal covering model, a p-median model or a p-center model according to different needs in large-scale emergencies. The objective of this model is to maximize the demand with a sufficient quantity of facility and quantity level. Balcik and Benita M. Beamon [33] proposed a maximal covering model to determine the location and the number of a distribution center for the convenience of relief distribution. The amount of relief supplies to be stored at each distribution center to meet the necessity of people affected by disasters can also be determined. The objective of their model is to maximize the coverage of demand from the established distribution center. In their model, they emphasized the inventory level of commodities in the distribution center, the capacity of the distribution center, and consideration of budget for establishing the distribution center.

Barzinpour and Esmaeili [34] proposed a multi-objective model for the preparation phase of disaster management to determine the emergency shelter location, allocate the affected people to shelter, increase the total coverage of people of a specific region, store the commodities in the facility and transfer to the demand points. This multi-objective model consists of three objectives—maximize the cumulative coverage of the population in pixels of the region, minimize the total facility setup cost, minimize the transportation cost, equipment holding cost, and shortage cost. As it is a multi-objective model, the authors used a goal programming approach to prioritize the objectives and used optimization software, LINGO, to solve this model. Das [35] studied the importance of integrating the disaster preparedness and response task. According to their study, the demand for relief items is a key factor in disaster preparedness and they identified seven influencing factors of the demand for relief items. They considered the maximal covering problem where their objective is to maximize the coverage of the local warehouse and to minimize the distribution cost.

P-Centre Problem

A p-center is a minimax facility location problem that consists of a set of p points that minimizes the maximum distance between a demand point and the closest point belonging to that set. In humanitarian logistics, the p-center problem can be applied for planning the location of the hospital, fire station, shelter, and other facilities. Mark S. Daskin [36] proposed the mixed integer programming (MIP) formulation for the discrete p-center problem. Before Mark S. Daskin [36] proposed the MIP formulation, C.S. ReVelle, Eiselt, and Daskin [20] proposed a vertex p-center problem, where locations are allowed to serve as a node of a network. According to S.L. Hakimi [37] the p center model is as follows:

Decision Variables:	
D	The maximum distance between a selected location and a demand point.

$$Minimize \ \ D \tag{13}$$

$$Subject \ to \ \ \sum_J d_{ij} y_{ij} \leq D \quad \forall i, \tag{14}$$

The objective function in Equation (13) will minimize the maximum distance between a selected location and a demand node. In addition, other constraints of this model are considered, such as Constraints (2)–(5) with two decision variables (x_j, y_{ij}) from the section of the median problem.

Ye. F [38] proposes a *p*-center model for an emergency warehouse location problem (EWLP). The main aim of this model is to determine the location of the warehouse that would be assigned to the demand points and be operated during the emergency relief distribution operation to minimize the number of the warehouse. The considered constraints ensure that the number of the warehouse will be sufficient to supply emergency materials, and the longest distance (longest distance should be less than the distance limit) will also be covered from the warehouse. The (variable neighborhood search) VNS algorithm is used to solve the problem as it a non-linear problem. Also, an optimization software CPLEX is used to solve some part of the model.

Other Models on FLPs

In addition to the three main categories of the facility location problem, there are some other categories such as the dynamic facility location problem, uncapacitated facility location, and capacitated facility location problem. Khayal [39] proposed the model for a temporary facility location, which is a dynamic facility location model. The objective of this model is to minimize the logistics and penalty cost to determine the temporary distribution center (TDC) location, the location of supply points, and resource allocation quantity. The facility capacity (FC), supply capacity (SC), commodity flow (CF), and demand satisfaction (DS) are considered as constraints and solved the model using optimization software, CPLEX. Under the dynamic facility location problem, Wapee Manopiniwes and Tabana both integrated the location problem with the routing problem which is seldomly seen in the location problem. For the capacitated facility location model, Chen and Yu [40] proposed an integer programming formulation to improve the effectiveness of emergency medical service (EMS). To enhance the post-disaster medical service operation, planning for emergency medical service Service (EMS) is important. Due to this importance, the authors determined the temporary locations for on-post EMS facilities by applying network-based partitioning in their model. The reduced Lagrangian relaxation, greedy algorithm, and K-medoids algorithm were used as a solution method. On the other hand, Cotes and Cantillo [41] proposed a model of capacitated facility location, attempting to minimize the global social costs which are the sum of both private costs (cost of transportation, inventory costs, fixed cost of facilities) and deprivation costs, determining the amount per type of product to be prepositioned for serving the areas affected by a disaster. This model was solved in GAMS using the CPLEX solver. Pérez-Galarce and Akbari-Jafarabadi [42,43] proposed the un-capacited and r-interdiction median problem, respectively, where their objective is to minimize the total travel distance by the victim and minimize total cost before and after the interdiction, respectively. Pérez-Galarce [42] proposed their model for locating and assigning the refuge centers to provide shelter, medical and psychological assistance to the victims, and the objective of this model is to minimize the total distance traveled by victims. On the contrary, Akbari-Jafarabadi [43] proposed a model of man-made disaster, while they focussed on reducing the effect on system loss (linkage between key facilities) brought by the intentional attack. The authors proposed a tri-level facility location r-interdiction median (TFLRIM) model intending to minimize the total cost before and after the interdiction. To get the knowledge of r-interdiction median model readers are advised to read the article written by R.L. Church, Scaparra, and Richard S. Middleton [44]. The abbreviations used in Table 2 are as follows: Solution approach: AECA: adaptive epsilon-constraint algorithm, GIS: geographic information system, GAMS: general algebraic modeling system, GA: genetic algorithm, LR: Lagrangian relaxation. Constraints: ADC: assignment of distribution center, ACS: assignment of the community to the shelter, AM: assignment of medical center to refugee, BC: budget constraint, CF: commodity flow, CTC: commodity transportation condition, CC: contiguity constraint, CAF: customer assignment to the facility, CLW: coverage of local warehouse, CR: capacity of refuge, DC: demand coverage, DS: demand satisfaction, DT: deprivation time, DPC: demand point coverage, DSOW: demand will only be satisfied by open warehouse, FA: facility assignment, FC: facility capacity, FLC: flow conservation constraint, FCP: flow conservation of

product, IL: inventory level, LC: link capacity, LD: longest distance, MCC: maximal covering constraint, MAF: maximum allowed facility, NV: number of vehicle, NWSE: number of warehouse to supply emergency material, NW: number of warehouse to establish, SC: supply capacity, SP: shortage of product, SRS: service range of shelter, TT: travel time, TOC: transportation operating constraint, VC: vehicle capacity, WT: working time.

