Optimising Shelter Location and Evacuation Routing Operations: The Critical Issues

A. Esposito Amideo[1], M.P. Scaparra*[1], K. Kotiadis[2]
[1]Kent Business School, University of Kent, Canterbury, Kent, UK
ae306, m.p.scaparra@{kent.ac.uk}
[2]Business School, Canterbury Christ Church University, Canterbury, Kent, UK
kathy.kotiadis@canterbury.ac.uk

Abstract

Shelter opening and evacuation of vulnerable populations are operations crucial to disaster response, which is one of the four phases of Disaster Operations Management (DOM). Optimisation has tried to capture some of the different issues related to shelter location and evacuation routing: several models have been developed over the years. However, they are still far from being fully comprehensive. The aim of this paper is to identify the current challenges in devising realistic and applicable optimisation models in the shelter location and evacuation routing context, with the ultimate goal of outlining a roadmap for future research in this topical area. A critical analysis of the most recent combined models is provided, including insights from the authors of the existing papers. The analysis highlights numerous gaps and research opportunities, such as the need for future optimisation models to involve stakeholders, include evacuee as well as system behaviour, be application-oriented rather than theoretical or model-driven, and interdisciplinary.

Keywords: Humanitarian logistics, Disaster management, Shelter location, Evacuation routing, Optimisation

1. Introduction

The International Federation of Red Cross and Red Crescent Societies (IFRC) defines a *disaster* as the sudden occurrence of an hazardous event that severely affects the members of an entire community, leading to various unfavourable consequences (e.g., life-threatening circumstances, economic losses) that the community cannot tackle on its own (IFRC 2017).

A disaster can be classified as either *natural* or *man-made* (Van Wassenhove 2006). Examples of *natural disasters* are earthquakes (Italy, 2017), hurricanes (US, 2017), floods (Central Europe, 2015), bushfires (Australia, 2009) while terroristic attacks (UK, 2005) are examples of *man-made disasters*. Diverse types of disasters require a different evacuation process. For example, hurricanes and wildfires allow for preventive evacuation while earthquakes and floods demand immediate evacuation. Inefficient evacuation plans can have severe consequences such as life losses, or evacuees suffering from psychological harm and feeling resentment towards governmental organizations (Camp Coordination and Camp Management (CCCM) Cluster 2014). Therefore, it is paramount to plan for efficient evacuation procedures.

In this paper, we focus on two key evacuation planning operations, belonging to disaster response: *shelter location* and *evacuation routing*. We identify the current challenges in optimising these operations, with the ultimate goal of outlining a roadmap for future research. In particular, our aim is to highlight not only the gaps but also the issues around the real implementation of optimisation models in this research area.

Over the years, optimisation has tried to capture some of the issues related to disaster management problems, including the ones within the specific context of shelter location and evacuation routing. Traditionally, these problems have been addressed separately and only recently researchers have started to propose combined models. However, despite these first attempts, the optimisation models that have been proposed are still far from being fully comprehensive and, most importantly, their application in the real world is still scarce (Van Wassenhove and Besiou 2013; Pedraza-Martinez and Van Wassenhove 2016).

The contribution of this paper is fourfold. Firstly, we review and compare some surveys on disaster management, paying specific attention to how operations research, and optimisation in particular, has contributed to this field so far. Secondly, we analyse the most recent optimisation models combining shelter location and evacuation routing problems within disaster response. To clarify some ambiguities arising from the analysis of existent models and gather additional insights, an ad-hoc questionnaire was sent to the authors of these papers and the responses, included in this manuscript, are critically discussed. Thirdly, building on this analysis, we identify the current challenges emerging in this research field. Finally, we highlight further research directions, linking our findings with those arising from previous surveys.

The remainder of this paper is organised as follows. Section 2 sets the research background providing three different outlines. The first one is about disaster management, and discusses how to cope with disaster-related issues and what to consider when planning for an evacuation. The second one describes the role of operations research for disaster management, and reviews field-specific survey papers. The third one is a discussion of optimisation models tackling shelter location and evacuation routing, either separately or in an integrated manner. Section 3 reports the results of our critical analysis, concurrently with the responses of the authors of existing papers, and discusses the emergent challenges of shelter location and evacuation routing in optimisation. Section 4 outlines a roadmap for future research in this topical area. Finally, Section 5 offers some conclusive remarks.

2. Background

2.1 Disaster management

Disasters are catastrophic events that threaten and endanger the world we live in. The upward trend of their occurrence, as displayed in Figure 2.1, puts a lot of strain onto the humanitarian system, leading to an increased focus on disaster management issues.

Figure 2.1 shows the rise in number for four different natural disaster categories over the time range 1980-2016: both geophysical and meteorological events have nearly doubled, climatological events have increased threefold, and hydrological events have almost registered a sevenfold rise. The occurrence of these events is exacerbated by climate change given that, *"often, climate change acts mainly through adding new dimensions and complications to sometimes longstanding challenges"* (Barros 2014, Preface, p. ix), already present in the disaster-affected regions. Hence, these data undoubtedly warrant further investigation to improve disaster management practices.

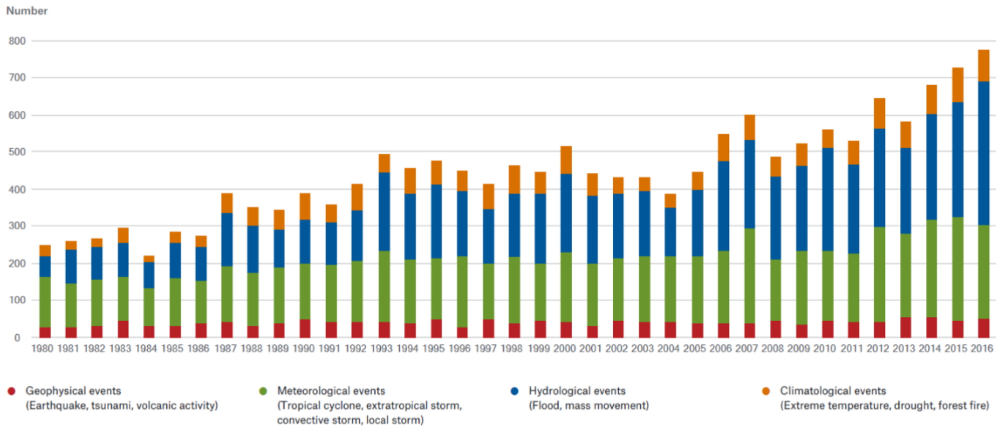

Figure 2.1. Relevant natural loss events worldwide 1980 – 2016 (Source: MunichRe 2017)

Disaster operations are usually categorized according to the *Disaster Operations Management (DOM)* framework (Altay and Green 2006), which is composed of four programmatic phases: 1) *mitigation*, which includes activities to prevent the onset of a disaster or reduce its impact (e.g., risk assessment procedures, protection planning); 2) *preparedness*, which include plans to handle an emergency (e.g., personnel training, communication system development, emergency supply stocking); 3) *response*, which is about the implementation of plans, policies and strategies developed in the preparedness phase (e.g., to put into action an evacuation plan); and 4) *recovery*, which involves long-term planning actions to bring the life conditions of a community back to normality (e.g., debris removal, infrastructure restoration). The former two phases focus on pre-disaster issues while the latter two deal with post-disaster ones.

Shelter location and evacuation routing operations lie on the boundary between disaster preparedness and disaster response. The specific DOM phase these operations fit into may differ, as highlighted by Gama, Santos and Scaparra (2016), also depending on the type of disaster. In line with the framework proposed by Altay and Green (2006), we assume that shelter opening and evacuation routing are disaster response operations. A *shelter* is a facility where people belonging to a community hit by a disaster are provided with different kinds of services (e.g., medical assistance, food). The role of a shelter is fundamental for two categories of people: those who are unable to make arrangements to other safe places (e.g., family or friends are too far), and those who belong to *special-needs populations*. These include transit-dependent and vulnerable people, such as *"those with disabilities,* *the elderly, the medically homebound, and poor or immigrants who are dependent on transit for transport"* (Transportation Research Board 2008). London Resilience Team (2014) identifies three types of shelters: *Emergency Evacuation Centres (EEC)*, *Short Term Shelters (STS)*, and *Emergency Rest Centres (ERC)*. These three types of shelters differ in terms of size, services provided to the evacuees and opening times. EECs offer immediate, basic shelter to a large number of people for a maximum staying of about 12 hours; services at EECs include basic sanitation and drinkable water, but exclude beds and food. STSs accommodate evacuees coming from either an EEC or who need to be directed to an ERC or an alternative safe destination; in addition to EECs services, STSs provide also food for up to 48 hours. ERCs provide dormitory facilities, on top of STSs services, to accommodate those people with no other alternative accommodation options. An ERC can be open up to the transition to the recovery phase or even during that phase, depending on the specific circumstances. People move towards shelter sites, or alternative safe destinations, when they either face or are going to face perilous circumstances. The process of leaving their own houses to seek refuge in safe zones goes under the name of *evacuation*. London Resilience Team (2014) identifies three types of evacuation: *self-evacuation*: individuals move towards safe sites (either shelter or not) autonomously, without receiving any kind of assistance from the responder community; *assisted evacuation*: individuals arrange their own transportation towards shelters, but require some advice from public authorities (e.g., directions); *supported evacuation*: special-needs populations (e.g., disabled, elderly) require support from emergency services and public authorities to reach some shelter facilities. An evacuation process may deploy different transportation modes: this goes under the name of *multimodal evacuation*. For example, under flood circumstances, evacuation may be carried out using a combination of land (buses), water (boats) and air (helicopters) transport.

2.2 Operations Research for disaster management

Operations Research, and optimisation in particular, has been applied to disaster management since the early 1980s (Altay and Green 2006; Simpson and Hancock 2009). A variety of problems, pertaining to different DOM stages, have been modelled through optimisation techniques as reported in the surveys by Altay and Green (2006); Simpson and Hancock (2009); Caunhye, Nie and Pokharel (2012); Galindo and Batta (2013); Hoyos, Morales and Akhavan-Tabatabaei (2015); Özdamar and Ertem (2015); and Bayram (2016). In the following, we briefly review these seven surveys, which deal with either disaster management in general or evacuation planning operations, and compare them in terms of research area, journal outlets, state-of-the-art and their proposed research directions. Our discussion does not include surveys that do not explicitly discuss shelter location and evacuation planning problems such as De La Torre, Dolinskaya and Smilowitz (2012) and Çelik (2016), which focus only on disaster relief routing and disaster recovery, respectively. We also exclude surveys that are limited in scope (Grass and Fischer 2016), only offer a qualitative outlook (Jabbour et al. 2017) and tutorials (Kara and Savaşer 2017). The seven surveys are reviewed in chronological order. A summary of the main issues can be found in the supplementary material (Table B.1).

