Invited Review

# Mass Casualty Management in Disaster Scene: A Systematic Review of OR&MS research in Humanitarian Operations


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## ABSTRACT

Disasters are usually managed through a four-phase cycle including mitigation, preparedness, response and recovery. The first two phases happen before a disaster and the last two after it. This survey focuses on casualty management (CM), which is one of the actions taken in the response phase of a disaster. Right after a severe disaster strikes, we may be confronted with a large number of casualties in a very short period of time. These casualties are in need of urgent treatment and their survival depends on a rapid response. Therefore, managing resources in the first few hours after a disaster is critical and efficient CM can significantly increase the survival rate of casualties. Uncertainty in the location of a disaster, disruption to transportation networks, scarcity of resources and possible deaths of rescue and medical teams due to the disaster in such situations make it hard to manage casualties. In this survey, we focus on CM for disasters where the following five steps are taken respectively: (i) Resource dispatching/search and rescue, (ii) on-site triage, (iii) on-site medical assistance, (iv) transportation to hospitals and (v) triage and comprehensive treatment. With a special focus on Operations Research (OR) techniques, we categorize the existing research papers and case studies in each of these steps. Then, by critically observing and investigating gaps, trends and the practicality of the extant research studies, we suggest future directions for academics and practitioners.



**Keywords:** Humanitarian Logistics; Casualty management; Disaster; Relief operations; Health operations.



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## 1. INTRODUCTION AND MOTIVATION

Observation of historical data shows that the number and severity of disasters and catastrophes over recent decades has been increasing across the world. This fact applies to not only natural disasters but also terrorist attacks. According to CRED (2018), 1.3 million people lost their lives and 4.4 billion people were injured or became homeless due to natural disasters between 1998 and 2017. As reported by the Emergency Events Database (EM-DAT, 2017), 4.2 billion people (i.e., more than half of the world's population) were potentially exposed to natural disasters in 2017. Although fewer natural disasters, deaths and total affected people were declared in 2017, the mortality rate in African and American continents was higher than the annual average of the last decade due to the occurrence of landslide, earthquake and hurricane catastrophes (EM-DAT, 2017). These facts confirm that recent advances in science, technology and management have not been able to significantly decrease the number of disasters and their aftershocks.

All the decisions and operations regarding the management of a disaster are embedded in a four-phase cycle including (1) strategic *mitigation* to reduce/eliminate the impact of disasters, (2) tactical *preparedness* to lessen/avoid the effects of disasters, (3) operational *response* to preserve lives, properties and the environment and finally, (4) long-term *recovery* to return affected sites to pre-disaster conditions. Although each step has its own goals and importance, rebating negative consequences is, to a large extent, a function of the quality of decision making and the efficiency of operations management during the response phase. Post-disaster circumstances are extremely challenging due to the loss of human life, human suffering, damaged infrastructure, limited availability of resources (transportation, relief commodities, equipment, manpower and medical capacity) and uncertain and incomplete information. Having an effective real-time response in the aftermath of a disaster requires several inter-dependent decisions to be made and numerous coordinated operations to be arranged quickly within a volatile, uncertain and stressful environment.

### 1.1. Casualty management

In the first few hours after a sudden, or slow-onset mass casualty incident (MCI), thousands of casualties, which disrupt the normal functioning of emergency and healthcare services, need primary on-field assistance and treatment to survive before being taken to hospitals. Casualty management (CM) is one of the most important functions in the response phase, which needs in-place comprehensive planning. According to the definition of the World Health Organization (WHO), CM is the process of efficiently utilizing limited resources to manage casualties in affected areas and transfer them to hospitals by a group of units and organizations, which work together aiming at minimizing the number of deaths and disabilities, maximizing the number of survivors and preventing possible outbreaks of diseases (Dean and Nair, 2014). In fact, all of the following human-related decisions made (or activities designed and operated) to save as many lives as possible fall under the term CM: searching, rescuing and prioritizing casualties, transferring them to safer places (e.g., field hospitals or shelters), allocating timely relief teams, equipment and supplies (e.g., food, clothing and medicine) to affected areas, providing treatment services either temporarily on-site or comprehensively in hospital and coordinating the related flows of information. The actual experiences show that efficient CM practices in the first 72 hours after an incident are crucial because the affected people cannot survive on their own for a long time (Balcik et al., 2008).

CM is basically a complex, multi-disciplinary and multi-agency effort as it may call for many organizations and the coordination of executives and practitioners, engineers, scientists, information technology (IT) experts, physicians and medical personnel and social scientists from governmental, public, private and nonprofit organizations in unpredictable, time-limited and resource-constrained post-disaster circumstances. The importance of Operations

Research and Management Science (OR&MS) in solving such complex decision making/optimization problems is obvious. The increasing trend of relevant publications in the area within OR&MS journals to solve such problems is a substantial piece of evidence to support this fact (Besiou et al., 2018).

### 1.2. Relevant survey papers

In this subsection, we present the most relevant review papers that studied the application of OR&MS techniques for disaster management and humanitarian operations, as a basis to establish the need for a new, broader and updated review. In Table 1, we present a comprehensive list of survey papers related to humanitarian operations and disaster management published in top OR&MS journals. The scope of each article is given in the column *subject area*. The OR&MS techniques used in the review papers include both the analytical (simulation, optimization, probability and statistics) and soft (decision theory, systems dynamics, multi-criteria decision making and expert systems) techniques.

**Table 1.** Review papers related to humanitarian operations and disaster management.

| Reference (sorted chronologically) | Subject area | Review level | Phase: Mitigation | Phase: Preparedness | Phase: Response | Phase: Recovery | Survey period |
|---|---|---|---|---|---|---|---|
| Altay and Green (2006) | Disaster management | Macro | ✓ | ✓ | ✓ | ✓ | 1980–2004 |
| Abdelgawad and Abdulhai (2009) | Emergency evacuation planning | Macro | ✓ | ✓ | ✓ | ✓ | 1982–2009 |
| Natarajarathinam et al. (2009)* | SC crisis management | Macro | ✓ | ✓ | ✓ | ✓ | 1975–2008 |
| Simpson and Hancock (2009) | Emergency response | Macro | ✓ | ✓ | ✓ | ✓ | 1965–2007 |
| Overstreet et al. (2011) | Humanitarian logistics | Macro | ✓ | ✓ | ✓ | ✓ | 1995–2009 |
| Caunhye et al. (2012) | Emergency logistics | Micro | ✓ | ✓ | ✓ | ✓ | 1970–2012 |
| De la Torre et al. (2012) | Disaster relief routing | Micro | ✓ | ✓ | ✓ | ✓ | 1987–2011 |
| Galindo and Batta (2013) | Disaster management | Macro | ✓ | ✓ | ✓ | ✓ | 2005–2010 |
| Liberatore et al. (2013) | Humanitarian logistics | Macro | ✓ | ✓ | ✓ | ✓ | 2005-2012 |
| Ortuño et al. (2013) | Humanitarian logistics | Macro | ✓ | ✓ | ✓ | ✓ | 2005-2012 |
| Abidi et al. (2014)* | Humanitarian SCM | Micro | ✓ | ✓ | ✓ | ✓ | 1970-2012 |
| Anaya-Arenas et al. (2014) | Relief distribution networks | Micro | - | ✓ | ✓ | - | 1990–2013 |
| Leiras et al. (2014)* | Humanitarian logistics | Macro | ✓ | ✓ | ✓ | ✓ | 1980–2012 |
| Ozdamar and Ertem (2015) | Humanitarian logistics | Micro | - | - | ✓ | ✓ | 1998–2014 |
| Hoyos et al. (2015)*** | Disaster operations management | Micro | ✓ | ✓ | ✓ | ✓ | 2006–2012 |
| Zheng et al. (2015) | Disaster relief operations | Macro | ✓ | ✓ | ✓ | ✓ | 2004–2014 |
| Balcik et al. (2016) | Inventory management in humanitarian SC | Micro | - | ✓ | ✓ | - | 2008–2015 |
| Gupta et al. (2016)* | Disaster operations management | Macro | ✓ | ✓ | ✓ | ✓ | 1957–2014 |
| Gutjahr and Nolz (2016)** | Humanitarian aid | Macro | ✓ | ✓ | ✓ | ✓ | 2007-2015 |
| Habib et al. (2016) | Humanitarian SCM | Micro | - | - | - | ✓ | 2005–2015 |
| Boonmee et al. (2017) | Emergency humanitarian logistics | Micro | - | ✓ | ✓ | - | 1950-2016 |
| Zhou et al. (2018) | Natural disaster management | Macro | ✓ | ✓ | ✓ | ✓ | 2000-2016 |
| Ameideo et al. (2019) | Disaster management | Micro | - | - | ✓ | - | 1980-2016 |
| Behl and Dutta (2019)* | Humanitarian SCM | Macro | ✓ | ✓ | ✓ | ✓ | 2011-2017 |
| Esposito Amideo et al. (2019) | Shelter location and evacuation routing | Micro | - | - | ✓ | - | 2012-2017 |
| Kovacs and Moshtari (2019) | Humanitarian operations | Micro | ✓ | ✓ | ✓ | ✓ | 2006-2018 |
| Sabbaghtorkan et al. (2019) | Humanitarian Logistics | Micro | - | ✓ | - | - | 2000-2018 |
| **Our research** | Casualty management | Micro | - | - | ✓ | - | 1977–2019 |

* Both quantitative (i.e., optimization/OR models) and qualitative (empirical) methods ** MCDM methods *** Stochastic OR models

Altay and Green (2006) reviewed disaster operations management (DOM) models and classified research papers in each phase of DOM based on the disaster type, solution methodology, operational stage, research contribution and problem scenario. Abdelgawad and Abdulhai (2009) studied network design approaches and emergency evacuation planning models and analyzed corresponding limitations, gaps and challenges. They also surveyed the role of simulation tools and proposed a framework for emergency evacuation planning. Natarajarathinam et al. (2009) proposed a framework for classifying supply chain management (SCM) problems during a crisis based on the source, scale, respondent and research method. Simpson and Hancok (2009) categorized 361 papers related to operations research

(OR) in the emergency response into four groups: urban services, disaster services, specific hazards and general emergency. They indicated that 'hard' OR focusing on quantitative modelling is the dominant approach while 'soft' OR with its emphasis on modelling for problem insight and learning is a less common approach. The gaps and opportunities were also presented. By reviewing and analyzing 51 papers in humanitarian logistics, Overstreet et al. (2011) developed a new framework and proposed some directions for future research.

Considering book sections, journal papers and conference proceedings, Caunhye et al. (2012) divided optimization models in emergency logistics into the categories of facility location, casualty transportation and relief distribution and others and proposed future research directions in each category. De la Torre et al. (2012) reviewed OR models in relief item transportation and distribution focusing on a vehicle routing problem (VRP) between distribution points and affected areas. In addition, they interviewed small and large non-governmental organizations (NGOs), local, state, as well as federal relief organizations and their commercial partners to gather knowledge about current practices and challenges. According to the classification scheme presented by Altay and Green (2006), Galindo and Batta (2013) reviewed 155 papers in DOM from 2005 to 2010 and classified the most common assumptions into reasonable, limited and unrealistic categories. Liberatore et al. (2013) surveyed the sources and methodologies used to deal with the uncertainty in humanitarian logistics. They considered the problem type, DOM phase, objective function and the uncertainty type and methodology for each paper. Ortuño et al. (2013) reviewed papers that formulated mathematical models with deterministic solution techniques and classified them based on the problem type, DOM phase and solution approach. Abidi et al. (2014) reviewed 52 papers in humanitarian supply chain (SC) performance management and categorized them based on the research scope, methodology and characteristics. The papers were grouped into three categories: i) the definition and measurement of success, ii) the performance management and iii) existing challenges. Then, the main outcomes were highlighted and future research directions were provided. Anaya-Arenas et al. (2014) reviewed 83 papers in relief distribution networks regarding location-allocation and network design, transportation and combined location and transportation. Leiras et al. (2014) reviewed 228 papers based on ten criteria including general information, disaster type and phase, research method, geographical perspective, optimization methodology, decision level, stakeholder views and coordination perspective. By surveying the papers between 2006 and 2012, Hoyos et al. (2015) analyzed stochastic OR techniques and optimization methods for different phases of DOM in terms of the technique (mathematical programming, simulation, probabilistic and statistical modeling, artificial intelligence and expert systems, decision systems, multi-attribute utility theory and queuing theory). Ozdamar and Ertem (2015) provided a review on the vehicle representation, relief delivery and casualty transportation and mass evacuation models in the response phase and on the infrastructure restoration and debris management in the recovery phase. Zheng et al. (2015) examined the use of genetic algorithm (GA), particle swarm optimization (PSO), ant colony optimization (ACO) and other more exotic metaheuristic methods for DOM functions including facility location, transportation planning, routing, roadway repair and integrated problems. Balcik et al. (2016) reviewed 45 papers focusing on the pre- and post-disaster inventory management. The decision maker, stakeholder, disaster type, commodity, facility type and performance measure were considered as problem aspects. They also included methodological aspects such as the policy type, model and solution approach.

Gupta et al. (2016) provided a macro level study on 278 disaster management research papers published between 1957 and 2014 according to five attributes: (1) disaster management functions, (2) disaster time, (3) disaster type, (4) data type and (5) data analysis technique. They proposed recommendations for future research. Gutjahr and Nolz (2016) reviewed the application of multi-criteria optimization to the management of natural disasters, epidemics or other humanitarian crises. They discussed different optimization criteria and multi-criteria decision making (MCDM) techniques and classified the available literature according to several attributes. Habib et al. (2016), considered three major subjects including facility location, network design and relief distribution and mass evacuation and reviewed 94 papers in the Humanitarian SC field in terms of objectives, constraints, decisions and problem types.

Boonmee et al. (2017) conducted a survey on the facility (i.e., distribution centers, warehouses, shelters, debris removal sites and medical centers) location problems for emergency humanitarian logistics based on both data modeling types and problem types. They examined all the deterministic, dynamic, stochastic and robust facility location problems. Zhou et al. (2018) elaborated on the concept and characteristics of emergency decision making in natural disasters and provided a methodological perspective for the review of related theory and methods. They illustrated the construction of emergency decision support system in detail. Ameideo et al. (2019) surveyed optimization models in the shelter location and evacuation routing problems to provide a roadmap for future research. They highlighted numerous gaps and research opportunities. Behl and Dutta (2019) presented an extensive review of 362 papers around key themes including humanitarian logistics, theory focused research, case studies, mathematical models, humanitarian SC properties and resources needed for efficient and effective management of humanitarian operations, and drew a roadmap to performance evaluation of related studies. Esposito Amideo et al. (2019) studied the current challenges and provided a roadmap for future research related to optimization models in the shelter location and evacuation routing operations. A critical analysis highlighted numerous gaps and opportunities, such as the need for involving stakeholders, including evacuee as well as system behavior and being application-oriented rather than theoretical or model-driven. Kovacs and Moshtari (2019) focused on the methodologies applied for humanitarian operations studies and highlighted critical items including problem structuring, understanding the contextual factors, incorporating the uncertainty, enabling technologies in model development and implementation and selecting appropriate data and research methods. They suggested a meta-process for high-quality research on humanitarian operations. Sabbaghtorkan et al. (2019) reviewed the main OR&MS journal papers on the prepositioning of assets and supplies for natural disasters. They categorized the papers into Allocation, Location and Location-Allocation papers and identified the research gaps.

### 1.3. Contribution

The last row in Table 1 depicts the differences and the contribution of the present paper against the existing reviews from the literature. By proposing a new classification for the tasks involved in casualty management in the response phase of a disaster, in this paper, we aim to cover the following aspects: (1) a micro-level study on the features and outcomes of the studied problems, and developed models and solution techniques and (2) a critical discussion by presenting trends, gaps and innovative directions for future research. The main contribution of this paper is that we review CM on a micro level and analyze in detail all related papers. In fact, the objective function, main decision variables and constraints, involved uncertainties and dynamics, assumptions, solution technique/s, proposed heuristics and rule of thumb, reported insights, future research directions, and the studied cases are discussed for each paper. The details of our micro analysis on the features of developed models as well as the details on how some papers addressed the involved uncertainty and dynamics and proposed practical heuristics and insights are provided. This is the first survey paper that critically analyzes CM research papers in this level of detail, depth and time span.

We use the following abbreviations in different columns of tables in sections 3 to 7:

- Column **"Problem category"- A:** Allocation; **L:** Location; **P:** Prioritization; **R:** Routing; **S:** Scheduling.
- Columns "**Key decision variables", "Main assumptions", "Largest problem solved**"- **AF:** Affected site; **CCP:**

Casualty collection point; **CL:** Candidate location; **DC:** Distribution center; **DHC:** Deteriorating health condition.

- Column **"Main constraints"- CF:** Capacity of facilities; **CR:** Capacity of resources; **NR:** Number of resources.
- Column **"Objective functions"- MC:** Minimizing cost; **MF:** Minimizing fatalities; **MS:** Maximizing survivors; **MT:** Minimizing time; **O:** Other objectives.
- Column **"Solution approach"- ACO**: Ant Colony Optimization; **B&C:** Branch & Cut; **BBA:** Biography-Based Algorithm; **BD:** Benders Decomposition; **CG:** Column Generation; **GA**: Genetic Algorithm; **GR**: Greedy Algorithm; **H:** Heuristic; **ICA:** Imperialist Competitive Algorithm; **LP:** Linear programming; **MA**: Memetic Algorithm; **MDP:** Markov Decision Process; **MOO**: Multi-objective optimization; **OP:** Optimization; **QT:** Queuing theory; **S:** Simulation; **SA:** Simulated Annealing; **SAA**: Sample average approximation; **SDP:** Stochastic dynamic programming; **SP**: Stochastic programming; **SSA:** Scatter Search Algorithm; **TS:** Tabu Search; **VNS:** Variable Neighborhood Search.

The paper is organized as follows. Section 2 describes the research methodology and scope. In sections 3 to 7, we critically review the literature to explore research directions on a micro level. Section 8 concludes and presents future research directions on a macro level.

## 2. RESEARCH METHODOLOGY AND SCOPE

In this section, first, we describe our research methodology. Then, we clarify some basic concepts in the field and the research scope.