3.1.2. Non-Deterministic Models

Two approaches, namely, stochastic optimization and robust optimization are mostly studied for the non-deterministic model in the facility location problems. Besides these two-optimization models, there are a few other approaches to deal with uncertain parameters. The uncertain parameters in facility location problems, which are mostly seen in HL, are listed in Table 3. The detailed review of these non-deterministic models in the facility location problem is as follows:

Stochastic Programming Approach

In stochastic optimization, uncertain parameters are dispensed to a probability distribution, and parameters are usually modeled through a set of discrete scenarios with known probabilities. Most of the articles use the two-stage stochastic programming approach and very few articles are using a single-stage or three-stage stochastic programming approach. For example, Chang, Tseng, and Chen [45] proposed a two-stage stochastic programming model for flood emergency logistics to determine the location of rescue storehouses, allocation of rescue resources, considering the demand uncertainty. The two objectives of this model are minimizing the expected shipping distance of rescue equipment and minimizing the cost (sum of the facility set up cost and the average cost of all rescue equipment). The location of the rescue demand point and the quantity of rescue equipment for different flooding scenarios were estimated by the GIS analysis function and the model was solved by LINGO. Similarly, Rawls and Turnquist [46] proposed a model for prepositioning the emergency supplies and also the location to preposition. This stochastic mixed integer-programming model provides a robust model that considers the demand uncertainty as well as uncertainty regarding the transportation network availability after a natural disaster such as hurricanes. Another study for the location selection of temporary medical centers was performed by Oksuz and Satoglu [47]. They proposed a two-stage stochastic programming approach to minimize the transportation cost and set-up cost of temporary medical centers. Rawls and Turnquist [48] proposed a prepositioning plan for short-term planning considering the demand as an uncertain component. Their objective is to minimize the cost and the considered constraints are facility capacity and some requirements and bounds such as restriction on shipping extra material to minimize the holding cost on unused stocks, limitation on the number of open facilities, and limitation on stocking quantity at the shelters. A case study was analyzed using this model for meeting the demands of consumable and non-consumable goods in shelters for hurricane events that affect coastal North Carolina. Finally, the authors solved their model using CPLEX. In most cases, after the large-scale disaster the condition of transportation network becomes inaccessible and, realizing this problem, Monzón and Liberatore [49] proposed a two-stage stochastic programming model where the unavailability of the transportation network is considered.

To make sure the network reliability is at a certain level, Hong, Lejeune, and Noyan [50] introduced a risk-averse stochastic programming approach for pre-disaster relief network design with the determination of the size and location of response facilities and the inventory level of relief supplies at each facility. At the first stage of this stochastic model, the objective is to minimize the sum of the cost of opening facilities and purchasing the relief supplies, and the objective of the second stage is to minimize the expected total cost while ensuring the facility capacity for prepositioning the commodity, facility location at each node. As a solution method, the authors used the preprocessing algorithm and combinatorial patterns to formulate their proposed model as an MIP model and are implemented in

MATLAB, AMPL, and CPLEX. On the contrary, Bozorgi-Amiri and Khorsi [51] proposed a multi-objective dynamic stochastic programming model to integrate strategic, tactical, and operational decisions. Apprehending the relationship between the location of facilities, the allocation of suppliers, vehicles, and customers with the facilities, the authors proposed this model, intending to minimize the maximum amount of shortage among the relief commodity in all periods, the total travel time, and the sum of pre and post-disaster cost. The uncertain component of this model is the demand, cost, and travel time. The authors applied the ϵ-constraint method to make their multi-objective model a single objective model and implemented their model in CPLEX. To respond effectively in the aftermath of a disaster, Moreno [52] proposed a model to optimize the location, transportation, and fleet sizing decisions with the aim of minimizing the expected logistics cost and human suffering cost. The author presents a two-stage stochastic programming model to hedge against the uncertainty regarding demand, incoming supply, and availability of routes. The authors devised three heuristics based on decomposition and mathematical programming techniques, namely, a fix-and-optimize heuristic (FXO), a two-step heuristic (TSH), and a hybrid heuristic (FSO + TSH). On the other hand, to enhance the emergency service reliability, An and Shi [53] proposed a scenario-based stochastic mixed-integer non-linear programming model by integrating the facility disruption risk, en-route traffic congestion, and in-facility queuing delay into an integrated facility location problem. The objective of this model is to minimize the expected system cost by considering the constraints of the traffic flow assignment to each origin and destination pair, time of emergency facility establishment (an emergency service facility should be built before assigning to a victim group), victim assignment to an emergency facility, and warehouse capacity. Finally, the authors proposed a Lagrangian Relaxation algorithm to find a near-optimum solution to their model.

Robust Optimization and Other Non-Deterministic Approaches

In robust optimization, uncertainty is handled in two ways: robust models with discrete scenarios and robust models with interval uncertainty. Mulvey [54] proposed the concept of robust optimization in 1995. They considered uncertainty via a set of discrete scenarios. Later, Bertsimas and Sim [55] proposed a robust optimization approach for parameter uncertainty. Both types of approaches to robust optimization are studied in facility location problems in HL. Rezaei-Malek [56] proposed a robust stochastic optimization modeling technique for designing a relief logistics network for the preparation and response phase of a disaster. The objective of their model is to minimize the cost in both the pre-and post-disaster phases. As their model is multi-objective, they applied the Tchbycheff metric-based approach. Those who are interested in the Tchbycheff metric-based approach are referred to the article written by Reeves and MacLeod [57]. To test the significance and efficiency of their model, they conducted a case study in Iran. Another robust stochastic optimization approach is proposed by Muggy and Heier Stamm [58] for the post-disaster health care facility location problem. To make the accessibility of people who may need to take service from health care facilities and to make the equity among people affected by disasters less negatively impacted, the authors emphasized the coordination system among facility location decisions and responding organizations of health care facility providers. They introduced a dynamic, scenario-based, robust optimization model to quantify the impact on accessibility and equity resulting from the lack of coordination in locating post-disaster healthcare service facilities. Ni, Shu, and Song [59] proposed a min–max robust model to optimize the decisions of facility location, inventory pre-positioning, and relief delivery operations. On the other hand, S. Mohammadi, and Soroush Avakh [60] proposed a model for facility location and routing of victims to the safest place where authors have considered the aftershock of earthquakes. Unlike Rezaei-Malek [56] and Muggy and Heier Stamm [58], Yahyaei and Bozorgi-Amiri [61] applied the interval uncertainty procedure to design a reliable humanitarian relief network. The authors considered the disruption scenario of distribution centers and, to support the disrupted centers, they considered

the good sharing service from the undisrupted center. The use of aeromedical facilities after the disaster was not frequently studied until 2019. To determine the location of aeromedical facilities, the optimum number to use in a certain situation is explored by Phillip R. Jenkins [62]. Gao et al. in [63], suggested a robust mathematical model that handles large-scale evacuations. The problem was divided into two phases, the assembling site identification phase, which was formulated as a non-linear model, and the second phase, whereby scheduling and vehicle routing were solved using the genetic algorithm.

Some probabilistic models are reviewed where the authors used the chance-constrained method in their model. As pre-disaster planning, Renkli and Duran [64] emphasized reducing the arrival time of relief items to the affected areas and efficient allocation of relief items. The authors developed a mixed-integer programming model for the pre-positioning of warehouses throughout a potential area. In addition, probabilistic constraints are used to ensure the arrival of relief items within a certain time window. Kınay [65] developed a modeling framework to find out the location of the shelter under demand uncertainty. In their probabilistic model, the utilization rate of shelters and their capacity is considered as the probabilistic constraint.