Altay and Green (2006) provide a literature survey of OR/MS applied to disaster management over the time period 1980 – 2004. The authors group all the collected papers according to several aspects such as deployed methodology, DOM phase, and research contribution across different journal categories. The following findings can be inferred from their analysis: 1) the most favoured methodology is mathematical programming while the least deployed are Soft OR approaches, also known as Problem Structuring Methods (PSMs) (Rosenhead and Mingers 2001); 2) among the four DOM phases, the most investigated one is mitigation while the least enquired is recovery; and 3) the research aim is highly model-based rather than theory-oriented or application-driven. Altay and Green (2006) propose various research directions. Firstly, hierarchical and multi-objective approaches need to be developed to account for the multi-agency nature of DOM operations. Secondly, methodologies so far underutilised, such as Soft OR approaches, and more advanced technologies, such as sensing algorithms, should be further investigated. Thirdly, more research should be devoted to the recovery phase given its crucial role in restoring lifeline services and normal life conditions. Finally, business continuity models and disruption management models that incorporate sustainability issues in infrastructure design are required to ensure efficient response and recovery operations.

Simpson and Hancock (2009) focus on emergency response-related OR articles during the period 1965-2007. They group papers into four focus categories: urban services (e.g., police, fire and ambulance services); disaster services (e.g., evacuation planning); hazard specific (e.g., hurricanes, earthquakes or floods), and general emergency. They use this categorization to analyse trends in volume, focus and outlets of emergency OR research and observe a shift in focus over time from urban services to general emergencies. As for the methodologies, they confirm Altay and Green (2006) findings: mathematical programming is the most common methodology across all focus categories with the exception of hazard specific, whereas Soft OR approaches are still scarcely used in spite of their suitability to address the unstructured nature of emergency problems. Simpson and Hancock (2009) identify four main areas for further research: 1) development of Soft OR approaches as key tools to enable policy-maker involvement in the modelling process, encourage a sense of ownership, and ultimately lead to impact on policy making; 2) development of more sophisticated information and decision support systems (DSS); 3) inclusion of volunteer coordination within a multi-agency framework; 4) definition of ad-hoc key performance indicators able to capture the ill-defined and unique nature of emergency problems.

Caunhye, Nie and Pokharel (2012) review optimisation models for emergency logistics developed during the period 1976-2011. They focus on core DOM operations such as facility location, stock pre-positioning, evacuation, relief distribution and casualty transportation. Through their analysis, the authors first observe three main gaps: optimisation models addressing different DOM operations in an integrated manner are scarce, multi-objective approaches are underutilised due to solving difficulties, and more advanced algorithms are required. They also identify several research opportunities. Optimisation models are needed for some operation-specific problems such as: facility siting as a post-disaster operation, possibly including stock transfer activities; pre- and post-disaster capacity planning; dynamic post-disaster inventory; casualty transportation incorporating aspects such as transportation time, injury severity and medical centre service load. As previously noted by Simpson and Hancock (2009), suitable performance measures, which go beyond timely responsiveness and cost-efficiency, need to be defined (e.g. multi-agency coordination effectiveness and relief planning robustness). Finally, the uncertainties related to human behaviour in post-disaster environments need to be addressed, for example by using robust optimisation and chance constraints.

Galindo and Batta (2013) continue the review of Altay and Green (2006), with the ultimate goal of evaluating if any changes emerged in OR applied to disaster management during the timeframe 2005-2010. Their comparative analysis reveals that no drastic changes have occurred in the field. In fact: (1) the most favoured methodology is still mathematical programming while Soft OR is still underused; (2) the most investigated DOM phase is response, immediately followed by preparedness, but the least studied is still recovery; and (3) the research aim is even more model-driven and even less application-oriented. Novelties include the combination of different methodologies (Afshar, Rasekh and Afshar 2009), the integration of DOM phases (Fiorucci et al. 2005) and the development of case studies, although these mostly rely on unrealistic assumptions. In addition to those identified by Altay and Green (2006), they suggest the following research directions: improvement of the coordination among DOM actors; development of cutting-edge technologies (e.g., GIS-based); thorough understanding of DOM problems and use of statistical analysis to build realistic assumptions, define disruption scenarios, and deal with information unavailability; exploration of Soft OR approaches and interdisciplinary techniques; and use of performance indicators to evaluate strategies.

Hoyos, Morales and Akhavan-Tabatabaei (2015) present a review on OR techniques with stochastic components in DOM during the time period 2006-2012. The authors classify the collected papers according to DOM phase and deployed methodology. The results of their analysis are: (1) the most deployed methodology is stochastic mathematical programming, in particular for preparedness and response operations such as facility pre-positioning, resource allocation, relief distribution, and casualty transportation, while the least deployed is queuing theory; (2) in the mitigation phase, research mostly focuses on probabilistic and statistical models such as logistic regression and artificial networks (e.g. for demand prediction); and (3) stochastic methods for the recovery phase are largely understudied. The authors identify several research directions: a better understanding of the features related to a specific disaster is needed to formulate accurate and realistic assumptions; combination of different methodologies should be encouraged as well as the usage of multi-period models to tackle the evolving aspects of disasters; several topics including inventory planning, search and rescue activities and especially recovery operations deserve greater attention; consideration and integration of issues such as infrastructure damage, secondary (or even cascading) disasters, multi-agency coordination and communication are needed for building more applicable models.

Özdamar and Ertem (2015) review logistics models for response operations (relief delivery, casualty transportation and mass evacuation) and recovery operations (road and infrastructure restoration, and debris management). They analyse both structural (e.g., objectives, constraints) and methodological (e.g., solution methods) aspects of these problems. Moreover, they provide a brief discussion on the use of information systems in humanitarian logistics. The authors identify various areas for improvement, including: 1) development of on-line, fast optimisation algorithms that are able to handle large-scale disasters; 2) development of integrated models that combine multiple recovery issues (e.g., debris clean-up, infrastructure restoration); 3) integration of practitioner and academic researcher best practices (e.g., user-friendly interfaces from the former, sophisticated mathematical models from the latter); 4) development of globally accessible databases and holistic commercial software for disaster management so as to overcome implementation issues linked to the lack of real-time data and stakeholder coordination.

Bayram (2016) provides a survey of OR papers for large-scale evacuation planning. In particular, the author reviews traffic assignment models (e.g., user equilibrium, system optimal, etc.), typical objectives in evacuation modelling (e.g., clearance time minimization, total evacuation time minimization, etc.), and evacuee behaviour issues (e.g., perceived risk, ethnicity, gender, etc.). Moreover, deterministic and stochastic models tackling self-evacuation are described, followed by those including shelter decisions and addressing mass-transit-based evacuation. Bayram (2016) concludes the survey with some suggestions, aimed at making future optimisation models more realistic and implementable. These include: better modelling of human behaviour; more focus on special-needs population, mass-transit-based and multi-modal evacuation as opposed to self-evacuation; usage of strategies based on intelligent transportation systems; development of stochastic and dynamic models, models integrating shelter location and evacuation decisions, and game-theoretic approaches for man-made disasters.

2.3 Optimisation for shelter location and evacuation routing

Within the disaster management context, optimisation researchers have proposed several models tackling shelter location and evacuation routing problems, either separately or in an integrated manner. As noted in Bayram (2016), the majority of evacuation studies focus on evacuation with private vehicles (often referred to as *car-based* evacuation), whereas mass-transit-based (or *bus-based*) evacuation models are more sparse. Shelter location problems have also received considerable attention over time. Overall, most of the focus so far has been on models that address shelter location, car-based and bus-based evacuation as separate problems. Table 2.1 briefly summarises the main features of these problems in terms of objectives, constraints and case studies.

Table 2.1 – Features of shelter location, car-based, and bus-based evacuation as separated problems

Problem	Objectives	Constraints	Case Studies
Shelter Location	Total Evacuation Time (Sherali et al. 1991; Zhao et al. 2015), Total Travel Distance (Chen et al. 2013; Xu et al. 2016), Total Risk (Chowdhury et al. 1998), Total Shelter Cost (Zhao et al. 2015), Shelter Coverage (Xu et al. 2016)	Maximum Shelter Capacity (Sherali et al. 1991; Zhao et al. 2015), Budgetary Restriction (Chen et al. 2013; Chowdhury et al. 1998), Maximum Evacuation Distance (Zhao et al. 2015; Xu et al. 2016), Minimum Coverage Requirement (Xu et al. 2016)	Hurricanes (Sherali et al. 1991), Cyclones (Chowdhury et al. 1998), Earthquakes (Chen et al. 2013; Zhao et al. 2015; Xu et al. 2016)
Car-based Evacuation	Total Travel Distance (Cova and Johnson 2003), Network Clearance Time (Miller-Hooks and Patterson 2004), Total Evacuation Time (Xie and Turnquist 2011), Total Number of Evacuees (Lim et al. 2012), Total Travel Time (Ren et al. 2013), Network Congestion (Lim et al. 2015)	Flow Conservation (Cova and Johnson 2003; Miller-Hooks and Patterson 2004; Xie and Turnquist 2011; Lim et al. 2012; Ren et al. 2013)	Bomb threat (Cova and Johnson 2003), Hurricanes (Lim et al. 2012), Nuclear plant evacuation (Xie and Turnquist 2011), Terrorist attack (Ren et al. 2013)
Bus-based Evacuation	Maximum Evacuation Time (Bish 2011; Goerigk, Grün and Heßler 2013; Goerigk and Grün 2014; Goerigk, Deghdak and T'Kindt 2015) Maximum number of transferred evacuees with lowest risk (Shahparvari et al. 2017; Shahparvari, Abbasi and Chhetri 2017; Shahparvari and Abbasi 2017)	Flow Conservation (Bish 2011; Shahparvari et al. 2017; Shahparvari, Abbasi and Chhetri 2017; Shahparvari and Abbasi 2017) Bus capacity (Bish 2011; Shahparvari et al. 2017; Shahparvari, Abbasi and Chhetri 2017; Shahparvari and Abbasi 2017)	Bomb disposal (Goerigk and Grün 2014; G Goerigk, Deghdak and T'Kindt 2015) Bushfire (Shahparvari et al. 2017; Shahparvari, Abbasi and Chhetri 2017; Shahparvari and Abbasi 2017)

Recently, more attention has been paid to *combined shelter location and evacuation routing problems.* Combined models can integrate 1) shelter location and car-based evacuation decisions; 2) shelter location and bus-based evacuation decisions; or 3) shelter location and both car- and bus-based evacuation issues, as displayed in Figure 2.2.

