OPTIMIZATION APPROACHES FOR IMPROVING MITIGATION AND RESPONSE OPERATIONS IN DISASTER MANAGEMENT

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Ad astra per aspera

(To the stars through hard work)

Abstract

Disasters are calamitous events that severely affect the life conditions of an entire community, being the disasters either nature-based (e.g., earthquake) or man-made (e.g., terroristic attack). Disaster-related issues are usually dealt with according to the Disaster Operations Management (DOM) framework, which is composed of four phases: mitigation and preparedness, which address pre-disaster issues, and response and recovery, which tackle problems arising after the occurrence of a disaster. The ultimate scope of this dissertation is to present novel optimization models and algorithms aimed at improving operations belonging to the mitigation and response phases of the DOM.

On the *mitigation* side, this thesis focuses on the protection of *Critical Information Infrastructures (CII)*, which are commonly deemed to include communication and information networks. The majority of all the other *Critical Infrastructures (CI)*, such as electricity, fuel and water supply as well as transportation systems, are crucially dependent on CII. Therefore, problems associated with CII that disrupt the services they are able to provide (whether to a single end-user or to another CI) are of increasing interest. This dissertation reviews several issues emerging in the *Critical Information Infrastructures Protection (CIIP)*, field such as: how to identify the most critical components of a communication network whose disruption would affect the overall system functioning; how to mitigate the consequences of such calamitous events through protection strategies; and how to design a system which is intrinsically able to hedge against disruptions. To this end, this thesis provides a description of the seminal optimization models that have been developed to address the aforementioned issues in the general field of *Critical Infrastructures Protection (CIP)*. Models are grouped in three categories which address the aforementioned issues: *survivability-oriented interdiction*, *resource allocation strategy*, and *survivable design models*; existing models are reviewed and possible extensions are proposed. In fact, some models have already been developed for CII (i.e., survivability-interdiction and design models), while others have been adapted from the literature on other CI (i.e., resource allocation strategy models). The main gap emerging in the CII field is that CII protection has been quite overlooked which has led to review optimization models that have been developed for the protection of other CI. Hence, this dissertation contributes to the literature in the field by also providing a survey of the multi-level programs that have been developed for protecting supply chains, transportation systems (e.g., railway infrastructures), and utility networks (e.g., power and water supply systems), in order to adapt them for CII protection. Based on the review outcomes, this thesis proposes a novel

linear bi-level program for CIIP to mitigate worst-case disruptions through protection investments entailing network design operations, namely the *Critical Node Detection Problem with Fortification (CNDPF)*, which integrates network survivability assessment, resource allocation strategies and design operations. To the best of my knowledge, this is the first bi-level program developed for CIIP. The model is solved through a Super Valid Inequalities (SVI) decomposition approach and a Greedy Constructive and Local Search (GCLS) heuristic. Computational results are reported for real communication networks and for different levels of both disaster magnitude and protection resources.

On the *response* side, this thesis identifies the current challenges in devising realistic and applicable optimization models in the *shelter location* and *evacuation routing* context and outlines a roadmap for future research in this topical area. 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 (e.g., disabled, elderly). 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*. Two main types of evacuation can be identified: *self-evacuation (or car-based evacuation)* where individuals move towards safe sites autonomously, without receiving any kind of assistance from the responder community, and *supported evacuation* where special-needs populations (e.g., disabled, elderly) require support from emergency services and public authorities to reach some shelter facilities. This dissertation aims at identifying the central issues that should be addressed in a comprehensive shelter location/evacuation routing model. This is achieved by a novel meta-analysis that entail: (1) analysing existing disaster management surveys, (2) reviewing optimization models tackling shelter location and evacuation routing operations, either separately or in an integrated manner, (3) performing a critical analysis of existing papers combining shelter location and evacuation routing, concurrently with the responses of their authors, and (4) comparing the findings of the analysis of the papers with the findings of the existing disaster management surveys. The thesis also provides a discussion on the emergent challenges of shelter location and evacuation routing in optimization such as the need for future optimization models to involve stakeholders, include evacuee as well as system behaviour, be application-oriented rather than theoretical or model-driven, and interdisciplinary and, eventually, outlines a roadmap for future research. Based on the

identified challenges, this thesis presents a novel scenario-based mixed-integer program which integrates shelter location, self-evacuation and supported-evacuation decisions, namely the *Scenario-Indexed Shelter Location and Evacuation Routing (SISLER)* problem. To the best of my knowledges, this is the second model including shelter location, self-evacuation and supported-evacuation however, SISLER deals with them based on the provided meta-analysis. The model is solved through a Branch-and-Cut algorithm of an off-the-shelf software, enriched with valid inequalities adapted from the literature. Computational results are reported for both testbed instances and a realistic case study.

Acknowledgements

When I started the Ph.D. journey, I thought it would have been a marathon, exactly like both bachelor's and master's degrees had been. However, the more I went through the doctoral path, the more I understood it would have been an amazing climb plenty of slopes and tricky bends (e.g., code debugging, experimentation) as well as rewarding milestones (e.g., paper publication, conference acceptance). Now that I have reached the end of this journey, despite its difficulties, I can safely say that I would take this path again and again because it made me grow as an academic but, most importantly, as a human being.

Ph.D. is not just about research but also personal growth. During both my bachelor's and master's degrees, I was living in my parents' house in my home country and my only worry was to attend lectures, pass exams with good marks and graduate. Ph.D. life has been quite different given that I had to adjust to a foreign country and be able to take care of myself while aiming at getting the highest level of education. What got me through, together with my strong determination and my passionate willingness to learn, has been the people who have supported me over these three years of doctoral life and to whom I owe a very huge thanks.

First and foremost, I would like to thank my Ph.D. supervisor, Professor Maria Paola Scaparra. She has been extremely supportive even before starting my Ph.D., has guided me in the best possible way I could have ever asked for and I truly look forward to keeping working with her in the future. Secondly, I would like to thank my second Ph.D. supervisor, Dr Jesse O'Hanley, for his contribution at the early stage of my doctorate. Thirdly, I would like to thank my master's supervisors, Professor Antonio Sforza and Dr Claudio Sterle, who have introduced me to Operations Research, have been the first to believe in my academic capabilities, suggested me to undertake this Ph.D., and supported me during the doctoral journey. Fourthly, I would like to thank my Ph.D. friends without whom this journey would have not been the same. In particular, I would like to thank Elmira, who is a colleague, a friend, and that has become the sister I have never had (being me an only child): we shared laughter, tears, and, hopefully, many life moments that are yet to come. Finally, I would like to thank my parents, Tina and Strato, for their unconditional support and their courage to cope with the distance among us that has not been easy to handle, especially for my mother. They taught me the values of hard work, sacrifice, and persistence which have been fundamental throughout my entire academic path (and my life as well). I would also like to thank my uncle, Enzo, who has always accompanied me in the search for the "why" underpinning any problem. And, the last but not the least, I would like to thank Marco who has entered my life at the end of my first year of Ph.D. and has not left me ever since (at least for now!).

To conclude, I dedicate this piece of academic work to all the dreamers out there. Just remember that if you deeply want something, you will get it because, as Albert Einstein said: *"There is a driving force more powerful than steam, electricity and nuclear power: the will"*.

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List of Abbreviations

ABS	**Agent-Based Simulation**
ACC	**Aggregated Capacity Constraints**
A-RESCUE	**Agent-based Regional Evacuation Simulator Coupled with User Enriched Behavior**
BCRIMF-CE	**Budget Constrained R-Interdiction Median problem with Capacity Expansion**
BEP	**Bus Evacuation Problem**
BFCLP	**Bi-level Fixed Charge Location Problem**
BOR	**Behavioral Operational Research**
BPFIP	**Bi-level Partial Facility Interdiction Problem**
BPPCF	**Bi-level p-median problem for the Planning and Protection of Critical Facilities**
BPR	**Bureau of Public Roads**
C&CG	**Column-and-Constraint-Generation**
CC-CNP	**Cardinality Constrained Critical Node Detection Problem**
CCTV	**Closed Circuit Television**
CEP	**Comprehensive Evacuation Problem**
CFLP	**Capacitated Facility Location Problem**
CI	**Critical Infrastructures**
CII	**Critical Information Infrastructures**
CIIP	**Critical Information Infrastructure Protection**
CIP	**Critical Infrastructure Protection**
CM	**Conceptual Modelling**
CNDPF	**Critical Node Detection Problem with Fortification**
CNP	**Critical Node Detection Problem**
CSO	**Constrained System Optimal**
DA	**Dragonfly Algorithm**
DAD	**Defender-Attacker-Defender**
DES	**Discrete Event Simulation**
DM	**Disaster Management**
DNP	**Dynamic Network Protection model**
DOM	**Disaster Operations Management**

D-RIMF	**R-Interdiction Median problem with Fortification for Decentralized supply systems**
DSS	**Decision Support System**
E	**Experimentation**
EEC	**Emergency Evacuation Centres**
ERC	**Emergency Rest Centres**
FEMA	**Federal Emergency Management Agency**
FMMA	**Fortification Median problem for disruptions caused by Mixed types of Attacks**
FRIMT	**Fortification and R-Interdiction Median problem with facility recovery Time and frequent disruptions**
GA	**Genetic Algorithm**
GC	**Greedy Constructive**
GCLS	**Greedy Constructive and Local Search**
GRASP	**Greedy Randomized Adaptive Search Procedure**
GUB	**Generalized Upper Bound**
I	**Implementation**
ICT	**Information and Communications Technology**
IE	**Implicit Enumeration**
IFRC	**International Federation of Red Cross and Red Crescent Societies**
IP	**Integer Programming**
KKT	**Karush-Kuhn-Tucker**
LS	**Local Search**
MAS	**Multiple-Attack-Scenario**
MC	**Model Coding**
MCFP	**Multi-Commodity Flow Problem**
MCND	**Multi-Commodity Capacitated Fixed-Charge Network Design**
MIF	**Multi-period Interdiction problem with Fortification**
MILP	**Mixed-Integer Linear Programming**
MIR	**Mixed-Integer Rounding**
MSS	**Multi-start revised Simplex Search**
NA	**Nearest Allocation**
NPVDL	**Network Protection Problem with Variable Demand Loss**

OSI	**Open Systems Interconnection**
PGS	**Progressive Grid Search**
PIDS	**Perimeter Intruder Detection Systems**
PSM	**Problem Structuring Methods**
PSO	**Particle Swarm Optimization**
PSTN	**Public Switched Telephone Network**
RC	**Residual Capacity**
RFO	**Rain-Fall Optimization**
RIMF	**R-Interdiction Median problem with Fortification**
RIMP	**R-Interdiction Median problem with Probabilistic protection**
RIMP-MI	**R-Interdiction Median problem with Probabilistic protection with Multiple Interdictors**
RMP	**Relaxed Master Problem**
RPI	**Railway Protection Investment problem**
SA	**Simulated Annealing**
SDG	**Sustainable Development Goal**
SE	**Supported Evacuees who move towards a shelter**
SED	**Self-Evacuess who move towards other Destinations**
SES	**Self-Evacuees who move towards a Shelter**
SI	**Strong Inequalities**
SIM	**Survivability Interdiction Model**
SISLER	**Scenario-Indexed Shelter Location and Evacuation Routing**
SLER	**Shelter Location and Evacuation Routing**
SND	**Survivable Network Design**
SO	**System Optimal**
SP	**Sub-Problem**
SPIF	**Shortest-Path interdiction Problem with Fortification**
SPP	**Survivability Protection Problem**
S-RIMF	**Stochastic R-Interdiction Median problem with Fortification**
SSM	**Sequential Solution Method**
STS	**Short Term Shelters**
SVI	**Super Valid Inequalities**
TFLRIM	**Tri-level Facility Location R-Interdiction Median**
TLBO	**Teaching Learning Based Optimization**

TRC	**Turkish Red Crescent**
TS	**Tabu Search**
UE	**User Equilibrium**
UN	**United Nations**
VDNS	**Variable Decomposition Neighborhood Search**
VMS	**Variable Message Signs**
VNS	**Variable Neighborhood Search**
VRP	**Vehicle Routing Problem**
VUB	**Variable Upper Bounds**
WHA	**Whale Optimization Algorithm**
WWO	**Water Wave Optimization**

1 Introduction

This chapter describes the context where this doctoral activity has been set, specifies the topics that have been investigated, illustrates the research questions that have been posed, details the contributions to knowledge that have been produced and, finally, outlines the structure of this dissertation.