3.2. Relief Distribution

Research in the field of the relief distribution model in humanitarian logistics has been conducted in a variety of ways and, because of this, the relief distribution model can be classified into three main domains, namely, location and network design, transportation, location, and transportation. A varied mathematical model has been formulated in humanitarian logistics with some variation in objective functions and constraints for each area of relief distribution. Usually, the constraints, which are considered for the location and network design, are capacity limit (whether or not the model or author considers the capacity limit of the facility), sourcing (sourcing indicates the supply sources are considered or not and sourcing can be single and multiple), period (single period or multi-period), commodity (single commodity or multi-commodity), resource allocation, and others. The transportation problem for relief distribution adds some more constraints such as fleet composition, vehicle capacity, depots, and transportation mode. All the constraints, objectives, decisions, and solution methods are mentioned in Tables 4 and 5.

Table 4. Deterministic models of relief distribution.

Authors	Objective Function	Constraints	Decisions	Stage of Disaster	Solution Approach/Technique	Problem Type
Ozdamar et al., (2004)	Minimize the sum of unsatisfied demand	FBC (commodity and vehicle), VC	NVT, ACT, AUDN	Preparation	LRIA	Relief distribution and transportation
Tzeng et al., (2007)	Minimize total cost, minimize travel time, maximize satisfaction	SP, SD	ACT, CLSTD	Response	LINGO	Relief distribution
Yi et al., (2007)	Minimize the weighted sum of (unsatisfied demand and unserved wounded people)	FBC (wounded people), NV, VC, VL	ACT, NWP, AUDC, NUWP, NVT	Response	ACO algorithm, CPLEX	Multi-commodity network flow
Balcik et al., (2008)	Minimize the sum of routing and penalty cost	DT, VC, FC, DF	ARS, DDS, DDR	Preparation and response	GAMS/CPLEX	Last-mile relief distribution
Yan et al., (2008)	Minimize the cost in emergency repair network and the relief distribution network	FCC, FBC (commodity), WTA, AF	Repair team, arc selection	Mitigation and response	CPLEX, ACO	Relief distribution and scheduling of emergency roadway repair
Campbell et al., (2008)	Minimize the maximum travel time and minimize the average arrival time	STE, VC, AT, VRD	Vehicle travel decision	Response	Insertion heuristics and improvement algorithm	Relief distribution and Vehicle routing
Horner et al., (2010)	Minimize the cost of distributing relief goods	FA, FC, MND	Quantity of relief item, distribution center type selection, affected area selection for distribution center	Response	CPLEX	Relief distribution and transportation
Vitriano et al., (2011)	Minimize (time, cost), maximize (equity, reliability)	FBC (vehicle), NV, STE, VC, BC	Quantity of relief item, quantity of a stored item, number of vehicles	Response	GAMS/CPLEX	Relief distribution
Afsar et al., (2012)	Minimize the total amount of weighted unsatisfied demand	FC, VC, FBC (commodity and vehicle)	Location selection, number of the vehicle, amount of commodity	Response	CPLEX	Relief distribution, location, and routing
Liberatore et al., (2014)	Maximize demand satisfaction	AT, DC, AF, MRP, AR	The flow of people passing arc, the flow of people at arc, arrival time	Response and recovery	GAMS/CPLEX	Relief distribution
Sheu et al., (2014)	Minimize (travel distance, operational cost, psychological cost)	FBC (evacuee), EFC, VC, FC	Distribution center selection, quantity of relief resource to transfer, number of injured people	Response	LINGO	Relief distribution and network design

Table 4. *Cont.*

Authors	Objective Function	Constraints	Decisions	Stage of Disaster	Solution Approach/Technique	Problem Type
Wang et al., (2014)	Maximization of the maximum vehicle route traveling time, minimization of relief distribution cost, maximization of the minimum route reliability	FA, FC, VC, VAD	Location selection, node selection, quantity of relief item, quantity of unsatisfied demand	Response	NSGA-II and NSDE algorithm	Location and routing
Pradhananga et al., (2016)	Minimize pre-disaster cost and expected post-disaster cost	FC, FBC (supply point), AQ	SPS, LSCP, TQP, TQPP, QTD, IN, SQ, AQDC	Preparation and response	CPLEX	Relief distribution and allocation
Rivera-Royero et al., (2016)	Minimize the total remaining fraction of unsatisfied demand	BC, VC, DC, IL	Number of trips, number of pallets, inventory of pallets, remaining budget	Response	Run and fix multi-period heuristic, run and fix multi-period multi-stage heuristic, greedy algorithm, simulated annealing	Relief distribution
Lu et al., (2016)	Minimize total relief distribution time	FC, FCC, VC	Amount of commodity flow	Response	C++ programming language, GUROBI 6.5	Relief distribution
Al Theeb et al., (2017)	Minimize the quantities of unsatisfied demand, unserved wounded, and non-transferred workers	VT, VC, FBC (vehicle), NW	Quantity of commodity, number of workers, number of evacuees	Response	CPLEX, four-phased heuristic	Relief distribution and vehicle routing
Mollah et al., (2017)	Minimize total cost (transportation and penalty)	FC, ET, VC	Available shelter selection, number of trips	Response	CPLEX, genetic algorithm	Shelter allocation and relief distribution
Rabta et al., (2018)	Minimize a cost function (which represents the total traveling distance, total traveling time or total traveling costs)	DC, EC, PC	Number of moves by drone, quantity of package to carry	Response	GAMS	Last-mile distribution, drone routing system
Wang et al., (2018)	Minimize the total service completion time	DC, FC, FBC (arc), STE	Service starting time, quantity of relief item	Response	ABC algorithm, the Rh algorithm	Medical team assistance scheduling and relief distribution

The abbreviations used in Table 4 are as follows: Solution approach—LRIA: Lagrangian-based iterative algorithm, ABC algorithm: artificial bee colony algorithm, ACO: ant colony optimization, GAMS: generic algebraic modeling system. Constraints—AT: arrival time, AF: arc flow, AQ: available quantity, AR: arc reliability, BC: budget constraint, DT: delivery time, DF: demand fulfillment, DC: demand constraint, ET: evacuation time, EC: energy constraint, EFC: evacuee flow capacity, FCC: flow conservation constraint, FC: facility capacity, FA: facility assignment to distribution center, FBC: flow balance constraint, IL: inventory level, MRP: maximum ransack probability, MND: maximum number of distribution center, NW: number of workers, NV: number of vehicles, PC: priority constraint, SP: shipment period, STE: sub-tour elimination, SD: selection of depot, VC: vehicle capacity, VL: vehicle load, VRD: vehicle route destination, VAD: vehicle arrival and destination, WTA: work team assignment. Decisions—AUDN: amount of unsatisfied demand at the nodes, AQDC: available quantity at the distribution center, ACT: amount of commodity to transfer, ARS: amount of relief supply, AUDC: amount of unsatisfied demand of commodity, CLSTD: candidate location selection for transfer depot, DDS: determine delivery schedule, DDR: determine delivery route, IN: inventory at the node, LSCP: location selection for commodity prepositioning, NUWP: number of unserved wounded people, NVT: number of vehicle types, NWP: number of wounded people to transfer, QTD: quantity to be delivered, SQ: storage quantity, SPS: supply point selection, TQP: total quantity to be purchased, TQPP: total quantity to be pre-positioned.