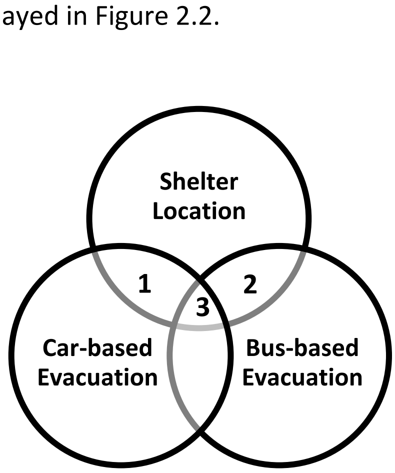

Figure 2.2. Combination of shelter location and evacuation routing problems

As noted in Caunhye, Nie and Pokharel (2012), only a few optimisation models have addressed shelter location and evacuation routing in an integrated manner prior to 2011. Also, these early combined models only integrated shelter location and car-based evacuation decisions (problem category 1, Figure 2.2). These are briefly described below.

Kongsomsaksakul, Yang and Chen (2005) present a bi-level program under flood circumstances. The upper level mimics the public authority objective (i.e., to minimize the total evacuation time by identifying optimal shelter locations); the lower level models the evacuee target (i.e., to reach a shelter facility as quickly as possible). The authors develop a genetic algorithm to solve the proposed optimisation model and they apply it to the Logan network, Utah (USA).

Alçada-Almeida et al. (2009) develop a multi-objective optimisation model for fire disasters. The objectives to be minimized are: (1) total travelling distance from evacuation zones to shelter sites; (2) evacuee fire risk while reaching a shelter facility; (3) evacuee fire risk while staying at a shelter site; and (4) total evacuation time from shelters to hospitals. The proposed optimisation model is embedded into a GIS-based decision support system and applied to the city of Coimbra (Portugal).

Ng, Park and Waller (2010) present a bi-level program that considers both system and user optimal approaches. The system optimal approach is adopted in the upper level to optimally locate shelter facilities while the user optimal approach is deployed at the lower level to identify the optimal evacuation routes. The authors solve the model with a Simulated Annealing algorithm and present a realistic case study for Sioux Falls, North Dakota (USA), under a hypothetical man-made threat.

Li et al. (2011) introduce a scenario-based bi-level program under hurricane circumstances. The ultimate goal of the model is to find optimal shelter sites while considering the effect of this decision onto driver route-choice behaviour. The authors apply the proposed optimisation model to the state of North Carolina (USA) as a realistic case study.

In summary, prior to 2011, the main emphasis has been on modelling shelter location and car-based evacuation as separate problems, with only a handful of models combining the two problems. In 2011, the seminal paper for bus-based evacuation was introduced (Bish 2011), thus enabling the development of models in the other combined categories (2 and 3). An in-depth analysis of recent combined shelter location and evacuation routing models developed from 2012 onwards is the subject of our investigation and will be discussed next.

3. Emergent challenges in optimising shelter location and evacuation routing

In this section, we first provide a brief overview of the existing articles, to which we will refer as case studies. We will then present a structured analysis of the case studies, which also includes a discussion of the responses of the authors to an ad-hoc questionnaire.

3.1 Case studies overview

Our analysis focuses on the timeframe January 2012 – December 2017. The existing papers have been collected by exploring the INFORMS journal database, Science Direct, and the Springer Journal Database, which have been queried with two main keywords: “shelter” and “evacuation”. Nine articles matched the search criteria whose outlet-based distribution is as follows: three papers in *Transportation Research Part E*, two in the *EURO Journal on Computational Optimization*, one in the *European Journal of Operational Research*, one in the *Journal of Transport Geography*, one in *Transportation Research Part B*, and one in *Transportation Science*. These papers are briefly discussed in chronological order to illustrate the temporal evolution of the field (in case of year ties, papers are ordered by first author surname).

Coutinho-Rodrigues, Tralhão and Alçada-Almeida (2012) define a multi-objective location-routing model to address the evacuation of self-evacuees. In particular, the authors extend the model proposed by Alçada-Almeida et al. (2009) by optimising the location decisions and including two additional criteria in the objective function. The objectives to be minimized are: (1) total travelling distance from evacuation zones to shelter sites on primary paths (i.e., best available evacuation routes); (2) evacuee risk while reaching a shelter facility on primary paths; (3) total travelling distance from evacuation zones to shelter sites on backup paths (i.e., best available evacuation routes when primary paths are unavailable); (4) evacuee risk while staying at a shelter site; (5) total evacuation time from shelters to an hospital; and (6) total number of shelters to be opened. The model is solved with an off-the-shelf optimisation software and is tested on a realistic case study for the Baixa region of the city of Coimbra (Portugal).

Li et al. (2012) tackle the evacuation of self-evacuees, who move towards either a shelter site or an alternative destination, under different hurricane scenarios. They present a scenario-indexed bi-level program where shelter location and evacuation routing problems are addressed conjunctively. The upper-level model is a two-stage stochastic location and allocation problem and entails shelter decisions. The lower level deploys a Dynamic User Equilibrium model to mimic evacuee behaviour and account for congestion-related issues, in line with a user optimal approach. The ultimate goal is to identify optimal evacuation planning decisions by taking into consideration how different shelter locations can influence evacuee route choice. The bi-level program is solved with heuristic algorithms whose applicability is tested on a realistic case study for the state of North Carolina (USA).

Goerigk, Deghdak and Heßler (2014) address the evacuation towards shelter sites of both self-evacuees and supported evacuees through a multi-period, multi-criteria mixed-integer program. To the best of our knowledge, this is the only paper to address shelter location, car-, and bus-based evacuation into a combined optimisation model, called the Comprehensive Evacuation Problem. The authors model the dynamic aspect of an evacuation process and account for different planning objectives conjunctively such as the evacuation time, the number of shelters to be opened, and the risk exposure of the evacuees. The authors assume a System Optimal (SO) approach where a planning authority is in charge of both shelter and evacuation routing decisions. The optimisation model is solved with a genetic algorithm and tested on two realistic case studies: the evacuation of the city of Kaiserslautern (Germany) due to a bomb defusion and the evacuation of the city of Nice (France) due to an earthquake with a subsequent flood.

Bayram, Tansel and Yaman (2015) present a non-linear mixed integer program for self-evacuation towards shelter destinations. The model is based on a Constrained System Optimal (CSO) approach. A CSO perspective assumes that evacuees are willing to accept, to a certain level of tolerance, to travel routes that are not the shortest ones. The proposed CSO model accounts for both shelter and evacuation routing decisions while minimizing the total evacuation time, which is modelled through a non-linear function of the traffic volume. Furthermore, the authors formulate a system optimal model whose results are compared with the CSO one to evaluate the fairness, with respect to both routes and shelters, of the emergent planning decisions. They also investigate the evacuation plan efficiency. The problem is solved by using a second order cone programming approach and results are presented for both test and realistic case studies, such as the Istanbul European and Istanbul Anatolian networks under earthquake circumstances.

Kılcı, Kara and Bozkaya (2015) address shelter location and self-evacuation with the ultimate goal of improving the Turkish Red Crescent (TRC) approach. TRC considers ten different criteria (e.g., transportation of relief items, healthcare providers, road connections) to rank candidate shelter sites: each candidate area receives a score per each criterion, then potential areas are sorted in decreasing order of the total score, and shelters are built in the areas with the highest score. The authors improve the TRC approach by developing a mathematical model that considers evacuation zones-to-shelters distances and shelter site utilization. The aim is to identify the optimal location of temporary shelter areas and match evacuation districts to shelter areas so as to satisfy several utilization and efficiency criteria. The model is solved through a commercial solver and applied to two realistic case studies under earthquake circumstances: the Kartal district of Istanbul and the province of Van (Turkey).

Gama, Santos and Scaparra (2016) present a multi-period mixed integer program for self-evacuation towards shelter sites. The proposed optimisation model tackles together shelter location, warning signals dissemination, and evacuation routing decisions under flood circumstances. The aim is to optimally identify, based on a flood propagation model, opening times and locations for shelter sites, timings for evacuation order dissemination, and optimal evacuees-to-shelter allocation while minimizing the total travelling time between evacuation zones and shelter destinations. The model is solved with a Simulated Annealing algorithm whose applicability is tested on a realistic case study for Wake County, North Carolina (USA).

Heßler and Hamacher (2016) propose a sink location problem to mimic a self-evacuation process, where evacuees are at given nodes (evacuation zones) and shelter sites are assumed to be the sinks. The model objective is to minimize the opening costs of the shelters while guaranteeing that shelter capacities and link capacities (used to model road traffic) are not exceeded. The authors present different variations of the sink location problem that can be used in different disaster situations (e.g. bomb disposal). The models are solved through adaptations of source location heuristics and their applicability is tested on both random and realistic instances (i.e., the evacuation of the city of Kaiserslautern, Germany, under a bomb disposal scenario).

Shahparvari et al. (2016) deal with evacuation under bushfire circumstances and focus on a specific category of supported evacuees: late evacuees who initially shelter in place (American Red Cross 2003) as a precautionary measure but then need to evacuate with the support of public authorities (hence, by buses), under short notice scenario. The authors present a multi-objective integer program that identifies the best shelter location and evacuation routes while optimising two conflicting objectives: maximizing the number of evacuees employing the least risk-prone routes and minimizing the utilization of resources (in terms of both shelters and vehicles). The model is solved with an ε-constraint approach and is tested on the 2009 Black Saturday bushfire in Victoria (Australia).