### 2.1. Research methodology

The research approach is a systematic literature review to guarantee that relevant and high-quality studies are surveyed. We follow a conservative search and screening methodology in six steps, drawn in Figure 1, to ensure the inclusion of all relevant papers. There are several academic search engines such as Google Scholar, Web of Science and SCOPUS that could be used in our search interchangeably. We use SCOPUS with a larger number of covered journals than Web of Science which provides greater flexibility in searching for specific keywords or phrases. Key terms and aspects, mentioned in the first two steps in Figure 1, are searched for hierarchically in the title, abstract and keywords of journal papers published in the English language until 2019. We only focus on journal papers and exclude conference proceedings, book chapters, books, working papers, master theses, Ph.D. theses and technical reports. While this screening might seem overly strict, one has to consider the sheer amount of results (as shown in Figure 1) as well as the fact that most high-quality research is routinely published in journals after completion of master theses, Ph.D. theses and technical reports, as well as special issues in journals following conference proceedings. In step 3, we exclude journals that do not meet a quality criterion according to the lists published by (i) Academic Journal Guide 2018- Chartered Association of Business Schools, (ii) Australian Business Deans Council 2018 and (iii) Scientific Journal Rankings (JCR 2018). Then, by screening titles, abstracts and full-texts, respectively, in the next three steps, we omit those not related to the abovementioned research scope. The "scope check" in the last three steps of Figure 1 shows that we screen the corresponding content (mentioned as the title of the step) keeping our scope in mind to see whether the paper is relevant or not. If we were in doubt at a given step that the paper is relevant or not, we conservatively left it for a closer examination in the next step where we will naturally have additional content to decide. Additionally, the references of all papers are screened in the last step to include any relevant papers which may fall within the search scope. In the end, a total of 88 papers are comprehensively considered in this survey.

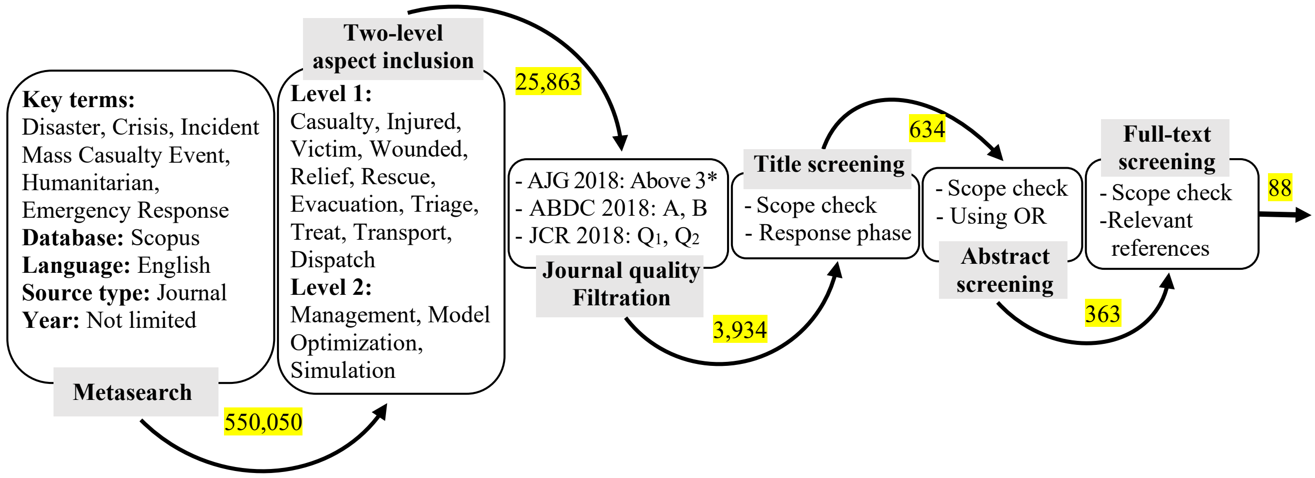


**Figure 1.** Proposed search and screening methodology.

The frequency of papers per year is depicted in Figure 2. The first paper in the field was published in 1977, but surprisingly, for three decades (until 2006) only 4 papers appear that meet our methodology criteria. A plausible hypothesis is that some of the 21st century's deadliest man-made and natural disasters, such as the September 11 attacks, 2004 Indian Ocean earthquake in Indonesia, 2005 Kashmir earthquake and 2005 Hurricane Katrina urged researchers to carry out research in the area. The number of papers peaks in 2014, 2018, and 2019.

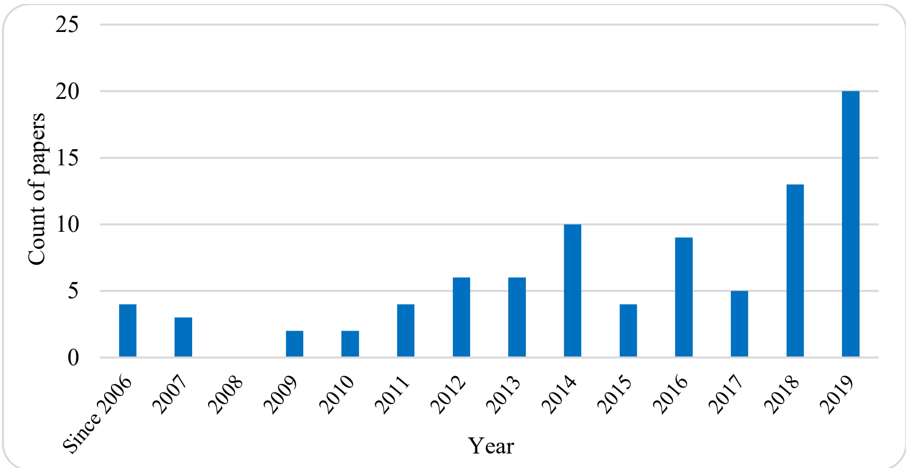


**Figure 2.** Total number of published CM papers by year.

When it comes to journals that have published in the area, Figure 3 lists them in decreasing order of the total number of published papers. For equal frequencies, journals are alphabetically sorted. As illustrated, European Journal of Operational Research (EJOR) has published the most papers in the field.

### 2.2. Basic concepts and background

The same incident could be an accident (emergency), disaster or catastrophe depending upon the scale of impact (i.e., the amount of damage and number of deaths). The difference between disaster/catastrophe and emergency situations is mainly related to the number of casualties to be managed. In major accidents, the number of casualties usually amounts to tens, while in mass and catastrophic incidents, this amounts to hundreds or thousands. A comprehensive planning for CM guarantees the timely transportation of casualties to hospitals considering the type and the level of injuries and hospital capacity.

When a disaster occurs, first, a strategic meeting is held by organizations such as relief and rescue, police, fire stations, hospitals, ambulances, aviation and the military. The initial estimates of preliminary information including the identification of the disaster (severity and spread), the precise location of affected sites, potential risks and the number of injuries and fatalities are made by assessment teams right after the disaster.

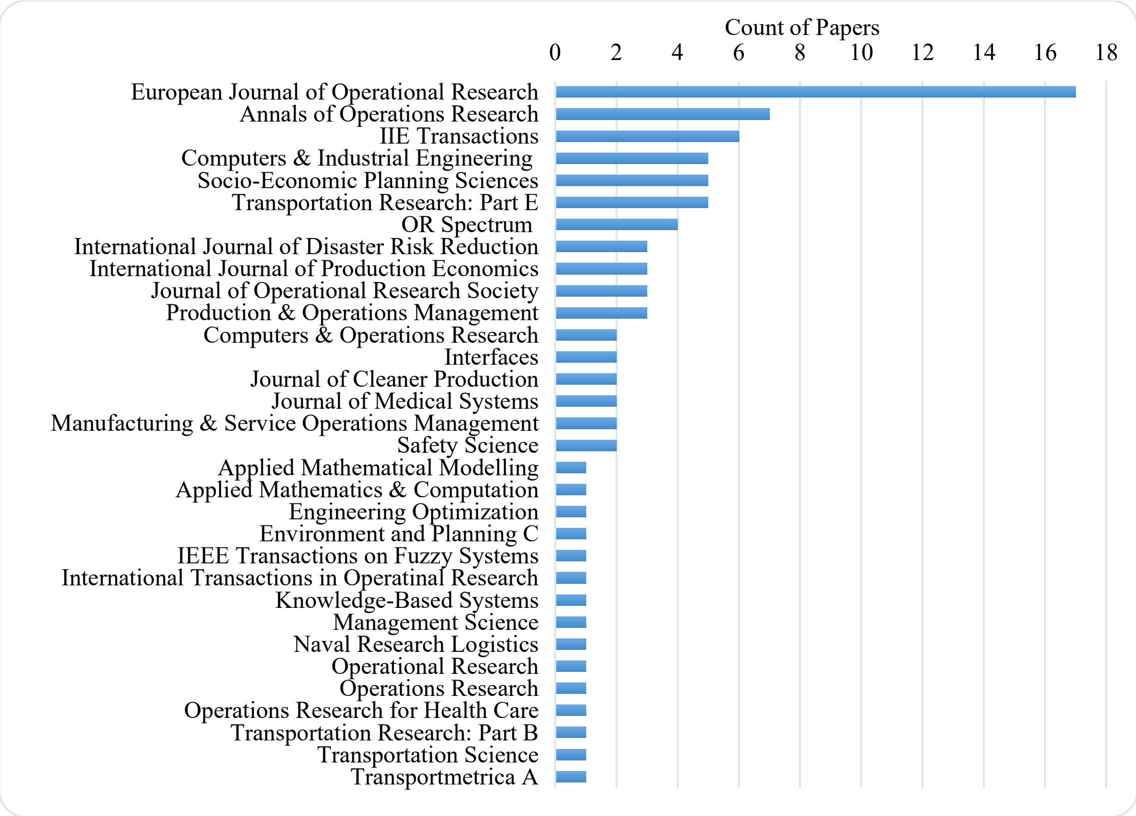


**Figure 3.** The number of published CM papers per journal.

The number of affected people and, in particular, the number of casualties and their types of injuries at a specific location provide necessary input for CM. After a rapid on-field initial assessment by the related organizations, the CM function starts, involving several tasks as illustrated in Figure 4. Following Figure 4, we explain the tasks of CM briefly. Later, in sections 3 to 7, they will be extensively and critically discussed.

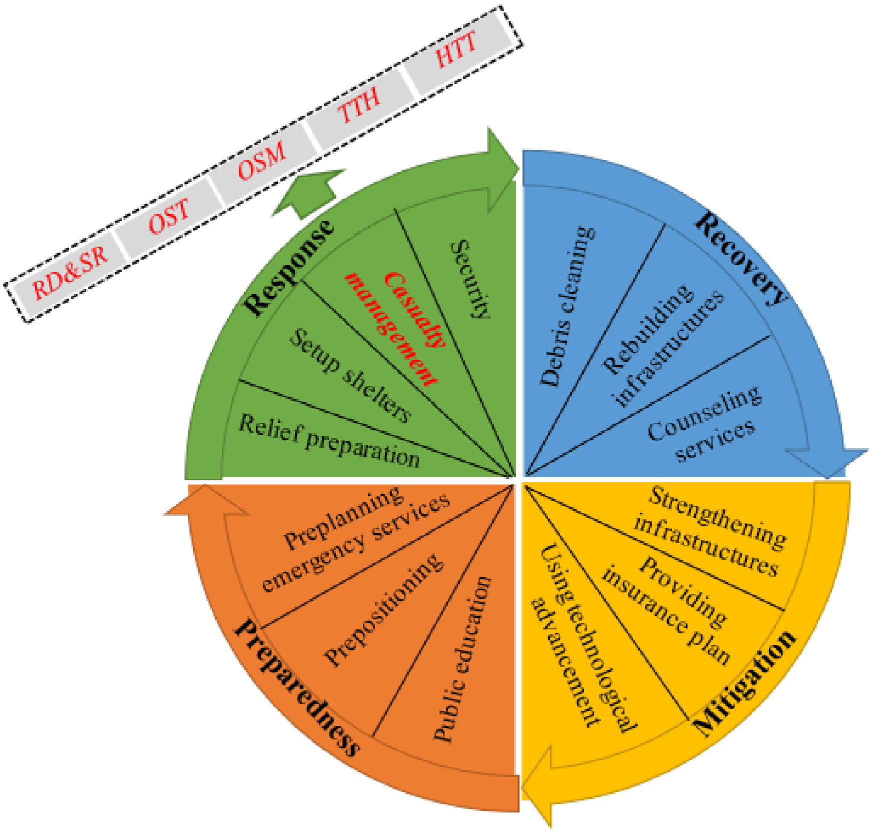


**Figure 4.** Scope of this review paper in terms of the CM processes.

**a)** ***Resource dispatching/search and rescue*** **(*RD&SR*):** Natural disasters result in a large number of incidents such as collapsed structures, fires and car accidents dispersed across different locations which require immediate operations by Search and Rescue (SAR) teams at the affected sites. SAR teams are trained to locate, extricate and assist trapped or wounded people (FEMA, 2008). They may be involved in digging, breaking, lifting and removing activities using light tools and heavy equipment. For example, finding trapped people under the debris of collapsed structures by using specially trained dogs and electronic search equipment is a prevalent activity performed by SAR teams.

**b) *On-site triage* (*OST*)**: Field triage is to categorize casualties according to their medical condition and the characteristics of their injuries. This is carried out by trained triage teams who take medical measures to rapidly evaluate and prioritize casualties to stabilize them before being transferred to hospitals.

**c) *On-site medical assistance* (*OSM*)**: After on-site triage, casualties are usually transported to nearby safe locations referred to as casualty treatment stations (CTS) to receive the emergency care assistance and stabilization needed for the subsequent safe transportation to hospitals (Frykberg, 2005). Medical teams usually consist of emergency technicians, nurses and doctors. On-site medical treatment is limited to pre-planned quick remedies that effectively help the patients' survival prior to transportation to hospitals.

**d) *Transportation to hospital* (*TTH*):** Medically stabilized casualties are dispatched to nearby hospitals to receive comprehensive treatment. To do this, various transportation modes such as land, air or water may be utilized. Consequently, vehicles such as ambulances, cars, trains, helicopters, aircraft, boats and ferries may be used. The availability of vehicles, their fleet size and capacities and possible damage to infrastructures are key determinants in choosing a specific transportation mode or a mixture of them.

**e) *Hospital triage and comprehensive treatment* (*HTT*):** Trained teams including doctors, nurses and other medical personnel in emergency departments prioritize patients to increase their chance of survival by medical interventions. While hospital triage has similarities to on-site triage, in section 7, we will see that they also have significant differences in terms of objectives and processes. During a disaster, hospitals usually work under extreme pressure and have to endure acute resource limitations. Patients who need advanced surgeries, long-term hospitalization and intensive care units (e.g., in cardiac care units) are serviced in hospitals that are not categorized under the term CM.

Table 2 categorizes published papers in the CM field based upon the basic groups described here. As given, some papers contributed to more than one category. Figure 5 provides a comparison by the percentage of the number of published papers in five problem categories.

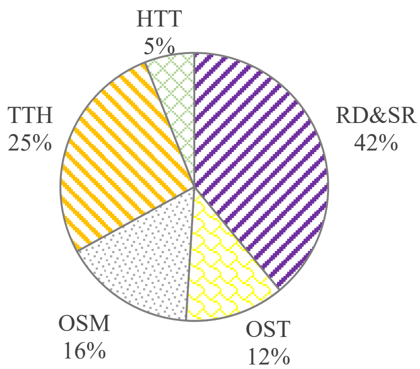


**Figure 5.** The percentage of papers in each category.

### 2.3. Scope of this survey

The aim of this paper is to assess the literature related to CM operations in the response phase at the disaster scene. The focus of our paper is MCIs which cover both disasters and catastrophes. The paper provides a basis to determine and to analyze research gaps in the field that require further investigation. The ORish papers related to RD&SR, OST, OSM, TTH and HTT are reviewed. We do not limit OR to any narrow definitions but consider a wider optimization view to include not only modeling techniques, stochastic programming, and multi-criteria decision making (MCDM), but also solution techniques such as dynamic programming and robust optimization. We even consider decision theory, systems dynamics, expert systems and simulation. However, in terms of applications, the scope of the selected papers must totally or partially be related to CM in the response phase of disasters. Therefore, all activities needed to save people's lives, like the distribution of relief items and equipment, the location of temporary facilities and the allocation of vehicles to facilities, can be relevant as far as they serve CM.

**Table 2.** CM-related papers reviewed in this paper.

| REFERENCES (sorted chronologically) | RD & SR | OST | OSM | TTH | HTT |
|---|---|---|---|---|---|
| Cook (1977) | | | ✓* | ✓ | |
| Christie and Levary (1998) | | | | ✓ | |
| Fiedrich et al. (2000) | ✓ | | | | |
| Drezner (2004) | | | ✓ | | |
| Gong and Batta (2007) | | | | ✓ | |
| Yi and Kumar (2007) | ✓ | | | ✓* | |
| Yi and Ozdmar (2007) | ✓ | | | ✓* | |
| Jotshi et al. (2009) | | | | ✓ | |
| Lee et al. (2009) | | | ✓ | | |
| Li and Glazebrook (2010) | | ✓ | | | |
| Salmeron and Apte (2010) | | | ✓ | | |
| Cotta (2011) | | ✓ | | | |
| Nolz et al. (2011) | ✓ | | | | |
| Ozdamar (2011) | ✓ | | | ✓* | |
| Paul and Batta (2011) | | | | ✓ | |
| Berkoune et al. (2012) | ✓ | | | | |
| Chen and Miller-Hooks (2012) | ✓ | | | | |
| Jacobson et al. (2012) | | ✓ | | | |
| Paul and Hariharan (2012) | ✓ | | ✓* | | |
| Rachaniotis et al. (2012) | | ✓ | | | |
| Wang et al. (2012) | | | | ✓ | |
| Chan et al. (2013) | | | | | ✓ |
| Edrissi et al. (2013) | ✓ | | | | |
| Kilic et al. (2013) | | ✓ | | | |
| Mills et al. (2013) | | ✓* | | ✓ | |
| Najafi et al. (2013) | ✓ | | | ✓* | |
| Wilson et al. (2013) | ✓ | | ✓* | ✓ | |
| Apte et al. (2014) | ✓ | | ✓ | ✓* | |
| Cohen et al. (2014) | | | | | ✓ |
| Dean and Nair (2014) | | | | ✓ | |
| Jin et al. (2014) | | | ✓ | ✓ | ✓* |
| Najafi et al. (2014) | ✓ | | | ✓* | |
| Salman and Gül (2014) | | | | ✓ | |
| Wex et al. (2014) | ✓ | | | | |
| Wilson et al. (2014) | | | | ✓ | |
| Xiang and Zhuang (2014) | | ✓ | | | |
| Zheng et al. (2014) | | ✓ | | | |
| Caunhye et al. (2015) | | ✓ | ✓* | | |
| Edrissi et al. (2015) | ✓ | | | | |
| Na and Banerjee (2015) | ✓ | | | ✓* | |
| Talarico et al. (2015) | | | | ✓ | |
| Debacker et al. (2016) | | ✓ | ✓* | ✓ | |
| Mills (2016) | | ✓ | | | |
| Paul and MacDonald (2016a) | | | ✓ | | |
| Paul and MacDonald (2016b) | | | ✓ | | |
| Repoussis et al. (2016) | | | | ✓* | ✓ |
| Su et al. (2016) | ✓ | | | | |
| Sung and Lee (2016) | | | | ✓ | |
| Wanying et al. (2016) | | | | | ✓ |
| Wilson et al. (2016) | ✓ | | ✓* | ✓ | |
| Al Theeb and Murray (2017) | ✓ | | | | |
| Haghi et al. (2017) | ✓ | | | | |
| Kamali et al. (2017) | | | ✓ | ✓* | |
| Karatas et al. (2017) | ✓ | | | | |
| Zhang et al. (2017) | ✓ | | | | |
| Cao et al. (2018) | ✓ | | | | |
| Caunhye and Nie (2018) | | | | ✓ | |
| Gu et al. (2018) | ✓ | | | | |
| Kim et al. (2018) | ✓ | | | | |
| Mahootchi and Golmohammadi (2018) | ✓ | | | | |
| Mills et al. (2018) | | | | ✓ | |
| Mollah et al. (2018) | ✓ | | | | |
| Niessner et al. (2018) | ✓ | ✓ | ✓* | ✓ | |
| Rezapour et al. (2018) | ✓ | | ✓* | | |
| Rodríguez-Espíndola et al. (2018) | ✓ | | | | |
| Safaei et al. (2018) | ✓ | | | | |
| Shiripour and Mahdavi-Amiri (2018) | ✓ | | | | |
| Sun et al. (2018) | | ✓ | | | |
| Alinaghian et al. (2019) | ✓ | | | | |
| Alizadeh et al. (2019) | | ✓ | ✓* | ✓ | |
| Baharmand et al. (2019) | ✓ | | | | |
| Bravo et al. (2019) | ✓ | | | | |
| Çankaya et al. (2019) | ✓ | | | | |
| Davoodi and Goli (2019) | ✓ | | | | |
| Doan and Shaw (2019) | ✓ | | | | |
| Ghasemi et al. (2019) | ✓* | | | ✓ | |
| Li and Chung (2019) | ✓ | | | | |
| Li et al. (2019) | ✓ | | | | |
| Liu et al. (2019) | ✓ | | | | |
| Liu et al. (2019) | ✓ | | | | |
| Lodree et al. (2019) | | | ✓ | | |
| Ozbay et al. (2019) | ✓ | | | | |
| Paul and Zhang (2019) | ✓ | | | | |
| Rauchecker and Schryen (2019) | ✓ | | | | |
| Sabouhi et al. (2019) | ✓ | | | ✓* | |
| Setiawan et al. (2019) | ✓ | | | | |
| Yu et al. (2019) | ✓ | | | | |
| Zhu et al. (2019) | ✓ | | | | |

[*] The focus of the paper is supposed to be on this category; therefore, the micro analysis will be presented in this section.