Table 5. Non-deterministic models of relief distribution.

Authors	Objective Function	Uncertain Components	Stage of Disaster	Solution Technique/Approach	Model Type	Problem Type
Barbarosoglu et al., (2004)	Minimize the total transportation cost and recourse cost	Demand, supply, capacity of vehicle	Response	GAMS/OSL	Two-stage stochastic programming	Relief distribution and transportation
Salmeron et al., (2010)	Minimize expected casualties, minimize expected unmet transfer population	Demand, number of relief worker, travel time	Preparedness	CPLEX	Two-stage stochastic programming	Asset prepositioning and relief operations
Mete et al., (2010)	Minimize the total warehouse operating cost and total transportation time	Transportation time, demand	Preparation	CPLEX	Two-stage stochastic programming	Location-routing and relief distribution
Doyen et al., (2012)	Minimize the total cost (transportation, facility establishment, inventory holding, the penalty for shortage)	Capacity, unit transportation cost, demand, transportation time	Preparedness and response	Lagrangean relaxation-based heuristics, CPLEX	Two-stage stochastic programming	Location and distribution (network design)
Li et al., (2011)	Minimize total cost (fixed cost of operating shelters, inventory cost) and total transportation cost	Evacuees number, transportation cost, the operational cost of one evacuee	Preparedness and response	CPLEX	Two-stage stochastic programming	Location and distribution (network design)
Noyan et al., (2015)	Maximize the expected total accessibility	Demand, transportation network	Response	Branch and cut algorithm	Two-stage stochastic programming	Last mile relief distribution model (network)
Tofigi et al., (2016)	Minimize the total cost (warehouse and distribution center operating, inventory), distribution time, maximum weighted travel time	Supply, demand, road availability	Preparedness and response	DEA	Two-stage stochastic programming	Relief distribution (network)
Ahmadi et al., (2015)	Minimize the total distribution time, penalty cost of unsatisfied demand and fixed cost of opening DC	Road destruction, location	Response	GAMS, Neighborhood search algorithm	Two-stage stochastic programming	Location-routing and last mile relief distribution
Moreno et al., (2015)	Minimize the total expected cost (opening and operating relief center, vehicle assignment, transportation, inventory, unmet demand, demand satisfaction)	Demand, supply, inventory, road availability	Response	Relax-and-fix heuristics, Fix-and-optimize heuristics	Stochastic programming	Location and transportation
Alem et al., (2016)	Minimize the cost of stock prepositioning, vehicle hiring, inventory, and unmet demand	Demand, supply, budget	Preparedness	Two-phase heuristic	Two-stage stochastic programming	Relief distribution (network)
Zheng et al., (2013)	Minimize total time delay, total transportation cost, and total transportation risk	Quantity of good, cost, arrival time, travel time	Preparation	MOTS, MOGA	Fuzzy optimization	Transportation planning and relief distribution

Table 5. *Cont.*

Authors	Objective Function	Uncertain Components	Stage of Disaster	Solution Technique/Approach	Model Type	Problem Type
Najafi et al., (2013)	(a) Minimize the total weighted unserved injured people (b) Minimize the total weighted unsatisfied demand (c) Minimize the total number of vehicles utilized in response	Demand, number of injured people, supply of the commodity	Response	CPLEX	Robust optimization, stochastic model	Transportation and relief distribution
Fereidumi et al., (2017)	Minimize the total cost	Demand, rescue operation time, transportation cost, operational cost	Preparedness and response	GAMS	Robust optimization	Distribution and evacuation
Hagi et al., (2017)	(a) Minimize the total cost (facility establishment, commodity procurement, transportation, shortage, inventory holding) (b) Maximize the satisfaction level by minimizing the maximum shortage (c) Minimize the cost of health center establishment, casualty transportation (d) Maximize the satisfaction level by minimizing the sum of maximum neglected casualties	Demand, supply, and cost	Preparedness and response	MOGSA	Robust stochastic optimization	Location and distribution
Vahdani et al., (2018)	(a) Minimize the cost (facility establishment, storing goods in facilities) (b) Minimize the vehicle travel cost (c) Minimize the vehicle travel time (d) Maximize the route reliability	Storage capacity	Response	NSGAII and MOPSO	Robust optimization	Location, routing, and distribution
Yuchen Li et al., (2020)	Minimize the fixed cost of opened supply facilities, and the cost of prepositioned relief goods	Demand, transportation time	Preparation and response	CPLEX, MATLAB	Three stage stochastic programming	Distribution and location
Peiman Ghasemi1 et al., (2020)	(a) Minimize the untreated injured people (b) Minimize the shortage of commodities	Demand	Preparation and response	NSGAII	Two-stage stochastic programming	Distribution and evacuation

The abbreviations used in Table 5 are as follows: Solution technique: MOTA: multi-objective tabu search, MOGA: multi-objective genetic algorithm, DEA: differential evolution algorithm, NSGAII: non-dominated sorting genetic algorithm II, MOPSO: multi-objective particle swarm optimization.

3.2.1. Deterministic Models

As the relief distribution models diversify in many ways, the effort has been given to review every diversified section in the following Table 4 of the deterministic model. Sometimes, the relief distribution model also associates with location problems and routing problems. Afshar and Haghani [66] suggested a model that serves both location and routing problems. H. Wang, Du, and Ma [67] considered a multi-objective location-routing model with split delivery to facilitate the relief distribution activities. The authors take into account the travel time, the total cost, and reliability with split delivery in their proposed model. To solve the model, the authors proposed the non-dominated sorting genetic algorithm and non-dominated sorting differential evolution algorithm, and a case study was conducted on the great Sichuan Earthquake in China to validate their proposed model. The commercial solver, CPLEX, was also used to solve the model. Yi and Kumar [68] proposed a network flow problem and used a meta-heuristic called ant colony optimization (ACO) to solve the problem. This model minimizes the weighted sum of unsatisfied demand of all commodities and unserved wounded people at demand nodes and emergency units. In their model, they considered a coordination center to obtain the information for predicting future demand so that they can make a balance of the commodity flow and vehicle flow on the demand nodes. Another network flow the problem that is integrated with the vehicle routing problem is proposed by Özdamar, Ekinci, and Küçükyazici [69]. They decomposed the model into two multi-commodity network flow problems; the first one is for transporting commodities and the second one is for vehicle flows. The objective of this model is to minimize the sum of the unsatisfied demand of all commodities with the determination of the number of vehicles to be used for transportation, the amount of the commodity to be transferred, and the amount of unsatisfied demand of a commodity at a specific node. The authors proposed a Lagrangean relaxation-based iterative algorithm to solve their model. On the other hand, Campbell, Vandenbussche, Hermann, and Al Theeb and Murray [70,71], did not integrate the vehicle routing problem with location problems. They only considered the vehicle routing problem for relief distribution. Campbell, Vandenbussche, and Hermann [70] developed a model by considering two objective functions for the classical traveling salesman problem (TSP) and the vehicle routing problem (VRP). The objective of this TSP is to minimize the maximum arrival time (minmax routing) and the objective of VRP is to minimize the average arrival time (minavg routing). The sub tour elimination (STE—for a given set of nodes, a TSP sub tour may be visiting some nodes among a given set of nodes and this sub tour is not the feasible solution so it must be eliminated), customer visit by vehicle and vehicle capacity are considered in the constraints. The authors proposed the insertion heuristic and improvement algorithm to solve their model. Al Theeb and Murray [71] considered a vehicle routing problem to minimize the quantities of unsatisfied demand, unserved wounded and non-transferred workers while distributing the relief commodities in the post-disaster phase. The authors suggested a vehicle routing problem with split delivery to expedite the relief distribution process. The authors proposed this multi-depot, multi-period, and multi-commodity model to determine the quantity of the commodity to pick up from the node, the number of workers to transfer from a node, the number of evacuees to pick up from a node, the quantity of the commodity to deliver, and the number of evacuees to deliver. The authors developed a four-phased heuristic to solve their problem for a large-scale instance.