Bayram and Yaman (2017) present a scenario-based two-stage stochastic non-linear mixed integer program for self-evacuation towards shelter destinations. They extend the work of Bayram, Tansel and Yaman (2015) by addressing the uncertainty affecting evacuation demand as well as potential alteration to the network structure (both roads and shelter sites) due to the disaster occurrence. The authors develop an ad-hoc exact solution approach based on both Benders decomposition and cutting plane methods. Results are presented for both test and realistic case studies, such as the Istanbul European and Istanbul Anatolian networks under earthquake circumstances.

3.2 The analysis of the nine case studies

The analysis of the nine case studies has been carried out according to the lifecycle underpinning hard OR disciplines (e.g., simulation), which is structured into four phases: *conceptual modelling*, *model coding*, *experimentation*, and *implementation* (Robinson 2014).

Several issues have been identified for each block of the optimisation lifecycle for shelter location and evacuation routing. Aspects belonging to the *conceptual modelling* phase include: *stakeholder involvement*; *data collection*; *evacuee categories*, *behaviour and demographics*; *equity of the evacuation process*; *evacuation zones and shelter sites definition*; *resource availability*; and *communication and infrastructures*. *Model coding* themes are those related to the different *types of* *programming* (e.g., multi-period, multi-objective, scenario-based, stochastic) and *solution methods* (e.g., exact algorithms, heuristics, commercial solvers), along with the deployment of *user-friendly interfaces* (e.g., GIS-based). *Realistic case studies*, *stakeholder involvement at both experimentation and calibration stages*, and usage of *additional data sources* are aspects addressed in the *experimentation* block. *Implementation* consists in using the modelling approaches in real situations and includes aspects such as *model dissemination to stakeholders* and *practical applications*.

Each case study has been analysed according to these aspects. To clarify some ambiguities that have arisen, an ad-hoc questionnaire was sent to all the authors of the nine case studies. However, in eight out of nine cases, only one author answered, mainly the corresponding author. In the only case where more than one author answered, results have been evaluated for clashes and the responses of the corresponding author are reported. The questionnaire was developed using Qualtrics survey software, in line with survey design principles (Saris and Gallhofer 2007). The questionnaire, which should be intended as a supplemental validation tool of our analysis, has been structured into four main blocks that mimic the four phases of the optimisation lifecycle. An additional block of questions was added to the questionnaire to gain further insights, such as the kind of contribution the authors meant to provide. The questionnaire has undergone a pilot phase, where it has been evaluated by an NGO member, an academic and one of the authors of the existing papers. The pilot phase helped structure the final questionnaire that the interested reader can find in Appendix A.

Results have been critically analysed and compared across the papers and the author responses. This process has led to the identification of the main challenges of shelter location and evacuation routing in optimisation at the present time, which can be grouped as follows: *stakeholder involvement*, *evacuation modes*, *clear definition of modelling inputs*, *evacuee behaviour*, *system behaviour*, and *methodology*. We discuss each of these next. A summary of the results emerging from our analysis and the author questionnaire responses can be found in Table C.1 of the supplementary material.

3.2.1 Stakeholder involvement

The analysis of questions pertaining to stakeholder involvement revealed that there was no previous agreement with any stakeholders (Q1) in any of the nine case studies. The responses suggest that those who engaged with stakeholders did not clearly explain the extent of the involvement (i.e., in which phase of the optimisation process the stakeholders participated, what kind of contribution they provided to the study) (Q2, Q26). Evacuation planning operations involves a multitude of stakeholders, including "emergency management practitioners, civil protection agencies, local disasters preparedness and response workers, disaster-affected and host communities, and public service providers" (Camp Coordination and Camp Management (CCCM) Cluster 2014). Stakeholder engagement is an essential component of decision-making in multi-organisation settings (Huxham

1991). As discussed by Edelenbos and Klijn (2005), stakeholders involved in *interactive decision-making* allow to tackle the changing aspects of the problem under study and to create solutions that are better than those produced in absence of engagement.

Among the papers analysed, only three reported stakeholder participation (Q2) and use of primary data (Q3). Li et al. (2012) report that through the involvement of the State Department of Emergency Management and the American Red Cross, the modelling team organized focus groups with emergency managers and was provided with the set of candidate shelter sites for the study; they also conducted phone surveys to residents of the area under study. Kılcı, Kara and Bozkaya (2015) state that Turkish Red Crescent officials were aware of the study but did not directly contribute to it. Finally, Shahparvari et al. (2016) report some stakeholder engagement and primary data collection, and mention handing over their optimisation model to stakeholders (Q28). In all the three cases, the information about stakeholder participation was retrieved from the questionnaire responses, but was not mentioned in the papers.

Arguably the case studies analysed have provided a "realistic", rather than real, application of the proposed models (Q25), mostly relying only on secondary data sources (Q4). Realistic case studies, albeit useful to prove concepts, do not translate into practical implementations (Q29). According to the questionnaire responses (Q31), the major barrier to develop realistic, and therefore applicable, models was the access to people and data. Moreover, most of the authors contributed either theoretically, methodologically, or technically to optimisation modelling rather than practically to the field of disaster management (Q30). Reasons for this can be the nature of the academic incentive system, which tends to reward researchers based on their theoretical rather than practical work, as well as the adoption of an isolationist approach that does not entail engagement with communities external to OR (Mortenson, Doherty and Robinson 2015).

In summary, our analysis seems to suggest that lack of stakeholder involvement leads to missed opportunities for primary data collection, which in turns lead to the development of realistic, as opposed to real, case studies and eventually to lack of real implementation of optimisation models.

3.2.2 Evacuation modes

An evacuation process can occur in different ways: evacuees can move autonomously towards either a shelter or an alternative destination while public authorities can arrange transportation for those evacuees in need of support. Hence, it is possible to identify three main different *categories of evacuees* (Q6): self-evacuees who move towards a shelter (SES), self-evacuees who move towards other destinations (SED), and supported evacuees who move towards a shelter (SE).

Six case studies tackle only one category of evacuees: five focus on SES (Coutinho-Rodrigues, Tralhão and Alçada-Almeida 2012; Bayram, Tansel and Yaman 2015; Kılcı, Kara and Bozkaya 2015;

Gama, Santos and Scaparra 2016; Bayram and Yaman 2017) while only one addresses SE (Shahparvari et al. 2016). The remaining three case studies integrate two categories of evacuees together. Li et al. (2012) and Heßler and Hamacher (2016) deal with both SES and SED while Goerigk, Deghdak and Heßler (2014) address SES and SE. Hence, none of the nine case studies considers the three categories of evacuees in an integrated manner. In addition, in all the case studies evacuation takes place exclusively on road networks. Other types of transport or multi-modal evacuation have so far been neglected in combined optimisation models.

3.2.3 Clear definition of modelling inputs and parameters

As observed in Galindo and Batta (2013), a major drawback of many DOM optimisation models is that the assumptions about the inputs for such models are often unclear, limited or unrealistic. This observation was confirmed in our analysis, for example in relation to inputs such as evacuation starting positions (Q7), candidate shelter sites (Q13) and resource availability (Q14).

Evacuation starting points (Q7) are usually either area centroids (i.e., a point where the population of a certain evacuation zone is assumed to be concentrated) for self-evacuation, or bus stops (where evacuees are picked up) for supported evacuation. Six out of the nine case studies did not explicitly specify the assumption concerning the evacuation starting positions. The questionnaire responses clarified that Coutinho-Rodrigues, Tralhão and Alçada-Almeida (2012), Li et al. (2012), Bayram, Tansel and Yaman (2015), and Bayram and Yaman (2017) consider centroids; Goerigk, Deghdak and Heßler (2014) assume bus stops; while Heßler and Hamacher (2016) and Shahparvari et al. (2016) consider evacuee houses and designated assembly points, respectively.

Shelter candidate site categories (Q13) can be defined according to the classification given by Riverside County Fire Department (2011), which includes: city and/or county owned facilities (e.g., school sites, community centres), congregations (e.g., churches), open spaces (e.g., camping areas), and alternative sites (e.g., medical care sites). Assumptions regarding possible shelter locations were often omitted in our case studies. The questionnaire answers revealed that Goerigk, Deghdak and Heßler (2014) assume county-owned facilities as shelters to be, and Bayram, Tansel and Yaman (2015) consider all the possible shelter categories, while Li et al. (2012) were provided with shelter site information by the American Red Cross who runs them.

In terms of resource availability (Q14), Gama, Santos and Scaparra (2016) report a specific formula (Lorena and Senne 2004) for computing shelter capacities. Kılcı, Kara and Bozkaya (2015) adopt specific realistic measures (e.g., *"at least 3.5 square meters covered living space should be assigned to each person in the shelter areas"*, p. 326). However, the remaining case studies do not mention how shelter capacities were computed. Clear definitions or assumptions concerning other resources (e.g., vehicles, shelter staff, shelter type or road availability) were also mostly neglected. In particular, Goerigk, Deghdak and Heßler (2014) and Shahparvari et al. (2016), who account for SE, did not consider the vehicle procurement aspect (Q6.1). Vehicles can be procured by public authorities as well as volunteers (e.g., NGOs). Vehicles suppliers should therefore be clearly defined given that, if different parties are involved, a further level of coordination may be required and this needs to be captured within an optimization model.

In summary, what emerges in our analysis is that a limited number of authors provided clear specifications of modelling inputs and other relevant parameters.

3.2.4 Evacuee behaviour

In our analysis of evacuee behaviour, we reflect on five dimensions affecting the way people evacuate during an emergency (Figure 3.1): *time of day* (Q8), *route diversion* (Q9), *evacuee demographics* (Q10), *route preference* (Q9), and *warning signals* (Q9). We next explore these in turn.

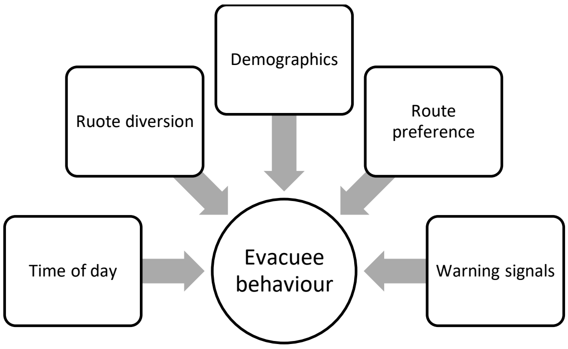

Figure 3.1. Evacuee behaviour aspects of an evacuation process

Time of day (Q8)*, route diversion* (Q9)*, and evacuee demographics* (Q10) are three extremely intertwined aspects that, according to social science studies (Liu, Murray-Tuite and Schweitzer 2012; King and Jones 2015; Preston and Kolokitha 2015; Preston et al. 2015) should be accounted for when planning for an evacuation because of their impact onto evacuee behaviour. Despite their relevance, these elements have not been addressed in our case studies.