## 3. RESOURCE DISPATCHING / SEARCH AND RESCUE (RD&SR)

Depending on the severity, spread and location of a disaster, there may be some casualties trapped in stricken areas. In particular, when a sudden-onset disaster strikes a densely populated residential area, it is very likely that many casualties are trapped (e.g., under a fallen debris). In these circumstances, the first CM-related operations are relief resource dispatching and search and rescue. In this regard, some researchers investigated the use of new technologies for the search and rescue of trapped people. Hamp et al. (2014) presented and compared new wireless search and auxiliary assistive technologies for the detection and localization of trapped or buried unconscious casualties. Hallak et al. (2019) used GIS (Geographic Information Systems) for a multi-objective shelter location model. Hu et al. (2019) developed a crowdsourcing model to improve the quality of identifying post-earthquake trapped casualties. Sánchez-García et al. (2019) proposed a PSO (Particle Swarm Optimization) algorithm to explore a disaster area where particles were unmanned aerial vehicles (UAV). Alotaibi et al. (2019) developed an algorithm, named LSAR, to employ multiple UAVs to accomplish a SAR mission in the minimum possible time to save the highest number of survivors.

After an initial damage assessment, available local and national emergency resources, as well as emergency units must be immediately dispatched to affected sites. Efficient RD&SR operations consisting of several decisions are crucial in increasing the survival rate of an affected population. The deployment of emergency facilities such as CTSs near stricken areas is governed by locational decisions. Allocation decisions determine the assignment scheme of affected sites to located facilities to minimize total response time and costs. Mobile resources such as SAR and medical units are moved to affected sites and CTSs respectively. The corresponding sequence and timing of such movements are handled by routing and scheduling decisions respectively. Tables 3 and 4 demonstrate the details of our micro-analysis on RD&SR papers.

### 3.1. Problem category description

In this subsection, we explain the most relevant papers published in each problem category:

**Allocation:** Fiedrich et al. (2000) studied the network-based resource allocation problem for three important operations including SAR, secondary disaster prevention and transportation lifeline rehabilitation in six interrelated areas immediately after earthquakes. They found the best policy to minimize the total number of fatalities due to secondary disasters, duration of rescue operations, lack of rescue attempts, delayed transport, duration of transport and lack of transport. Su et al. (2016) proposed an optimization model based on a “disaster response coalition” concept for the problem of allocating, in parallel, multiple emergency resources to heterogeneous simultaneous disasters, taking into account the response time and emergency resource cost altogether. They showed that the parallel allocation of emergency resources for concurrent incidents is significantly more economical and efficient than traditional serial allocation. Cao et al. (2018) formulated a multi-objective MINLP model for dynamic relief distribution in large-scale natural disasters to maximize sustainability (i.e., access, equity and needs fulfillment). The response phase was refined into golden rescue, buffer rescue and emergency recovery stages. Real-time post-disaster information is usually unknown. Therefore, in the centralized relief distribution network during the response phase, the proposed sustainable relief distribution may be useful. Rodríguez-Espíndola et al. (2018) developed a multi-modal, multi-commodity model to support resource allocation and relief distribution during a disaster response that incorporates human and material resources from multiple organizations. The objective functions were to maximize the casualty service level and to minimize total costs. The results showed the importance of coordination among relief organizations and the inefficiency stemming from the independent decision-making at a disaster scene.

Doan and Shaw (2019) developed stochastic optimization techniques to make resource allocation decisions in the preparedness phase and resource request decisions in the response phase of three concurrent incidents across eight cities. Three models were proposed: (1) a penalty-based model to minimize the risk related to the achievement of response targets given existing resources, (2) a resource-based model to determine the resource requirements to meet response targets and (3) a hybrid budget-based model to analyze the different financial budgets. They introduced local importance parameters in the models to partially balance out the political dimensions of implementation. Li et al. (2019) developed an optimization model based on a matching concept for the assignment of rescuers with different professional skills and subjective preferences. Matching degrees between rescuers and rescue tasks at disaster sites were obtained by aggregating related task fitness degrees and time fitness degrees. Task fitness degrees were calculated by the corresponding satisfaction degrees and competence degrees of rescuers. Time fitness degrees were determined based on actual travel times and rescue time requirements at affected sites. Liu et al. (2019) presented a rolling horizon-based framework, based on the robust model predictive control for distributing both relief commodities and injured people to minimize the total weighted unmet demand. Yu et al. (2019) proposed a nonlinear integer model and an equivalent dynamic programming model to allocating limited resources among different affected sites considering three metrics; i.e., deprivation cost, service quality, and fairness.

**Scheduling:** Wex et al. (2014) addressed the rescue unit scheduling and assignment problem as a generalization of the parallel-machine scheduling with unrelated machines and non-batch sequence-dependent setup times. Several heuristics including a Monte Carlo-based heuristic, a combination of 8 construction heuristics, 5 improvement heuristics and GRASP metaheuristic were developed. Kim et al. (2018) proposed a model and two greedy algorithms to find the allocation and scheduling plan for responders in an early stage response problem to prevent further hazards. The model reflects dynamic changes in the hazard intensity and working time to eliminate dangerous targets. They considered a large public area as a graph. The initial location of responders and affected locations were represented as source and sink nodes, respectively. The objective function was to maximize the prevention of potential risks (fire spread, gas leaks, explosions, etc.). Notably, when the field information is updated in real-time, the solution can be updated within a short time frame even if the emergency situation changes dramatically. Rauchecker and Schryen (2019) proposed a model and an efficient branch-and-price algorithm for the scheduling of rescue units, being able to non-preemptively process multiple incidents depending on their capabilities. The proposed approach was shown to be competitive to the optimal solution especially when the decision time is limited to a very few minutes.

**Location-Allocation:** Edrissi et al. (2013) developed a multi-agent optimization model and a heuristic solution for the three post-earthquake sub-problems under budget limitations: (1) renovating deteriorated and low-quality buildings and developments to maximize the number of saved casualties; (2) locating/allocating emergency aid levels to maximize the total rescued population under supply and demand constraints; and (3) strengthening the existing transportation infrastructures to maximize reliability. The results showed a considerable improvement in the death toll of the multi-agent model. Edrissi et al. (2015) proposed a network improvement problem and a heuristic algorithm to minimize the death toll. In finding critical links, link importance values were derived using the concept of network reliability. They indicated that initial incremental investments in network improvement can reduce the number of fatalities more than later higher budget increments. Moreover, higher relief inventories greatly reduce the deaths under the network reliability. Haghi et al. (2017) proposed a two-phase multi-objective robust optimization for locating distribution centers and CTSs and distributing relief goods and casualties to health centers, with pre/post-disaster budget constraints on the logistics system. The model was to establish a reasonable trade-off between humanitarian factors and total costs and to spend the budgets more efficiently.

**Table 3.** The details of RD&SR papers.

| Reference | Problem category | Key decision variable(s) | Main assumption(s) | Parameters: Disaster sites | Demand | Survival probability | Travel time | Service time | Miscellaneous | Main constraints | Objective function(s) | Solution approach | Largest problem solved |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Fiedrich et al. (2000) | A | No. of allocated resources | Various casualty groups, Homogenous resources | ✓ | - | ✓ | ✓ | - | ✓ | NR | MF | TS, SA | - |
| Nolz et al. (2011) | L-R | Locate DCs and Routing between AFs and DCs | Damages to infrastructure and related risks | ✓ | ✓ | - | ✓ | - | ✓ | CR | MT, O | MOO, MA | 12 CLs, 217 intersections |
| Berkoune et al. (2012) | A-R | Allocate items to AFs and Routing vehicles | Fixed DCs, Multi-item, Multi-vehicle type | ✓ | ✓ | - | ✓ | - | - | CF,CR | MT | OP, H, GA | 100 DCs, 100 AFs |
| Chen and Miller-Hooks (2012) | R | Allocate USAR teams to AFs | Homogenous resources, Non-preemptive service | ✓ | ✓ | - | ✓ | ✓ | - | NR | MS | SP, CG | 15 teams, 88 AFs |
| Edrissi et al. (2013) | L-A | - Locate/allocate relief supplies<br>- No. of rescued people | DHC, Deteriorating zones | ✓ | ✓ | ✓ | ✓ | - | - | CF | O | H | 4,500 casualties |
| Wex et al. (2014) | S | Order of visiting AFs by SAR teams | Known number of teams and casualties | ✓ | - | - | ✓ | - | ✓ | NR | MT | H | 40 teams, 40 AFs |
| Edrissi et al. (2015) | L-A | Like Edrissi et al. (2013) | DHC | ✓ | ✓ | ✓ | ✓ | - | - | CF | MF | H | 4,500 casualties |
| Su et al. (2016) | A | Allocate resources to incidents | Multi-incident, Multi-resource | - | ✓ | - | ✓ | - | ✓ | CR | MT, MC | OP, H | 5 incidents, 5 products |
| Al Theeb and Murray (2017) | A-R | - Allocate items/workers/casualties to nodes<br>- Routing of vehicles among nodes | Multi-commodity/ vehicle/ depot, Split delivery | ✓ | ✓ | - | ✓ | - | - | NR, CR, CF | O | ILP, H | 46 nodes, 40 vehicles |
| Haghi et al. (2017) | L-A | - Locate DCs and CTSs<br>- Allocate relief items and casualties | Known candidate DCs/ CTSs, Multi-item/ casualty type | ✓ | ✓ | - | - | - | ✓ | CF, CR | MC, O | MOO, GA | 10 AFs, 4 CLs, 3 items, 4 scenarios |
| Karatas et al. (2017) | L-A | - Allocate helicopters to stations<br>- Allocate stations to CLs | Multi type helicopters | ✓ | ✓ | - | ✓ | - | - | NR, CR, CF | MT | ILP, S | 716 AFs, 9 CTSs, 4 types of helicopter |
| Zhang et al. (2017) | L-A | Locate depots and Allocate teams to AFs | Known route conditions, Limited budget | ✓ | ✓ | - | ✓ | - | - | CF | MT, O | MOO, GA | 375,000 casualty, 5 depot, 8 AFs |
| Cao et al. (2018) | A | Allocate relief items to AFs | Known CLs, Split delivery, Multi-product | ✓ | ✓ | - | ✓ | - | - | CF, CR | O | OP, GA | 237 AFs |
| Gu et al. (2018) | L-A | - Location and capacity of shelters<br>- Allocate supplies/ casualties to shelters | Known candidate shelters, Known severity and distribution of casualties | ✓ | ✓ | - | - | - | - | CR, CF | MS | OP, GR | 30 CLs, 500 casualties |
| Kim et al. (2018) | A-S | - Allocate responders to AFs<br>- Scheduling of responders at nodes | Discrete time | ✓ | - | - | ✓ | ✓ | ✓ | CF | O | OP, GR | 44 nodes |
| Mahootchi and Golmohammadi (2018) | L-A | - Locate warehouse and relief items<br>- Allocate warehouses to AFs | Multi-product, Bi-directional relation among warehouses | ✓ | ✓ | - | - | - | ✓ | CR, CF | MC | OP | 22 regions, 108,000 casualties |
| Mollah et al. (2018) | L-A | - Locate shelters<br>- Number of trips among temporary locations | Known shelters and their availability, Heterogeneous vehicles | ✓ | ✓ | - | ✓ | - | ✓ | CF, CR | MC | OP, GA | 27 shelters, 17,000 casualties |
| Rodríguez-Espíndola et al. (2018) | A | - Allocate relief teams/ items to facilities<br>- Allocate facilities to shelters | Centralized operations, Multi-agent/ item, Multiple transportation modes | ✓ | ✓ | - | - | - | ✓ | CF, CR, NR | MC, O | OP | 44,000 casualties |
| Safaei et al. (2018) | L-A | - Locate dispatching depots<br>- Allocate relief items among nodes | Multi-period, Multi-product, Known CLs | ✓ | ✓ | - | - | - | - | CF, CR, NR | MC, O | OP | 3 AFs, 3 scenario, 2 item, 4 CLs |
| Shiripour and Mahdavi-Amiri (2018) | L-A-R | - Locate CTSs and Allocate casualties to CTSs<br>- Routing of vehicles between AFs and CTSs | Triple transportation modes, Various infrastructure states | ✓ | ✓ | - | ✓ | - | ✓ | CF, CR, NR | MT | OP, ICA | 14 AFs, 20 CLs, 215,000 casualties |
| Alinaghian et al. (2019) | L-A-R | - Locate CTSs and Allocate AFs to CTSs<br>- Routing of helicopters among CTSs | Single item, Homogeneous fleet | ✓ | ✓ | - | ✓ | - | - | CR, NR | MT | OP, SSA, GA | 80 nodes, 10 helicopters |
| Baharmand et al. (2019) | L-A | - Locate DCs<br>- Allocate AFs to DCs | Covering all demands, Ground and air transportation, AFs independency | ✓ | ✓ | - | ✓ | - | ✓ | CF, CR, NR | MC, MT | MOO | 8 DCs, 7 AFs |
| Bravo et al. (2019) | R | Order of site visits | Known number of casualties | ✓ | ✓ | - | ✓ | ✓ | ✓ | NR | MS | MDP | 100,000 casualties |
| Çankaya et al. (2019) | A | - Distribute commodities/casualties among nodes<br>- Allocation of helicopters to nodes | Multiple commodities | ✓ | ✓ | - | ✓ | - | ✓ | CR, NR | O | OP | 8 AFs, 3 CTSs, 2 commodities, 3 transport modes |
| Davoodi and Goli (2019) | L-A-R | - Locate CTSs and Allocate items to CTSs<br>- Routing of vehicles between AFs and CTSs | Single item, Homogeneous vehicles | ✓ | ✓ | - | ✓ | - | - | CR, NR | MT | OP, BD, VNS | 120 vehicle, 210 AFs |
| Doan and Shaw (2019) | A | Allocate resources to AFs | Three simultaneous disasters, Multi-scenario | ✓ | ✓ | - | ✓ | - | ✓ | CR, NR | O | SP | 8 AFs, 72 unit, 20 USAR unit |
| Ghasemi et al. (2019) | L-A | - Locate CTSs/ DCs and Allocate AFs to CTSs<br>- Flow of casualties/ items among facilities | Five-echelon network, Multi-scenario, Known CLs | ✓ | ✓ | - | - | - | ✓ | CF, NR | MC, O | SP | 10 AFs, 11 hospital, 10 DCs, 4 CTSs |
| Li and Chung (2019) | R | - Routing of vehicles among AFs | Homogeneous vehicles | ✓ | ✓ | - | ✓ | - | - | NR, CR | MT | H | 101 nodes |
| Li et al. (2019) | A | Assign rescuers to AFs | Multi-task, Various capability criteria | ✓ | - | - | ✓ | - | ✓ | NR | O | OP | 50 rescuers, 6 tasks, 6 criteria |
| Liu et al. (2019) | L-A | - Locate facilities and Allocate casualties<br>- Allocate doctors/ resources to casualties | Two-mode homogeneous transportation, DHC | ✓ | ✓ | ✓ | ✓ | - | - | CF, CR, NR | MS, MC | MOO | 1,120 casualties, 150 CTSs, 11 ambulances, 6 helicopters |
| Liu et al. (2019) | A-R | - Allocate AFs to depots<br>- Routing of vehicles among AFs | Allowed shortage, Known/constant demand | ✓ | ✓ | - | ✓ | - | ✓ | NR | MT, MC | H | 100 AFs, 16 vehicles, |
| Ozbay et al. (2019) | L-A | Locate shelters and Allocate AFs to shelters | Multiple successive disasters, Known CLs | ✓ | ✓ | - | - | - | ✓ | CF | O | SP, H | 25 shelter, 500 scenarios |
| Paul and Zhang (2019) | L-A | Locate DCs and Allocate resources to AFs | Various injury levels, Multi-scenario, DHC | ✓ | ✓ | ✓ | ✓ | - | ✓ | CF, CR | MC | SP | 50 DCs, 30 AFs, 30,000 casualties |
| Rauchecker and Schryen (2019) | S | Order of incidents | Known number of rescue units | ✓ | ✓ | - | ✓ | ✓ | ✓ | NR | MT | LP | 40 incidents, 10 unit, 8 capability |
| Setiawan et al. (2019) | L-A | - Locate CTSs and DCs<br>- Allocate CTSs, DCs, and vehicles to AFs | The further ahead the time is, the longer the period between two adjacent new periods, | ✓ | ✓ | - | ✓ | - | ✓ | CF, NR, CR | O | OP, H | 47 AFs, 139 vehicles |
| Yu et al. (2019) | A | - Allocate resources to AFs | Inventory is not allowed | ✓ | ✓ | - | - | - | - | CF | MC | DP, H | 10 AFs |
| Zhu et al. (2019) | R | - Routing of vehicles among CTSs and AFs | Fixed capacity identical vehicles | ✓ | ✓ | - | ✓ | - | ✓ | CR, NR | MC | ACO, GA | 20 AFs |