After the disaster, international donations are received from different sources and to store the commodities they are transferred to central warehouses. Finally, from the central warehouses, relief goods are sorted out and sent to the regional warehouse or distribution center. The regional distribution center is the final stage from where the relief goods are dispatched to the disaster-affected areas. Due to the complexity in the final stage of relief distribution, some researchers follow the last mile distribution strategy. Balcik, Beamon, and Smilowitz [72] are some of the pioneers who developed the last mile distribution model in humanitarian logistics. In this study, they considered a vehicle based last-mile

distribution system. Their main decisions are to allocate the relief supplies at the last-mile distribution centers and determine the delivery schedule/route for each vehicle. The objective of their mixed integer-programming model is to minimize the routing cost and penalty cost for back-ordered demand based on supply, vehicle capacity, and delivery time restrictions. Another research on last-mile distribution in HL was carried out by Rabta, Wankmüller, and Reiner [73]. Due to the destroyed roads and debris-covered areas after the disaster, aid agencies have to confront some difficulties to distribute relief goods. To overcome this problem, Rabta, Wankmüller, and Reiner [73] proposed a drone fleet model. In their drone fleet model, they used unmanned aerial vehicles (UAVs) as the drone fleet and the objective of the model is to minimize the total traveling distance (or time/cost) of the drones. As the constraints, they considered the degree constraints (a drone can visit the recharging station and depots as many times as possible, but the in-degree must be equal to out-degree), demand constraints, and energy constraints.

Horner and Downs [74] proposed a facility location model to transport and distribute the relief goods to the affected areas. This is a capacitated warehouse location model where the location decisions are taken only for the warehouse to store the commodities. The authors present a geographic information system (GIS)-based model to transport the relief goods from warehouses to people in the affected areas. The objective of their model is to minimize the costs of distributing relief goods with the determination of the location of distribution centers, the number of relief good packages to deliver. A case study was analyzed using their model for the hurricane disaster relief plan in Leon County, Florida, USA. Tzeng, Cheng, and Huang [75] constructed a multi-objective relief distribution model with three objectives: minimizing the total cost, minimizing the total travel time, and maximizing minimal satisfaction. In the constraints, the authors considered the control over shipment and insufficient shipment of goods, that goods shipped in and out of transfer depots should be on the same period, and predetermined quantities of relief goods. Vitoriano [76] proposed a decision support system to assist the organizations in charge of distributing relief goods after a disaster. The decisions that can be determined through this multi-criteria model are the number of vehicles that should travel from one node to another, and the amount of relief goods that will be sent and received to the destination node. The objective of this model is to minimize (transportation time and cost) and maximize (equity and reliability); the constraints are flow balance of vehicles, a number of operating vehicles at the node should be equal to the available number of the vehicle, sub-tour elimination, and vehicle capacity. Pradhananga [77] proposed a three-echelon network model for the distribution of emergency supplies. This model is proposed for both pre- and post-disaster planning and response operation, respectively, where the objective of the pre-disaster phase is to minimize the fixed cost of establishing facilities, purchasing emergency supplies, and the transportation cost. On the other hand, the objective of the post-disaster phase is to minimize logistics and deprivation costs. Lu, Ying, and Chen [78] proposed a real-time relief distribution model based on a rolling horizon-based framework in the aftermath of the disaster. The rolling horizon framework has two modules—one is a state estimation and prediction module, and another is a relief distribution module. In the first module, this framework will predict the relief demands and delivery time and, according to the prediction, the second module will solve the optimal relief distribution flows. The main goal of their model is to minimize the total travel time to deliver relief goods to satisfy the demand of people in need. They conduct a case study to demonstrate their model on the large-scale earthquake that occurred in Taiwan.

3.2.2. Non-Deterministic Models

In search of non-deterministic models, we have found both stochastic programming and robust optimization approaches. In stochastic programming approaches, the literature is divided into the first stage and two-stage stochastic programming approaches.

The Stochastic Programming Model for Relief Distribution

Similar to the deterministic model, the non-deterministic model also covered all the possible diversified ways of relief distribution. All the reviewed papers, with their special characteristics, are mentioned in Table 5.

In emergency management, decision-makers usually make decisions about HL network design and relief distribution, confronting some uncertainties. To make the decision efficiently, researchers have studied many stochastic models. Among the HL network's decisions, the selection of facility location (i.e., location for distribution centers, temporary medical service center, and others) is one of the main decisions frequently considered by the researchers. One of the early works for a two-stage stochastic programming approach is conducted by Li, Jin, and Zhang [79]. Their stochastic model is for making decisions in both the pre-and post-disaster phases of the disaster. Their proposed model for the pre-disaster stage helps to decide the locations of facilities, capacities of facilities, and resources of new permanent shelters. On the other side, in the response stage, resources will be distributed to shelters and evacuees will be rescued to shelters. The objective of the first stage of their model is to minimize the fixed cost to have new permanent shelters, and the inventory cost of resources at the shelters, while the second stage cost is to minimize the transportation cost of evacuees, transportation cost of resource distribution, the surplus and shortage costs for resources after an evacuation. Noyan, Balcik, and Atakan [80] developed a two-stage stochastic model to determine the locations and capacities of the relief distribution points in the last-mile relief distribution networks where the uncertain elements are demand and transportation networks. The authors focused on two types of supply allocation policies and proposed the hybrid allocation policy considering their accessibility and equity. Finally, the author devised a branch-and-cut algorithm based on Benders decomposition to solve the large-scale problem. Tofighi, Torabi, and Mansouri [81] developed a two-stage scenario-based possibilistic-stochastic programming approach to design the HL network. The first stage involves selecting the location of the warehouse and distribution center where the uncertain elements are the demand, supply, and availability level of the transportation network's routes after the earthquake. In the second stage, relying on the distribution plan is required to minimize the total distribution time and the maximum weighted shortage cost of unmet demands. In this model, authors classify the relief items into the critical and non-critical item, and, in the constraint, they enforce the restrictions on the available capacity of warehouse and distribution centers for non-critical relief items. Another important constraint for their model is to consider a restriction on establishing no more than one warehouse at a candidate location. Alem, Clark, and Moreno [82] proposed a two-stage stochastic network flow model to expedite the process of distributing humanitarian aid to victims of disaster-affected areas. Some practical characteristics such as allocation of budget, procurement, varying lead-time over a dynamic multi-period horizon, and the fleet size of multi-type of vehicles are considered in this model, which are seldom considered in network flow models. Finally, the author provided a case study on the floods and landslides in the Rio de Janeiro state, Brazil. To minimize the expected number of casualties, Salmero [83] developed a two-stage stochastic programming model where the first stage decision is to expand the facilities such as warehouses, medical centers with personnel, shelters and the second stage decisions were about logistical problems.