1.1 Research background

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), and bushfires (Australia, 2009), while terroristic attacks (UK, 2005) are examples of *man-made disasters*. The upward trend of disaster occurrence, as displayed in Figure 1, puts a lot of strain onto the humanitarian system, leading to an increased focus on Disaster Management (DM) issues.

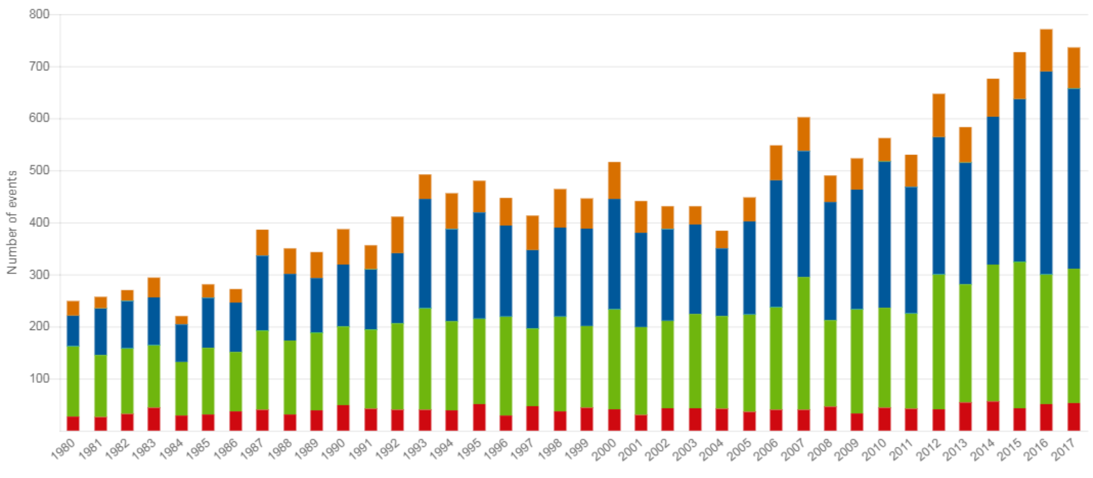

Figure 1. Relevant natural loss events worldwide 1980 – 2017 (MunichRe 2018)

Figure 1 shows the rise in number for four different natural disaster categories over the time range 1980 – 2017: geophysical events (in red), such as earthquakes, tsunamis, and volcanic activity; meteorological events (in green), such as tropical cyclones, extratropical, convective or local storms; hydrological events (in blue), such as flood and mass movement; and climatological events (in orange), such as extreme temperatures, droughts, and forest fires. Both geophysical events and meteorological events have nearly doubled, climatological events have increased threefold, and hydrological events have almost registered a sevenfold rise. The variegated nature of disasters highlights the importance of sensing/forecasting algorithms, in fact, disasters like hurricanes can be predicted. However, the fact that a disaster can be predicted is not enough and prompts issue related to the accuracy of the prediction itself. Nevertheless, forecast data can be deployed to inform decision-makers prior to the occurrence of a disaster and take relevant actions (e.g., preventive evacuation). The occurrence of disasters is exacerbated by climate change given that, *"often, climate change acts mainly through adding new dimensions and complications to sometimes longstanding challenges"* (Barros 2014), already present in the disaster-affected regions. Hence, these data undoubtedly warrant further investigation to improve DM practices.

Disaster operations are usually categorized according to the *Disaster Operations Management (DOM)* framework (Altay and Green 2006), which is composed of four programmatic phases, as illustrated in Figure 2: 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).

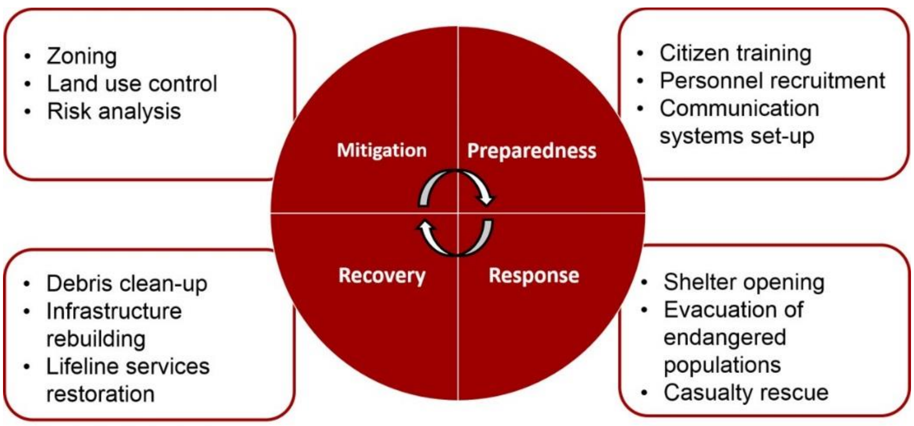

Figure 2. Disaster Operations Management (DOM) framework

The former two phases focus on pre-disaster issues while the latter two deal with post-disaster ones. The operations embedded within each one of the DOM phases correspond to different actions to be taken and, more specifically, to different levels of decision-making: *strategic* (i.e., set in the long-term), *tactical* (i.e., set in the medium-term), and *operational* (i.e., set in the short-term) decisions. Table 1 provides a more detailed explanation of DOM from a decision-making perspective.

Table 1. Decision-making levels and DOM phases

	Mitigation	**Preparedness**	**Response**	**Recovery**
Strategic	Zoning	Emergency planning	Urban search and rescue	Rebuilding of roads and bridges and key facilities
Tactical	Active preventive measures to control developing situations	Construction of an emergency operations centre	Shelter opening	Disaster debris clean-up
Operational	Controls on rebuilding after events	Maintaining emergency supplies	Evacuation routing	Financial assistance to individuals and governments

Specifically, on the rows, the three different decision-making levels are depicted (i.e., strategic, tactical, and operational) while, on the columns, the four different DOM phases (i.e., mitigation, preparedness, response, and recovery) are considered. Despite examples are provided for each possible combination (decision-making level, DOM phase), it has to be clear that DM operations are extremely interrelated. For example, the zoning procedure (strategic, mitigation) is propaedeutic to shelter opening (tactical, response) and evacuation routing (operational, response).

This thesis aims at improving specific operations belonging to the mitigation and response phases of the DOM, which are infrastructure protection and evacuation planning, respectively, as it is described in a more in-depth way in the next section (Section 1.2). On one side, infrastructure protection investment planning aims at mitigating disastrous circumstances, including climate change-driven ones, and eventually, make infrastructures more resilient to withstand disruptive events. On the other side, evacuation planning aims at responding to calamitous circumstances so as to improve [1]community resilience after the occurrence of a disaster. Hence, this research activity is in line with the philosophy underpinning the 2030 Agenda for Sustainable Development, which is to promote and to progress towards the achievement of sustainable development for all the communities around the world. In particular, this thesis proposes research which can contribute to the implementation of three out of the seventeen United Nations (UN) Sustainable Development Goals (SDGs), which are illustrated in Figure 3: SDG 9 (industry, innovation, and infrastructure); SDG 11 (sustainable cities and communities); and SDG 13 (climate action). Specifically, this dissertation touches upon lines of research dealing with infrastructure-based systems such as communication and transportation networks (SDG 9) which can be potentially affected by either man-made or climate-prompted disasters (such as floods). The contribution of this dissertation is to provide mathematical tools to mitigate the effects of such disastrous circumstances (SDG 13) through approaches aimed at increasing systems resilience (e.g., network design, disruptive scenarios evaluation) so as to make them more sustainable (SDG 11) while hedging against disruptions.

Figure 3. United Nations (UN) Sustainable Development Goals (SDGs) (United Nations)

[1]The IFRC defines resilience as “the ability of individuals, communities, organizations or countries exposed to disasters, crises and underlying vulnerabilities to anticipate, prepare for, reduce the impact of, cope with and recover from the effects of shocks and stresses without compromising their long-term prospects” (IFRC Framework for Community Resilience 2014).

1.2 Research topics

This thesis deals with operations belonging to the mitigation and response phases of the DOM. In particular, on the mitigation side, the attention is devoted to the protection of *Critical Information Infrastructures (CII)*, which are a specific category of Critical Infrastructures (CI). On the response side, the focus is on two key evacuation planning operations, which are *shelter location and evacuation of endangered populations*. The motivations underpinning the need to investigate these specific topics are the following:

- Over time, various optimization models tackling Critical Infrastructure Protection (CIP) issues have been developed. These models, which are multi-level programs, have been designed for CI such as: supply chains (Scaparra and Church 2008); transportation systems (Cappanera and Scaparra 2011), including railway systems (Scaparra, Starita and Sterle 2015); and utility networks, such as electricity (Brown, Carlyle, Salmeron and Wood 2006) and water supply (Jiang and Liu 2018) systems. However, to the best of my knowledge, no multi-level program has been yet proposed to tackle Critical Information Infrastructure Protection (CIIP).
- Over the years, optimization has tried to capture some of the issues related to DM 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 optimization 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).

To redress these two gaps in the literature, some background information on these two topics, i.e., CIIP as well as shelter location and evacuation routing, is provided in Sections 1.2.1 and 1.2.2, respectively.

1.2.1 Critical Information Infrastructure Protection

Critical Infrastructures are those physical and virtual assets, networks and systems whose disruption would have a debilitating impact on vital societal functions, thus affecting a nation's security, economy, and public health and safety (Nickolov 2006). The nature of these infrastructures, along with the potential threats arising from disasters, whether nature-based or man-made, has prompted a significant amount of research into what is referred to as Critical Infrastructure Protection.

This thesis focuses on a specific category of CI, namely the *Critical Information Infrastructures*, and reviews recent developments in the optimization field aimed at addressing *Critical Information Infrastructure Protection* issues. CIIP is defined as those plans and strategies developed by network operators, infrastructure owners and others, aimed at keeping the service level of CII above a pre-determined threshold, despite the occurrence of disruptive events of various natures (Suter and Brunner 2008). CII, such as the public telephone network, Internet, terrestrial and satellite wireless networks (Patterson and Personick 2003), are those systems, belonging to the information and communications technology (ICT), whose correct functioning is fundamental not only for the services they provide but also for other kinds of CI which either rely or are based on them. Examples of CII are backbone networks that ensure connectivity among distributed systems in order to allow remote monitoring, access control, data sharing as well as payment services. Network nodes are either servers, routers or switches whose main tasks are to regulate network traffic and manage data transmission over the network arcs. Network components (i.e., nodes and arcs) are prone to either physical or cyber-attacks.