**Table 4.** Micro analysis of RD&SR papers: uncertainty, dynamics, heuristics, and insights.

| Reference | Uncertain parameter |
|---|---|
| Fiedrich et al. (2000) | Survival rates (E), Occurrence of secondary disasters (W), Survival rate of casualties without treatment (S-shaped) |
| Chen and Miller-Hooks (2012) | Casualty flows (G), Service times (G), Travel times (G) |
| Haghi et al. (2017) | Operational costs (S), Commodity demands (S), Casualty flows (S), Failure of health centers (S) |
| Karatas et al. (2017) | Inter-incident times (E), Weather condition (S), Helicopter failure (S) |
| Mahootchi and Golmohammadi (2018) | Link capacities (S), Commodity demands (S), Operational costs (S) |
| Safaei et al. (2018) | Commodity demands (S) |
| Doan and Shaw (2019) | Potential simultaneous disaster happenings (S) |
| Ghasemi et al. (2019) | Establishment and operational costs (S), Commodity demands (S), Casualty flows (S), Capacities (S) |
| Li and Chung (2019) | Travel times (S), Demands (S) |
| Liu et al. (2019) | Commodity demands/supplies (I), Casualty flows (I), Capacities (I) |
| Ozbay et al. (2019) | Casualty flows (S) |
| Paul and Zhang (2019) | Casualty flows (S), Undamaged supplies (S), Transport cost and time (S), Travel times (E), Truck's travel times (GM) |
| Zhu et al. (2019) | Deprivation cost (Author-defined) |

E: Exponential, W: Weibull, G: General, S: Scenario-based, I: Interval, GM: Gamma

| Reference | Dynamic parameter/Information update mechanism* |
|---|---|
| Fiedrich et al. (2000) | Finished/started affected sites, Set of depots, New affected sites due to secondary disasters, Destroyed affected sites/links |
| Chen and Miller-Hooks (2012) | Affected disaster sites, Casualty flows, Service times<br>* A renewal process for decision epochs including several periods |
| Wex et al. (2014) | * Frequently update data and refresh decisions via a DSS in less than a second |
| Rodríguez-Espíndola et al. (2018) | Availability of rescue organizations |
| Alinaghian et al. (2019) | Casualty flows, Aftershocks, Damaged road networks<br>* Updating procedure for location and demand of disaster sites, Dynamic routing |
| Doan and Shaw (2019) | Disaster resource requirements |
| Liu et al. (2019) | Commodity demands/supplies, Casualty flows, Capacities<br>* Real-time adjustment framework based on robust model predictive control |
| Yu et al. (2019) | State of affected sites: number of periods that each AF can withstand the demand using the on-hand resources |
| Zhu et al. (2019) | Deprivation costs, Travelling velocities among nodes |

| Reference | Heuristic/Rule of thumb/Insight* |
|---|---|
| Li and Chung (2019) | Split Delivery Vehicle Routing<br>* Minimize the sum of arrival times, sum of demand-weighted arrival times, and latest arrival time for fast and fair deliveries |
| Setiawan et al. (2019) | Resource sharing measures<br>* Coordinate between evacuation and distribution for further improvements |

Karatas et al. (2017) developed a hybrid approach combining optimization and simulation to determine the location, number and type of helicopter stations to be established for evacuation, rescue and firefighting operations by the Turkish coast guard. They argued that the proposed hybrid approach leads to more effective resource utilization than the optimization model alone because the simulation model adds the weather conditions and failure concepts to the optimization. Zhang et al. (2017) developed a multi-objective model for the multistage dynamic assignment of rescue teams to a disaster chain and proposed three priority scheduling strategies defined under the burden-benefit accord principle. The overall performance of the proposed model was satisfactory, regardless of whether secondary disasters occurred sooner or later. The appropriateness of the three priority strategies for a specific disaster situation depends on the maximum allowable rescue time. Gu et al. (2018) proposed an optimization model to determine the locations of temporary medical shelters and the allocation of medical supplies under a limited relief budget. The severities and geographical locations of casualties were considered. Mahootchi and Golmohammadi (2018) developed a multi-product two-stage stochastic optimization model to determine the location of warehouse and pre-positioned relief items and the allocation of warehouses to affected sites. They considered bi-directional relations between warehouses, which can increase the flexibility of the constructed network to handle the needs of casualties in a shorter time interval. Moreover, it leads to a reduction in total costs and the number of warehouses. Mollah et al. (2018) developed a cost optimization block-shelter allocation model and a genetic algorithm for the evacuation of casualties, their reallocation to safe places and the quick distribution of relief materials to combat the spread of disease and suffering of casualties in slow-onset disasters like floods. The performance of GA in terms of both survivors and costs is reported to be higher than the MIP solution as the number of blocks and shelters increases and the evacuation time decreases. Safaei et al. (2018) developed a robust optimization model for a supply-distribution relief network that optimized relief operating costs and unsatisfied casualty' demands in the upper level, and the supply risk and unsatisfied demands in the lower level. Suppliers with lower risks were determined by a TOPSIS method and introduced to the optimization model. As distribution decisions are inherently more important than supply decisions, the proposed bi-level model was shown to work better than the multi-objective optimization.

To establish a balance between the complexity and uncertainty, Baharmand et al. (2019) proposed a location-allocation model that divided the topography of affected sites into multiple layers and allowed decision-makers to explore trade-offs between response time and logistics costs. Ghasemi et al. (2019) proposed a scenario-based probabilistic location-allocation model in a five-echelon humanitarian logistics network to minimize the facility-related costs and the shortage of relief supplies. The model was solved using a modified multiple-objective PSO (MMOPSO), NSGA-II and ε-constraint. The results revealed the superiority of MMOPSO. A sensitivity analysis indicates that increasing the failure probability of temporary care and accommodation centers would increase relief costs. Liu et al. (2019) developed a bi-objective model to determine the location of CTSs and the allocation of medical resources to transfer casualties to CTSs and to provide on-field treatment in CTSs to maximize the number of expected survivals and minimize total operational costs. They showed that locating CTSs with large capacities near the disaster sites may result in more efficient response operations. Ozbay et al. (2019) developed a three-stage stochastic programming model to locate shelter sites and allocate the affected population to the established set of shelters in cases of secondary aftershocks following the main earthquake. Shelter location decisions for primary and secondary disasters were made in the first and second stages, respectively, while casualties are transferred to the nearest shelters, respectively, in the second and third stages. To manage the risk inherent to the demand and capacity of shelter sites when allocating casualties, the conditional value-at-risk was utilized. They argued that it is important to consider secondary disasters while locating shelter sites. Paul and Zhang (2019) developed a two-stage stochastic programming model for hurricanes to optimize the location of distribution points, medical supply levels and transportation capacity in the first stage and the flow of resources in the second stage. The total social cost, comprised of deprivation and commercial logistics costs, was minimized. Three deprivation cost functions due to the delayed treatment for three casualty severity levels were proposed. Setiawan et al. (2019) developed three location-allocation models for the problem of positioning medical and relief distribution facilities after a sudden-onset disaster. In the first model, relief distribution and victim evacuation are performed separately, and relief is distributed by distribution centers within administrative boundaries. The second model allows relief to be distributed across boundaries by any distribution center. In the third model, the evacuation and relief distribution operations share vehicles.

**Routing:** Nolz et al. (2011) formulated an optimization model to make robust tours to assure an adequate distribution of relief aid in a post-natural-disaster situation considering damages to the infrastructure. Objective functions were the tour-dependent risk, the provided coverage to casualties and the total travel time. To measure the risk of delivery tours, five alternative approaches were analyzed. The “unreachability” risk approach as the sum of risk values of all the alternative connections between a pair of affected sites was shown to establish the best compromise among objectives. Berkoune et al. (2012) developed a model for the transportation of humanitarian items and equipment located at fixed distribution points to casualties at numerous delivery points. The proposed solutions were robust against small changes in the demand for affected sites and travel times. Chen and Miller-Hooks (2012) proposed a two-stage stochastic program to determine the best set of tours for homogeneous USAR units providing assistance to casualties. They studied the value of the information update, the required accuracy levels of information and the role of misinformation. Al Theeb and Murray (2017) formulated a MILP model for the coordination of numerous heterogeneous vehicles in a post-disaster logistics network to optimize the commodity delivery and workforce transfer to affected sites and casualty evacuation to CTSs. They demonstrated that the integration of the workforce transfers with the commodity distribution and the casualty evacuation will improve distribution efforts. Shiripour and Mahdavi-Amiri (2018) developed an integer nonlinear program, a GA and an imperialist competitive algorithm for the distribution of casualties in a three-mode transportation network with separate connection links. They proposed a circle-based approach to estimate the impacts of a disaster and some relations for computing the percentage of casualties, destruction percentage and the damage-dependent travel times. The casualty and destruction percentages are determined based on the disaster center and severity, distances and the type of infrastructure.

Alinaghian et al. (2019) developed a model for the location of CTSs and the dynamic routing of helicopters distributing basic supplies to minimize the arrival time at the last CTS. Inaccurate information regarding casualties, aftershocks, damaged road networks and the location and level of demands were considered to be dynamic. The proposed dynamic routing significantly reduces the total distribution time compared to traditional static routing. Bravo et al. (2019) proposed a partially observable Markov decision process for the routing of UAVs to search for casualties at affected sites. The vehicles' path planning was formulated to assign higher priorities to sites that are more likely to have casualties. They evaluated the performance of their approach against a greedy heuristic algorithm on three sudden, and slow-onset disasters. Moreover, ethical, legal and social acceptance issues that can influence the application of the methodology, were discussed. The proposed solution achieved a full coverage of affected sites while optimizing the time to find casualties. The coverage is vital as casualties are distributed across all affected areas and need help equally. The number of states is crucial for determining the traveled distance and operation duration; hence, they recommended applying specialists who know the area well to set the state's priorities. Çankaya et al. (2019) studied an application of the inventory Routing Problem with the goal of equitable distribution of relief supplies to the affected areas. They proposed a three-phase (clustering, routing and improvement) solution approach. Both variants of the proposed solution outperformed the algorithms in the literature. Davoodi and Goli (2019) proposed a model for the location of CTSs in affected sites and the allocation and routing of first-aid commodities to minimize the late arrival of relief vehicles. A covering tour approach considerably increased the operational speed of dispatching vehicles that carry essential commodities. They recommended the best coverage radius in terms of the objective function and analyzed the results when the demand is increased. Li and Chung (2019) developed a robust optimization approach for the Capacitated Vehicle Routing and the Split Delivery Vehicle Routing problems for the casualties trapped in the affected sites. Zhu et al. (2019) developed two models for the identical and diverse casualty severities where the relative deprivation cost was proposed to emphasize equity, and the in-transit tolerable suffering duration was employed to highlight the rescue priority. Various measures were investigated to extend the in-transit tolerable suffering duration for achieving a better emergency relief.

### 3.2. Critical discussion

We discuss possible gaps and trends to make suggestions for future research directions on RD&SR:

*Deteriorating health conditions*: As given in Table 3, most papers assumed stable health conditions for affected people during RD&SR operations while this is usually not the case. In fact, the health condition of casualties is a function of the timing and quality of relief operations, particularly the RD&SR, in the early aftermath of MCIs and vice versa. Accordingly, formulating practical but effective survival probability functions for such models is specifically demanded.

*Heterogeneous vehicles of multiple modes*: As a function of type, severity, location and spread of a disaster, various transportation modes of different types and capacities may be called. The proposed models have to consider the transportation needs of all relief resources and the characteristics of relevant transportation modes.

*Various relief items*: Beamon et al. (2004) discussed the characteristics of commercial versus humanitarian supply chains according to the key aspects such as the demand pattern, inventory control, lead time, etc. Depending on the disaster type, various relief items including medical items, food, clothing, tools, etc. may be needed to be dispatched to the affected demand nodes. Moreover, these items are generally different in terms of the usage, perishability, supplying and dispatching method and so on. The existing RD&SR models mostly assumed a single dominant item or did not consider the above differences.

*Studying RD&SR operations on a micro-level*: The existing models decided on how to optimize the allocation, scheduling or routing of SAR teams among the affected sites. A strongly demanded area of research is to optimize the above decisions on RD&SR activities at a given affected site aiming at minimizing the number of casualties to be positioned in serious triage groups.

*Impact of preparedness*: Slow-onset disasters can be easier to manage that sudden-onset ones as we have ample time to prepare. The impact of disaster preparedness on the post-disaster response of RD&SR operations is underexplored in the literature of slow-onset disasters.

## 4. ON-SITE TRIAGE (OST)

Extricated casualties need first-aid assistance and medical stabilization. Due to the scarcity of medical resources (e.g., medical teams and nurses) in the initial hours after a disaster, it is usually impossible to provide first-aid assistance for all casualties immediately. Therefore, it is vital to determine treatment priorities according to their injury levels, which is referred to as on-site triage. The main purpose of OST is to categorize casualties into different groups to which limited medical resources are allocated in a way so as to maximize the survival rate. Normally, sufficient resources for treating casualties with severe injuries are available at the emergency units of hospitals. The order of treatment for hospital triage is often classified with the labels black, red, yellow and green. Lack of enough resources and simultaneous generation of mass casualties in disaster scenarios makes field triage difficult when compared to hospital triage. Field triage, therefore, is done by a figure referred to as incident commander and the order of treatment is red, yellow, green and black to try to save the highest number of casualties (Venkat et al., 2015). Simplicity in implementation and reliability are the most important features of an efficient field triage. Notably, triage is a dynamic process because the medical condition of casualties deteriorates as time goes on and re-triage may be needed several times. There are several OST methods: Simple Triage and Rapid Treatment (START) by Super et al. (1994), Triage Sieve by Hodgetts and Mackway-Jones (1995), Sacco Triage Method (STM) by Sacco et al. (2005), Sort, Assess, Life-saving interventions, Treatment and/or Transport (SALT) by Lerner et al. (2008) and Severity Adjusted Victim Evacuation (SAVE) by Dean and Nair (2014).

START, as one of the most common triage methods, categorizes casualties according to the severity of injuries into four color-labeled groups: red, yellow, green and black. People with mild lesions (e.g., minor fractures, soft tissue injuries, mild mental and neural disorders, stomachache or headache), who will not lose their lives or suffer from permanent side effects, are placed in the ***green*** group (or outpatient). The ***Yellow*** group (or delayed) includes casualties with severe injuries (e.g., mild burns, severe bone, joint and muscle lesions, mild spinal lesions, diabetes without disturbance in consciousness, eye injuries and bad wounds) who need treatment in the 2 to 12 hours ahead. Urgent casualties with high risks (e.g., respiratory diseases, intense bleeding, consciousness loss, severe internal problems, severe burns, serious injuries, partial amputation, heart attack and severe poisoning), who will die or experience severe problems if they do not receive medical treatment within one to two hours are positioned in the ***red*** group (or critical). Finally, the ***black*** group (or deceased) includes dead people or casualties that are expected to die in less than an hour (e.g., full and irreversible heart failure) despite receiving medical treatment. Sometimes, dying people are called expectant and marked with a blue color. To increase the survival rate, START usually gives priority to the red-group casualties.

Triage Sieve, as the most common method in the UK, also categorizes casualties into four groups. At first, it uses a walking filter to determine the ***delayed*** group due to the large number of casualties with minor injuries. Then, the breathing, respiration rate and capillary refill time or heart rate, depending on the ambient weather and temperature conditions, are used to categorize casualties in the other three groups. If there is not an airway, casualties are grouped in the ***dead*** class. A respiratory rate below 10 and over 29 leads to being grouped in the ***immediate*** class. Otherwise, if a capillary refill is under 2 seconds, the priority of casualties is ***urgent*** (Hodgetts and Mackway-Jones, 1995). In the STM method, three scores of Respiration, Pulse and Motor (RPM) on a zero-to-four scale are assigned to each casualty. Adding the scores leads to thirteen possible triage classes ranging from 0 to 12. The Delphi technique is used to estimate the deterioration of casualties' health in each class (Sacco et al., 2005). The prioritization of the casualty classes in STM can be formulated as a linear programming model aiming at the maximization of the expected number of survivors. The variables are subject to constraints on the timing and availability of transportation and resources for treatment. The SALT method includes four steps to reflect the fact that OST is more than just assessing casualties' conditions. Similar to STM, it considers the resource availabilities. This method creates an extra gray-colored group named ***expectant*** whose casualties are not expected to survive given the available resources (Lerner et al., 2008). Tables 5 and 6 demonstrate the details of OST papers.

**Table 5.** Details of papers addressing OST.

| Reference | Problem category | Key decision variable(s) | Main assumptions | Parameters: Disaster site | Demand | Survival probability | Travel time | Service time | Miscellaneous | Main constraints | Objective functions | Solution approach | largest problem solved |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Li and Glazebrook (2010) | S | Order of jobs | Known jobs, Non-preemptive service | - | - | ✓ | - | ✓ | ✓ | NR | MS | H | - |
| Jacobson et al. (2012) | S | Order of jobs | Known jobs, Non-preemptive service, DHC | - | - | ✓ | - | ✓ | - | NR | MS | SDP | 100 jobs |
| Rachaniotis et al. (2012) | S | Order of infected subpopulation | DHC | - | ✓ | ✓ | - | - | ✓ | NR | MF | Enumeration | - |
| Kilic et al. (2013) | S | Service rate | Non-preemptive service, DHC | - | - | ✓ | - | ✓ | ✓ | NR, CR | O | QT | - |
| Mills et al. (2013) | S | Prioritize casualty transportation | Known casualties | - | ✓ | ✓ | ✓ | - | - | NR | MS | OPT | 50 casualties, 15 ambulances |
| Xiang and Zhuang (2014) | S | Service rate | DHC | - | - | ✓ | - | ✓ | ✓ | NR, CR | MS, O | QT | - |
| Zheng et al. (2014) | A | Urgent necessity index for casualties | - | - | ✓ | - | - | - | - | - | O | BBA | 1,281 casualties |
| Mills (2016) | S | Sequence of serving/ transporting triage groups | DHC | - | - | - | - | ✓ | ✓ | NR | MF | H | - |
| Sun et al. (2018) | S | Order of casualties | Known casualties | - | - | ✓ | - | ✓ | ✓ | NR | MF | MDP | 25 casualties |

### 4.1. Problem category description

Due to the lack of enough resources in MCIs, extricated casualties are classified according to their injury levels for subsequent operations (evacuation or treatment). Field triage is an essential tool in CM. Some of the most recent papers addressing OST are explained in detail in the following.