Once the logistics network is established, the relief delivery plans are taken to transfer the relief goods to safe shelters as soon as possible. Transportation or distribution problems can make the relief delivery plan more efficient. Normally in transportation problems for distributing relief items, the demand of the commodity, the supply of the commodity,

the capacity of the vehicle, transportation arrival time, and travel time are considered as an uncertain element. Barbarosoğlu and Arda [84] proposed a two-stage stochastic programming model for transportation planning in the disaster response phase. The main objective of their model is to minimize the total transportation cost and recourse cost. To make the model more dynamic, the authors considered multi-commodity and multi-modal transportation system in their model. Apart from the logistics network establishment, another important area of crisis management is to research routing problems along with location and relief distribution. To decide for both pre and post-disaster rescue center location and the amount of relief item to be stocked and the flow of relief item at each echelon of the HL network, Döyen, Aras, and Barbarosoğlu [85] developed a two-stage stochastic programming model. The objective of their study is to minimize the total cost of facility location, inventory holding cost, transportation, and shortage cost where the uncertain elements are facility capacity, unit transportation cost, transportation time, and the demand for relief goods. In 2010, Mete and Zabinsky [86] proposed a two-stage stochastic programming model for medical supply storage, location, and distribution. They considered the vehicle routing problem in their sub-problem to transport the medical supplies in disaster response. In the multi-modal transportation context under some uncertainties, Moreno, Alem, and Ferreira [87] proposed a two-stage stochastic programming model for multi-commodity distribution. Their model is the integration of a few different decisions, namely, location decision, transportation, and fleet sizing decisions in a multi-period context. One special characteristic of this model is to reuse the vehicle within the same period to cover extra routes. Morteza, Abbas, and Behnam [88] proposed a multi-depot location routing model to facilitate the disaster relief operation. There are many studies where routing is considered with a location problem, but few studies considered the routing for last-mile distribution. Morteza, Abbas, and Behnam [88] are among those who considered the location and routing simultaneously with the last-mile distribution. The objective of this model is to minimize the total distribution time, penalty cost, and fixed costs of opening the distribution center. In an attempt to combine distribution and evacuation activities, Peiman Ghasemi and Kaveh Khalili-Damghani [89] proposed a two-stage stochastic programming approach. Their proposed model is for both pre- and post-disaster phases, where in the pre-disaster phase the authors tried to find the optimum location for the permanent relief distribution center and in the post-disaster phase, their concentration is on temporary treatment centers to facilitate the treatment of injured people. On the other hand, a three-stage stochastic programming model, a unique approach to making a correlation between primary and secondary disaster is proposed by Li. Y, Yu, and Zhang [90].

Robust Optimization and Others

Measuring the exact value of the probability distribution of the uncertain parameter is sometimes difficult. In a disaster scenario, it is tough to find out the exact value of uncertain parameters. Robust optimization is suitable in such cases by employing different robust measures for uncertain parameters. In robust optimization, uncertainty is handled in two ways, namely, robust models with discrete scenarios and robust models with interval uncertainty. Most of the published papers related to the robust optimization model in the case of relief distribution problems use the interval uncertainty to represent the uncertain parameters.

Usually, when a disaster such as an earthquake occurs, relief organizations are not prepared with enough resources to meet the demand of disaster-affected areas. By addressing this problem, Najafi, Eshghi, and Dullaert [91] proposed a robust optimization model to distribute scarce resources efficiently. In their multi-objective model, they considered a multi-modal transportation system for transporting the commodities and evacuees as well. The objective of this model is to minimize the total weighted unserved injured people, total weighted unsatisfied demands, and the number of vehicles where the uncertain elements are the demand of the commodity, number of injured people, and supply of the commodity. On the other side, Fereiduni and Shahanaghi [92] considered the disrup-

tion scenario (distribution infrastructure bridges) along with the parameter uncertainty, namely, the operational cost of relief centers, unit transportation cost, rescue operation time, and demand of affected areas. Initially, the authors considered a single-objective optimization model to make a decision about the location of facilities, allocation of resources, and evacuation of people for multiple disaster periods. To generate different scenarios, a Monte Carlo simulation is used and afterward, the p-robust approach is used to predict the damages along pathways and facilities. Haghi, Fatemi Ghomi, and Jolai [93] proposed a multi-objective model to distribute the commodities and transport the casualties. To make the model realistic, the authors considered some uncertainties and, to handle the uncertainties, a robust optimization approach was utilized and, finally, the ε-constraint method was used to solve the model. Another multi-objective robust optimization model was proposed by Vahdani, B., Veysmoradi, D., Noori, F., and Mansour, F. [94]. Between the two phases of their proposed model, in the first phase, the establishment of the distribution center and warehouse, as well as the storing of relief goods, was considered and, in the second phase, the distribution of relief goods to the affected areas was considered. Two meta-heuristic algorithms of NSGA-II and MOPSO were used to solve the model. Zheng and Ling [95] proposed a multi-objective fuzzy optimization model for emergency transportation planning where uncertainty is tackled by fuzzy theory. Sarma et al. in [96] used the neutrosophic concept to minimize the cost and time of the redistribution of resources during disaster management.

3.3. Mass Evacuation

This area of study can be divided into two groups—the evacuation model for rural areas; evacuation model for the urban areas. The rural area evacuation model is further divided into two categories—the transport system run by the government and the transport system run privately. In the public transport evacuation model, evacuee pickup points, depots, and a shelter for evacuees are optimized along with bus routes, while in the private transport evacuation model, traffic flow management is more highly prioritized. Evacuation models related to the urban area have different characteristics. In urban areas, because of the high density of population traffic congestion, route capacity, flow conservation, lane reversal, etc., are optimized. In the following sections, we review relevant public and private transport evacuation models and urban area evacuation models according to their specific characteristics and functionality. Table 6 summarizes the mass evacuation models in humanitarian logistics.

Table 6. Mass evacuation model in humanitarian logistics (HL).