It is clear that CII are key elements in production and service systems. Even a local failure at the single CII level (e.g., shut down servers, interrupted cable connections, etc.) may prompt far-reaching adverse effects on the CI relying on it. Bigger disruptions may have even more catastrophic cascading consequences. For example, the 2001 World Trade Center attacks crippled communications by destroying telephone and Internet lines, electric circuits and cellular towers (Grubesic, O'Kelly and Murray 2003, Murray 2013). This caused a cascade of disruptions at all levels, from fuel shortages, to transportation and financial services interruptions. Kwasinski (2011) reports the catastrophic effects that some notable natural disasters have produced on communication networks. For example, the storm surge of Hurricane Katrina of 2005 halted 2.5 million of conventional public switched telephone network (PSTN) lines which, eventually, led to loss of service in wireless networks due to system interdependency. Another example is the Great East Japan earthquake of 2011 as well as the resulting tsunami. In fact, the occurrence of this calamitous event affected all the CI in the country: 1.5 million households were reported not to have access to their water supply, 4.4 million households were left without electricity, nuclear power plants were affected by explosions and radioactive leakage, all railway services were suspended, and communications were interrupted. In particular, 1.5 million PSTN lines were not able to provide service due to power outages as well as severed transmission links, in fact, the tsunami destroyed many bridges where the fibre optic transmission cables were installed (Kwasinski 2011). These events claim that more research is needed towards CIIP.

1.2.2 Shelter location and evacuation routing

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).

This thesis focuses on shelter location and evacuation routing operations, which 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. However, in line with the framework proposed by Altay and Green (2006), it is assumed 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, p. 52). 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. An EEC offers immediate, basic shelter to a large number of people for a maximum staying of about 12 hours; services at an EEC include basic sanitation and drinkable water, but exclude beds and food. An STS can accommodate evacuees coming from either an EEC or who need to be directed to an ERC or an alternative safe destination; in addition to EEC services, an STS can provide also food for up to 48 hours. An ERC provides dormitory facilities, on top of STS services, to accommodate those people without any other alternative. An ERC can be kept 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 a 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. Figure 4 summarizes what has been described in terms of both shelter and evacuation types. Therefore, it is paramount to plan for efficient evacuation procedures.

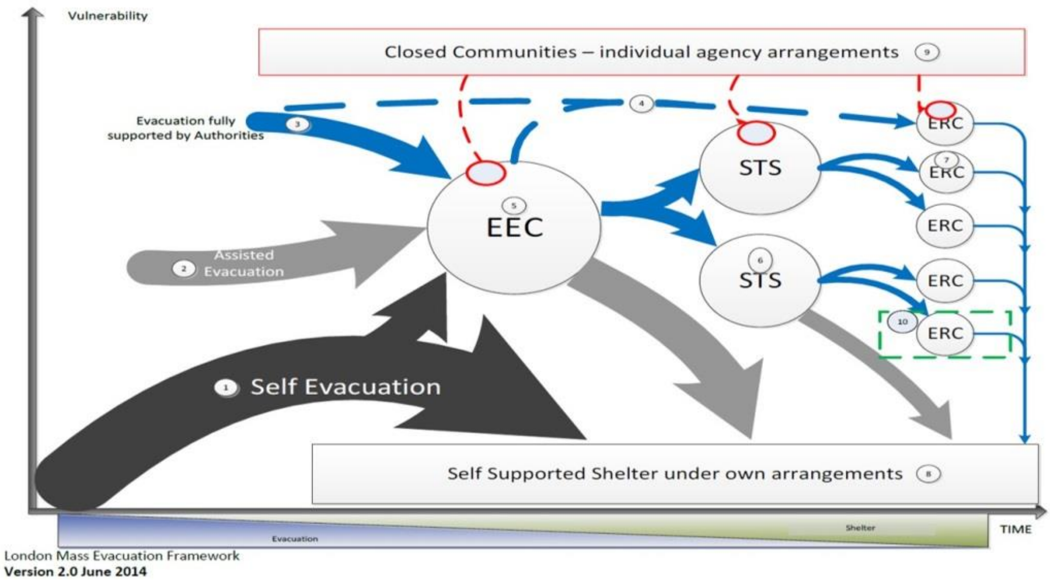

Figure 4. Shelter and evacuation types (London Resilience Team 2014, p. 22)

Despite Critical Information Infrastructure Protection and Shelter Location and Evacuation Routing belong to two different DOM phases, mitigation and response, respectively, they are extremely intertwined. As an example, a potential failure in (tele-)communication networks could prompt a failure in a Decision Support System (DSS) for evacuation planning based on a GIS interface, real-time data evaluation and optimization thus affecting disaster response procedures. Another reason why mitigation and response operations could also be addressed together is that, during a disaster, 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 direct 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, each area shall be investigated as separate first, as in this dissertation, prior to put forward the potential integration of these different operations. This, eventually, would not only lead to advances in the OR discipline towards the challenging and interdisciplinary nature of DM problems but also help to bridge the gap between theory and practice.

1.3 Research questions

The research questions that are posed in this thesis are firstly introduced within the CIIP field and, subsequently, within the context of shelter location and evacuation routing operations.

Research questions emerging in the *Critical Information Infrastructure Protection* field are as follows:

- CIIP.1. What are the most critical elements of a system that, if disrupted, would interrupt or significantly degrade the system's normal functioning?
- CIIP.2. How can such an interruption be prevented or mitigated by resource allocation plans aimed at hardening system elements?
- CIIP.3. Is it possible and worthwhile to design and establish infrastructures that are intrinsically able to resist service failure when a disruptive event occurs?

Research questions emerging in the *shelter location and evacuation routing* context (abbreviated as SLER to categorize the questions) are as follows:

- SLER.1. What are the current challenges emerging in the shelter location and evacuation routing field from an optimization-based perspective?
- SLER.2. When planning for efficient evacuation plans:

a. How many shelters should be opened and where should they be located?
b. How should self-evacuation be addressed in the planning framework?
c. How should supported-evacuation be organized in order to assist people belonging to sensitive categories (e.g., disabled, elderly)?

1.4 Research contributions

The aim of this dissertation is to contribute to research on mitigation and response operations for DM. In particular, novel optimization models are developed to shed light on aspects that have not been fully considered or neglected in the existing literature.

Research contributions related to the *Critical Information Infrastructure Protection* arena, aimed at answering the research questions that have been detailed in the previous section (Section 1.3), are as follows:

- Optimization models to assess CII survivability are reviewed and summarized in three categories: *survivability-oriented interdiction models*, *resource allocation strategy models*, and *survivable design models*. The first class of models is aimed at identifying interdiction scenarios of CII and quantifying the consequences deriving from potential losses of system critical components in terms of ability to provide service. The second class of models is aimed at optimizing the allocation of resources (i.e., budget) among the components of already existent systems in order to protect them. The third class of models is aimed at planning new CII which are able to meet survivability criteria when disruptive events occur. This thesis provides a description of the seminal models in each of the aforementioned categories thus answering questions CIIP.1, CIIP.2, and CIIP.3. In fact: survivability-oriented interdiction models allow to identify the most critical components of a system whose disruption would compromise its correct functioning (CIIP.1); resource allocation strategy models individuate how protection means should be distributed among the components of an existing system thus representing a viable tactic to withstand disruptive circumstances (CIIP.2); and survivable design models outline how to create a system which is intrinsically able to hedge against disastrous events (CIIP.3). Based on the analysis, among the three research spheres, resource allocation strategy models for CII seems to have been overlooked during the years, while, on the contrary, it has been quite a prolific research area when it comes to other CI (e.g., supply chains, transportation systems, and utility networks).

- Based on the findings of the previous analysis, an attempt at filling the current gap in resource allocation strategy models for CII consists in proposing a novel protection optimization model, namely the *Critical Node Detection Problem with Fortification (CNDPF)*. In this case, system nodes are vulnerable to disruptions however, instead of protecting nodes through the installation of security measures (e.g., alarms, motion detectors, biometric scanners, badge swipes, access codes, and human and electronic surveillance such as Perimeter Intruder Detection Systems (PIDS) and Closed Circuit Television (CCTV) (Nickolov 2006)) the adopted approach consists in altering the infrastructure design by augmenting the network with additional arcs. In fact, this type of defense strategy would increase the network redundancy, and its resilience to a greater extent, thus allowing the system to maintain a certain level of service and withstand disruptive circumstances. This approach is based on the inner characteristics of ICT network-based systems. Nodes usually store algorithms, databases and network management tools whose failure can severely compromise the correct system functioning, while arcs are transmission cables that allow to transfer data from a node to another but do not store any sensitive information. Hence, additional arcs could alter the configuration of the most critical network nodes and permit to preserve a certain level of service despite disaster occurrence. More specifically, the problem addressed in this thesis is the following: within a limited amount of budgetary resources, a connectivity augmentation problem needs to be solved (Eswaran and Tarjan 1976) in order to minimize the negative impact on connectivity due to worst-case scenario losses affecting the network nodes. The introduction of the CNDPF permits to build a novel model which combines survivability assessment, protection strategies, and survivable design, thus providing an integrated answer to questions CIIP.1, CIIP.2, and CIIP.3.
- The CNDPF is modeled through a bi-level program which is solved through a decomposition method based on Super Valid Inequalities (SVI) (Wood 1993; O’Hanley and Church 2011; Losada, Scaparra and O’Hanley 2012; Starita and Scaparra 2016) and through a Greedy Constructive and Local Search (GCLS) heuristic. Computational results are reported for real communication networks and for different levels of both disaster magnitude and protection resources.

Research contributions related to the *shelter location and evacuation routing* arena, aimed at answering the research questions that have been detailed in the previous section (Section 1.3), are as follows:

- DM surveys paying specific attention to how operations research, and optimization in particular, has contributed to the shelter location and evacuation routing field are analyzed and compared. The most recent optimization models combining the aforementioned operations are reviewed and, 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 thesis, are critically examined. This process has led to identify the current challenges in this research field which are discussed together with further research directions, linking the emerging findings with those arising from previous surveys, thus answering question SLER.1.
- Based on the findings of the previous analysis, an attempt at filling some gaps in the literature consists in proposing a novel scenario-based flow-location-allocation-routing model to optimize evacuation planning decisions, including where and how many shelters to open and how to route both car-based evacuees (i.e., self-evacuees) and bus-based evacuees (i.e., supported-evacuees) to them, across different network disruption scenarios, namely the *Scenario-Indexed Shelter Location and Evacuation Routing (SISLER)* problem. The definition of this new model answers question SLER.2 in each aspect (a, b, and c). In fact, it is clear that shelter location, self-evacuation and supported-evacuation are highly interconnected and must be addressed simultaneously. In fact, self-evacuees and supported-evacuees must share the same resources (e.g., capacitated shelters, evacuation routes, etc.). Moreover, the scenarios are used to capture the uncertainty characterizing road conditions in the aftermath of a disaster. Although both shelter location and evacuation routing operations belong to the disaster response phase, shelters must often be set up and equipped with personnel and relief supplies when the disaster is still evolving and road conditions are uncertain or subject to changes. Therefore, it is paramount to identify shelter locations which are easily accessible in different disruption scenarios and guarantee an efficient evacuation in every scenario.

1.5 Outline

The remainder of this thesis is organized as follows.

Chapter 2 provides a review of survivability-oriented interdiction, resource allocation strategy, and survivable design optimization models for CIIP. It also offers an outlook on how multi-level programming has been deployed to develop protection models for CIP, in the context of supply chains, transportation systems (e.g., railway infrastructures), and utility networks (e.g., electric and water supply), so as to lay the foundations for future work within the CIIP field.

Chapter 3 introduces the Critical Node Detection Problem with Fortification, describes the model formulation as well as the solution methodologies that have been developed to solve it, which are a SVI decomposition algorithm and a heuristic approach (GCLS), and provides computational results on real communication networks.

Chapter 4 illustrates the emergent challenges of shelter location and evacuation routing in optimization by reviewing DM-specific survey papers, discussing optimization models tackling shelter location and evacuation routing operations, either separately or in an integrated manner, and reporting the results of the critical analysis of existing papers combining shelter location and evacuation routing, concurrently with the responses of their authors. The chapter concludes with a discussion on the challenges that have been identified, leading to a roadmap for future research.

Chapter 5 presents the Scenario-Indexed Shelter Location and Evacuation Routing problem, details the model formulation, and offers experimental results on both testbed instances and a realistic case study.