**Allocation:** Zheng et al. (2014) proposed a hybrid neuro-fuzzy approach to the online classification of earthquake-stricken casualties. A key component of the system is a main network for evaluating urgent necessity index values (Casualty classification) and a sub-network for recognizing movement patterns of casualties. They developed a differential biogeography-based algorithm for parameter optimization of both networks. Notably, the results indicated good classification performance compared to some other typical neuro-fuzzy networks. The proposed algorithm outperformed some state-of-the-art evolutionary algorithms in network learning.

**Table 6.** Micro analysis of OST papers: uncertainty, dynamics, heuristics, and insights.

| **Reference** | **Uncertain parameter** |
|---|---|
| Li and Glazebrook (2010) | Survival times (G), Casualty treatment times (G) |
| Jacobson et al. (2012) | Survival times (G), Treatment times (G), Survival probabilities after service (G) |
| Kilic et al. (2013) | Arrival rates (P), Service times (E), Fatality time when in queue and when under treatment (E) |
| Xiang and Zhuang (2014) | Arrival rates (P), Service times (E) |
| G: General, P: Poisson process, E: Exponential | |
| **Reference** | **Dynamic parameter/Information update mechanism*** |
| Rachaniotis et al. (2012) | Number of susceptible, infected, and removed casualties, Rates of sufficient contact, immunizing, and removal |
| Kilic et al. (2013) | Arrival of casualties, Service times<br>* Arrival rates will reach a steady-state 2 days after occurrence of disaster |
| Mills et al. (2013) | Service rates, Survival probabilities |
| Mills et al. (2016) | Survival probabilities |
| **Reference** | **Heuristic/Rule of thumb/Insight*** |
| Jacobson et al. (2012) | (1) 2-step heuristic, (2) Threshold heuristic, (3) Myopic policy, (4) $\alpha r\mu$-rule, (5) Time-critical-first rule<br>* Priority to less urgent patients when severe resource limitations<br>* Priority to time-critical casualties if below a threshold |
| Mills et al. (2013) | (1) Resource-based START, (2) QuickStatic- ReSTART, (3) QuickDynamic- ReSTART<br>* Priority to delayed casualties depending on resource availability and number of casualties |
| Mills et al. (2016) | Survival lookahead decision support rule |
| Sun et al. (2018) | A switching curve and its mathematical expression for when to triage casualties<br>* Skip triage when relatively few red casualties<br>* Fast triage aiming at leaving yellow casualties |

**Prioritization/Scheduling:** Li and Glazebrook (2010) formulated the OST problem as a single-server, multiple-class non-preemptive job scheduling system. The goal was to maximize the expected number served to completion. They improved an existing heuristic by proposing a robust heuristic and analyzed it considering three general scenarios. Jacobson et al. (2012) formulated the casualty triage, considering the I) resource limitations (ambulances and operating rooms), II) disaster scale and III) injury, as a priority assignment problem. Casualties (jobs) were classified based on their lifetimes, service times and reward (survival probability) distributions. Both constant and diminishing rewards over time were studied. Sample-path methods and stochastic dynamic programming were used to remove conditions under which the state information is not needed for prioritization decisions. They partially characterized the optimal policy and developed a number of heuristic policies. Rachaniotis et al. (2012) formulated a deteriorating job scheduling model for a single resource (mobile medical team) scheduling problem in several areas affected by a mass epidemic infection. The model represented an increasing loss rate as being more susceptible to become infected. It outperforms a random solution both in terms of the number of infections and completion time. However, the results should be interpreted with caution because of neglected uncertainties and heterogeneities.

Kilic et al. (2013) formulated a two-priority non-preemptive multiple server (medical teams) queuing system with a finite capacity to determine the service rate of red and yellow casualty classes with Poisson arrivals and deteriorating health conditions. They used Chapman–Kolmogorov differential equations and the Pontryagin's minimum principle to calculate optimal treatment rates for each priority class. The goal was to minimize both the difference between the number of servers and patients in the system and the related service costs. While arrival rates have almost a steady-state increase, there is also an increase in service rate values. This is not the case when arrival rates for both classes are sufficiently high. While the class deterioration rate increases, the service rate rises for red class patients but decreases for yellow ones. Mills et al. (2013) proposed a fluid model to characterize the optimal policy to prioritize the transportation of serious casualties to hospitals which explicitly considered the disaster size, resource limitations and time-varying survival probabilities. They showed that the recommended policy called ReSTART outperforms START in all considered scenarios, sometimes substantially. Xiang and Zhuang (2014) developed a two-priority queuing system to model the deterioration in health conditions and prioritize/schedule the treatment process of both classes of casualties. Two resource allocation models were formulated to minimize the total expected death rate and total waiting time respectively. The results showed that most, but not all, resources should be allocated to the queue of mildly injured casualties which is ethical.

Mills (2016) studied the casualty prioritization problem of an arbitrary number of casualty classifications with different survival probabilities deteriorating over time. Using simple heuristic parameterizations, they achieved an expected number of survivors similar to that of mathematical programming but with minimal computational support. The resulting rules are intuitive and easy to use and to understand in the aftermath of an MCI when resources are limited and the time is of the essence. Sun et al. (2018) formulated a static many casualty scheduling problem with a single medical provider who has two options: choosing casualties randomly for treatment or spending some time on triage and prioritizing them before treatment which will come at the expense of delaying the service. Each class of casualties is characterized by its waiting cost and expected service time. They identified a dynamic that balances the time spent on triage with the time spent on service by minimizing the total expected cost. When the number of casualties is not small, neither skipping a triage entirely nor performing triage on all patients works well and a decision depends on the state (number of casualties that are untriaged and triaged as a low priority).

### 4.2. Critical discussion

We discuss possible gaps and trends to make suggestions for future research directions on OST:

*Simple yet effective triage rules*: The total time required for OST is a key factor in speeding up the whole process of CM; therefore, complex and data-intensive decision-making models for OST are naturally inefficient and inapplicable. The tradeoff between speed and optimality is critical in designing OST methods. New studies are required on the development of dynamically robust, fast and simple to implement OST rules.

*Impact of over/under-triage*: Casualties in the same triage group are in diverse positions in terms of the type and level of injury. This leads to over- or under-triage and creates some difficulties and inefficiencies in OSM operations (Wilson et al., 2016). Frykberg (2005) studied the accuracy of triage after MCIs and found an almost linear relation between over-triage and poor patient outcomes. Thus, one direction for future study may be to enrich the triage operations by addressing intragroup classification/prioritization to have more effective OSM operations.

*Cross-disciplinary characteristics*: Although scholars tried to propose innovative OST systems, cross-disciplinary studies are still required to introduce novel, comprehensive and more flexible OST systems considering all the important factors regarding, for example, the severity and geographical spread of a disaster, dominant types of injury, field conditions, arrival patterns and relief resource limitations.

## 5. ON-SITE MEDICAL ASSISTANCE (OSM)

Casualties receive first-aid assistance in compliance with their triage groups at a nearby CTS to stabilize their medical condition before transportation to hospitals. CTSs are situated close to affected areas in safe locations such as schools, stadiums, shopping malls, parks so that the transportation of casualties is swift and easy. These safe locations also consist of some shelters for evacuees that need relief items. At the stations, there are medical personnel (doctors, nurses, etc.) and required equipment to service casualties immediately. Several decisions should be made for OSM operations such as the location/re-location of CTSs, allocation/re-allocation of medical personnel and equipment to stations, allocation/re-allocation of medical personnel and equipment to casualty groups, scheduling casualties in medical units, etc. Tables 7 and 8 show the details of OSM papers.

### 5.1. Problem category description

**Allocation:** Salmeron and Apte (2010) developed a two-stage stochastic optimization model for the allocation of budget to acquire and position relief assets in natural disaster areas. First-stage decisions addressed the expansion of facilities like warehouses, medical facilities, ramp spaces and shelters. Second-stage decisions concerned the deployment of allocated resources to rescue and transport casualties. Casualties were categorized into three groups: I) critical, II) stay-back and III) transfer population and each group needed a different relief service. Rezapour et al. (2018) determined the best strategies to allocate emergency units to affected sites and critical casualty groups in the early aftermath of sudden-onset MCIs when the capacity of emergency units is often inadequate. The studied treatment strategy was a “streaming without overflow” in which a number of medical teams are dedicated to each triage group. They found that the strategy does make the solutions more robust against any biases in medical teams’ streaming. Lodree et al. (2019) developed a discrete-time finite horizon stochastic dynamic programming problem and heuristic policies for the allocation of heterogeneous teams to serve queues of three different prioritization levels in the context of an MCI. While nurses and doctors serve their dedicated queues, collaborative teams of doctors and nurses serve critical casualties.

**Location-Allocation:** Drezner (2004) addressed the location problem of CCPs in case of an MCI. Five objective functions were analyzed: p-median, p-center, p-max cover, min-variance and Lorenz curve. The study showed that p-max cover was the recommended one. The multi-objective solution was close to the single objective solutions if the Lorenz curve was not involved. Lee et al. (2009) combined mathematical modeling, large-scale simulation, powerful optimization engines and automatic graph-drawing tools for the I) location and planning of the point of dispensing (POD) facility setup, II) allocation of required staff to stations in a POD, III) deriving dynamic response strategies to mitigate casualties and IV) designing a variety of dispensing exercises to train personnel. Because of the proposed tool’s rapid speed, it facilitates the analysis of what-if scenarios and serves as a decision tool for operational planning, actual drill preparation and personnel training. Paul and Hariharan (2012) proposed a robust optimization model for the locations and capacities of stockpile sites and their allocation to different casualty severity and types in the aftermath of a sudden, or slow-onset disaster. Three delays in providing medical assistance to casualties were considered.

Caunhye et al. (2015) developed a model to locate alternative care facilities for triage and treatment and to consider the triage and movement of self-evacuees in devising a casualty allocation plan for catastrophic radiological events. They considered three disaster zones around a radiological source: an inner zone containing severely-injured causalities and intermediate and outer zones including mildly-and lightly-injured casualties. Casualties were classified into self-evacuee and non-self-evacuee groups. They recommended that 1) if excess resources are available, the budget of care facilities is limited and the remaining resources are assigned to SAR and capacity building, 2) if the total resources are fixed, a right balance is found between the choice of more locations and the increase in transportation times, 3) if a hospital is far from the radiation zones, most resources are used for treatment and 4) for an overwhelmed CTS, a sufficient triage capacity is allocated. Paul and MacDonald (2016a) developed a stochastic optimization model and evolutionary heuristic to determine the location of distribution centers and the allocation of emergency stockpiles for treating casualties in the event of a disaster.

**Table 7.** Details of papers studying OSM operations.

| Reference | Problem category | Key decision variable(s) | Main assumption(s) | Parameters: Disaster site | Demand | Survival probability | Travel time | Service time | Miscellaneous | Main Constraints | Objective function(s) | Solution approach | Largest problem solved |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Cook (1977) | A-S | - Allocate/ schedule personnel in CTSs<br>- Transport casualties to hospital | Identical resource | - | ✓ | - | - | - | ✓ | NR | MC | LP | - |
| Drezner (2004) | L | Locate CCPs | Euclidean distance, Damaged infrastructure | ✓ | ✓ | - | - | - | ✓ | - | O | MOO | 2,846,289 people, 143 CLs |
| Lee et al. (2009) | L-A | No. of workers | Identical resource | - | - | - | ✓ | ✓ | ✓ | NR | MC | S | - |
| Salmeron and Apte (2010) | A | - Transport casualties to CTSs<br>- Allocate items/workers to facilities | DHC, Similar priority of casualties | ✓ | ✓ | ✓ | ✓ | - | ✓ | CF,CF, NR | O | SP | 6 AFs, 5 CTSs |
| Paul and Hariharan (2012) | L-A | - Locate stockpile in AFs<br>- Allocate casualties to facilities | DHC | ✓ | ✓ | ✓ | ✓ | - | ✓ | CF | MC | OP | 100 CLs, 15 AFs |
| Wilson et al. (2013) | S | Order of tasks | DHC | ✓ | - | ✓ | ✓ | - | - | NR, CF | MF, MT, O | VNS | - |
| Caunhye et al. (2015) | L-A | - Locate care facilities<br>- Allocate casualties to CTSs | Identical resource | ✓ | ✓ | - | ✓ | - | ✓ | NR, CF | MT | LP | 20,000 casualties, 36 AFs |
| Debacker et al. (2016) | A-S | - Allocate casualties to hospitals<br>- Allocate relief teams | DHC | - | ✓ | ✓ | - | ✓ | - | CR, NR | MF | S | 32 CTSs, 32 Ambulances, 10 teams |
| Paul and MacDonald (2016a) | L-A | - Locate DCs<br>- Allocate supplies to casualties | DHC | ✓ | ✓ | ✓ | ✓ | - | ✓ | CF | MC | SP, H | 100 DCs, 34 AFs |
| Paul and MacDonald (2016b) | L-A | - Locate dispensing sites<br>- Allocate supplies to casualties | DHC | ✓ | ✓ | ✓ | ✓ | - | ✓ | CF | MC | SP, H | 50 CLs, 30 AFs |
| Wilson et al. (2016) | S | - Allocate casualties to CTSs<br>- Allocate tasks to responder<br>- Order of tasks | DHC | ✓ | - | ✓ | ✓ | ✓ | - | NR, CF | MF, O | S | - |
| Niessner et al. (2018) | S | Allocate physicians to operations | DHC, Identical resource | - | ✓ | - | - | ✓ | - | CR | MF, MT | S-OP | 80 casualties |
| Rezapour et al. (2018) | A | Allocate teams to triage groups | DHC | ✓ | ✓ | ✓ | - | ✓ | - | NR | MS | LP, QT | 5 AFs, 1,500 casualties |
| Alizadeh et al. (2019) | L-A | - Locate CCPs<br>- Allocate AFs to CCPs/ hospitals<br>- Allocate casualties to CCPs/ hospitals | - | ✓ | ✓ | - | ✓ | ✓ | ✓ | CR | MC | OP, SAA | 33 AFs, 65 CLs, 700,000 casualties |
| Lodree et al. (2019) | A | - Allocate medical teams to casualty queues | DHC, Three priority levels | - | ✓ | ✓ | - | ✓ | - | NR | MC | SDP | - |

**Table 8.** Micro analysis of OSM papers: uncertainty, dynamics, heuristics, and insights.

| Reference | Uncertain parameter |
|---|---|
| Salmeron and Apte (2010) | Location and magnitude of disaster (S), Casualty flows (S), Commodity demands (S), Survival rates (S), Travel times (S) |
| Paul and Hariharan (2012) | Severity of disaster (S), Casualty flows (S), Available capacity (S), Survival times (S), Transport times (S) |
| Paul and MacDonald (2016a) | Casualty flows (G), Supply transport times (G), Survival times (G), damages to affected sites (G) |
| Paul and MacDonald (2016b) | Casualty flows (G), Supply transport times (G), Survival times (G), Wind speed (G), Damages (G) |
| Wilson et al. (2016) | Waiting times and self-presentation times of casualties (E), Rescue times (N), Travel times (L) |
| Rezapour et al. (2018) | Arrival rate (P), Treatment rates (P) |
| Alizadeh et al. (2019) | Casualty flows (S), Number of lives lost (S), Transportation capacity (S) |
| Lodree et al. (2019) | Arrival rate of medical teams and casualties (P) |

S: Scenario-based, G: General, E: Exponential, N: Normal, L: Lognormal, P: Poisson process

| Reference | Dynamic parameter/Information update mechanism* |
|---|---|
| Lee et al. (2009) | * Rapid analysis of what-if scenarios |
| Salmeron and Apte (2010) | Affected disaster sites in the first stage (location and capacity expansion) |
| Paul and Hariharan (2012) | * Considering delays in requesting and releasing federal assets and dispatching supplies to affected sites |
| Wilson et al. (2013) | Hospital available capacities, Casualty states, Arrival time to CTSs |
| Paul and MacDonald (2016b) | Setup and supply costs, Wind speed |
| Wilson et al. (2016) | Available responder units, Casualty flows, Waiting times and self-presentation times of casualties, Rescue times, Travel times<br>* Continuous communication between the optimization model and disaster field |
| Niessner et al. (2018) | Casualty flows, Available physicians, Resource allocation priorities, Casualty queue length<br>* Introducing some time points for re-allocating decisions |
| Alizadeh et al. (2019) | Daily casualty flows |
| Lodree et al. (2019) | Casualty flows, Number of medical teams |

| Reference | Heuristic/Rule of thumb/Insight* |
|---|---|
| Lee et al. (2009) | RealOpt©: fast and practical decision-support tool |
| Salmeron and Apte (2010) | * Match transportation and health capacities for critical casualties unless low survival rates or high penalties for unmet demand<br>* Priority to expand warehouses and delivery of commodities as more budget availability |
| Paul and MacDonald (2016b) | An optimal stopping time framework to determine optimal deployment time of dispensing sites |
| Niessner et al. (2018) | Three optimized automated policies<br>* Policy implications for disaster commanders to determine the criticality of positions and related queues |
| Rezapour et al. (2018) | * Distribute emergency units among affected sites proportional to their casualty populations not casualty mix ratios<br>* Stream fairly emergency units among casualty groups to smooth workload among medical teams |
| Lodree et al. (2019) | Effective heuristic policy |

Paul and MacDonald (2016b) developed a stochastic dynamic optimization to determine the stockpile location and capacities of medical supplies for casualty treatment in the event of a hurricane. The survival time of casualties had a significant impact on the location of dispensing sites, particularly when a location was far away from an affected site to reduce the storm-related damage. Alizadeh et al. (2019) formulated a two-stage robust stochastic optimization model for network design decisions and multi-period response operational decisions. The results indicated both the improved proximity and accessibility to CCPs and the decreased number of lost lives. The optimality gap could be improved by taking a risk aversion attitude which results in a lower variability of objectives.

**Scheduling:** Wilson et al. (2013) formulated the extrication, treatment and transporting problem of casualties (jobs) in responder units (machines) as a static flexible job-shop scheduling problem. Each job is a sequence of operations such as pre-rescue treatment, rescue, transportation and pre-transportation stabilization. Each machine has a known processing time and can work non-preemptively on one operation at a time. Five objective functions indicating fatality, suffering and efficiency factors were analyzed both individually and simultaneously. A reduction in fatalities can be achieved primarily through the improved processing of trapped casualties while hospital allocation decisions have a little influence. They showed that an increase in the inter-site coordination of responders during a multi-site MCI can lead to improved performance. Finally, they recommended an appropriate tradeoff analysis among the three objective function factors. Niessner et al. (2018) proposed advanced simulation-optimization techniques to improve the on-field policy decisions about staff and casualty scheduling and transportation made by simple heuristics or disaster management players. They presented a generic method consisting of (i) an automated policy for dynamic staff re-allocation to different mass casualty management operations and (ii) three simulation-optimization approaches, namely Kiefer-Wolfowitz, metaheuristic OptQuest and Response Surface. Their results showed that optimized automated policies outperform decisions made by simple heuristics or human decision-makers. The Kiefer-Wolfowitz algorithm with full coverage achieved significant reductions in the rescue time and number of fatalities.