Authors	Objective Function	Uncertain Components	Decisions	Deterministic Model	Non-Deterministic Model	Solution Technique/Approach
Murray-Tuite et al., (2003)	Minimize the travel time and evacuee waiting time	–	Link selection, meeting place selection of people	√		Traffic simulation software
Goerigk et al., (2013)	Minimize the maximum travel distance	–	Traveling decision of bus decision, travel time	√		Greedy algorithm
Goerigk et al., (2014)	Minimize the total evacuation time	Number of evacuees			√	CPLEX
Margulis et al., (2006)	Maximize the total evacuated number of people	–	Bus trip selection	√		
Swamy et al., (2017)	Minimize the total distance between the pickup locations and shelters	–	Evacuee pickup point selection	√		Python 2.7 for simulation code generation and optimization solver Gurobi 6.5
Bish et al., (2011)	Minimize the evacuation time and total cost	–	Number of evacuees, bus trip selection	√		Two heuristic algorithms
Ashish et al., (2014)	Minimize the total evacuation time	Number of transit-dependent evacuees	Trip number of bus, pick up the point of evacuees, allocation of bus		√	GAMS/CPLEX
Song et al., (2009)	Minimize the total evacuation time	Number of evacuees	Shelter selection, vehicles' travel		√	Hybrid GA, artificial neural network, hill climbing heuristic algorithms
Liu et al., (2006)	Maximize the total number of vehicles entering all destinations, minimize the total trip time (including the waiting time of evacuees)	–	Number of vehicles	√		LINGO 8.0
Wang et al., (2016)	Minimize the total evacuation times	Link travel times and link capacities			√	Relaxation-based heuristic, K-shortest path
Kongsomsaksakul et al., (2005)	Minimize the total travel time for all evacuees to safe shelters	–	Safe shelter selection	√		Genetic algorithm
Sayyady et al., (2010)	Minimize the total evacuation time and number of casualties	–	Flow of evacuees	√		Traffic simulation package, CPLEX

Table 6. *Cont.*

Authors	Objective Function	Uncertain Components	Decisions	Deterministic Model	Non-Deterministic Model	Solution Technique/Approach
Bretschneider et al., (2011)	Minimize the average evacuation time	–	Number of the vehicle, number of lanes	√		CPLEX
Ye et al., (2012)	Maximizing the coverage population	–	Number of a single residential building for evacuation	√		Arc GIS, shortest path algorithm
Goerigk et al., (2014)	Minimize the evacuation time and number of used shelters	–	Number of evacuees using cars and bus	√		Genetic algorithm
Kimms et al., (2018)	Minimize the total exposed hazard, minimize the deviation of cell capacity utilization	–	Number of the vehicle for starting the evacuation, number of vehicles used between two cells	√		Path generation algorithm
Li Wang (2020)	Minimize the evacuation time	Travel time and link capacity	Flow of people in a specific link		√	Lagrangian relaxation-based algorithm

3.3.1. Public and Private Transport Evacuation Model

The transportation system, which is run by the government, can be named as bus evacuation model, and most of the model in the mass evacuation domain is a bus evacuation model. Murray-Tuite and Mahmassani [97] studied household members' behavior at the time of evacuation. For example, it is an innate behavior of household members to seek each other out to evacuate as a single unit; they try to find relatives to evacuate the area. The authors studied this behavior of the people and point out that this behavior will lead the people towards the danger instead of away from it and this behavior leads to longer than expected evacuation time. They formulated a capacitated vehicle routing model aiming to minimize the travel time including evacuee waiting time. Further, Goerigk, Grün, and Heßler [98] presented a bus evacuation problem as a vehicle routing problem. The objective of their model is to minimize the maximum total travel distance. Another study of Goerigk and Grün [99] is to consider the evacuees' number as an uncertain element to make their bus evacuation model more robust and applied a scenario based approach to tackle the uncertainty. The authors considered the simplified version of the bus evacuation problem, which is a vehicle scheduling problem that aims to minimize the total time to evacuate the evacuees. For hurricane evacuation planning, Swamy and Margulis [100,101] used the public transport system in the model. Margulis proposed a decision support system that will help decision-makers with decisions about maximizing the number of evacuated people. Their model can decide on the number of the trip of the bus between pickup points and shelter points in the evacuation process. On the other hand, Swamy provides a mass evacuation strategy before striking the hurricane. In their multi-stage approaches, the first stage is about the determination of pickup locations, assigning the busses to the shelters, and the generation of routes for the pickup and shelter points. The second stage is about assigning the trip number for each route. For example, the route with higher demand requires more trips and lower demand requires fewer trips. Bish [102] provides a mixed-integer programming formulation for the bus evacuation problem. They tried to provide the difference between the classical vehicle routing problem and the bus evacuation problem. The objective of their mixed-integer programming model for the bus evacuation problem is to minimize the duration of the evacuation. Song, He and Zhang [103] present a location-routing model for the people who do not own a car and who are entirely dependent on public transport. Thus, they need to go to the transit point to be evacuated. The number of evacuees is considered to be an uncertain number. The authors introduced the chance constraint method for demand uncertainty and a stochastic number of evacuees. Another transit-based evacuation model under demand uncertainty is proposed by Ashish, Yingyan, and Yafeng [104]. To determine the optimal pickup points for evacuees and allocate the available buses to transport the evacuees, the authors proposed a robust optimization model aiming to minimize the total evacuation time. Liu, Lai, and Chang [105] presented a simulation-based two-level integrated optimization system where the higher level maximizes the throughput during evacuation time and the lower level minimizes the total travel time as well as the waiting time of evacuees. The authors used a cell transmission concept to show the relationship of traffic flow with mathematical formulations. Another cell transmission model based on evacuation planning is proposed by Chiu and Zheng [106]. They considered the multi-priority groups where some groups have more priority over others. Their cell transmission-based linear-programming model helps to make the decision on departure schedule, traffic assignment, and mobilization destination. L. Wang [107] considered the stochastic link travel times and capacity in their proposed traffic routing problem for disaster response. To guarantee the traveling efficiency and to reduce the congestion, they considered the capacity of each link where the number of agents on a specific link is considered limited over different scenarios. To solve their model, they proposed a heuristic algorithm which is the combination of the Lagrangian relaxation-based approach and the k-shortest path technique.

3.3.2. Urban Area Evacuation Model

Concerning the urban area evacuation model, a shelter location-allocation model is formulated by Kongsomsaksakul, Chen, and Yang [26] for flood evacuation planning. In their bi-level programming model, the upper level is a location problem where the authority will decide on the location, but at the lower level, evacuees will take a decision. The upper and lower-level decisions are modeled according to game theory and, finally, a genetic algorithm is used to solve the model. To find optimal evacuation routes for transit-dependent citizens during no-notice disasters, a mixed-integer linear programming model is proposed by Sayyady and Eksioglu [108]. The objective of this model is to minimize the total evacuation time and the number of casualties. Bretschneider and Kimms [109] developed a mixed-integer mathematical model for fast and safe evacuation planning in the case of disasters such as floods, hurricanes, and chemical accidents. Their proposed model provides a reorganization of the traffic routing of a certain area. Their dynamic network flow problem minimizes the evacuation time while prohibiting conflicts within intersections. Spatial analysis techniques of Geographical Information System (GIS) are employed by Ye, M. [110] for urban area evacuation planning in case of an earthquake. Their methodology encompasses three aspects: the distribution analysis of emergency evacuation demands, the shelter space accessibility calculation, and the evacuation destinations optimization. Goerigk, Deghdak, and Heßler [111] proposed a macroscopic multi-criteria optimization model for evacuation planning under different scenarios and they named their model the Comprehensive Evacuation Problem (CEP). Their objective is to minimize the evacuation time, the risk, and the number of used shelters (safe places, e.g., stadiums or gymnasiums). As their proposed CEP is a non-deterministic polynomial-time hardness (NP hard) model, a genetic algorithm is established as a method of choice for large-scale multicriteria problems. Kimms and Maiwald [112] presented a bi-objective-path-based evacuation model based on the assumption of the Cell-Transmission Model. They tried to minimize the overall hazard under some restrictions (e.g., rescuing all evacuees) and introduced the aspect of resilience in the context of evacuation planning. As they modeled two conflicting objective functions, the authors dealt with these objective functions by applying the ε-constraint method. As it is tough to predict the condition of traffic after the disaster, Li Wang [113] considered the travel time and capacity of the road as an uncertain element and proposed a two-stage stochastic programming model to evacuate the urban people. Apart from the mass evacuation model and rural area evacuation model, an interesting study is conducted by Goniewicz Krzysztof, Patrycja Misztal-Okonska, and Witold Pawłowski [114] where authors analyzed the requirements of a safe evacuation plan for the patients in the hospital and they observed an obligation of polish law in the case of safe evacuation.