Route preferences (Q9) play a critical role in evacuation planning and clearly affect the outcome of an evacuation process. Evacuation planning models embed traffic assignment models to simulate evacuee movements on the network. Traffic assignment models include: *user equilibrium (UE)*, *nearest allocation (NA)*, *system optimal (SO)*, and *constrained system optimal (CSO)* approaches (Bayram 2016). A *user-equilibrium (UE)* approach mimics the selfish attitude of evacuees, who choose evacuation routes to minimize their individual travel time. This approach is based on the assumption that such a behaviour on the individual level creates an equilibrium at the system level. It also assumes that evacuees have full information of the network conditions, something that is not realistic during an emergency (i.e., potential disruptions may affect links on certain routes). A *nearest allocation (NA)* approach mimics evacuees who follow their shortest path based on geographical distances and free-flow traffic to move towards the nearest shelter facility. Although reasonable form a practical point of view, this approach may led to poor system efficiency. On the other side of the spectrum, a *system optimal (SO)* approach simulates the perspective of a facility planner who has full control on the route assignment and aims at maximizing the system benefit (including congestion reduction). This may lead to the assignment of evacuees to routes that are longer than their preferred ones. Although SO approaches are easier to model and solve, they fail to capture the evacuee route preferences. A *constrained system optimal (CSO)* approach can be seen as a trade-off between the SO and the UE/NA approaches. CSO stipulates that evacuees are assigned to "acceptable" paths only (i.e., paths whose length does not exceed the one of their shortest path by more than a given *tolerance level*).

Only three case studies explicitly consider the evacuee route preference, by using a dynamic user equilibrium model (Li et al. 2012) and a CSO approach (Bayram, Tansel and Yaman 2015; Bayram and Yaman 2017). In the remaining studies, a SO approach is adopted where the allocation of evacuees to shelters is done centrally using assignment, network flow or vehicle routing-based approaches.

The issuance of a *warning signal* (Q9) can prompt different reactions among the evacuees: to ignore the warning, to inform neighbours/relatives of the disaster, to start to evacuate immediately. Once the warning is clearly received and understood, people do not evacuate simultaneously but over time. The evacuation pattern often follows an *S-shaped curve* (Perry, Lindell and Greene 1981; Rawls and Turnquist 2012; Murray-Tuite and Wolshon 2013; Li et al. 2013; Gama, Santos and Scaparra 2016). Among our existing case studies, only Gama, Santos and Scaparra (2016) tackle shelter location, evacuation routing and warning signal dissemination in an integrated manner so as to model the impact of warning signals on the evacuation process.

To summarize, our analysis shows that evacuee behaviour aspects of an evacuation process have been scarcely tackled. In fact, three out of the five aspects (i.e., time of day, route diversion, and evacuee demographics) have been entirely neglected while route preferences and warning signals have been addressed only by three and one out of the nine case studies, respectively.

3.2.5 System behaviour

Our analysis of the system behaviour includes *dynamic aspects* related to the system status over time and issues related to the *system performance criteria*.

Dynamic aspects include *shelter resources* (Q14), *shelter categories* (Q12), *congestion* (Q16), and *infrastructure disruptions* (Q17). The term *shelter resources* captures several issues such as capacities (i.e., the amount of space available to accommodate evacuees), budget and staff (to set up the shelters), and relief supplies (to be provided to the evacuees). *Shelter resources* are considered to be a dynamic aspect of the evacuation process because budget, staff members, supplies and shelters are usually not readily available at the onset of a disaster but become available over time (Gama, Santos and Scaparra 2016). Although the issue of *shelter resources*, modelled through either cardinality, budgetary, capacity or staff constraints, has been somehow captured in all the case studies, the availability of resources over time has been mostly neglected. The only exception is the dynamic model proposed by Gama, Santos and Scaparra 2016, which assumes that only a limited number of shelters can be opened in each time period of the planning horizon. The issue of considering *different kinds of shelter facilities* (Q12), which satisfy different evacuee needs over time, has also been largely neglected. As described in Section 2.1, three categories of shelters can be considered, all providing different services. All the models in our case studies only consider one type of shelter.

Six of the case studies have attempted at incorporating *congestion issues* (Q16). Goerigk, Deghdak and Heßler (2014), Heßler and Hamacher (2016) and Shahparvari et al. (2016) tackle congestion in a simplified way by using capacitated network arcs. In Li et al. (2012), congestion is captured in the dynamic UE model, which computes time-dependent travel times. Bayram, Tansel and Yaman (2015) and Bayram and Yaman (2017) model congestion through a link performance function developed by the US Bureau of Public Roads (BPR), according to a transportation-based approach.

With the exception of two case studies, *infrastructure disruption* (Q17) has been largely unaddressed. The optimisation model by Gama, Santos and Scaparra (2016) considers road disruptions during flood disasters. Specifically, the model assumes that, according to flood propagation, the water depth on roads changes over time, thus affecting speed and travel times or making roads unavailable. Shahparvari et al. (2016) also considers road accessibility over time, which depends on the propagation of bushfires on various segments of transport routes. Bayram and Yaman (2017) address the occurrence of potential disruptions affecting both nodes and arcs of the road network (i.e., shelter sites and road connections, respectively).

The need to develop suitable performance criteria for DOM problems has been widely recognized, as discussed in Section 2.2. The models of the nine case studies use the following objectives as *performance criteria*: expected unmet shelter demand and expected total network travel time (Li et al. 2012); total evacuation time, total evacuee risk, and total number of shelters (Coutinho-Rodrigues, Tralhão and Alçada-Almeida 2012; Goerigk, Deghdak and Heßler 2014; Bayram and Yaman 2017); total travelling time (Bayram, Tansel and Yaman 2015; Gama, Santos and Scaparra 2016; Bayram and Yaman 2017); shelter opening cost (Coutinho-Rodrigues, Tralhão and Alçada-Almeida 2012; Heßler and Hamacher 2016); combination of characteristics of open shelter areas (Kılcı, Kara and Bozkaya 2015); and cumulative disruption risk and shelter and vehicle usage (Shahparvari et al. 2016). Overall, the major emphasis has been on efficiency (evacuation time) and some measure of shelter/resource costs. Only three case studies have considered risks, whereas fairness, a key criteria to guarantee egalitarianism in emergency situations, has only been addressed in the CSO model by Bayram, Tansel and Yaman (2015). In this model, fairness is evaluated through a specific indicator, named *price of* *fairness*, which measures the difference between the evacuation times of a CSO and SO solutions. The authors consider two different indicators, *normal* and *loaded unfairness* (see Jahn et al. 2005), which are evaluated with respect to both routes and shelters. A comprehensive sensitivity analysis is carried out to provide insights on the relationship between the CSO tolerance level (used to embed fairness) and the price of fairness.

To recap, system behaviour aspects of an evacuation process have been tackled to different extents: shelter resources have been addressed across all the nine case studies although not in a dynamic context; congestion issues have been considered in six studies, sometimes through simplified models; infrastructure disruptions, risk and fairness issues are still largely understudied.

3.2.6 Methodology

Different modelling techniques and solution methodologies are deployed in optimisation. In terms of modelling, three case studies propose *multi-period* models (Q19) (Li et al. 2012; Goerigk, Deghdak and Heßler 2014; Gama, Santos and Scaparra 2016). *Multi-objective* programming (Q20) is used in five case studies, with different combinations of objectives (Coutinho-Rodrigues, Tralhão and Alçada-Almeida 2012; Li et al. 2012; Goerigk, Deghdak and Heßler 2014; Kılcı, Kara and Bozkaya 2015; Shahparvari et al. 2016). Uncertainty has been explicitly modelled only in the *scenario-based* (Q21) bi-level model proposed by Li et al. (2012), where the upper level is a *stochastic program* (Q22), and the scenarios represent different hurricane circumstances, and by Bayram and Yaman (2017).

The mathematical models have been solved using a range of different methodologies (Q23), including off-the-shelf optimisation solvers, exact methods and ad-hoc heuristics. In some cases, more than one method has been used for comparative analysis. As to be expected considering the difficulty of these models, five case studies developed ad-hoc heuristics, such as simulated annealing and genetic algorithms (Li et al. 2012; Goerigk, Deghdak and Heßler 2014; Gama, Santos and Scaparra 2016; Heßler and Hamacher 2016; Shahparvari et al. 2016). In some cases, heuristic solutions have been compared with those of commercial optimisation software (Gama, Santos and Scaparra 2016) or exact methods, such as source location algorithms (Heßler and Hamacher 2016) and ε-constraint techniques (Shahparvari et al. 2016). None of the nine case studies included the development of a user-friendly GIS-based interface (Q24) as a supporting tool for using the models.

To summarize, our analysis shows that a few case studies developed multi-period and multi-objective models while scenario and stochastic programming was used in one case only. The complexity of combined models has favoured the usage of heuristic approaches as solution methodology. User-friendly GIS-based interfaces have so far been overlooked.

4. Discussion and roadmap for future research

The nine case studies encompass different aspects of shelter location and evacuation routing operations. Through their analysis, we have identified various challenges that optimisation should tackle to embed more realism into future models so that they can be used to inform decision making in real disaster situations. We now outline further research directions: some of them confirm gaps identified in previous surveys (Section 2.2) while others newly stem from our analysis of the nine case studies.