Finally, Chapter 6 offers some conclusive remarks.

2 A synthesis of optimization approaches for tackling Critical Information Infrastructure survivability

This chapter discusses several issues emerging in the CIIP field such as: how to identify the most critical components of a communication network whose disruption would affect the overall system functioning; how to mitigate the consequences of such calamitous events through protection strategies; and how to design a system which is intrinsically able to hedge against disruptions. This chapter provides a description of the seminal optimization models that have been developed to address the aforementioned issues in the general field of CIP. Models are grouped in three categories: *survivability-oriented interdiction*, *resource allocation strategy*, and *survivable design models*; existing models are reviewed and possible extensions are proposed. In fact, some models have already been developed for CII (i.e., survivability-interdiction and design models), while others have been adapted from the literature on other CI (i.e., resource allocation strategy models). Hence, the main gap emerging in the CII field is that CII protection has been quite overlooked which has led to review optimization models that have been developed for the protection of other CI. Hence, this chapter provides also a survey of the multi-level programs that have been developed for protecting supply chains, transportation systems (e.g., railway infrastructures), and utility networks (e.g., power and water supply systems), in order to adapt them for CII protection.

2.1 Identifying critical network components: survivability-oriented interdiction models

The identification of critical components in network-based systems can be traced back to a few decades ago in the context of transportation infrastructures for military purposes (Wollmer 1964). More recently, Church, Scaparra and Middleton (2004) introduced optimization models for identifying critical facilities in service and supply systems.

Interdiction models, as referred to in the literature, identify network components which are the most critical, i.e., the ones that, if disrupted, inflict the most serious damage to the system. The importance of these kinds of models is easily understandable: they not only shed light on a system's major vulnerabilities, but also help form the basis for developing protection and/or recovery plans.

Interdiction models are driven by specified criteria (also called impact metrics). When dealing with CII, such as communication and information networks, the two important criteria are *network reliability* and *network survivability*. In (Soni, Gupta and Pirkul 1999), *network reliability* is defined as the probability measure that a network functions according to a predefined specification; whereas, *network survivability* is defined as the ability of a network to maintain its communication capabilities in the face of equipment failure. Moreover, according to Soni, Gupta and Pirkul (1999), it is possible to subdivide *network survivability* into two categories: *physical survivability* and *logical survivability*. A network is physically survivable if after the physical failure of some nodes or arcs, a path connecting all the nodes still exists. Logical survivability is about survivability at higher levels of the Open Systems Interconnection (OSI) model and assumes that the underlying physical network is survivable.

The focus of this section is on evaluating how disruptive events impact a network's physical survivability by identifying its critical components, which can be nodes and/or arcs. In the case of communication and information networks, nodes can be switches, multiplexers, cross-connects, routers; arcs represent connections among them (Soni, Gupta and Pirkul 1999; Soni and Pirkul 2002).

Murray (2013) identifies four metrics to evaluate *network physical survivability*: *maximal flow* (Wollmer 1964), *shortest path* (Corley and David 1982), *connectivity* (Lin et al. 2011; Soni, Gupta and Pirkul 1999), and *system flow* (Myung and Kim 2004; Murray, Matisziw and Grubesic 2007). Here an example of an optimization model designed to ascertain the survivability of system flow is provided. This model is a variation of the model introduced in (Myung and Kim 2004) and later extended and streamlined in (Murray, Matisziw and Grubesic 2007). It identifies the *r* most vital components of a network, i.e., those components which, if disrupted, maximize the amount of flow that can no longer be routed over the network. In the specific case of CII, the flow represents data and information. In the following, this model will be referred to as the Survivability Interdiction Model (SIM).

[2]Given a network $G(N, A)$, where N is the set of nodes and A is the set of arcs, let Ω be the set of origin nodes, indexed by o; H the set of elements (nodes/arcs) that can be disrupted, indexed by h; Δ the set of destination nodes, indexed by d; P the set of paths,

[2] For the sake of clarity, the reader is informed that the mathematical notations hereby introduced are for this specific chapter and do not relate with those introduced in other chapters of this dissertation.

indexed by p; N_{od} the set of paths enabling flow between an origin-destination pair $o-d$; Φ_p the set of components belonging to path p; f_{od} the flow routed between an *o-d* pair; and r the number of components to be disabled. The decision variables are: S_h equal to 1 if component h is disrupted, 0 otherwise; and X_{od} equal to 1 if flow cannot be routed between a pair $o-d$, 0 otherwise. The mathematical formulation is:

$$max\ z = \sum_{o\in\Omega}\sum_{d\in\Delta} f_{od}X_{od} \quad (1)$$

s.t.

$$\sum_{h\in\Phi_p} S_h \geq X_{od} \qquad \forall\ o\in\Omega, d\in\Delta, p\in N_{od} \quad (2)$$

$$\sum_{h\in H} S_h = r \quad (3)$$

$$S_h \in \{0,1\} \qquad \forall\ h\in H \quad (4)$$

$$X_{od} \in \{0,1\} \qquad \forall\ o\in\Omega, d\in\Delta \quad (5)$$

The objective function (1) maximizes the total flow disrupted (or interdicted). Constraints (2) state that the flow between an $o-d$ pair can be considered lost ($\mathrm{X}_{od}=1$), only if every path connecting nodes o and d is affected by the disruption (i.e., at least one of its arc is disrupted). Constraint (3) is a typical cardinality constraint which stipulates that exactly r arcs/nodes are to be disrupted. Finally, constraints (4) and (5) represent the binary restrictions on the interdiction and flow variables, respectively.

The original SIM in (Myung and Kim 2004) only considers arc disruption. It was later modified to address node disruption in (Murray, Matisziw and Grubesic 2007). This work also presents a variant of SIM which identifies lower bounds to the flow loss caused by the disruption of r nodes, thus allowing the assessment of both best-case and worst-case scenario losses. This kind of analysis is useful to build the so-called *reliability envelope*, a diagram originally developed in (O'Kelly and Kim 2007) to depict possible outcomes for the failure of communication systems. In (Murray, Matisziw and Grubesic 2007), SIM was applied to the Abilene network, an Internet-2 backbone with 11 routers and 14 linkages connecting US institutions. The analysis shows that the worst-case interdiction of one node (Washington, D.C.) can cause a data flow decrease of over 37%; a two-node interdiction scenario (Washington, D.C. and Indianapolis) a decrease of over 73%.

One arguable aspect of existing interdiction models such as SIM is that the number of components to be disrupted is fixed to a specific and known value r. This assumption is made to capture the possible extents of disruptive events: large values of r mimic large disruptions involving the simultaneous loss of several components, while small values are used to model minor disruptions (Losada et al. 2012). In practice, it is difficult to anticipate the extent of a disruption and therefore select a suitable r value. In addition, the critical components identified for a small r value are not necessarily a subset of the critical components identified for larger values. Consequently, these models are usually run for several values of r so as to identify the most vital components across disruption scenarios of different magnitude (Murray, Matisziw and Grubesic 2007).

Another aspect worth mentioning is that the use of cardinality constraints like (3) is useful for identifying worst-case scenario losses caused by natural disasters. However, in case of malicious attacks, models must capture the fact that different amount and type of resources (e.g., human, financial, etc.) may be needed in a concerted attack to fully disable network components and cause maximum damage (Scaparra and Church 2015). From an attacker's perspective, in fact, resources may vary significantly according to the target. This is particularly true within the context of physical survivability as opposed to logical survivability. For example, a physical attack on a relatively small number of major switching centers for long-distance telecommunications may require considerably more resources than launching a logic denial-of-service attack on the Internet. However, the former type of attack may cause much longer lasting damage (Lin, Patterson and Hennessy 2003).

This aspect can be captured by either replacing (3) with a budget constraint (see (Aksen, Piyade and Aras 2010) and (Losada et al. 2012) in the context of distribution systems) or by developing models that directly minimize the attacker expenditure to achieve a given level of disruption. Examples of the latter can be found in (Lin et al. 2011). This work presents some mixed integer programming models which minimize the cost incurred by an attacker to disconnect the network according to different survivability metrics (e.g., degree of disconnectivity). These attacker models are then used to assess the robustness of two protection resource allocation strategies: a uniform allocation (the defense budget is distributed equally among the nodes) and a degree-based allocation (the budget is distributed among the nodes proportionally to their degree of connectivity). As it will be discussed in the next section, this approach, where protection decisions are not tackled explicitly within a mathematical model but are only assessed and/or developed on the basis of the results of an interdiction model, often leads to a suboptimal allocation of protective resources.

Another aspect that interdiction models must capture is the fact that the outcome of an attack is highly uncertain. When dealing with malicious disruptions, this is a crucial issue as attackers, such as terrorists or hackers, aim at allocating their offensive resources so as to maximize their probability of success. Clearly, there is a correlation between the amount of offensive resources invested and the probability of success of an attack: the more the former, the higher the latter. Church and Scaparra (2007a) introduce an interdiction model for distribution systems where an interdiction is successful with a given probability and the objective is to maximize the expected disruption of an attack on r facilities. Losada et al. (2012) further extend this model by assuming that the probability of success of an interdiction attempt is dependent on the magnitude/intensity of the disruption. Similar extensions could be developed for SIM to assess the survivability of physical networks to attacks with uncertain outcomes.

To summarize, survivability-oriented interdiction models have been reviewed in this section. Specifically, SIM identifies the r most vital components of a network which, if disrupted, maximize the amount of information flow that can no longer be routed over the network. Moreover, a discussion of potential limitations introduced by the assumptions underpinning SIM has been provided, together with possible lines of research for variants of SIM. For example: (1) usage of either a cardinality-like constraint or budget-like constraint to mimic interdiction resources availability based on the disastrous circumstances to be addressed: natural disasters and malicious attacks, respectively; (2) do not assume a deterministic outcome for an attack but account for uncertainty: the amount of interdiction resources to be invested on a specific target shall be linked to the probability of success of the interdiction itself.

2.2 Enhancing critical network survivability: resource allocation strategy models

Optimization approaches can be used to improve CII survivability by optimizing investments in protection measures. CII protection measures may be divided into three different categories: *technical* (e.g., security administration), *management* (e.g., security awareness, technical training) and *operational (*e.g., physical security) (see (Viduto et al. 2012)). The interest of this chapter lies in the last category. Examples of physical security measures include: alarms, motion detectors, biometric scanners, badge swipes, access codes, and human and electronic surveillance, e.g., Perimeter Intruder Detection Systems (PIDS) and

Closed Circuit Television (CCTV) (Nickolov 2006). In a broader sense, protection strategies may include increasing redundancy and diversity (Sterbenz et al. 2010a). Redundancy consists in creating one or more copies of the same network element/content and is key to tackle random uncorrelated failures. Diversity aims at avoiding components of a system to undergo the same kind of failure and is used to tackle correlated failures.

Although interdiction models like SIM are instrumental for the identification of the most critical CII components, protection resource allocation approaches which solely rely on this information to prioritize protection investments often result in suboptimal defensive strategies (Cappanera and Scaparra 2011;Church and Scaparra 2007). This is due to the fact that when a component (e.g., the most critical) is protected, the criticality of the other components may change. Protections and interdictions decisions must therefore be addressed in an integrated way. This is typically done by using bi-level optimization programs (Dempe 2002). These programs are hierarchical optimization models which emulate the game between two players, referred to as *leader* and *follower*. In the CIIP context, the leader is the network operator or infrastructure owner, who decides which system components to protect; the follower represents a saboteur (hacker or terrorist) who tries to inflict maximum damage to the system by disabling some of its components. The defender decisions are modeled in the upper level program, whereas the lower level program models the attacker decisions and, therefore, computes worst-case scenario losses in response to the protection strategy identified in the upper level.