4. Future Research Direction

A rigorous review of selected articles indicates that most of the focus on HL is on the preparedness and response phase considering facility location, relief distribution, and mass evacuation. After exploring the current research trend, an effort has been paid to the direction of future research according to the four phases of the disaster life cycle. The lowest concentrated phase among the four phases of the disaster life cycle is the mitigation and recovery phase. In the mitigation phase, a reallocation strategy can be an area for facility location problems where the researcher should focus more. Reallocation of inhabitants to the safest place from the disastrous areas is very important for minimizing the vulnerability of people.

As ensuring the safety of the inhabitants is an important and long-term planning issue, the mathematical model for safety planning should be robust. In the preparation stage, even though there is some research where researchers investigated the optimum location of shelters, permanent distribution centers, and permanent medical centers location, there is not enough study on the long-term planning and preparation to decide the location of the warehouse. Countries such as China, Indonesia, Japan, the Philippines, and the USA

are disaster-prone and, therefore, these countries should have optimum planning for the selection of national emergency warehouse locations [38].

The allocation of resources is not widely studied in both response and preparedness stages. There are some studies for single-period allocation, but multi-period allocation is seldomly seen. The relief distribution network consists of distribution centers and demand points and the capacity of the distribution centers is limited but the demand for relief is an uncertain parameter. As a result, the transfer of relief items between facilities or inter-facility stock can be studied for the efficient allocation of resources. If the assigned distribution center cannot meet the demand, then distribution centers are charged with dissatisfaction costs. However, for the farther period's demand, if the distribution center can be assigned, the probability of demand satisfaction would be higher. This is caused by the lack of multi-period and inter-facility stock transfer consideration. Recently, some authors have used multi-period analysis in their model, but still, this is not enough. For further studies in the preparation and response stage, the inclusion of the multi-period model is an important aspect.

Response for the disaster-relief operation does not always work according to the pre-planning. Response operations that have been running for a long time after a major disaster sometimes may face fuel shortage and an inadequate number of vehicles. In addition, some disasters are responsible for the debris in the road and block the roadways that can cause trouble in the response of disaster-relief operations. Eventually, this kind of situation increases lead time. Due to increased lead time, some distribution centers may have an excessive inventory of relief goods and some may have a scarcity of relief goods. To replenish the scarce distribution center, a redistribution strategy of relief goods among distribution centers and demand points can become handy. Another important issue in such a case is the short life of relief goods. Due to the short life, with the passage of time, these relief goods will decay. In the present literature, the study of short life relief goods in the response stage of HL is missing.

Additionally, in the response stage, there are some published works where authors consider the temporary distribution center and medical center establishment for relief distribution and causality transportation operation, but the consideration of uncertainty and employing a robust model is missing. In addition, obnoxious facility location problems have not been studied widely. Another topic that has not been studied intensively in the response stage is inventory planning. The study of inventory for both warehouse and distribution centers is an important sector for efficient distribution of relief. The uncertainty associated with demand and supply in HL is higher than the uncertainty in the commercial supply chain and logistics. As a result of that, consideration of inventory decisions in relief allocation and distribution models is seldom seen. In such a case, stochastic programming and robust optimization model can be used to respond to the real situation (e.g., consideration of uncertainty).

In the response phase, the causality transportation is also limited and can be furthered by combining with uncertain parameters. The injury level of patients, transportation time, and the demand for medical kits can be considered as probabilistic parameters. Disruption events can also be included. This may include damage to facilities, stock, and other resources. Sometimes redistribution planning of medical kits can help to minimize the demand for a particular treatment center. In the post-disaster phase, the crew scheduling of debris collection is an important part of disaster management. Research on debris collection is lacking. On the other hand, many parties want to work together in the response phase of the disaster. Thus, manpower management is a challenging part too.

The combination of different phases of the disaster life cycle is an unavoidable field to study. In most cases, a single phase is dealt with to conduct the study. Moreover, three major areas of HL (facility location, relief distribution, and evacuation) also should be combined; even though in recent years there has been an effort to combine them, more focus is needed. In this effort to combine the areas, the problem becomes complex to solve, over and above the probabilistic nature of the parameters making them more complex. To deal

with the probabilistic nature, most of the researchers are using stochastic programming and robust optimization approaches. There are other approaches such as fuzzy programming, fuzzy set theory, neutrosophic approach, and others to hedge against the probabilistic nature of the model, and the solution obtained by different approaches can be compared for the effectiveness of the model.

One of the challenges in the optimization model is having adequate data. In large-scale disasters, data may not be available or may not be easily readable. Even if data are available sometimes, it takes a long time to solve the model. In disaster situations, having the desired result from the optimization model in a short time is very crucial. Therefore, directives are needed urgently in an emergency and, thus, improvements in solution algorithms are very essential. Appropriate algorithms can help decision-makers to make decisions in a short time.

5. Conclusions

This research aims to address the current research trend of HL, especially the optimization problem used to achieve the different objectives of core sectors of HL, and to provide the future research direction. The three main sectors where decision-makers should emphasize before and after the disaster for avoiding the devastation of disaster and vulnerability of affected people are facility location problem, relief distribution, and mass evacuation. An effort has been given for further classification of those three main sectors into deterministic and non-deterministic models as well. In the case of facility location problems, all the variants of the facility location problem are studied and, in the table of the deterministic model's constraints, decision variables, model type, and solution procedures are included.

It can be noted from the reviewed article that the response stage of the disaster receives the highest priority, and emphasis on the preparation stage has a lower priority. However, the mitigation and recovery stages receive the lowest attention from the researchers. The integration of two different stages of disaster is an important sector to explore also. Another important observation is the development and exertion of different models to hedge against the uncertain parameters. The uncertain elements and the model used so far to tackle the uncertainty is also presented in the tables.

The limitation of this literature review study is that it considers only the mathematical model. Secondly, research articles published before 2004 are not included in this study. In non-deterministic models, this study mostly covered the stochastic programming approach and robust optimization. There are other approaches such as fuzzy set theory, neutrosophic sets, and others that are overlooked in this study.

Finally, it can be concluded that this study can be useful for the researchers to understand the current trend of the optimization problem in HL and the modeling techniques. Researchers can find out the research gap easily and contribute to society through their research.

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