4.1 Stakeholder involvement

Five surveys explored in section 2.2 (Altay and Green 2006; Simpson and Hancock 2009; Galindo and Batta 2013; Hoyos, Morales and Akhavan-Tabatabaei 2015; Özdamar and Ertem 2015) propose research on optimisation modelling that involves engaging with stakeholders to enable the actual implementation of optimisation models (e.g., arrangements for a future evacuation plan). The case studies analysed in our study report limited engagement with stakeholders. However, the authors who did involve them report that they were able to collect primary data (Li et al. 2012; Shahparvari et al. 2016). Stakeholder identification and involvement can be achieved through Problem Structuring Methods (PSMs), such as Soft Systems Methodology and System Dynamics (Pidd 2003; Wang, Liu and Mingers 2015), whose deployment for disaster management problems has been explicitly advocated (Altay and Green 2006; Simpson and Hancock 2009; Galindo and Batta 2013). In particular, Simpson and Hancock (2009) propose the investigation of the combination of Hard and Soft OR/PSM techniques in disaster response and their deployment within a multi-methodology approach (Sachdeva, Williams and Quigley 2007). They put forward two main reasons: (1) the capability of PSMs to deal with the unstructured nature of the problems arising from an emergency response context, and (2) the scarcity of truly high-impact application of results emerging from Hard OR methodologies, mainly due to a lack of structured involvement of all the stakeholders, echoed by Franco and Montibeller (2010). Van Wassenhove and Besiou (2013) propose System Dynamics to be paired with common OR methods to capture the complex reality of systems such as reverse logistics and humanitarian logistics. However, to the best of our knowledge, PSMs have not yet been proposed to tackle evacuation planning issues, offering new research opportunities. Optimisation could look to Discrete Event Simulation (DES) studies that have used PSMs to engage stakeholders in the modelling process through facilitated workshops (Tako and Kotiadis 2015; Kotiadis and Tako 2018).

4.2 Evacuation modes

Among the seven surveys, only Bayram (2016), who carries out an evacuation planning-oriented literature review, suggests to account for special-needs population (i.e., supported evacuees). Our analysis of the nine case studies shows that three different categories of evacuees can be identified: SES, SED, and SE. However, these evacuee categories have been considered either as separate ones

(Coutinho-Rodrigues, Tralhão and Alçada-Almeida 2012; Bayram, Tansel and Yaman 2015; Kılcı, Kara and Bozkaya 2015; Gama, Santos and Scaparra 2016; Shahparvari et al. 2016; Bayram and Yaman 2017) or as a combination of two out of three (Li et al. 2012; Goerigk, Deghdak and Heßler 2014; Heßler and Hamacher 2016). To be more comprehensive, even if undoubtedly more complex, all the three different categories should be considered in an integrated manner given that they share common resources. In fact, SES and SE share shelter facilities, which affects both shelter capacity (i.e., number of people who can be accommodated) and resources (e.g., relief supplies). All the evacuees share the road network, leading to congestion and, ultimately, affecting the evacuation time. Moreover, what emerges in our analysis is that optimisation researchers have so far neglected to account for *assisted evacuation* and *multimodal evacuation*. Assisted evacuation, as mentioned in Section 2.1, deals with evacuees who drive their own vehicles but are in need of advice from public authorities (e.g., directions) while multimodal evacuation requires different transportation modes. To model *assisted evacuation*, collateral problems should be considered such as how and where evacuees would be informed about the adopted evacuation strategies (e.g., contraflow lane reversal). For example, advanced traveller information can be provided through the deployment of portable Variable Message Signs (VMS), which can be opportunely located and re-located (Sterle, Sforza and Esposito Amideo 2016). On the other side, *multimodal evacuation* would require to investigate the optimisation of different kinds of evacuation (each one related to a different mean of transportation) and their coordination. The use of alternative transport modes has been investigated for other emergency logistics operations (e.g. helicopter operations for disaster relief in Ozdamar (2011)). Multimodal emergency evacuation of large cities has been investigated in Abdelgawad and Abdulhai (2010). However, combined optimisation models for shelter location and evacuation planning have so far only considered evacuation by cars and buses. More research is definitely warranted for the development of combined models integrating different kinds of transportation.

4.3 Clear definition of modelling inputs and parameters

Evacuation planning operations should be more application-oriented rather than theoretical or model-driven. Pedraza-Martinez and Van Wassenhove (2016) have recently edited a special issue on humanitarian operations management problems focused on collaborative journal articles with field practitioners or articles exploring how the research fits practical issues. This can be thought of as a first step to push researchers towards a more application-oriented perspective. To foster real application, more realistic assumptions underpinning optimisation models are needed, as already pointed out in the survey by Galindo and Batta (2013). Our analysis reveals that there is a lack of realistic assumptions when referring to modelling inputs and parameters. Indeed, few authors provide a clear specification of inputs such as evacuee starting points, shelter candidate positions, and shelter capacities. On the other hand, those authors who explicitly pointed out their modelling assumptions were able to embed more realism into the proposed optimisation models. In order to provide more realistic modelling assumptions, our suggestion is to favour primary data collection over secondary data collection. In fact, all the nine case studies relied on secondary data sources (e.g., government publications, websites) while only two out of these used primary data (e.g., personal interviews, surveys). Primary data can be collected if researchers establish a kind of contact with relevant stakeholders (e.g., civil protection agencies). Embedding more realism through the use of primary data can be fostered through stakeholder involvement (Tako and Kotiadis 2015; Kotiadis and Tako 2018). In addition, the uncertainty of some problem inputs, such as evacuee demand, arrival time at pick up location, and travel times, needs to be clearly understood and reliably modelled by using probabilistic analysis, statistics methods and social science studies.

4.4 Evacuee behaviour

Two surveys (Caunhye, Nie and Pokharel 2012; Bayram 2016) advocate the integration of human behaviour in optimisation models. Human behaviour, in fact, adds an additional layer to the uncertainty characterising evacuation processes and should therefore be addressed, for example through the use of robust optimisation (Caunhye, Nie and Pokharel 2012). We broke down the analysis of human behaviour into five main aspects: *time of day, route diversion, evacuee demographics*, *route preference*, and *warning signals*. Our analysis shows that the former three aspects, which are extremely intertwined, have been completely neglected despite their impact in determining how people evacuate. To the best of our knowledge, in the broad field of optimisation, few studies, which do not belong to our sample of case studies, have attempted to consider the above issues. Alçada-Almeida et al. (2009) tackled the *time of day* as an evacuation issue for major fires with an application to the city of Coimbra (Portugal). Murray-Tuite and Mahmassani (2003) propose two linear integer programming models in the context of emergency evacuation to account for *route diversion*. The first model defines the meeting location for the different family members. The second model identifies who is the one in charge of family member pick-up and how pick-up is scheduled. The emerging results are fed into a simulation software that allows to analyse traffic conditions and eventually re-schedule what has been decided previously. More recently, Ukkusuri et al. (2016) develop what they name "A-RESCUE: Agent-based Regional Evacuation Simulator Coupled with User Enriched Behaviour", which is a simulation tool that combines household behaviour and traffic assignment issues. This may suggest to put forward a combination of optimisation and simulation for evacuation planning where optimisation could be deployed for shelter location decisions while simulation for evacuation routing ones.

The criticality of the *time of day*, *route diversion*, and *evacuee demographics* is explored in a study on child pick-up during daytime emergency situations (Liu, Murray-Tuite and Schweitzer 2012). The authors, through more than three hundred interviews, identify diverse behavioural parental patterns across three diverse scenarios: a usual weekday and two hypothetical emergency situations (i.e., two sudden incidents at daytime). Distance between parents and children is a crucial aspect. Usually a mother's workplace is nearer than a father's to schools/homes, which contributes to a gender difference in the behaviour with the nearest parent more likely to pick the children up in an emergency situation. In addition, the study highlights that household economic status-related aspects, such as income, ethnicity, and education level (hence, demographics) are also relevant. Indeed high income households are more likely to pick up children in all the different scenarios. As evidenced in this study, *time of day* and *demographics* critically affect *route diversion*, eventually leading to delay and re-routing during an evacuation process. These three aspects should be further examined from a social science point of view and then incorporated into optimisation models at the conceptual modelling stage. For example, *evacuee demographics* can be analysed through the analysis of census data (Camp Coordination and Camp Management (CCCM) Cluster 2014).

Route preference and *warning signals dissemination and perception* have been partly addressed but their integration into optimisation models still requires some enhancements. Two case studies adopted traffic assignment models to account for *route preference* (Li et al. 2012; Bayram, Tansel and Yaman 2015). The issue with these approaches is that they do not account for related aspects that can affect the evacuation process. Traffic assignment models could be integrated with evacuation strategies such as contraflow lane reversal (i.e., one or more lanes of a highway are used in the opposing traffic direction), deletion of crossing manoeuvres in correspondence of network intersections, traffic signals, and usage of shoulders (Murray-Tuite and Wolshon 2013). Recently, more advances in this area have been achieved through simulation-based approaches (Takabatake et al. 2017; Yuan et al. 2017). Route preference approaches could also take into account background traffic (i.e., the one generated by those who do not take active part in the evacuation), intermediate trips (i.e., the ones dictated by route preference as child-pick up), and shadow evacuation (i.e., the one put into action by those people who are not in need of evacuating but do so for own precautionary measure). Only one case study has addressed *warning signals dissemination and perception* (Gama, Santos and Scaparra 2016). A recent advance towards optimisation for warning signals dissemination is due to Yi et al. (2017) who developed a bi-level program. The upper-level is a multi-stage stochastic program that optimises the issuance of warning signals across several hurricane scenarios while the lower-level evaluates the costs and risks associated with the resulting evacuation process.

Sorensen and Mileti (1988) define three main sources through which warning information are disseminated: official channels (e.g., police officers), informal channels (e.g., friends, relatives), and media (e.g., television), where different *warning dissemination channels* affect the *response to a warning signal* (Sorensen 1991). In particular, Camp Coordination and Camp Management (CCCM) Cluster (2014) report that *"the media plays a very important and relevant role in all phases of evacuation"* (p. 35). Nowadays, clear examples are social media platforms such as Facebook whose Safety Check tool allows people to communicate their status (safe or not) if they are in a disaster-affected area. Fry and Binner (2016) address the role of social media in supporting emergency evacuation operations through a means of both mathematical modelling and Behavioural OR (BOR). For example, social media platforms could be deployed to manage vehicle procurement so as to coordinate both original fleet and volunteer cars. Moreover, social media could be paired with advanced simulation techniques such as agent-based modelling to produce a more trustworthy estimation of the evacuation demand (i.e., number of people who need to evacuate). As an example, Nagarajan, Shaw and Albores (2012) develop an Agent-Based Simulation (ABS) model to analyse the role of *evacuee behaviour* as an unofficial and implicit channel of *warning dissemination*. In particular, the authors evaluate if evacuees, who have been warned, forward their message to their neighbours and how this affects the overall warning dissemination. This is different from the common perspective that evacuee behaviour is an output, rather than an input, for warning signals and could be considered in future optimisation research. Hence, the analysis of social media data through machine learning, artificial intelligence and/or statistics-based techniques, and ABS could be used to mitigate spatial/temporal evacuation demand uncertainty and, eventually, arrange a more efficient distribution of evacuation resources. Examples of evacuation resources include different types of vehicles, relief items to equip the shelters, and personnel (first responders, drivers, volunteers, clinical staffing and emergency officers). In conclusion, a combined social media mining-simulation approach to model evacuee behaviour could benefit not just disaster response (i.e., evacuation) but also disaster preparedness (i.e., relief supply pre-positioning) and foster the development of integrated models which combine operations across different DOM phases. Undoubtedly, incorporating evacuee behaviour poses significant challenges: 1) it requires advanced tools to collect and analyse data and expertise in other disciplines (e.g., social sciences, machine learning, and psychology); 2) it results in highly complex hybrid models that may be difficult to solve, thus requiring novel and cutting-edge solution methodologies. However, the inclusion of behavioural aspects would result in models that are more reliable and more likely to be used in real disaster situations.