**Allocation-scheduling:** Cook (1977) formulated LP models for the allocation and scheduling of medical personnel and identical aircraft during the treatment in a field hospital at a crisis zone and the transportation to a permanent hospital. He considered several types of casualties and medical personnel. Different objectives were studied: minimizing staff requirements for a fixed service level, minimizing resources (i.e., personnel, space and aircraft) costs and maximizing casualty service for fixed staff levels. He reported no numerical analyses. Debacker et al. (2016) proposed a simulation model; SIMEDIS, consisting of 3 interacting components: I) the casualty creation model, II) the casualty monitoring model and III) the medical response model, to handle rescue and triage procedures, the casualty allocation and treatment and the medical supervision during the transportation to hospitals. The objective was to minimize the mortality and morbidity of survivors. The casualties evolved in parallel through both the victim monitoring model and the medical response model. The victim creation model generates very detailed casualty profiles and the victim monitoring model continually updates the clinical conditions of casualties, triggered by the elapsed time if no treatment is provided or by the medical interventions administered by healthcare responders. Wilson et al. (2016) built a real-time system to capture the dynamic and uncertain nature of the MCI response environment by extending the static model described in Wilson et al. (2013). They provided a detailed simulation of the model performance, identifying several potential explanatory parameters and exploring to what extent they impact upon the application of the optimization model. The extension of the model from a 'static' design to the online case allowing for continual communication between the model and problem environment resulted in a significant improvement in terms of both fatality and suffering factors. They emphasized the accurate estimation of task durations.

## 5.2. Critical discussion

We discuss possible gaps and trends to propose future research directions on OSM:

*Various aspects of OSM decision making*: OSM is a central task in CM to maximize the number of survivors in the first hours after a disaster; but, as a main shortcoming, we observe a limited number of research papers in this area, especially regarding treatment strategies, allocation of medical teams to casualty groups and scheduling casualty treatment for each medical team.

*Practical objective functions*: As a necessary objective, maximizing the number of survivors is considered in most papers in this area. However, there are other conflicting objectives raised by practitioners such as equity (reducing service level variability) and fairness (e.g., in transportation and treatment) that were not addressed in the existing studies. For example, Huang et al. (2015) considered lifesaving effectiveness, human suffering and fairness as objective functions. Analyzing trade-offs among the objectives will produce valuable managerial insights for practitioners in aid agencies.

*Heterogeneous treatment resources*: Medical teams may be of multiple modes in terms of treatment type, skill level and type and level of equipment. To improve the efficiency of OSM operations, proper matching is necessary to allocate preferred medical teams to casualties in the same triage group according to the type and level of injury.

*Multiple injuries for each casualty*: Existing OSM models implicitly assume that each casualty suffers from a single injury whereas casualties with multiple injuries are common in MCIs that need several treatment operations. Therefore, developed models may be more realistic if they consider this research gap.

*Volunteer resources*: The people who get out alive or volunteer persons from nearby areas are potential resources, which can systematically be involved in relief operations, especially in OSM operations. Therefore, fast training and involving volunteers for treatment of green-group casualties or participation in non-skilled parts of treatment operations may be a promising area of research.

*Realistic survival probability functions*: The deteriorating health condition of casualties is a function of both time passage and quality of operations (Wilson et al., 2016). In fact, the survival probability before triage, during the transportation from affected sites to CTSs, while waiting for treatment and during the treatment will reduce by different functions over time. This means we need a hybrid survival probability function to introduce health deterioration into the models well.

*Integrated decision-support models*: All the decisions embedded in the OSM operations are significantly interdependent. A challenging issue ignored by the existing studies is to create decision-support solutions and insights by developing and solving the comprehensive models, which integrate the different aspects of such problems including location, transportation, allocation and scheduling.

*Resource/capacity sharing*: The efficiency of OSM decisions is significantly dependent upon the efficiency in the usage of all relief resources and facilities. Existing models have paid less explicit attention to this issue. Due to the dynamics and uncertainty involved in post-disaster environments, resources tend to be constantly unbalanced regarding their supply and demand. In such conditions, designing capacity and resource sharing mechanisms among the neighboring facilities is a promising strategy that demands future researches.

# 6. TRANSPORTATION TO HOSPITAL (TTH)

After stabilization in CTSs, severely-injured casualties must be transported to nearby hospitals to receive comprehensive medical treatment. Depending on injury levels and the availability of facilities, such movements are performed by various transportation modes such as land (e.g., ambulance and train), water (e.g., ship, boat and hovercraft) and air (e.g., helicopter). Various types of injury may also need different specialists and treatment equipment. The transportation prioritization, resource allocation/scheduling, vehicle routing and casualty assignment to hospitals are critical decisions. Inefficient TTH delays the medical service for casualties and increases death tolls. Tables 9 and 10 demonstrate the details of TTH papers.

### 6.1. Problem category description

**Allocation:** Christie and Levary (1998) developed a simulation of a multi-server queuing system for the transportation of seriously injured casualties to hospitals after a major, human-caused disaster like an air-crash in a crowded city given limited resources. Simulation results indicated that the casualties' waiting times for transportation increase rapidly with an increase in their inter-arrival rates. Gong and Batta (2007) proposed two models for the allocation/re-allocation of ambulances to casualty clusters in disasters. All ambulances had identical service rates and capacities and were initially located at hospitals. First, a casualty cluster deterministic model was developed to calculate the completion time for each cluster. Second, an ambulance reallocation problem was presented on the basis of a discrete-time policy. With the proposed weights to casualty clusters, the solution for minimizing makespan and weighted total flow time are the same, which points to the robustness of the recommended allocation. Yi and Kumar (2007) presented the two sub-problems of vehicle route construction and multi-commodity dispatch for the model of Yi and Ozdamar (2007). A fast two-phased algorithm iteratively built stochastic vehicle paths and the assignment between vehicle flows and commodities. Ozdamar (2011) proposed a mathematical model and a route management procedure to allocate helicopters to affected sites for the last mile delivery of emergency items and for transporting severely injured casualties to hospitals. The special aviation constraints of helicopters and large-scale helicopter missions were considered. The route management procedure provided the flexibility of adjusting the mission completion time against the number of utilized helicopters. Paul and Batta (2011) developed models to allocate ambulances to hospitals in the pre-disaster preparedness phase aiming at minimizing the social cost as "the cost of a person who dies when he/she does not receive treatment in a survivability time". Travel time to hospitals was estimated using stochastic simulation. Dijkstra algorithm was used to determine the shortest paths. They developed an algorithm to dynamically update pre-disaster plans to post-disaster reality considering the hospital status, travel times and the survivability time of casualties. Prior allocations might not be optimal in the event of the emergence of new casualties and a constant reevaluation of reallocation decisions is necessary.

Wang et al. (2012) developed an agent-based model to simulate the dynamic emergency medical response to an urban MCI with three heterogeneous responders. The model was constructed from a geographic information system and data on hospital resources. The simulation results showed that using only partial information may have no benefit or a harmful impact on decision making. Moreover, utilizing all available facility resources helps balance the load among hospitals and avoids unnecessary waiting and transferring of casualties. Najafi et al. (2013) developed a three-objective, multi-mode, multi-commodity and multi-period robust stochastic model for the post-earthquake logistics of both relief items and casualties. A solution methodology was suggested, which converted the model into three sub-models and used three steps to optimize three objectives hierarchically. Dean and Nair (2014) developed a resource-constrained model to prioritize casualties to effectively be transferred to different area hospitals in order not to overwhelm any single hospital. It outperformed all low- and high-score first heuristics of the order of 10–30% on average. As the number of available ambulances varies but the hospital capacities remain constant, the SAVE model performs better than the closest-first heuristic.

**Table 9.** Characteristics of the TTH problems investigated in the papers.

| Reference | Problem category | Key decision variable(s) | Main assumption(s) | Parameter: Disaster site | Parameter: Demand | Parameter: Survival probability | Parameter: Travel time | Parameter: Service time | Parameter: Miscellaneous | Main constraints | Objective function(s) | Solution approach | Largest problem solved |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Christie and Levary (1998) | A | Allocate casualties to hospitals | Only red triage group with adult casualties | ✓ | - | - | ✓* | - | ✓* | CR | MT | S | 100 casualties, 2 hospitals |
| Gong and Batta (2007) | A | - Allocate and reallocate ambulances | Incapacitated hospitals | - | ✓ | - | - | ✓ | ✓ | NR | MT | H | 100 clusters, 98 ambulances, 19 hospitals |
| Yi and Ozdmar (2007) | L-A | - Locate CTSs<br>- Allocate items and vehicles<br>- Transport casualties | Single transportation mode, Link disruption possibility | ✓ | ✓ | - | ✓ | ✓ | ✓ | NR | O | LP | 60 nodes, 5 CLs, 170 vehicles |
| Yi and Kumar (2007) | A | Like Yi and Ozdmar (2007) | One transportation mode, Link disruption possibility | ✓ | ✓ | - | ✓ | ✓ | ✓ | NR | O | ACO | 80 nodes, 1,600 arcs, 55 vehicles |
| Jotshi et al. (2009) | R | - Routing of emergency vehicles<br>- Transport casualties to hospitals | DHC, 4 casualty classes, 5 levels of road damage | ✓ | ✓ | - | ✓ | - | ✓ | CR, NR | MS | S | 34,890 nodes, 43,445 links, 76 vehicles, 20 hospitals, 1,190 casualties |
| Ozdamar (2011) | A | - Dispatch items to AFs<br>- Transport causalities to hospitals<br>- Allocate vehicles to links | One helicopter type, Limited cargo weight, Split pickup/ delivery | ✓ | ✓ | - | ✓ | - | ✓ | NR | MT | LP | 10,414 casualties |
| Paul and Batta (2011) | A | Allocate casualties to hospitals | Known AFs, Link disruption possibility, DHC | ✓ | ✓ | ✓ | ✓* | - | ✓ | NR | MC | OP, S | 14,449 nodes |
| Wang et al. (2012) | A | Allocate casualties to hospitals | Deteriorating health conditions | ✓ |  | ✓ | ✓ | - | - | CF | MF | S | 150 patients, 24 ambulances, 15 hospitals |
| Najafi et al. (2013) | A | - Transport casualties to hospitals<br>- Allocate vehicles and items | Known AFs, Heterogeneous vehicles, Different types of injured people and items | ✓ | ✓* | - | ✓ | - | ✓* | NR | MF, MT | H | 16 nodes, 91 arc, 74 vehicles |
| Apte et al. (2014) | L-A | - Locate CCPS and Allocate casualties to CCPs/ hospitals<br>- Allocate resources to CCPs | Identical resources, Correspondence between ambulances and CCPs | ✓ | - | - | ✓ | - | ✓ | NR | MS, MT | LP | 13,000 casualties |
| Dean and Nair (2014) | A | - Allocate casualties to hospitals<br>- Required ambulances and hospital capacity | DHC | - | - | ✓ | ✓ | - | - | NR | MS | LP | 45 casualties, 20 ambulances |
| Najafi et al. (2014) | A | Like Najafi et al. (2013) | Known CLs, Known demands, Six casualty levels, Multi-item, Multiple transportation modes | ✓ | ✓ | - | ✓ | - | ✓ | NR | MF, MT | H | 13 nodes, 38 arcs, 74 vehicles |
| Salman and Gul (2014) | A | Transport casualties to hospitals | Known demands | ✓ | ✓ | - | ✓ | ✓ | ✓ | NR | MT | H | 7,000 casualties |
| Wilson et al. (2014) | R | Select routing strategy | Transportation network disruption | ✓ | ✓ | - | ✓ | - | - | NR | MF, O | S | 210 casualties, 53 ambulances, 27 fire appliances, 21,214 nodes |
| Na and Banerjee (2015) | A | - Allocate vehicles to casualties<br>- Required beds in shelters | Known facility location | ✓ | ✓ | - | ✓ | - | ✓ | NR, CF | MC, MS | B&C | 2,500 beds, 100 medical resources, 60 ambulances, 10 helicopters |
| Talarico et al. (2015) | R | - Allocate ambulances to casualties<br>- Prioritize and allocate casualties to hospitals | Sufficient hospital capacity, Euclidian distance | - | - | - | ✓ | ✓ | ✓ | NR | MT | OP, VNS | 50 casualties, 4 hospitals, 25 ambulances |
| Repoussis et al. (2016) | A-S | - Allocate/ prioritize casualties in hospitals<br>- Scheduling ambulances | Identical resources, Correspondence between ambulances and casualties | - | ✓ | - | ✓ | ✓ | ✓ | NR | MT | H | 150 casualties, 50 ambulances, 10 hospitals |
| Sung and Lee (2016) | A-S | - Allocate ambulances to casualties<br>- Allocate/ prioritize casualties in hospitals<br>- Arrival time of casualties to hospitals | Known casualties, Identical resources, Correspondence between ambulances and casualties, DHC | - | ✓ | ✓ | ✓ | ✓ | ✓ | NR | MS | CG | 30 casualties in each class, 30 ambulances |
| Kamali et al. (2017) | A-S | No. of casualties served at a given time | All casualties are available at time zero, Non-preemptive service | - | ✓ | ✓ | ✓ | ✓ | - | NR | MS | H | 50 casualties, 5 servers |
| Caunhye and Nie (2018) | L-A | - Locate care facilities<br>- Allocate casualties to care facilities | DHC | ✓ | ✓ | - | ✓ | ✓ | ✓ | NR | MT | BD | 8 AFs, 52,502 casualties |
| Mills et al. (2018) | A | Allocate ambulances to AFs | DHC | ✓ | ✓ | - | ✓* | ✓* | - | NR | MF | H, S | 75 casualties, 7 ambulances, 3 hospitals |
| Sabouhi et al. (2019) | L-A | - Locate shelters and transfer points<br>- Allocate casualties to transfer points/ hospitals<br>- Allocate relief items to shelters | Two-mode heterogeneous vehicles, Three-layer transportation network, Instantaneous return | ✓ | ✓* | ✓ | ✓ | - | - | CF, CR, NR | MT | MOO | 9 AFs, 16 hospitals, 18 shelters, 9 CCPs |

* Uncertain parameter.

**Table 10.** Micro analysis of TTH papers: uncertainty, dynamics, heuristics, and insights.

| Reference | Uncertain parameter |
|---|---|
| Jotshi et al. (2009) | Casualty clusters (G), location of casualties (G), Road condition (G) |
| Najafi et al. (2013) | Commodity demands/supplies (G), Casualty flows (G), Hospital capacity (G) |
| Caunhye and Nie (2018) | Casualty flows (S), Self-evacuees (S), Transport times (S), Casualty priorities (S) |
| Mills et al. (2018) | Travel times (E), Service times (E) |
| Sabouhi et al. (2019) | Casualty flow (G) |
| G: General, S: Scenario-based, E: Exponential. | |
| **Reference** | **Dynamic parameter/Information update mechanism*** |
| Gong and Batta (2007) | Casualty flows, Arrival rates |
| Jotshi et al. (2009) | * Simulation is updated by an information fusion module |
| Najafi et al. (2013) | Casualty flows, Commodity demands/supplies, Vehicle availabilities, Hospital capacities |
| Apte et al. (2014) | Casualty flows, Resource availabilities |
| Dean and Nair (2014) | Survival probabilities |
| Najafi et al. (2014) | Casualty flows, Commodity demands/supplies, Vehicle availabilities, Hospital capacities |
| Salman and Gul (2014) | Casualty flows, Travel times, Available capacities<br>* A hierarchical analysis approach to gradually capture data realizations |
| Wilson et al. (2014) | * An online local search procedure using updated travel time estimates |
| Mills et al. (2018) | Casualty flows |
| **Reference** | **Heuristic/Rule of thumb/Insight*** |
| Gong and Batta (2007) | Two iterative allocation procedures |
| Dean and Nair (2014) | Severity-Adjusted Victim Evacuation (SAVE)<br>* SAVE is better than STM considering multiple hospitals of limited capacity |
| Najafi et al. (2014) | * Large number of low-capacity hospitals/suppliers leads to shorter waiting times than few ones with larger capacities |
| Wilson et al. (2014) | * Autonomous routing strategy for responders leads to improved overall performance<br>* Leave routing decisions to responders if they can share knowledge and learn together |
| Mills et al. (2018) | (1) Myopic heuristic, (2) Policy improvement heuristic<br>* Heuristics outperform the transportation to the nearest facility<br>* More sophisticated policy is reasonable only when casualties do not deteriorate rapidly |

Salman and Gul (2014) proposed a multi-period model to optimize location and casualty transportation decisions aiming at minimizing the weighted sum of total travel and waiting times of casualties and the total costs of locating new facilities. As more resources are acquired over time, the updated solution can guide the allocation of further capacity to improve service levels and achieve equity. Najafi et al. (2014) developed a multi-objective dynamic model to simultaneously plan commodity transportation to affected sites and casualty transportation to hospitals after earthquakes. There are several types of commodity, casualty and transportation vehicles (helicopter, truck, ambulance and train). They hierarchically minimized the total time until casualty arrival at a hospital and the total lead time to fulfill commodity needs. The model could dynamically re-route the path of en-route vehicles for shorter response times. They investigated the impact of network structure and the number of hospitals and suppliers on the model performance. Na and Banerjee (2015) proposed an integrated triage-allocation-transportation model to allocate casualties to facilities in which the number of survivors and the total evacuation cost are optimized simultaneously. Temporary staging areas were located to transport casualties to shelters such as medical facilities. They considered the priority of casualties, multiple vehicle types and several categories of relief resources. Mills et al. (2018) developed a Markov decision process and two heuristic policies to I) allocate ambulances to casualty locations and II) select hospitals for transportation.