A bi-level program for CIIP is presented below, which embeds SIM in the lower level, and is referred to as the Survivability Protection Problem (SPP). In addition to the parameters and variables defined in Section 2.1, SPP uses the following notation: B is the total budget available for protection; c_h is the unit cost for protecting component h; Z_h is a decision variable equal to 1 if component h is protected, 0 otherwise.

SPP can be formulated as follows:

$$min\ H(z) \tag{6}$$

s.t.

$$\sum_{h \in H} c_h Z_h \leq B \tag{7}$$

$$Z_h \in \{0,1\} \qquad \forall\ h \in H \tag{8}$$

$$H(z) = \ max\ \sum_{o \in \Omega} \sum_{d \in \Delta} f_{od} X_{od} \tag{9}$$

s.t.

(2) - (5)

$$S_h \leq 1 - Z_h \qquad \forall\, h \in H \qquad (10)$$

The upper level model identifies which network components to protect given limited budgetary resources (7) so as to minimize a function, $H(z)$, which represents the highest flow loss (6) resulting from the interdiction of r components. The lower level model is the SIM with the additional set of constraints (10) which guarantee that if a component is protected, it cannot be attacked.

Protection models like SPP can be extended in a number of ways. For example, protection investments over time could be considered, given that funds for enhancing CI security usually become available at different times. An example of bi-level protection model that considers dynamic investments can be found in (Starita and Scaparra 2016) within the context of transportation infrastructures. Probabilistic extensions of SPP should also be considered, where the protection of an element does not completely prevent its interdiction, but may reduce its probability of failure. Other issues that should be captured are the uncertainty in the number of simultaneous losses of components (see for example Liberatore, Scaparra and Daskin 2011a), and the correlation among components failures (Liberatore, Scaparra and Daskin 2012).

Obviously, there are other approaches other than bi-level programming which can be used to optimize protection strategies. For example, Viduto et al. (2012) combine a risk assessment procedure for the identification of system risks with a multi-objective optimization model for the selection of protection countermeasures. To mitigate cyber-threats, Sawik (2013) uses mixed integer models in conjunction with a conditional value-at-risk approach to identify optimal protection countermeasure portfolios under different risk preferences of the decision maker (risk-adverse vs. risk-neutral).

To summarize, a potential survivability protection model has been introduced in this section. Specifically, SPP is a bi-level program where the defender aims at minimizing the negative impact of an attacker, modelled through SIM. Additionally, features to be included for potential variants of SPP have been outlined. For example: (1) protection investments over time could be considered, given that funds usually become available at different periods in time; (2) the protection of an element could not completely prevent its interdiction, but may reduce its probability of failure; (3) uncertainty in the number of simultaneous losses of components and/or correlation among components failures could be addressed.

2.3 Planning survivable networks: design models

Given the crucial importance of CII to the vast majority of economic activities and services, telecommunication and information systems are designed in such a way that they are intrinsically survivable, i.e. they satisfy some more or less stringent connectivity criteria. The design of survivable network is a well-studied problem in the optimization field. For an early survey, the interested reader can refer to (Soni, Gupta and Pirkul 1999). A comprehensive review of survivable network design models would be outside the scope of this thesis. To provide a complete treatment of survivability related optimization problems, one of the earliest and most studied models, namely the Survivable Network Design (SND) model found in (Soni and Pirkul 2002), is discussed in the following.

Given an undirected graph $G(N, E)$, where N is the set of nodes and E is the set of undirected edges (i, j), each pair of communicating nodes is identified as a commodity k (being K the set of the commodities), whose origin and destination are labeled as $O(k)$ and $D(k)$, respectively. Let c_{ij} be the design cost of edge (i, j), and q the number of node disjoint paths required for all the commodities (so the system will be able to face $q - 1$ failures at most). The decision variables are: U_{ij} equal to 1 if edge (i, j) is included in the design, 0 otherwise; and X_{ij}^k equal to 1 if commodity k uses edge (i, j), 0 otherwise. The formulation is the following:

$$min\ z = \sum_{(i,j)\in E} c_{ij} U_{ij} \qquad (11)$$

s.t.

$$\sum_{j\in N} X_{ij}^k - \sum_{j\in N} X_{ji}^k = \begin{cases} Q\ if\ i\ \equiv O(k) \\ -Q\ if\ i\ \equiv D(k) \\ 0 \text{ otherwise} \end{cases} \qquad \forall\, k \in K \qquad (12)$$

$$X_{ij}^k \le U_{ij} \qquad \forall\, k \in K, (i, j) \in E \qquad (13)$$

$$X_{ji}^k \le U_{ij} \qquad \forall\, k \in K, (i, j) \in E \qquad (14)$$

$$\sum_{i\in N} X_{ij}^k \le 1 \qquad \forall\, k \in K, j \in N\ \wedge j \neq D(k) \qquad (15)$$

$$X_{ij}^k, X_{ji}^k = \{0,1\} \qquad \forall\, k \in K, i, j \in N \qquad (16)$$

$$U_{ij} = \{0,1\} \qquad \forall\, i, j \in N \qquad (17)$$

The objective function (11) minimizes the cost of the topological network design. Constraints (12) guarantee network flow conservation. Constraints (13) and (14) stipulate that flow can traverse an edge only if the edge is included in the design. The combined use of constraints (12), (13) and (14) enforce the edge-disjoint paths over the network. Constraints (15) guarantee that at most one unit of flow can traverse a node that is neither a commodity origin nor destination, thus ensuring the correct number of node-disjoint paths in the network. Finally, constraints (16) and (17) represent the binary restrictions on the variables.

Many other survivable network design models can be found in the literature which differ in terms of underlying network (wired vs. wireless), network topology (e.g., ring, mesh, star, line, tree, etc.), connectivity requirements (e.g., edge and/or vertex-connectivity), path-length restrictions (e.g., hop limits (Orlowski and Wessäly 2006)), cost minimization (Orlowski and Wessäly 2005), and dedicated settings (e.g., path protection, link and path restoration (Orlowski and Wessäly 2006)).

Note that recent survivability design models embed interdiction models to ascertain components criticality (Smith, Lim and Sudargho 2007; Chen, Cohn and Pinar 2011). Such models are able to identify cost-effective CII configurations which are inherently survivable without the need to specify the number of disjoint paths required between each pair of communicating nodes, like in SND.

To summarize, the most well-known survivability design model has been introduced in this section. Specifically, SND aims at minimizing the total design expenditure. SND, and design models in general, are well-established in the literature. However, potential variants could be prompted by the need to address different underlying networks (wired vs. wireless), network topology (e.g., ring, mesh, star, line, tree, etc.), connectivity requirements (e.g., edge and/or vertex-connectivity) and/or path-length restrictions.

Among the three aforementioned lines of research, the one that has been so far overlooked is the development of resource allocation strategy models to tackle CIIP issues. In the following section, an overview of the principal bi-level programs is provided and, in some specific cases, multi-level programs that have been developed for the protection of other CI.

2.4 Multi-level programming for Critical Infrastructure Protection

Bi-level programming, and multi-level programming more in general, has been widely deployed for CIP. Relevant studies are categorized according to the type of underlying CI: *supply chains*, *transportation systems* (such as railway networks), and *utility networks* (such as power and water supply systems). Eventually, an overview of CII is provided along with what makes them different from other kinds of CI.

2.4.1 Supply chains

A *supply chain system* is usually represented by a network whose nodes are grouped into two categories: *demand points* (or customers) and *service points* (or facilities), where the former require a certain amount of either a product or a service that should be supplied by the latter. A failure in a supply chain may prompt adverse effects such as inability to satisfy customer demands and bring either production or service provision to a halt. Hence, protection of supply chains has been investigated in-depth over the years. Bi-level, and multi-level, programs have accounted for several aspects that can be classified in two main groups: *interdiction-related features*, such as deterministic or stochastic interdiction, full or partial disruption, and single or multiple kinds of attacks, and *supply chain-related features*, such as a hierarchical or decentralized structure and facility capacity backups, as described in the following.

Scaparra and Church (2008) propose a bi-level program for the R-Interdiction Median problem with Fortification (RIMF), initially introduced as an integer linear program by Church and Scaparra (2007). The aim of the RIMF is to identify the optimal distribution of limited resources among existing facilities of a vulnerable system so as to minimize the effect of worst-case disruptions arising from the loss of r unprotected facilities. The effect of such disruptions is evaluated as the total demand-weighted distance between non-interdicted facilities and customers. The RIMF is solved through an Implicit Enumeration (IE) algorithm.

Aksen, Piyade and Aras (2010) define the Budget Constrained R-Interdiction Median problem with Capacity Expansion (BCRIMF-CE). BCRIMF-CE differs from RIMF because of: (1) the facility protection cardinality constraint is replaced with a budget constraint; and (2) facilities capacity can be expanded, subject to a certain expense, to withstand the aftermath of facility interdiction. An IE algorithm, similar to the one proposed in Scaparra and Church (2008), is deployed.

Liberatore, Scaparra, and Daskin (2011a) and Liberatore and Scaparra (2011b) provide the Stochastic R-Interdiction Median Problem with Fortification (S-RIMF) where the defender aims at finding the optimal allocation of hardening resources under uncertain circumstances regarding the system components to be disrupted. Liberatore, Scaparra, and Daskin (2011a) introduce expected cost-based models while Liberatore and Scaparra (2011b) describe regret-based models. Liberatore, Scaparra, and Daskin (2011a) reformulate the proposed model according to a max-covering formulation and solve it according to a heuristic concentration-based approach while Liberatore and Scaparra (2011b) deploy a commercial optimization software.

Losada, Scaparra and O'Hanley (2012) define the Fortification and R-Interdiction Median problem with facility recovery Time and frequent disruptions (FRIMT). Main assumptions underpinning FRIMT are: (1) the same facility can be disrupted more than once during different time periods; and (ii) a facility, once interdicted, is fully inoperative only during its recovery time. Hence, the allocation of protective resources is twofold: to withstand disruptions and to improve system resilience. A Benders decomposition, a SVI decomposition approach, and a hybridization of the previous two methods are used to solve the FRIMT model.

Aksen and Aras (2012) extend the BCRIMF-CE by proposing the Bi-level Fixed Charge Location Problem (BFCLP), which addresses conjunctively fixed charge facility location, interdiction and protection. The authors identify two sets of costs the system planner incurs, those prior and those after an interdiction. Two heuristic methods are proposed to solve the BFCLP: a Tabu Search (TS) and a Sequential Solution Method (SSM). Aksen, Aras and Piyade (2013) propose the Bi-level p-median problem for the Planning and Protection of Critical Facilities (BPPCF), similar to the BFCLP, and solve it through an exhaustive search algorithm as well as TS and SSM approaches.

Zhu, Zheng, Zhang, and Cai (2013) formulate a non-linear bi-level mixed-integer program to model the R-Interdiction Median problem with Probabilistic protection (RIMP) where it is assumed that facilities, once protected, can still be interdicted to a certain extent. The authors also propose the RIMP with Multiple Interdictors (RIMP-MI) where it is assumed that a facility can be stricken by multiple attackers at the same time. An iterated greedy search heuristic is proposed to solve both RIMP and RIMP-MI.

Aksen, Akca, and Aras (2014) introduce the Bi-level Partial Facility Interdiction Problem (BPFIP), which addresses partial interdiction for median-based systems with capacitated facilities and demand outsourcing. Partial interdiction is modelled through facility capacity reduction: if a facility is attacked, it may still be able to serve customers but with reduced capacity. A Progressive Grid Search (PGS) and a Multi-start revised Simplex Search heuristic (MSS) are deployed to solve the BPFIP.

Zhang, Zheng, Zhu, and Cai (2014) present the Fortification Median problem for disruptions caused by Mixed types of Attacks (FMMA) as a non-linear bi-level program. FMMA represents an all-hazards approach because it accounts for different proportions of both worst-case and random attacks thus providing a more trustworthy protection scheme. The authors solve the FMMA through an extension of the IE algorithm proposed in Scaparra and Church (2008).