4.5 System behaviour

System behaviour encompasses different aspects: *shelter resources*, *shelter categories*, *congestion*, *infrastructure disruptions* and *performance criteria*. The need to address some of these aspects (e.g. road disruptions and more suitable performance indicators) has been advocated in some previous surveys (e.g. Altay and Green 2006). Our analysis further refined the investigation into these issues.

Firstly, *shelter resources* have not been tackled in a comprehensive way. In fact, while shelter capacities have been considered, the availability of resources over time has not. In addition, *shelter categories* (hence, evacuee needs over time) have been entirely neglected. This is an aspect that has been addressed from a shelter location only perspective but not in conjunction with routing decisions. In a recent study, Chen et al. (2013) introduce a three-level-hierarchical shelter location model under earthquake circumstances: by considering different categories of shelters the model takes into account the temporal variance of evacuees' needs. Similar hierarchical location models could be embedded in comprehensive evacuation planning models. Secondly, *congestion* could be addressed more systematically. In fact, as in car-based evacuation routing models only (Cova and Johnson 2003; Xie and Turnquist 2011), congestion can be eased through the introduction of constraints aimed at preventing conflicts in correspondence of road intersections as well as through contraflow lane reversal assumptions (Brachman and Church 2009). Such issues could be integrated into user optimal traffic assignment models to simulate traffic more accurately and support decisions for congestion reduction during the evacuation. Thirdly, future models could account for *infrastructure disruptions* which are known to occur in reality. During a disaster, the transport network changes over time as some roads in the affected area may become unavailable. Road unavailability and disaster propagation clearly affect the evacuation process and need to be captured through the use of stochastic and dynamic models, as done for other disaster management operations such as vehicle procurement within disaster relief routing (Rath, Gendreau and Gutjahr 2016). Finally, *egalitarian policies* guaranteeing equal treatment among evacuees have not been adequately addressed in optimisation. Shelter location models only have attempted to tackle this aspect through the definition of specific constraints such as the distance between an evacuation zone and a shelter cannot exceed a specific threshold (Zhao et al. 2015; Xu et al. 2016) or each shelter should provide a minimum level of coverage (Xu et al. 2016). In addition to the usage of specific constraints, new field-specific *performance criteria* could be defined. For example, Caunhye, Nie and Pokharel (2012) report that performance measures such as *"coordination effectiveness and proper organizational structure"* (p.11) could be developed to account for the fact that humanitarian logistics is an environment with a plurality of actors (e.g., stakeholders, communities). Moreover, objectives such as risk, given the uncertain nature of disasters, and equity, to account for egalitarian treatment of evacuees, should be put forward.

4.6 Methodology

Three surveys advocate multi-objective models (Altay and Green 2006; Caunhye, Nie and Pokharel 2012; Hoyos, Morales and Akhavan-Tabatabaei 2015), with two of these suggesting multi-period and stochastic models (Hoyos, Morales and Akhavan-Tabatabaei 2015; Bayram 2016). Our analysis shows that multi-objective and multi-period models have been developed to a certain extent but there is a clear lack of stochastic models for evacuation planning, which supports (Hoyos, Morales and Akhavan-Tabatabaei 2015). In fact, the authors report that evacuation planning requires stochastic programming to address uncertain aspects such as evacuation demand, infrastructure disruptions, facility survivability, route reliability, and sudden traffic events. Hence, it is paramount to devise ad-hoc c*utting-edge algorithms*, as also outlined in the surveys of Altay and Green (2006); Caunhye, Nie and Pokharel (2012); and Bayram (2016). Further advances in the field would also be favoured by the development of user-friendly *GIS-based interfaces* as well as the usage of *information systems* (Hoyos, Morales and Akhavan-Tabatabaei 2015; Özdamar and Ertem 2015). Last but not the least, our analysis reveals that optimisation may not be able to tackle all the aforementioned aspects on its own but may need to be paired with other disciplines. For example, a better understanding of the features related to a specific disaster (e.g., probability of occurrence, evolution over time) requires the deployment of propagation models (as for floods) or the usage of ground motion records (as for earthquakes), whose expertise belongs to different disciplines such as climatology, hydrology, meteorology and civil engineering. Moreover, disastrous events involve handling large data sets for which appropriate data mining/management techniques are required. Similarly, the study of human reaction when facing perilous circumstances requires social scientists as psychologists. Again, warning signals could be analysed through the deployment of simulation approaches (e.g., agent-based modelling), whereas demand and scenario predictions could be obtained through advanced statistics techniques. The expertise of transport engineers could support the development of traffic assignment models along with evacuation strategies (e.g., contraflow lane reversal). In essence, the development of efficient evacuation plans requires holistic approaches merging the expertise of different researchers. Hence, our final suggestion is to aim for *interdisciplinarity*.

5. Conclusions

Shelter location and evacuation routing, and evacuation planning more in general, is a field which offers plenty of opportunities for both practitioners and researchers, belonging not just to the optimisation arena but also to other fields of expertise. We critically analysed the most recent optimisation models tackling shelter location and evacuation routing problems in an integrated manner. Through the analysis of these state of the art models, we identified the current challenges emerging in this research area and outlined a roadmap for future research.

Our analysis confirms some of the findings of previous surveys. Namely, the following issues need to be addressed: 1) usage of Soft OR/PSMs approaches; 2) modelling of infrastructure disruptions; 3) development of multi-objective, combined, multi-period and stochastic models, along with cutting edge algorithms; 4) clear and realistic modelling assumptions; and 5) deployment of information systems and user-friendly GIS-based platforms. In addition, what emerges in our work, which enriches and completes the previous surveys, are the following gaps: 1) primary data collection to embed more realism into optimisation models; 2) models which combine different evacuee categories; 3) models including assisted and multi-modal evacuation and issues such as evacuation vehicle procurement; 4) inclusion of issues such as time of day, route diversion, evacuee demographics, route preferences, and warning signals to model evacuee behaviour more accurately; 5) novel equity-based approaches for shelter location and evacuation routing; 6) integration of infrastructure disruption, congestion, and shelter categories into optimisation models; and 7) interdisciplinary research towards shelter location and evacuation routing.

In conclusion, researchers should aim at developing more complex models integrating: multiple objectives, dynamic perspective, uncertainty and behavioural aspects. Moreover, the integration of operations belonging to different DOM phases should be put forward. For example, preparedness and response phases could be treated together by combining relief supply pre-positioning, shelter opening operations and evacuation. In fact, shelters need to be equipped with different resources (e.g., first-aid kits, food) prior to be operative. Mitigation and response could also be addressed together. During a disaster, in fact, the dissemination of warning signals and the evacuation itself heavily rely on critical infrastructures (e.g. communication and transport systems). Damage to these infrastructures may have dire effects on the affected populations' ability to evacuate. Hence, models to evaluate the impact of critical infrastructure protection (mitigation) on the evacuation process itself (response) could be developed. Obviously, this ambitious vision requires developing ad-hoc sophisticated algorithms, able to deal with the complexity of comprehensive mathematical models and large scale real-time data. Eventually, this would not only lead to advances in the OR discipline towards the challenging and interdisciplinary nature of disaster management problems but also help to bridge the gap between the development of optimisation tools and their practical application in disaster situations so to propose novel approaches that are more closely aligned with technology and practice.

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Appendix A: Questionnaire

Shelter Location and Evacuation Routing in Disaster Management

	Conceptual Modelling (CM) Block
Q1	Has the author work been commissioned by someone?
Q1.1	If yes, who is (are) the commissioner(s)?
Q2	Have stakeholders (i.e., those who have interest in the problem) been involved in the study?
Q2.1	If yes, which stakeholders have been involved?
Q2.1	If no, explain why (more than one option is allowed): a) Difficult to identify relevant stakeholders b) Difficult to get stakeholder contact details c) Stakeholders too busy or not interested d) Stakeholders skeptical about potential study benefits e) Main focus of the paper is methodological f) Too time-consuming to involve the stakeholders
Q3	Has any primary data (e.g., interviews, surveys, etc.) collection been carried out?
Q3.1	If yes, which are the primary data that have been collected along with their sources?
Q4	Has any secondary data (i.e., available from the web) collection been conducted?
Q4.1	If yes, which are the secondary data that have been collected along with their sources?
Q5	Has a specific type of disaster (e.g., earthquake, flood) been analyzed?
Q5.1	If yes, which disaster?
Q6	Have the following evacuee categories been considered (more than one option is allowed): a) Self-evacuees who move towards a shelter b) Self-evacuees who move towards other destinations c) Supported evacuees who move towards a shelter
Q6.1	If supported evacuees have been considered, have the following aspects been included in the model (more than one option is allowed): a) Vehicle type b) Vehicle availability c) Qualified driver ability d) Driver willingness to expose him/herself to danger e) Multimodal transportation
Q7	How have the evacuee starting positions been defined? a) Centroids of evacuation zones b) Bus stops c) Others
Q7.1	If others, please explain.
Q8	Has the time of the day been considered when defining the evacuation starting points?
Q9	Has the evacuee behavior been accounted for (more than one option is allowed): a) Response to warning signals b) Individual route preference c) Route diversion to collect family members
Q10	Have the evacuee demographics (e.g., age, sex, disabilities, social class, etc.) been taken into account?
Q10.1	If yes, what is (are) the demographic aspect(s) that has (have) been considered?
Q11	Have you considered egalitarian policies requiring that the needs of all targeted populations are met?
Q12	Have different kinds of shelters been included in your model (i.e., providing different services such as food, first-aid, dormitory facilities, etc.)?