**Location-Allocation**: Yi and Ozdamar (2007) formulated a location-routing model to locate CTSs for less serious casualties, to dispatch commodities to affected sites and to evacuate and transfer casualties to CTSs and hospitals. The location sub-problem involves the sharing of scarce medical resources and achieving a service rate equilibrium among different emergency centers. A full exploitation of facility capacities is achieved by the interaction between an allocation sub-problem and the service rate equilibrium and location sub-problem. The model expedited a high priority evacuation while maintaining an equilibrium among the service rates of medical facilities. Scarce resources were exploited to their full extent. Apte et al. (2014) developed an optimization model equipping planners and policymakers with strategic and operational insights on the location of CCPs and the allocation of personnel, decontamination units and ambulances to maximize the casualty throughput. Accordingly, the substantial cost savings achieved allowed these funds to be used to secure other resources that were initially underestimated. The results indicated that the optimal order and timing for the activation of CCPs is not necessarily linear. Caunhye and Nie (2018) proposed a three-stage stochastic model to determine the location of care facilities and the allocation of casualties to hospitals and newly-located care facilities. Both non-self-evacuee and self-evacuee groups of casualties were divided into low-priority and high-priority classes. For a large number of scenarios, they proposed a two-stage approximation model to guess right third-stage solutions without corresponding decision variables and constraints. The model has a small EVPI; it does not benefit very much from having more accurate information. Sabouhi et al. (2019) developed a multi-objective robust possibilistic model for locating transfer points and shelters, transporting casualties to hospitals, transporting evacuees to shelters and supplying relief commodities to evacuees. Relief equity was achieved by minimizing the maximum transportation time to shelters, transfer points and hospitals and the maximum distribution time of relief commodities. The robust model yielded standard deviation values lower than those for a possibilistic chance-constrained model. Finally, the best values of shelters' and transfer points' capacities and the total service time were recommended.

**Routing:** Jotshi et al. (2009) developed a robust simulation for the dispatching and routing of emergency vehicles to casualty pickup locations and then to appropriate hospitals in a post-disaster environment with the support of data fusion. Key factors including casualty priorities, distances, waiting times in hospital emergency rooms, hospital capacity and road damage and congestion were considered. Wilson et al. (2014) developed a simulation study to show how the routing strategy of emergency responders affects both routing efficiency and uncertainty in travel time prediction. They proposed a methodology based on a Bayesian approach to update the travel time distributions for centralized routing strategies. Talarico et al. (2015) formulated two models for ambulance routing with two groups (on-field assisted green code, hospital-in-need red code) of casualties to minimize the latest service completion time. A route is a tour that starts from a hospital, picks up some casualties in a specific sequence and ends at a hospital. In the first model, they considered a 2-index variable for routing of identical ambulances while in the second one, the routing of heterogeneous ambulances was denoted by a 3-index variable. A large neighborhood search was proposed to solve the models.

**Allocation-Scheduling:** Repoussis et al. (2016) developed a model for three pre-hospital decisions: dispatching and scheduling of ambulances, allocation of casualties to hospitals and casualty prioritization in hospitals. The objectives were to hierarchically minimize the overall response time and the total flow time required to treat all casualties. They quantified the impact of capacity-based bottlenecks for both ambulances and available hospital beds. Moreover, a trade-off between accessing remote hospitals for demand smoothing versus reduced ambulance transportation times was established. Sung and Lee (2016) formulated an ambulance routing problem (i.e., the allocation and scheduling of the hospital transportation of casualties) as a set partitioning model. All casualties, categorized into immediate and delayed classes, were available at time zero. They solved the model for three survival probability scenarios (i.e., pessimistic, moderate and optimistic). The recommended solutions outperformed a fixed-priority resource allocation. Finally, the model was extended by assuming a hierarchical care capability structure, casualties in several affected sites and the sequential availability of ambulances. Kamali et al. (2017) studied the problem of resource-based prioritization of several casualty groups for service by medical persons and transportation by ambulances to hospitals. They analyzed the structure of the optimal solution and compared its performance to the current practice and other related models in the literature. Although more critical-first policies for triage might be optimal in some cases, in many others, the reverse or some other mixed strategies perform significantly better.

### 6.2. Critical discussion

Although the literature of the TTH problem is rich and scholars have developed various models for different aspects of the problem including scheduling, routing, location, allocation and some combinations of them, the examination of Table 9 hints at several gaps in this area:

*Coordination between TTH and road network restoration*: In current studies, transportation paths between supply (e.g., CTSs) and demand (e.g., hospitals) points are fixed and not updated over time. This means that the restoration of disrupted roads during response operations is ignored. Considering road restoration necessitates dynamic path selection and transportation planning in TTH models. Shortening transportation paths over time may significantly affect the survival probability of casualties.

*Multi-modal transportation plans*: In reality, depending on the geographical spread and population density of the affected areas, various transportation modes with multiple types of vehicle (having different features like capacity, speed, etc.) may be employed to efficiently transport casualties with different health conditions on the routes among the nodes of a network. Table 9 shows that most of the existing papers assume a single transportation mode.

*Design and planning of TTH networks*: In large-scale MCIs, numerous nodes and routes on both supply and demand sides of logistics networks may be damaged and be out of service partly or entirely. The status and capacity of hospitals in different nodes is also uncertain. This may prevent perfect point-to-point logistics and a hub-and-spoke solution may be an inevitable choice. More focus is needed on designing a hub network in which a limited number of hospitals and CTSs is considered as hubs to dispatch the arriving casualties and relief commodities to the other nodes as spokes. So, what is the best and most efficient design and planning for such a hub-and-spoke network?

*Integration between forward and reverse logistics*: Few papers study the integration of forward (flow of commodities from hospitals and supply centers to the field) and reverse (flow of casualties from the field to hospitals) logistics in TTH operations.

## 7. HOSPITAL TRIAGE AND COMPREHENSIVE TREATMENT (HTT)

MCIs may generate a vast amount of unplanned demand for hospitals (especially in emergency departments) in addition to their routine and daily demands. Therefore, efficient employment of limited medical resources (equipment, personnel, beds, surgery rooms, etc.) in the overwhelmed hospitals is vital. Effective hospital capacity planning can improve the capability and performance of urgent treatment for injured people affected in a disaster (Yi et al., 2010). The main decision which should be made for severely-injured casualties arriving at hospitals is prioritization and allocation of medical resources to them. Since the medical conditions of casualties may change during transportation, a re-triage is needed at hospitals; accordingly, casualties may be hospitalized in different departments. Tables 11 and 12 show the details of HTT papers.

### 7.1. Problem category description

Cotta (2011) addressed a multi-tier casualty prioritization problem for treatment in identical operating rooms considering lifetime expectancy and resource consumption. They applied four state-independent heuristics for the problem. To alleviate the locality of decision making, a metaheuristic layer was added. The results show that the proposed approach is competitive in multiple scenarios regarding the number of operating rooms, casualties and triage tiers. However, it is sensitive to the presence of large uncertainties in operation times. Chan et al. (2013) studied the problem of prioritization and bed allocation for two-groups of casualties with known survival probabilities after a fire disaster. As the existing burn centers were not sufficient to meet the surge in demand, a mix of burn-beds and non-burn beds was considered. Burn level, age and inhalation injuries were the main determinants of the survival probability. The casualty prioritization was implemented according to the length of stay and co-morbidity. Although the proposed method outperformed several other triage methods, it was shown to be highly unlikely that all casualties can be transferred into a tier 1 burn bed within five days. They recommended that the proposed tiered system may be sufficient in small to moderately sized events. Cohen et al. (2014) developed a fluid model to allocate surgeons among two treatment stations in the emergency department of a hospital after an MCI to minimize mortality during the treatment, operation or waiting. They only focused on the immediate group's casualties. The casualties arrived continuously and were admitted in two stations: a life-saving station or an operating station. The model was tested on two scenarios designed based on a real terror attack. In both of them, the optimal policy gave a treatment priority to the life-saving station over the operation station. Jin et al. (2014) studied medical resource allocation and casualty transportation in a three-layer network including disaster areas, an on-site clinic and hospitals. According to their survival probabilities, casualties might be transferred to general hospitals either directly or through the on-site clinic. They considered four scenarios based on the different factors of response logistics and compared the model for two objective functions under each or a combination of scenarios. Wanying et al. (2016) studied the logistic response to a bioterrorist anthrax attack and proposed an optimization model that linked the disease progression, medical interventions and the deployment of the logistics together to extract crucial insights. The model considered the change of recovery rate because of time lag among two periods: (1) the period when casualties transfer into different disease stages and (2) the period when the medical intervention begins.

**Table 11.** Detailed information about the papers addressing HTT operations.

| Reference | Problem category | Key decision variable(s) | Main assumption(s) | Parameter: Disaster site | Demand | Survival probability | Travel time | Service time | Miscellaneous | Main Constraints | Objective function(s) | Solution approach | Largest problem solved |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Cotta (2011) | P | Order of casualty treatment | Identical resource | - | ✓ | ✓ | - | ✓ | ✓ | NR | MS | H | 20 casualties in each class, 5 operating rooms |
| Chan et al. (2013) | P-A | Allocate casualties to beds | DHC, Exponential lifetime | - | ✓ | ✓ | - | ✓ | | NR | MS | H | 775 casualties 210 beds |
| Cohen et al. (2014) | A | No. of surgeons | First-come-First-service priority, Constant mortality rates | - | ✓ | - | - | ✓ | ✓ | NR | MF | S | 10 surgeons |
| Jin et al. (2014) | A | - Transport casualties to clinic/ hospital<br>- No. of casualties at clinic/ hospital<br>- Allocate doctors to clinic/ hospital | Known casualties, Fixed facility locations, DHC | ✓ | ✓ | ✓ | ✓ | ✓ | - | NR, CF | MS | LP | 1,400 casualties, 12 clinics, 3 hospitals |
| Wanying et al. (2016) | A-S | - Schedule the treatment<br>- Transport medicines to hospitals | DHC, Stochastic MDP between the disease stages | - | ✓ | ✓ | - | ✓ | ✓ | NR, CF | MF | MDP | 35,000 casualties/ day, 4 DCs |

**Table 12.** Micro analysis of HTT papers: uncertainty, dynamics, heuristics, and insights.

| **Reference** | Uncertain parameters |
|---|---|
| Cotta (2011) | Survival times (W), Operation times (E) |

W: Weibull, E: Exponential.

| **Reference** | **Dynamic parameters/Information update mechanism*** |
|---|---|
| Jin et al. (2014) | Casualty flows, Survival probabilities |
| Wanying et al. (2016) | Casualty flows, Survival probabilities, Service times |

| **Reference** | **Heuristic/Rule of thumb/Insight*** |
|---|---|
| Jin et al. (2014) | * Maximizing the number of survivors is more effective than minimizing the total cycle time |
| Wanying et al. (2016) | * Increasing both the detection ability and the capacity of dispensing centers decreases the number of deaths effectively |

### 7.2. Critical discussion

We discuss possible gaps and trends for future research directions on HTT:

*Large-scale disasters (overwhelmed conditions)*: Numerous works have been published on the HTT in regular conditions or when common emergency incidents happen. However, as seen in Table 11, an important gap is the limited number of studies focusing on the HTT in large-scale MCIs (sudden, or slow-onset disasters). There is a need to reformulate HTT models developed under regular conditions to address the requirements of a disaster environment.

*Conflicting objectives*: HTT is a multi-objective problem in nature. However, the objective function column in Table 11 shows that scholars have not considered important objectives such as hospital resource efficiency, total operations costs and equity and fairness in treatment. It seems that decision-makers should establish a logical trade-off between several more-or-less conflicting objectives.

*Cooperation among hospitals*: Several hospitals with different capacities and capabilities are naturally involved in the triage and treatment of arriving MCI casualties. Moreover, the induced uncertainty and dynamics make the hospital network significantly unbalanced regarding the demand and supply. So, the models may be enriched under cooperative arrangements among hospitals (for sharing capacity, resource, inventory and information) to enhance the whole performance of HTT operations.

*Re-arranging daily operations*: When disaster casualties with higher priorities arrive at hospitals, some minor or major modifications to the operations of current patients like delaying some elective patients and/or discharging the existing regular patients with lower priorities, etc. are necessary. Hence, an interesting area is to develop effective re-arrangement decision tools.

*Personnel scheduling and medical inventory management*: The extra workload of personnel and a shortage/wastage of medical resources are critical challenges for hospitals involved in HTT operations in response to MCIs. While Table 11 shows that existing models did not address such an issue, a direction for future study is to develop HTT models including hospital personnel scheduling and medical inventory management.

## 8. CONCLUSIONS AND FUTURE RESEARCH

The most relevant review papers on OR&MS techniques for humanitarian operations and disaster management and research related to post-disaster CM were reviewed by categorizing, analyzing and assessing the published papers by the end of 2019. Published papers were selected from leading journals that use OR techniques for modeling and solving CM problems. The reviewed papers were grouped into five categories, namely RD&SR, OST, OSM, TTH and HTT. The objective function, main constraints, important assumptions, decision variables, input parameters, solution techniques and the largest problem size solved were described for each paper. In each category, the related papers were critically discussed. According to this study, the RD&SR and TTH problems are richer than the other problems considered. Most models in different categories were on allocation and scheduling. We observed that the most popular objective function is to maximize the number of survivors. The main resource constraints are related to teams, ambulances and doctors. Non-preemptive services are the main assumption in most papers. The deteriorating health condition of casualties after the disaster was considered by scholars. However, developing more realistic survival probability functions is needed. Another micro analysis was presented on how some papers in each category developed approaches for dealing with the involved uncertainty and dynamics in the post-disaster environment. Only 35% of the papers paid attention to this issue. Accordingly, RD&SR and TTH categories are richer in this regard while OST, OSM, and HTT need more attention. Moreover, few (19) papers proposed any heuristic or rule-of-thumb to efficiently be implemented in the disaster scene instead of solving frequently the optimization models. It seems that all problem categories need special attention in this area. Specific research gaps and future research directions were suggested at the end of each section. We also systematically summarize in Table 13 the future research directions recommended in the reviewed papers (if any). When it comes to case-based studies among the papers published in the five problem categories, Table 14 gives the papers, categorization, case study and source of data.

Some papers used real-world data whereas others borrowed data from the literature. Accordingly, 47 papers (more than 50%) provided a case study to demonstrate practical aspects of their models and 28 of them are about earthquakes. Most case studies are in RD&SR operations while papers published in the OST and HTT category presented fewer case studies. Notably, case studies in man-made disasters (10 cases) are much less numerous than natural disasters.

**Table 13.** Future research directions suggested by scholars.

| References | Future direction suggested |
|---|---|
| Gong and Batta (2007) | - Continuous-time policy for allocating ambulances to casualty clusters<br>- Balance between frequent re-allocations and long waiting times |
| Salmeron and Apte (2010) | - Alternative objectives<br>- Survivability curve of casualties over time<br>- Other needs such as security and communication<br>- Budget as a decision variable. |
| Cotta (2011) | - Addressing uncertainties<br>- After-treatment survival probabilities |
| Nolz et al. (2011) | - Various mitigation activities to restore infrastructure more quickly |
| Paul and Batta (2011) | - Using simulation for other disasters such as earthquake<br>- Capacity re-allocation for other facilities like CTSs |
| Chen and Miller-Hooks (2012) | - Spatial correlations in travel times between affected sites<br>- Continuous representation of space<br>- Dynamic distribution of parameters<br>- Stochastic dynamic programming for USAR team deployment problem<br>- Subdivision of the population by risk group and disease stage<br>- Non-homogeneous mixing<br>- Different types of infectious contacts<br>- Different rates of exit from different groups |
| Jacobson et al. (2012) | - Simulation test-bed for priority decisions in emergency response |
| Paul and Hariharan (2012) | - Modeling hospital operations and casualty transport and their impacts on stockpiles<br>- Epidemics and manmade disasters<br>- Regions that are prone to multiple disasters<br>- Uncertainty regarding the epicenter |
| Rachaniotis et al. (2012) | - Examining the time horizon's impact and incorporating time-varying action rates<br>- Subdividing population by risk group and disease stage<br>- Non-homogeneous mixing<br>- Different types of infectious contacts<br>- Non-constant population size<br>- Different rates of exit from different groups<br>- Stochastic parameters |
| Wang et al. (2012) | - Other performance criteria<br>- Negotiated agreements or financial factors<br>- Deriving various concrete sub-types of casualties<br>- Ranking-and-selection methods to identify a single best policy with a few simulation runs |
| Edrissi et al. (2013) | - Bi-level model to allocate a lump sum of money between agencies<br>- Capture link travel times obtained from the stochastic behavior of evacuees<br>- Differences in time of operation for each agency |
| Dean and Nair (2014) | - Impact of increase in inpatient casualties on patient flow at hospitals<br>- Using some ambulances to transfer existing inpatients to a ''farther'' hospital |
| Jin et al. (2014) | - Addressing the vehicle dispatching |
| Najafi et al. (2014) | - Vehicle transportation costs<br>- Uncertainty and dynamics travel time, capacities and demands<br>- Dynamic and online scheduling model based on real data |
| Salman and Gül (2014) | - Trade-offs between performance and equity by optimization and simulation |
| Wex et al. (2014) | - Performance degradation of rescue units and preemptive scheduling<br>- Time windows for incidents<br>- Collaboration between rescue units and coordination of autonomous agents<br>- Uncertain parameters |
| Wilson et al. (2014) | - Time-varying disruption links and correlation among adjacent links |
| Xiang and Zhuang (2014) | - Multi-server<br>- Time-varying parameters<br>- Common resources for serving patients<br>- Batch arrivals |
| Zheng et al. (2014) | - Fine tuning the search using self-adaptive mechanisms<br>- multiple populations which interact with each other<br>- Multi-objective optimization |
| Caunhye et al. (2015) | - Monitor absorbed radiation doses of casualties over time, reassignment of facilities' capacities, reallocation of triage capacities and queues with waiting and service times<br>- How emergency responders pick casualties from demand points |
| Edrissi et al. (2015) | - Joint failure probability of multiple links<br>- Tradeoffs between the emergency response reliability measure and other day-to-day reliability measures<br>- Facility location problem |
| Na and Banerjee (2015) | - A large-scale stochastic optimization model<br>- Using geospatial methodologies |
| Talarico et al. (2015) | - Different types of ambulance<br>- Time windows<br>- Route length constraints |