Aliakbarian, Dehghanian and Salari (2015) extend the RIMF to hierarchical CI (e.g., oil refineries, food warehouses) and solve it with three different methodologies: (i) a Variable Neighbourhood Search-based approach (VDNS), (ii) a Simulated Annealing-based approach (SA), and (iii) a hybrid version of the aforementioned approaches (SA-VDNS).

Cheng, Lai, Yang, and Zhu (2016) develop three hybrid heuristics to tackle the RIMF. The proposed framework addresses the leader's problem with a metaheuristic to be chosen among a TS, SA, or a Genetic Algorithm (GA) while the follower's problem is solved through an off-the-shelf optimization software.

Akbari-Jafarabadi, Tavakkoli-Moghaddam, Mahmoodjanloo, and Rahimi (2017) define the Tri-level Facility Location R-Interdiction Median (TFLRIM) problem where the defender aim is to minimize the total costs prior to and following an interdiction. A TS and Rain-Fall Optimization (RFO) approaches are used to solve the TFLRIM.

Parajuli, Kuzgunkaya, and Vidyarthi (2017) extend the work of Aksen, Piyade and Aras (2010), by introducing a tri-level program which assumes protection through capacity backups subject to gradual availability. The model is solved through an extension of the IE algorithm of Scaparra and Church (2008).

Fard and Hajiaghaei-Keshteli (2018) extend the work of Aksen, Akca, and Aras (2014) by introducing a non-linear bi-level program to model partial interdiction of supply chain systems where the defender has two objectives to pursue: (1) to minimize the cost of deploying different defensive schemes, and (2) to minimize the total system cost. The authors produce two hybrid metaheuristics to solve the proposed model: the former combines Water Wave Optimization (WWO) and a GA while the latter combines a Whale

Optimization Algorithm (WHA) and Particle Swarm Optimization (PSO), which are all evolutionary-based solution methods.

Khanduzi and Maleki (2018) produce a dynamic variant of the RIMF, namely the Multi-period Interdiction problem with Fortification (MIF). The MIF is solved through an exact method (Benders decomposition) and three hybrid metaheuristics (the upper level model is solved through three possible population-based algorithms including a GA, a Teaching Learning Based Optimization (TLBO) algorithm, or a Dragonfly Algorithm (DA) while the lower level model is solved through a commercial optimization software).

Zhang, Zheng and Cai (2018) propose the R-Interdiction Median problem with Fortification for Decentralized supply systems (D-RIMF). The authors devise a bi-level multi-agent framework where each facility and each customer act as an independent agent. D-RIMF is solved through both exact (Scaparra and Church (2008)'s IE algorithm) and heuristic approaches (q-round algorithm).

2.4.2 Transportation systems

Transportation systems allow the movement of people and goods from an initial origin to a final destination. They are deemed to include infrastructures such as *railway networks* and *multi-modal systems*. Network nodes and arcs mimic train stations and network tracks in railway systems, while they represent terminals and connections among them, in multi-modal systems, respectively. Despite being less investigated than supply chains, various bi-level as well as multi-level programs have been developed for both railway networks and multi-modal systems, as described in the following.

Cappanera and Scaparra (2011) define a generic tri-level defender-attacker-user model, namely the Shortest-Path interdiction Problem with Fortification (SPIF) for shortest-path networks. SPIF aims at optimally distributing fortification resources across network arcs so to minimize the length of the shortest path connecting a supply and a demand node after worst-case disruptions affecting some unprotected network connections. SPIF is solved through Scaparra and Church (2008)'s IE algorithm after collapsing the bi-level attacker-user model into a single-level attacker model thus reducing the initial tri-level program to a bi-level program through dualization. Sadeghi, Seifi and Azizi (2017) provide an extension of the SPIF by assuming partial fortification and solve the resulting model through a decomposition-based approach.

A few papers have introduced protection models within the specific domain of railway networks protection. For example, Jin, Lu, Sun and Yin (2015) propose a tri-level model whose objective is to fortify vulnerable train stations so as to minimize the travel delay resulting from targeted attacks while assigning railway system users to alternative accessible paths. The authors account for several offensive strategies differing for their intensity and model a multiple origin-destination commuter flow. The proposed model is solved through a nested variable neighbourhood search algorithm.

Scaparra, Starita and Sterle (2015) introduce the Railway Protection Investment problem (RPI), a bi-level model whose aim is to identify the allocation of protective resources that minimizes the disruption of passenger flow due to worst-case interdictions affecting railway system components (i.e., either stations or tracks). The authors solve the RPI through SVI decomposition. Starita and Scaparra (2016) extend the RPI by assuming that protective resources are available over time thus adding the time perspective to the RPI and defining the Dynamic Network Protection (DNP) model. The DNP is solved through Benders decomposition and SVI decomposition. Starita and Scaparra (2018) further expand the two aforementioned works by introducing the Network Protection Problem with Variable Demand Loss (NPVDL), which considers the post-disruption passenger behaviour. Namely, the post-disruption passenger demand depends on the travelling times of the available alternative paths. The authors solve the NPVDL through an exact (SVI decomposition) and a heuristic approach (SA).

Within the context of multi-modal systems and, more specifically, those addressing a combination of rail and truck based transportations, the following contributions have been produced. Sarhadi, Tulett and Verma (2015) propose a tri-level model for the protection of a rail intermodal terminal network. The objective is to determine the optimal investment strategy aimed at fortifying some rail-truck intermodal terminals so to withstand system inefficiencies due to targeted attacks. The authors use three different solution techniques to solve the proposed optimization model: complete enumeration, Scaparra and Church (2008)'s IE algorithm, and a traffic-based heuristic. Sarhadi, Tulett and Verma (2017) extend this work by approaching the tri-level model with a two-stage solution method: the IE algorithm of Scaparra and Church (2008) is deployed at the first stage to break the tri-level model into smaller bi-level programs, each to be solved, at the second stage, with Benders decomposition.

2.4.3 Utility networks

Utility networks account for *power* and *water supply systems*. Network nodes and arcs mimic generators and buses as well as transmission lines in power supply systems, while they represent water storage facilities, treatment plants, and junctions, as well as pumps, valves, and pipes in water supply systems, respectively. Several multi-level programs have been developed for electric grids, which seem to be the power supply systems whose protection has been mostly investigated, while bi-level programming has been deployed only recently for water supply system protection, as described in the following.

Brown, Carlyle, Salmeron and Wood (2006) introduce a generic tri-level defender-attacker-defender (DAD) model for the protection of electric power grids. The objective is to identify the most effective transmission line hardening plan so as to minimize the damages resulting from possible outages due to a malicious attacker. The authors solve the model with Benders decomposition.

Yao, Edmunds, Papageorgiou and Alvarez (2007) develop a tri-level DAD model specific for power systems protection. The objective is to minimize the power generation costs and the level of unmet demand so as to withstand worst-case outages due to an attack on some unprotected network components (e.g., power lines, buses, and substations). The tri-level model is decomposed into smaller bi-level programs, each of them solved according to the set covering decomposition scheme reported in Israeli and Wood (2002).

Alguacil, Delgadillo and Arroyo (2014) propose another tri-level model for electric grid defence planning, based on the same principles of the one of Brown, Carlyle, Salmeron and Wood (2006). The tri-level model is collapsed into a bi-level program which is solved through the IE algorithm of Scaparra and Church (2008). Yuan, Zhao and Zeng (2014) basically solve the same model of Alguacil, Delgadillo and Arroyo (2014), where budget constraints substitute cardinality constraints for both defender and attacker decisions, through a Column-and-Constraint-Generation (C&CG) algorithm. Wu and Conejo (2017) solve the model of Alguacil, Delgadillo and Arroyo (2014) through Benders decomposition with primal cuts and compare the results with the application of Scaparra and Church (2008)'s IE algorithm. Xiang and Wang (2018) extend Alguacil, Delgadillo and Arroyo (2014)'s tri-level model by defining the Multiple-Attack-Scenario (MAS) DAD model. The MAS accounts for multiple offensive circumstances that are mimicked through multiple attacker scenarios which are represented through many middle-levels of the tri-level program. The model is solved through a C&CG algorithm.

Fang and Sansavini (2017) propose a novel tri-level model for electric systems protection that, differently from the previous contributions that are focused on power system defence planning, combines transmission expansion planning and transmission switching. Transmission expansion planning deals with the installation of additional network components while transmission switching consists in changing the system topology by switching either on or off some pre-existing system components. Hence, both transmission expansion planning and transmission switching perform network design operations. However, the former installs new components while the latter rearranges pre-existing ones. The aim of the model is to minimize the total investment cost, accounting for both transmission expansion planning and transmission switching measures, together with the system performance level so to withstand the aftermath of worst-case targeted attacks on the power network. The authors solve the proposed tri-level model through a cutting plane strategy based on primal cuts.

On the other side, Jiang and Liu (2018) are the first to propose a bi-level program to address water supply network protection. The authors introduce a multi-objective defender-attacker model where the defender aims at maximizing the expected network satisfaction rate along with the protection investments while the attacker aims at minimizing the expected network performance as well as the offensive resource expenditure. The authors solve the proposed model through a three step algorithm which comprises the deployment of different solution techniques: a nested heuristic GA, a heuristic GA, and a minimax regret approach.

2.4.4 Critical Information Infrastructures

Critical Information Infrastructures, such as the public telephone network, Internet, terrestrial and satellite wireless networks (Patterson and Personick 2003), are those systems, belonging to the information and communications technology (ICT), whose correct functioning is fundamental not only for the services they provide but also for other kinds of CI which either rely or are based on them. Examples of CII are backbone networks that ensure connectivity among distributed systems in order to allow remote monitoring, access control, data sharing as well as payment services. Network nodes are either servers, routers or switches whose main tasks are to regulate network traffic and manage data transmission over the network arcs. Network components (i.e., nodes and arcs) are prone to either physical or cyber-attacks.

However, the above features, make CII different from other CI thus requiring a novel bi-level program addressing them. Firstly, in case of supply chains, transportation infrastructures and utility networks, interdiction targets are also protection targets, e.g., if a node is to be attacked, the protection strategy will entail to fortify the node so as to make it less vulnerable and eventually hedge against the interdictor strategy. Differently, in the case of CII, given that nodes are more sensitive targets than arcs, it would be more sensible to deploy as a protection strategy the construction of additional connections so as to mitigate the loss of some nodes by increasing system redundancy and maintaining its functioning. The choice of the aforementioned protection strategy is also linked to the impact of disruptions. In fact, once a communication network has been severely damaged without the chance to keep its service, this may have not just an immediate negative effect but also a far-reaching adverse one due to the inoperability of other infrastructures (such as utility networks, dispatching framework of supply chain systems) linked to it, thus requiring longer recovery times and leading to large economical losses. Differently, the set-up of a protection strategy based on design will increase system resilience and redundancy thus allowing to mitigate negative crippling effects. Secondly, from a modelling perspective, typical objective functions for other CI involve system flow (e.g., flow of goods for supply chain systems, passenger flow for transportation infrastructures, power units for utility networks) while, despite information flows are routed over CII networks, the main objective would be to keep the network (and its components) connected the most so as to allow information to circulate.

Hence, CII are different from other CI thus requiring a specific protection framework to account for their protection.

2.5 Conclusions

This chapter reviewed the research activities conducted over recent years in the general field of CIP aimed at mitigating the effects of physical attacks against CII components from an optimization-based perspective. This chapter has investigated three main lines of research: survivability assessment models, resource allocation strategy models, and survivable design models. Each model category has been designed to identify different crucial aspects: under what circumstances the infrastructure is still able to provide its service; how resources should be allocated in order to protect the infrastructure; and how a new infrastructure should be designed in order to be naturally survivable.