Q13	Have the candidate sites for potential shelters been selected from the following (more than one option is allowed): a) City and/or County Owned Facilities (e.g., school sites, community centers, recreational facilities) b) Congregations (e.g., churches) c) Open Spaces (e.g., camping areas) d) Alternative sites (e.g., medical care sites) e) None of the above
Q13.1	If none of the above, please explain your assumptions on the candidate sites for potential shelters.
Q14	Has resource availability (e.g., staff, shelter capacity, budget, etc.) been considered?

Q15	Have communication issues (e.g., warning signals, evacuation instructions) been addressed?
Q16	Has road congestion been included in the model?
Q17	Have infrastructure disruptions (e.g., communications, road, etc.) been accounted for?
Q18	Has the intrinsic dynamic aspect of the evacuation process been tackled (e.g., disaster propagation, availability of resources over time)?
	Model Coding (MC) Block
Q19	Is the optimisation model multi-period (e.g., developed over time intervals)?
Q20	Is the optimisation model multi-objective?
Q20.1	If yes, what are the objectives that have been considered?
Q20.1	If no, which objective has been considered?
Q21	Has scenario-based modelling been deployed?
Q22	Has stochastic programming been employed?
Q23	Which kind of solution method has been deployed (more than one option is allowed): a) An off-the-shelf software (e.g., CPLEX) b) Ad hoc exact method c) Ad hoc heuristic
Q24	Has a friendly interface been developed to facilitate the use of the model (e.g., GIS-based)?
	Experimentation (E) Block
Q25	Has any realistic case study been presented in your paper?
Q26	Has any stakeholder been involved in the experimentation phase of the study?
Q26.1	If yes, in which experimentation phase of the study (more than one option is allowed): a) Development of the scenarios to be analyzed b) Sensitivity analysis to be conducted c) Other
Q26.1	If other, please explain.
Q27	Have additional data sources been used for further purposes (e.g., sensitivity analysis)?
Q27.1	If yes, which one(s)?
	Implementation (I) Block
Q28	Has the proposed model ever been handed over to the stakeholders (e.g., for a policy)?
Q29	As a result of your study, have any arrangements for a future evacuation plan been made?
	Further Questions (FQ) Block
Q30	What is the main contribution of your paper: a) Theoretical/Methodological/Technical contribution to optimisation modelling b) Practical contribution to disaster management
Q31	Which of the following aspects held you up the most in making your model realistic: a) Technical limitations b) Access to people and data
Q32	Are there any recent (January 2012 – December 2016 time frame) research articles on shelter location and evacuation planning that you would suggest us to look at?
Q33	Is there any other issue this questionnaire should have included?

Appendix B: Review of the seven surveys

Table B.1– Survey Review Summary

Survey	Research Area	Journal Outlets and Timeframe	State-of-the-art	Future Research Directions
Altay and Green (2006)	OR/MS applied to disaster management	**Outlets**: Both non-traditional OR and OR journals; top three OR journals: EJOR, JORS, MS **Timeframe**: 1980-2004	**Methodology**: Mathematical Programming (Most used) / Soft OR (Least used) **DOM phase research ranking**: Mitigation, Response, Preparedness, Recovery **Research aim ranking**: Model, Theory, Application	Development of hierarchical and multi-objective approaches, deployment of Soft OR methodologies, focus on recovery issues, and usage of disruption management models
Simpson and Hancock (2009)	Emergency response-related OR (EOR)	**Outlets**: Engineering-based, non-traditional OR and OR journals; top three OR journals for disaster services: EJOR, JORS, MS **Timeframe**: 1965-2007	**EOR categories**: Urban services, Emergency Management Services, Disaster services, General emergency **Methodology**: Mathematical Programming (Most used) / Soft OR (Least used)	Deployment of Soft OR approaches, development of ad-hoc DSS, inclusion of multi-agency coordination, and definition of specific efficiency criteria
Caunhye, Nie and Pokharel (2012)	Optimisation for emergency logistics	**Outlets**: TRE, EJOR, MS (mostly) **Timeframe**: 1976-2011	Review of optimisation models for facility location, stock- prepositioning, evacuation, relief distribution, and casualty transportation operations	Development of combined and multi-objective models, advanced algorithms, research effort towards recovery operations, definition of specific efficiency criteria, and inclusion of human behaviour
Galindo and Batta (2013)	OR/MS applied to disaster management	**Outlets**: Both non-traditional OR and OR outlets; top three OR journals: JORS, EJOR, COR **Timeframe**: 2005-2010	**Methodology**: Mathematical Programming (Most used) / Soft OR (Least used) **DOM phase research ranking**: Response, Preparedness, Mitigation, Recovery **Research aim ranking**: Model, Theory, Application	Stakeholder involvement, development of cutting-edge technologies, (more) realistic modelling assumptions, combination of different methodologies, deployment of Soft OR approaches, and definition of specific efficiency criteria
Hoyos, Morales and Akhavan-Tabatabaei (2015)	OR applied to disaster management	**Outlets**: EJOR, SEPS, TS, SS (mostly) **Timeframe**: 2006-2012	**Methodology**: Mathematical Programming (Most used) / Queuing Theory (Least used) **DOM phase research ranking**: Response, Mitigation, Preparedness, Recovery	Better understanding of specific disaster-related features, combination of different methodologies, usage of multi-period models, research effort towards inventory, evacuation planning, casualty transportation, and recovery activities, investigation into information systems, critical infrastructures and secondary (or even cascading) disasters, and development of multi-objective models for stakeholder coordination
Özdamar and Ertem (2015)	OR for response and recovery activities	**Outlets**: No journal-based analysis **Timeframe**: 1993-2014	Review of optimisation models for relief delivery, casualty transportation, mass evacuation, and recovery operations	Development of algorithms to handle large-scale disaster data sets, models tackling recovery issues in an integrated way, combination of practitioner and academic best practices, inclusion of real-time data, and stakeholder coordination
Bayram (2016)	Optimisation models for large scale evacuation planning	**Outlets**: OR/MS, disaster management, behavioural sciences, and engineering-based outlets; models mostly from TRB **Timeframe**: 1952-2016	Review on traffic assignment models, evacuation modelling, and behavioural studies	Inclusion of human behaviour and special-needs population, usage of Intelligent Transportation Systems (ITS), and development of stochastic, dynamic, and combined models

Legend: COR = Computers & Operations Research; EJOR = European Journal of Operational Research; JORS = Journal of the Operational Research Society; MS = Management Science; OR = Operations Research; SEPS = Socio-Economic Planning Sciences; SS = Safety Science; TRB = Transportation Research Part B; TRE = Transportation Research Part E; TS = Transportation Science.

Appendix C: Questionnaire responses

Table C.1 - Insights achieved through critical analysis of the existing papers (left column) and questionnaire responses of their authors (right column)

		Coutinho-Rodrigues et al., 2012		*Li et al., 2012*		*Goerigk et al., 2014*		*Bayram et al., 2015*		*Kilci et al., 2015*		*Gama et al., 2016*		*Hessler et al., 2016*		*Shahparvari et al., 2016*		*Bayram et al., 2017*	
CM	*Q1*		-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	Q2	-	-	-	✓	-	-	-	-	-	✓	-	-	-	-	-	✓	-	-
	Q3	-	-	✓	✓	-	-	-	-	-	-	-	-	-	-	-	✓	-	-
	Q4	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	Q5	-	-	✓	✓	✓	✓	-	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	Q6	SES	SES	SES,SED	SES,SED	SES,SE	SES,SE	SES	SES	SES	SES	SES	SES	SES,SED	SES, SED	SE	SE	SES	SES
	Q7	C	C	O	C	O	BS	O	C	C	C	C	C	O	O	O	O	O	C
	Q8	✓	-	-	-	-	-	-	✓	-	-	-	-	-	-	-	-	-	✓
	Q9	-	-	RP	WS, RP	-	-	RP	RP	-	RP	WS	WS	-	-	-	-	RP	RP
	Q10	-	-	-	✓	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	Q11	-	✓	-	✓	-	-	✓	✓	-	-	-	-	-	-	-	✓	✓	✓
	Q12	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	Q13	OS	OS	COF	-	-	COF	-	COF,CO,OS,AS	COF, OS	COF,OS	COF	COF,OS	COF	COF	COF,OS	COF,OS	-	COF,CO,OS
	Q14	✓	✓	✓	✓	✓	-	✓	✓	✓	✓	✓	✓	✓	-	✓	✓	✓	✓
	Q15	-	-	-	-	-	-	-	-	-	-	✓	✓	-	-	-	-	-	-
	Q16	-	-	✓	✓	✓	✓	✓	✓	-	-	-	-	✓	✓	✓	✓	✓	✓
	Q17	✓	✓	-	-	-	✓	-	-	-	-	✓	✓	-	-	✓	✓	✓	✓
	Q18	-	-	✓	✓	✓	-	-	-	-	-	✓	✓	-	-	-	✓	-	-
MC	*Q19*	-	-	✓	✓	✓	-	-	-	-	-	✓	✓	-	-	-	✓	-	-
	Q20	✓	✓	✓	✓	✓	✓	-	-	✓	✓	-	-	-	-	✓	✓	-	-
	Q21	-	-	✓	✓	-	-	-	-	-	✓	-	-	-	-	-	✓	✓	✓
	Q22	-	-	✓	✓	-	-	-	-	-	✓	-	-	-	-	-	✓	✓	✓
	Q23	S	S	H	H	GA	GA	S	S	-	S	S,SA	S,SA	EX,H	EX,H	S	S,EX,H	EX	EX
	Q24	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	✓	-	-
E	*Q25*	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	Q26	-	-	✓	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	Q27	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	✓	✓	✓
I	*Q28*	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	✓	-	-
	Q29	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-

Legend: CM = Conceptual Modelling; MC = Model Coding; E = Experimentation; I = Implementation; ✓ = Yes, - = No or No clear information; SES = Self-Evacuees who move towards a Shelter; SED = Self-Evacuees who move towards other Destinations, SE = Supported Evacuees (who move towards a shelter); C = Centroids; BS = Bus stops; O = Other; WS = Warning Signals; RP = Route Preference; COF = City/County Owned Facilities; CO = COngregations; OS = Open Spaces; AS = Alternative Sites; S = off-the-shelf Software; EX = EXact method; H = Heuristics; GA = Genetic Algorithm; SA = Simulated Annealing

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