| References | Future direction suggested |
|---|---|
| Debacker et al. (2016) | - Stochasticity in the SIMEDIS model<br>- Considering the emergency department |
| Mills (2016) | - Estimate survival probability curves for different types of disaster<br>- Coordination between first responders, their managers and hospitals |
| Paul and MacDonald (2016a) | - Specific needs for each casualty within the same severity<br>- Limited budgets<br>- Aftershocks and foreshocks |
| Su et al. (2016) | - Integration with GIS maps to visualize and understand essential information<br>- Secondary disasters |
| Wanying et al. (2016) | - A general model for most of human transmissible diseases |
| Wilson et al. (2016) | - Partially dynamic problem scenario<br>- Agent-based simulation with significantly accurate and up-to-date information |
| Al Theeb and Murray (2017) | - Assignment of vehicles and work crews for debris removal<br>- Multi-objective optimization |
| Haghi et al. (2017) | - Different types of vehicle and transportation costs<br>- Routing and scheduling of vehicles |
| Kamali et al. (2017) | - Considering the possibility of death before receiving service<br>- Stochastic casualty arrival<br>- Multiple affected sites<br>- Hospital selection |
| Zhang et al. (2017) | - Collaborative assignment model to coordinate resource collisions among emergency depots |
| Bravo et al. (2019) | - Other performance measures suggested by interviewees<br>- A real UAV in a private terrain or a military area |
| Cao et al. (2018) | - All dimensions of sustainability simultaneously |
| Caunhye and Nie (2018) | - Markov decision processes<br>- Interaction between responder and self-evacuees by game theory |
| Gu et al. (2018) | - Multiple periods<br>- Hierarchical medical shelters with different service levels<br>- Vehicle routing problem to pick up casualties |
| Mahootchi and Golmohammadi (2018) | - Evacuation of affected people<br>- Vehicle routing problem<br>- Sending medical personnel and supplies for ambulatory treatment of casualties |
| Rezapour et al. (2018) | - Integration with TTH and HTT operations<br>- Multi-period models<br>- The heterogeneous process for rescue and treatment operations |
| Rodríguez-Espíndola et al. (2018) | - Imperfect information and/or resilience<br>- Routing and scheduling problems and casualty transportation according to the organization hierarchy<br>- Adaptation of the model to function with real-time information<br>- Collaborative rather than centralized models |
| Safaei et al. (2018) | - Uncertain relief costs<br>- Study of fuzzy supplier risks<br>- Different transportation modes and the disruption of network<br>- Multi-dimensionality of the risk factor |
| Shiripour and Mahdavi-Amiri (2018) | - Multiple groups of casualties<br>- More accurate relations for casualty and destruction percentages |
| Sun et al. (2018) | - Estimating survival probability functions along with remaining lifetime probability distributions<br>- A priori analysis to recommend simple guidelines for training medics |
| Alinaghian et al. (2019) | - Multiple tours for vehicles |
| Alizadeh et al. (2019) | - Hybrid simulation-optimization approach for casualty evacuation<br>- A qualitative system dynamic<br>- Robust min-max regret stochastic programming model<br>- A maximal accessibility network design |
| Baharmand et al. (2019) | - Considering fairness or social cost |
| Ghasemi et al. (2019) | - Routing of relief distribution and evacuation of casualties<br>- Fuzzy sets or robust optimization approach |
| Li and Chung (2019) | - Considering uncertainty in loading and unloading times |
| Li et al. (2019) | - The complexity of rescue tasks and the collaborative effect among rescuers<br>- Inadequate number of rescuers |
| Liu et al. (2019) | - A quantitative empirical approach or mathematical method such as queue theory and stochastic scheduling method to classify casualties and study the survival probability function under time-varying number of casualties<br>- Determine the order of medical service for casualties |
| Liu et al. (2019) | - Intelligent forecast method for predicting the uncertainties in supply and demand<br>- Considering multi-modal transportation |
| Ozbay et al. (2019) | - The risk of losing some shelters |
| Paul and Zhang (2019) | - Hospital capacity and transportation<br>- Vehicle round trips to visit multiple points<br>- Priority for perishable products |
| Rauchecker and Schryen (2019) | - Preemption of the casualty processing<br>- Considering time windows<br>- Handling uncertainty |
| Sabouhi et al. (2019) | - Disruption of facilities or transportation links<br>- Uncertainty in transportation time, capacity of facilities and available relief items<br>- Classification of hospitals |
| Setiawan et al. (2019) | - More effective heuristic methods<br>- Road capacity |
| Yu et al. (2019) | - Varying or stochastic lead times and demands |
| Zhu et al. (2019) | - Relaxation of some assumptions<br>- Uncertain scenarios<br>- Investigating equity and priority in other aspects of CM |

**Table 14.** Details of case-based studies in the CM literature.

| Reference | Case study | Source of data | RD&SR | OST | OSM | TTH | HTT |
|---|---|---|---|---|---|---|---|
| Christie and Levary (1998) | Air crash in a residential area of St. Louis | City Emergency Management Agency, The EMS in St. Louis | | | | ✓ | |
| Drezner (2004) | Hypothetical earthquake in Orange County, California | 2000 Census data | | | ✓ | | |
| Gong and Batta (2007) | Earthquake in Northridge | Al-Momani and Harrald (2003) | | | | ✓ | |
| Yi and Ozdmar (2007) | Hypothetical earthquake in Istanbul | Bogazici University (2002) | ✓ | | | ✓ | |
| Jotshi et al. (2009) | Hypothetical earthquake in Northridge, Los Angeles | Tele-Atlas database | | | | ✓ | |
| Ozdmar (2011) | Earthquake in Istanbul 1999 | www.ibb.gov.tr/sites/akom/Documents/index.html | ✓ | | | ✓ | |
| Nolz et al. (2011) | Hypothetical earthquake in Manabí, Ecuador | Not reported | ✓ | | | | |
| Paul and Batta (2011) | Hurricane in New Orleans | Jotshi et al. (2009) | | | | ✓ | |
| Chen and Miller-Hooks (2012) | 2010 Earthquake in Port-au-Prince, Haiti | UNOSAT,2010 | ✓ | | | | |
| Paul and Hariharan (2012) | Hurricane Katrina in New Orleans, Earthquake Northridge, California | GPO Access Reports 2005, Klein and Nagel (2007), Franco et al. (2006) | ✓ | | ✓ | | |
| Rachaniotis et al. (2012) | Influenza in Greece, 2009 | www.statistics.gr/portal/page/portal/ESYE/PAGE-themes?p_param=A1604 | | ✓ | | | |
| Rauner et al. (2012) | Austria (general disaster) | Austrian informational sources | | | ✓ | | |
| Chan et al. (2013) | New York City World Trade Center attacks on September 11, 2001 | Yurt et al. (2005) | | | | | ✓ |
| Apte et al. (2014) | Columbia (general disaster) | National Medical Response Teams | ✓ | | ✓ | ✓ | |
| Jin et al. (2014) | Department store collapse South Korea-1995 | You et al. (1997) | | | ✓ | ✓ | ✓ |
| Salman and Gul (2014) | Earthquake in Istanbul | JICA report (2002) | | ✓ | | ✓ | |
| Zheng et al. (2014) | 2013 Ya'an Earthquake in China | Red Cross Society of China, Yang et al. (2013) | | ✓ | | | |
| Caunhye et al. (2015) | Radiological dispersal devices in Los Angeles | Department of Homeland Security (2005) | | ✓ | ✓ | | |
| Edrissi et al. (2015) | Earthquake in Tehran, Iran | Tehran Atlas, 2014 | ✓ | | | | |
| Debacker et al. (2016) | Airplane crash at Zaventem airport in Belgium | Belgian EMS system | | ✓ | ✓ | ✓ | |
| Paul and MacDonald (2016a) | Earthquake in Northridge region in Los Angeles California,1994 | RSMeansOnline, 2013 | | | ✓ | | |
| Repoussis et al. (2016) | Hypothetical Terror attack, New York | Randomly data | | | | ✓ | ✓ |
| Karatas et al. (2017) | Maritime incidents, Turkey | Turkish Coast Guard | ✓ | | | | |
| Zhang et al. (2017) | 2008 earthquake in Wenchuan, Sichuan Province, China | Not reported | ✓ | | | | |
| Bravo et al. (2019) | Tornado in Brazil, Refugee camp in South Sudan, Nuclear accident in Fukushima, Japan. | Canes (2015), Reach Resource Centre (2015), Verdu (2016) | ✓ | | | | |
| Cao et al. (2018) | Earthquake in Wenchuan of Sichuan in China on May 12, 2008 | Not reported | ✓ | | | | |
| Caunhye and Nie (2018) | Earthquake in California | Jones et al. (2008) | | | | ✓ | |
| Kim et al. (2018) | Terrorist attack, Seoul, Korea | Kang et al. (2015) | ✓ | | | | |
| Mahootchi and Golmohammadi (2018) | Hypothetical earthquake in Tehran, Iran | JICA- Japanese International Cooperation Agency (2000), Reports of Tehran Municipality | ✓ | | | | |
| Mills et al (2018) | Hypothetical Earthquake in San Francisco | California Office of Statewide Health Planning and Development (2016) | | | | ✓ | |
| Mollah et al. (2018) | Flood in Barrackpore Block II, India | State Government of West Bengal, India | ✓ | | | | |
| Niessner et al. (2018) | Gas explosion at a farmers' market in Austria | Rauner et al. (2016)* | ✓ | ✓ | ✓ | ✓ | |
| Rezapour et al. (2018) | Earthquake in New Madrid Seismic Zone of Illinois | New Madrid Seismic Zone (2009) | ✓ | | ✓ | | |
| Rodríguez-Espíndola et al. (2018) | Hurricanes in Veracruz and Guerrero, Mexico, 2010, 2013 | Multiple organizations reported in Table 2 of the paper | ✓ | | | | |
| Safaei et al. (2018) | Flood in villages of Mazandaran, Iran | Central warehouse of Mazandaran, Sari Municipality, historical data and published local studies | ✓ | | | | |
| Shiripour and Mahdavi-Amiri (2018) | Earthquakes in Tabriz, Iran | Statistical Center of Iran, Tabriz Crisis Management Organization, Tabriz municipality and Tabriz DEMMC | ✓ | | | | |
| Alizadeh et al. (2019) | Hypothetical leak of toxic gas in Bhopal, India | Indian Council of Medical Research (ICMR, 1985) | | ✓ | ✓ | ✓ | |
| Baharmand et al. (2019) | 2015 Nepal earthquake | UN World Food Program handbook, Logcluster.org, 2011 Nepal census report, Semi-structured interviews | ✓ | | | | |
| Davoodi and Goli (2019) | Hypothetical Earthquake in Tabriz, Iran | Expert estimations | ✓ | | | | |
| Doan and Shaw (2019) | Simultaneous hypothetical disasters in three different cities | Document review, retired commander interview, Double-check by two other commanders | ✓ | | | | |
| Ghasemi et al. (2019) | Hypothetical earthquake in district one of Tehran, Iran | Not reported | ✓ | | | ✓ | |
| Li et al. (2019) | 2014 earthquake in Ludian, China | Not reported | ✓ | | | | |
| Liu et al. (2019) | 2010 Earthquake in Yushu, China | http://www.qhnews.com/; Mills et al. (2013); Ni et al. (2018) | ✓ | | | | |
| Liu et al. (2019) | 2008 Great Wenchuan Earthquake, Sichuan Province, China | Earthquake Agency of P.R. China | ✓ | | | | |
| Sabouhi et al. (2019) | Hypothetical disaster in district 4 of Tehran, Iran | Reports of Tehran Municipality, Tehran City Council, Tehran Red Crescent Society and polls of experts | ✓ | | | ✓ | |
| Setiawan et al. (2019) | Padang Pariaman District after the West Sumatra earthquake | Ministry of Health Affairs office | ✓ | | | | |
| Zhu et al. (2019) | 2017 Houston Flood | FEMA, CNN report | ✓ | | | | |
| | | Total | 29 | 7 | 11 | 17 | 3 |

[*] Rauner, M.S., Niessner, H., Leopold-Wildburger, U., Peric, N., Herdlicka, T. (2016) A policy management game for mass casualty incidents: an experimental study. *Flexible Services and Manufacturing Journal*, 28(1-2), 336-365.
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Finally, in this section, some general directions are suggested which are applicable for all categories of CM:

***Coordination/Integration*:** Coordination among interrelated CM operations is critical in saving the highest number of casualties. Some researchers developed integrated models that simultaneously take into account two or more categories (among RD&SR, OST, OSM, TTH and HTT). However, there exists a space for improvement and extension. The coordination of RD&SR activities with downstream operations (e.g., OSM, TTH, etc.) was understudied. The prioritization made by OST methods depends on the balance between the supply and demand of relief resources which, in turn, is determined by the arrival rate of casualties (pushed by RD&SR operations) and service rate of medical units (pulled by OSM operations). Also, both OSM and TTH problems are strongly interrelated which calls for the integration of resource allocation and scheduling decisions. Finally, TTH decisions determine the casualty arrival patterns at HTT while the performance of HTT operations may mutually affect the hospital workload and accordingly, the acceptance rate of casualties sent by TTH operations. Well-established coordination allows addressing important issues like balancing the hospital workload to prevent overwhelming. Another path for future research is to incorporate other non-CM but relevant decision areas such as debris management, corpse management and volunteer management.

***Dynamisms*:** Extra sources of dynamics on both demand and supply sides of post-disaster circumstances are involved. The occurrence of new incidents, discovery of new affected sites and collapse of infrastructures, facilities and buildings during the relief operations cause some demand-side dynamics. Moreover, the survival probabilities of different casualty groups are not fixed and deteriorate over time. The unplanned arrival of new national and international resources at disaster scenarios and damage to the morale and mentality of relief personnel are examples of supply-side dynamics. The number and status of SAR and medical units and relief facilities (e.g., ambulances) changes significantly over time. In HTT operations, the arrival pattern of casualties and the service pattern of medical resources are also non-stationary and vary over time. These highlight the importance of employing novel but efficient methods to capture dynamics in CM models.

***Extreme uncertainty:*** Most developed models were formulated in deterministic and close-to-normal environments. In fact, the current literature mainly assumes the existence of perfect information about all aspects of CM problems which is not realistic and practical. The existing models mainly focused on uncertain parameters like arrival and treatment times and deteriorating health conditions. Considering various aspects of uncertainty and incomplete and asymmetric information is a severe demand in the CM field.

***Real-time decision making:*** Lack of valid data is one of the most critical challenges in a chaotic post-disaster environment in which data acquisition is difficult and time-consuming and perfect information is gradually provided by better assessment of affected areas over time. The number, location and condition of affected sites, number and status of affected people, the number and capacity of relief resources, etc. are updated continuously after collecting more precise information. However, most of the existing models are off-line and mostly ignore such facts. These unrealistic assumptions should be relaxed in future studies by developing real-time optimization to re-adjust decisions (i.e., re-locate, re-allocate, re-schedule, re-route, etc.) in a timely manner.

***Heuristics/rules of thumb:*** The majority of papers assumed the model will be solved every time a casualty management problem occurs. In fact, few papers employed the optimization models as policy-making tools for proposing simple yet effective heuristics/rules of thumb to help practitioners make on-time decisions in the scene of disaster without solving frequently the formulation itself. This is a highly demanded direction for future research.

***Continuous-time models:*** The majority of parameters in CM problems like the number of casualties, their types and situations change continuously. Discretizing the response time horizon at different intervals even of short enough length results in an inaccurate simulation of the environment. Though difficult-to-solve, a strong stream of future research is to develop continuous-time models for the different operations, especially RD&SR, OST and OSM.

***Empirical studies***: There are not enough empirical studies to provide valid historical data on parameter estimation in CM operations for any disaster occurrence in terms of critical factors like severity, spread, location, time and so on. Very little primary data regarding the early response of past MCIs was recorded and published in detail even by valid worldwide professional databases such as CRED, EM-DAT and WHO. This shortcoming questions the efficiency level of the proposed approaches.

***Disaster-specific research:*** The type of disaster is an important factor that can affect the relief operations. For example, there is no warning time in sudden-onset disasters, while some disasters occur with notice and provide ample time for deployment of relief teams. Therefore, real CM is dependent on the disaster type to identify a realistic decision-making problem.

***Role of other organizations:*** At the moment, the literature does not sufficiently pay attention to the interaction between all players acting in casualty management at disaster scenes, and that can be addressed in the future. In CM, humans are servicing humans while the parties are experiencing unusual physical and mental conditions and living in a chaotic environment. A single organization cannot manage an MCI due to the requirement for different resources and services. The multi-agent nature of post-disaster casualty management enforces the presence of various players (public, private and voluntary), each having their own missions, policies and authorities, but with the same objective in mind. Additionally, the significant role of volunteers should not be ignored. According to the Fritz Institute (2005), 90% of the people interviewed in Indonesia were rescued by volunteers. Many activities during the initial emergency response are done by civilians (Telford et al., 2006). This indicates a cooperative competition (named as 'coopetition') network of agents, which is a challenging issue. Game theory and multi-agent systems are two approaches to formulate the dynamics and interactions of several actors in casualty management well.

***Behavioral aspects:*** Even the best logistics models show bias in implementation due to civil intervention. The worsening morale and state of mind of all responders (SAR and medical teams, doctors, transporters, etc.) affects their efficiency, flexibility and consistency. In contrast, families that have lost their members are in severe mental health difficulties after a disaster. Studying the behavioral considerations in post-disaster situations is a serious request of practitioners. Therefore, incorporating behavioral and psychological considerations in developed decision-making tools is a way to make the studies more realistic. Perhaps developments in behavioral operations such as bounded rationality, prospect theory and immediacy can help scholars to come up with more existing and impactful models and techniques.

***Data-efficient/ data-driven models:*** Few papers studied real-world case studies and the rest lack empirical data. Most of the existing models are highly data-demanding. This field needs primary and secondary data to not only familiarize academics with detailed aspects of a practical problem in terms of assumptions, objectives and constrictions but also feed them with parameters to test the efficiency of their developed techniques. While in post-disaster situations, it is difficult to gather all the required information, run the models and generate results and insights. Therefore, there is a significant need for efficient models to be developed which can produce appropriate solutions despite limited available or easy-to-collect/estimate data.

***Impact of IT:*** The impact of various high-tech devices and data/big-data analytics cannot be ignored in any aspects of casualty management. Maps and geographic information systems can indicate the location, spread and severity of disasters as well as the availability of infrastructures and assess the assessment of the damage level after a disaster (Ozdmar and Ertem, 2015). Satellite, UAVs and radio frequency identification sensors are also other tools, which can be used in humanitarian logistics and relief operations, especially in the RD&SR activity. In the Fukushima nuclear power plant incident, only robots could be used to do any activity due to harmful radiation (Habib et al, 2016). There is little historical data in this field and finding the data for the estimation of parameters is usually very hard; hence, the internet of things may be used to constantly gather in-field real-data and data/big-data analytics. Additionally, machine learning possesses useful techniques that can be used to prepare this data with simulation and optimization models. Finally, the proposed CM approaches will only be effective if they are systematically and artistically embedded in easy-to-use IT-based decision support apps that allow real-time optimization and what-if analysis by updated data.

***Solution approaches:*** Metaheuristic and heuristic techniques were designed for the models in CM. According to Zheng et al. (2015), evolutionary algorithms are applied in a large variety of disaster relief operations problems. Exact methods or their combinations with heuristics or Metaheuristics can help to solve such models. The decomposition approach for combinatorial models is also suggested as an avenue for further research.

***Simulation-based Optimization:*** Total response time, as a priceless resource in post-disaster CM, should constantly be under control. In fact, practitioners need to make robust high-quality decisions in the shortest possible time to be able to do the greatest things for the greatest number. Therefore, model developers have to solve their models previously, extract, evaluate and validate the easy-yet-effective policies and decision rules and suggest them to practitioners. Simulation is one of the best methods to evaluate and validate the outcomes of models in the experimental environments that are similar to the disaster field. Moreover, to obtain the optimal solution with minimum computation time for the intractable integrated mathematical models in the field of CM with frequent data updates, the iterative simulation-based optimization technique is a well-known alternative.

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