The survivability optimization models discussed in this paper are basic models that can be extended in a number of ways. For example, interdiction and protection models could be extended to tackle both physical and logical survivability issues by incorporating routing and link capacity assignment decisions. In addition, most of the optimization models developed so far are deterministic. However, failures and disruptions are random events, often difficult to predict. The probabilistic behaviour of complex CII under disruptions would be better modelled by using stochastic models, including uncertain parameters (e.g., uncertainty on arc/node availability, extent of a disruption, etc.). Alternatively, the uncertainty characterizing disruptions could be captured in scenario-based models which incorporate robustness measures for the identification of solutions which perform well across different disruption scenarios. Future models could even combine the optimization of protection and restoration strategies in a unified framework so as to distribute resources efficiently across the different stages of the disaster management cycle (protection plans belong to the pre-disaster stage while recovery plans refer to the post-disaster stage). Other resource allocation models could consider identifying trade-off investments in physical protection and cyber-security to mitigate the impact of both physical and logical attacks. Models which address design and protection issues conjunctively also deserve further investigation. The models discussed in this paper have been solved by using a variety of optimization algorithms, including exact methods (e.g., decomposition) and heuristics (e.g., evolutionary algorithms). Obviously, the development of more complex models would necessarily require additional research into the development of more sophisticated solution techniques, possibly integrating exact and heuristic methodologies.

Some models were already present in the CIIP literature (i.e., survivability-oriented interdiction and survivable design models) while others have been adapted from application to other CI (i.e., resource allocation strategy models). In particular, what emerged is that the development of protection models for CII has been so far overlooked. This has prompted to review what has been done for the protection of other CI (e.g., supply chains, transportation systems, and utility networks), which has laid the foundation for the novel bi-level program for CIIP to be presented in Chapter 3.

3. Optimizing resource allocation investments for Critical Information Infrastructure Protection: a connectivity augmentation-based approach

This chapter presents a novel linear bi-level program for the protection of CII, which integrates network survivability assessment, resource allocation strategies and design operations, namely the *Critical Node Detection Problem with Fortification*. To the best of my knowledge, this is the first bi-level program devised to tackle CII protection issues. The model is solved through a SVI decomposition approach and a heuristic approach (GCLS). Computational results are reported for real communication networks and for different levels of both disaster magnitude and protection resources.

3.1 The Critical Node Detection Problem with Fortification

Information infrastructure security can be improved through the optimal allocation of protective resources among system components. To mitigate the risk of disruption, infrastructure elements whose failure would worsen the system functioning the most are to be identified and protection measures are to be implemented. Examples of protection measures are efficient investment of resources to either fortify the system most critical components or entail network design operations aimed at increasing system redundancy (as in this work).

Various approaches towards the identification of the most critical components of a system have been developed over the years. Starita, Esposito Amideo and Scaparra (2018) describe and compare two different methods: *vulnerability metrics* and *interdiction models*. *Vulnerability metrics* are indices that provide a criticality ranking of all the system components prior to the occurrence of an attack. Examples are *robustness metrics*, which Rueda, Calle and Marzo (2017) classify in three main categories: (1) *structural* measures, such as average nodal degree and vertex (edge) connectivity; (2) *centrality* measures, such as node degree and node betweenness; and (3) *functional* measures, such as elasticity and endurance. On the other side, *interdiction models*, as described in Section 2.1, are mathematical programs that optimally identify those network elements whose unavailability would disrupt the system the most. Interdiction models account for the existing interdependency among system components under different disastrous circumstances, an aspect that is entirely neglected by a vulnerability metric-based approach, eventually yielding more accurate results. Interdiction models have been largely used for network problems (e.g., shortest path (Wollmer 1964; Wood 1993), maximal flow problems (Myung and Kim 2004), and location problems (e.g., median and covering (Church, Scaparra and Middleton 2004)).

The identification of network criticalities is a prerequisite for the definition of optimal protection strategies. To this end, either a *sequential* or an *integrated* approach can be adopted. A *sequential* approach is composed of two stages: network criticalities are identified at the former stage, through either vulnerability metrics or interdiction models, and the results are used to prioritize the allocation of protective resources. This approach has been proven to lead to sub-optimal protection decisions because it fails to capture the changes in the component criticality when some components are protected over others (Cappanera and Scaparra 2011). This pitfall can be overcome with the adoption of an *integrated* approach that deploys *bi-level optimization models*. *Bi-level programs* (Dempe 2002), also known as *defender-attacker models*, mimic a game between two players: a defender (e.g., the infrastructure owner) and an attacker (e.g., a terrorist, a hacker, or a disaster). The upper level program models the defender decisions who aims at optimally distributing protective resources over the network while minimizing the impact of worst-case disruptions due to the attacker. The lower level program models the attacker actions whose target is to maximize the damage inflicted on the network. Hence, *bi-level programs* entail a series of subsequent defense/attack moves that allow to model the dynamic interaction of different players.

3.1.1 Model assumptions

The CNDPF problem is formulated as a bi-level linear mixed-integer program. The assumptions underpinning the model are as follows.

1. A limited budget is available to protect the network; similarly, interdiction resources are also assumed to be limited. The reason being that, from a practical perspective, the defender is the network operator who has to strategically allocate a portion of its finances to invest in infrastructure protection while the attacker is a malicious individual who can affect the network through limited opportunities. In fact, if either the attacker or the defender had unlimited resources, the problem under analysis could not be posed given that either the network would be fully unavailable (i.e.,

attacker with unlimited resources) or the network would be immune to attacks (i.e., defender with unlimited budget).

2. Only network nodes can be disrupted and, as such, become inoperative; however, all the arcs that are incident in an interdicted node are considered to become inoperative as well and, as such, are removed from the network. Specifically, in the case of CII, network nodes are either servers, routers or switches whose main tasks are to regulate network traffic and manage data transmission while network arcs are mere connection among nodes. Hence, network nodes store critical information thus making them more prone to attacks than arcs. Also, when a node becomes inoperable, it means that at least one of the terminal points of the corresponding arc is not functioning anymore which, eventually, makes the arc unable to fulfill its data transmission function. Consequently, if a node is inoperable, incident arcs are inoperable as well thus yielding more damage to the infrastructure.
3. Protection measures consist in building additional arcs to mitigate worst-case scenario losses of network nodes, the reason being to aim to increase system redundancy despite potential malicious attacks so as to keep the functioning standard of the infrastructure as high as possible.
4. The amount of resources needed to disrupt network nodes as well as installing additional arcs is known.
5. The upper level objective is to maximize the lowest network connectivity, resulting from worst-case scenario disruptions of network nodes modeled at the lower level, through the installation of additional arcs within a limited budget.

3.1.2 Model formulation

[3]The bi-level program for CNDPF deploys the following notation.

Sets, indices and parameters

$G(N, A)$: connected network

N: set of network nodes, indexed by i, j, or k

A: set of network arcs

[3] For the sake of clarity, the reader is informed that the mathematical notations hereby introduced are for this specific chapter and do not relate with those introduced in other chapters of this dissertation.

$\bar{A}$: set of potential arcs (i.e., all the possible arcs (i,j) such that $i,j \in N \land\ i \neq j, (i,j) \notin A$) to be added for protection

i,j,k: indices used for nodes

D: amount of disruption resources available

B: amount of protection resources available

d_i: amount of resources needed to disrupt node $i \in N$

c_{ij}: amount of resources needed to install arc $(i,j) \in \bar{A}$

Decision variables

V_i: 1 if node $i \in N$ is disrupted, 0 otherwise

Z_{ij}: 1 if arc $(i,j) \in \bar{A}$ is installed, 0 otherwise

U_{ij}: 1 if there is connectivity between nodes i and j, 0 otherwise

CNDPF is formulated as follows:

$$\text{[CNDPF]}\ max\ H(\boldsymbol{Z}) \tag{18}$$

s.t.

$$\sum_{(i,j)\in\bar{A}} c_{ij}Z_{ij} \leq B \tag{19}$$

$$Z_{ij} \in \{0,1\} \qquad \forall\ (i,j) \in \bar{A} \tag{20}$$

$$\text{where } H(\boldsymbol{Z}) =\ min \sum_{i\in N}\sum_{j\in N} U_{ij} \tag{21}$$

s.t.

$$U_{ij} + V_i + V_j \geq 1 \qquad \forall\ (i,j) \in A \tag{22}$$

$$U_{ij} + U_{jk} - U_{ik} \leq 1 \qquad \forall\ i,j,k \in N \tag{23}$$

$$\sum_{i\in N} d_i V_i \leq D \tag{24}$$

$$U_{ij} + V_i + V_j \geq 1 - M(1 - Z_{ij}) \qquad \forall\ (i,j) \in \bar{A} \tag{25}$$

$$V_i \in \{0,1\} \qquad \forall\ i \in N \tag{26}$$

$$U_{ij} \in \{0,1\} \qquad \forall\ i,j \in N \tag{27}$$

The upper level model aims at protecting the network through the installation of additional arcs within a limited budget (19) so as to maximize (18) a function, $H(\boldsymbol{Z})$, which represents the lowest network connectivity (21) resulting from node disruptions (24). Constraints (20) are binary restrictions on the protection variables. Constraints (22) state that, for each arc (i,j), nodes i and j must be connected ($U_{ij} = 1$) unless either i or j are disrupted ($V_i = 1 \vee V_j = 1$). Constraints (23) guarantee that if nodes i and j as well as nodes j and k are connected ($U_{ij} = 1 \wedge U_{jk} = 1$), then nodes i and k must also be connected ($U_{ik} = 1$). Constraints (24) state that nodes can be disrupted within limited interdiction resources equal to D. Constraints (25) connect the upper and lower level variables. Specifically, if a link is installed between nodes i and j ($Z_{ij} = 1$), then i and j must be connected ($U_{ij} = 1$) unless either i or j are interdicted ($V_i = 1 \vee V_j = 1$). Finally, constraints (26) and (27) are binary restrictions on the interdiction and connectivity variables, respectively.

Note that the lower level model is a variant of the CNP (Arulselvan et al. 2009) with a change to the circular constraints thereby defined, resulting in the new set of constraints (23) and the addition of constraints (25) that link the upper and the lower levels of the program. In fact, CNP can only be used for undirected network, while CNDPF is more general given that, real communication networks, based on the type of data transmission, are either undirected or directed. More specifically, given a transportation line, if information flows in both directions a *full-duplex* scheme is deployed, thus modeled as an undirected network, while if information is allowed through only one direction, a *half-duplex* scheme is used, thus modeled as a directed network (Fertin and Raspaud 1998).

3.2 Solution Methodology

Several solution techniques, either *exact* or *heuristic*, have been developed over the years to solve bi-level programs; some examples are provided as follows.

Depending on the type of decisional variables (e.g., continuous, integer, binary), different *exact methods* can be deployed. If none of the lower level variables are constrained to be integer, Karush-Kuhn-Tucker (KKT) conditions can be applied: in fact, in such case, the lower level model is dualized thus providing a single model to be solved (Bard 1998). However, when variables are constrained to be binary, IE algorithms and decomposition methods, such as Benders decomposition (Benders 1962) and SVI decomposition (Israeli and Wood 2002), are to be deployed. As emerges in Section 2.4, among the ten bi-level programs solved through exact methods, an IE algorithm (Scaparra and Church 2008; Aksen, Piyade and Aras 2010; Zhang, Zheng, Zhu, and Cai 2014; Zhang, Zheng and Cai 2018); a SVI decomposition approach (Losada, Scaparra and O'Hanley 2012; Scaparra, Starita and Sterle 2015; Starita and Scaparra 2016; Starita and Scaparra 2018); Benders decomposition (Losada, Scaparra and O'Hanley 2012; Starita and Scaparra 2016; Khanduzi and Maleki 2018); and a PGS method

(Aksen, Akca, and Aras 2014) were used. This shows that IE algorithms and SVI decomposition have been quite deployed over time.

Section 2.4 allowed also to appreciate a variety of heuristic approaches that have been devised to solve bi-level programs. These include: iterated greedy search (Zhu, Zheng, Zhang, and Cai 2013); MSS (Aksen, Akca, and Aras 2014); SSM (Aksen and Aras 2012; Aksen, Aras and Piyade 2013); metaheuristics such as SA (Aliakbarian, Dehghanian and Salari 2015; Cheng, Lai, Yang, and Zhu 2016; Starita and Scaparra 2018), TS (Aksen and Aras 2012; Aksen, Aras and Piyade 2013; Cheng, Lai, Yang, and Zhu 2016), and VNS (Aliakbarian, Dehghanian and Salari 2015); and evolutionary algorithms, such as DA (Khanduzi and Maleki 2018), GA (Cheng, Lai, Yang, and Zhu 2016; Fard and Hajiaghaei-Keshteli 2018; Jiang and Liu 201; Khanduzi and Maleki 2018), PSO (Fard and Hajiaghaei-Keshteli 2018), TLBO (Khanduzi and Maleki 2018), WHA (Fard and Hajiaghaei-Keshteli 2018), and WWO (Fard and Hajiaghaei-Keshteli 2018).

Based on the literature findings and the structure of the CNDPF, two solution approaches, both exact and heuristic, are proposed to solve model (18) – (27): a *SVI decomposition algorithm* and a *heuristic approach (GCLS)* composed of two phases (i.e., a greedy constructive search and a local search), which are described in the following.

3.2.1 SVI decomposition algorithm for the CNDPF

The proposed SVI algorithm is a decomposition approach (Israeli and Wood 2002). Similarly to standard Benders decomposition approaches, SVI algorithms partition the initial bi-level program into an upper level and a lower level problems, usually named the Relaxed Master Problem (RMP) and the Sub-Problem (SP), respectively. Once the RMP and SP for the specific problem under consideration have been formulated, both problems are solved sequentially at each iteration. The solutions obtained from SP are then used to generate SVIs, which are subsequently appended to the RMP to be re-solved.

The main difference between Benders and SVI decomposition methods is that the RMP of the latter is a feasibility seeking problem. Hence, as stated by Losada, Scaparra and O'Hanley (2012), Benders decomposition algorithms usually require a relatively small number of iterations that are quite computationally expensive. Differently, SVI decomposition algorithms usually require a more significant number of iterations that are less computationally expensive. However, the SVI decomposition method has proven to perform better than the Benders when solving bi-level programs (O'Hanley and Church 2011; Losada, Scaparra and O'Hanley 2012; Starita and Scaparra 2016). Therefore, despite both SVI and Benders decomposition have been quite used for solving bi-level programs, as stated in the preface to this section, the performance aspect has led to prefer SVI over Benders for the CNDPF.

The SVI decomposition algorithm for CNDPF is now described in terms of RMP, SP, and SVIs. The RMP is a feasibility seeking problem (i.e., there is no objective function), which is composed of a set of SVIs and constraints (19) and (20). At each iteration, RMP returns a feasible protection strategy $\widehat{\boldsymbol{Z}}$. Subsequently, SP is solved to obtain the best interdiction plan $\widehat{\boldsymbol{V}}$ in correspondence of $\widehat{\boldsymbol{Z}}$. Hence, SP corresponds to the lower level [CNDPF] where the protection variables have been fixed. We name it AP and formulate it as follows:

$$[\text{AP}(\widehat{\boldsymbol{Z}})] \; z_{AP} = min \sum_{i \in N} \sum_{j \in N} U_{ij} \tag{28}$$

s.t.

$$U_{ij} + V_i + V_j \geq 1 - M(1 - \hat{Z}_{ij}) \qquad \forall\, (i,j) \in \bar{A} \tag{29}$$

(22) – (24); (26) – (27)

AP yields a feasible solution $(\widehat{\boldsymbol{Z}}, \widehat{\boldsymbol{V}}, \widehat{\boldsymbol{U}})$ and a lower bound $(\widehat{z_{AP}})$ to CNDPF. The obtained $\widehat{\boldsymbol{V}}$ and $\widehat{\boldsymbol{U}}$ is then deployed to generate SVIs that are subsequently appended to the RMP. The constraints adopted as SVIs are described in the following proposition, where are also proven to be supervalid. In particular, an inequality is supervalid if the two following conditions are satisfied (O'Hanley and Church 2011): (1) the incumbent solution is infeasible once the inequality is appended; and (2) the inequality does not discard any optimal solution unless the current incumbent is optimal.

Proposition 1. Given a feasible lower bound H_{LB} for [CNDPF] and connectivity value $\widehat{H}$ following an interdiction, let $\bar{A}_t$ be a subset of the potential arcs to be added at iteration t where each arc $(i,j) \in \bar{A}_t$ satisfies the following three conditions at each iteration t: (i) $U_{ij} = 0$, (ii) $V_i = 0$, and (iii) $V_j = 0$. Namely, $\bar{A}_t$ includes all the arcs with the following features: the arc should link nodes that are not already connected (i) and neither the initial (ii) nor the terminal (iii) nodes of the arc are disrupted. If $\widehat{H} \leq H_{LB}$, the following inequality is supervalid for RMP

$$\sum_{(i,j) \in \bar{A}_t} Z_{ij} \geq 1 \tag{SVI-1}$$

(i.e., at least one arc in $\bar{A}_t$ must be added).

Proof. At iteration t, $\sum_{(i,j)\in\bar{A}_t} Z_{ij} \geq 1$ yields to the selection of one arc $(i,j) \in \bar{A}_t$, $(i,j)_{t*}$. At iteration $t+1$, $(i,j)_{t*}$ won't satisfy at least one of the three conditions (i.e., (i) $U_{ij} = 0$, (ii) $V_i = 0$, and (iii) $V_j = 0$). Hence, the current incumbent solution is removed through (SVI-1), which satisfies the first condition to be supervalid. If the current incumbent solution $(\widehat{\boldsymbol{Z}}, \widehat{\boldsymbol{V}}, \widehat{\boldsymbol{U}})$ is optimal, (SVI-1) is supervalid by default. Let us assume that $(\widehat{\boldsymbol{Z}}, \widehat{\boldsymbol{V}}, \widehat{\boldsymbol{U}})$ with objective value $\widehat{H} \leq H_{LB}$ is not optimal and that an optimal solution $(\widetilde{\boldsymbol{Z}}, \widetilde{\boldsymbol{V}}, \widetilde{\boldsymbol{U}})$ with objective value $\widetilde{H} > H_{LB}$ exists. If no arc $(i,j) \in \bar{A}_t$ is added at iteration t, $\widetilde{H} \leq \widehat{H}$, since no additional protection has been provided; hence, $\widetilde{H} \leq \widehat{H} \leq H_{LB}$, which would be a contradiction. Hence, this satisfies also the second condition for (SVI-1) to be supervalid. □

The SVI decomposition algorithm stops when, due to budgetary limitations, the addition of further arcs causes the RMP to be unfeasible: this guarantees that the algorithm produces a solution in a finite numbers of steps. For completeness, the pseudo-code of the SVI decomposition algorithm is reported in Figure 5.

Algorithm1 ***SVI decomposition algorithm***

$\boldsymbol{H_{opt}} = -\infty, \widehat{\boldsymbol{Z}} \leftarrow \boldsymbol{0}, \boldsymbol{Z^{best}} \leftarrow \boldsymbol{0}$

  Do

    Solve $AP(\hat{Z}) to\ find\ \widehat{H}, \widehat{\boldsymbol{V}}, and\ \widehat{\boldsymbol{U}}$

      if $H_{opt} < \widehat{H}$ **then**

        $H_{opt} = \widehat{H}$ and $\boldsymbol{Z^{best}} \leftarrow \widehat{\boldsymbol{Z}}$

      end if

    Add $SVI(\widehat{\boldsymbol{V}}, \widehat{\boldsymbol{U}}) to\ RMP$

    Solve RMP

  while $RMP\ is\ feasible$

return $(\boldsymbol{Z^{best}}, U_{opt})$

Figure 5. Pseudo-code of the SVI decomposition algorithm

3.2.2 Heuristic approach (GCLS) for the CNDPF

The Greedy Constructive and Local Search heuristic is composed of two sequential phases: (1) a greedy constructive algorithm to obtain a first feasible solution; and (2) a local search where the neighbourhood of the current solution is explored in order to enhance the greedy constructive procedure and eventually find potential better solutions. In addition to AP($\widehat{\boldsymbol{Z}}$), the heuristic uses DP($\widehat{\boldsymbol{Z}}, \widehat{\boldsymbol{V}}$), which is the defender model and computes the system value (i.e., connectivity) for a given pair of protection and disruption plans ($\widehat{\boldsymbol{Z}}, \widehat{\boldsymbol{V}}$). DP($\widehat{\boldsymbol{Z}}, \widehat{\boldsymbol{V}}$) is defined as follows.

$$[\text{DP}(\widehat{\boldsymbol{Z}}, \widehat{\boldsymbol{V}})] \; z_{DP} = max \sum_{i \in N} \sum_{j \in N} U_{ij} \tag{30}$$

$$\text{s.t. } U_{ij} + \widehat{V}_i + \widehat{V}_j \geq 1 \qquad \forall\, (i,j) \in A \tag{31}$$

$$U_{ij} + \widehat{V}_i + \widehat{V}_j \geq 1 - M(1 - \hat{Z}_{ij}) \qquad \forall\, (i,j) \in \bar{A} \tag{32}$$

(23); (27)

3.2.2.1 Greedy constructive algorithm

This phase of GCLS aims at building a first feasible solution. This stage starts by identifying the importance of each network node according to the attacker. The importance of node $k \in N$, ρ_k, is defined as follows

$$\rho_k = \frac{OD(k)}{d_k}$$

where $OD(k)$ is the value of the *outdegree* of node k and d_k is the amount of resources needed to disrupt node k. ρ_k is used as a proxy to estimate the likelihood that node k will appear in an interdiction plan. Network nodes can then be ordered according to descending values of ρ_k, thus yielding a criticality ranking of all the network nodes. The choice of the outdegree to define a node importance is twofold. Firstly, the degree of a node is a connectivity-based metric commonly used to evaluate the centrality (i.e., the importance) of a node. Secondly, if we consider a directed network, it is not possible to talk about degree but either indegree or outdegree. Hence, given the context of communication infrastructures where the importance is to disseminate information, we opted for the outdegree rather than the indegree. However, when dealing with undirected networks, we will simply refer to the value of the degree.

To identify a first feasible defense strategy, it is necessary to devise an arc ranking. To this end, the following additional notation is introduced:

- a = index used for network arcs where $a = (i,j) \in \bar{A}$,
- $\widehat{\boldsymbol{Z}}_a$ = protection plan where only arc $a \in \bar{A}$ is added,
- $\widehat{\boldsymbol{V}}_k$ = disruption plan where only node $k \in N$ is interdicted.

Next we define an arc-node matrix whose rows are arcs $a \in \bar{A}$ and whose columns are nodes $k \in N$. The generic element $b_{a,k}$ of this matrix is DP($\widehat{\boldsymbol{Z}}_a$, $\widehat{\boldsymbol{V}}_k$), which is the value of the objective function of DP when arc $a \in \bar{A}$ is added and node $k \in N$ is interdicted. We then introduce a new parameter φ_a, for each arc $a \in \bar{A}$, defined as follows

$$\varphi_a = \frac{\sum_{k=1}^{|N|} b_{a,k} * \rho_k}{c_a}$$

where the numerator is divided by the cost required to install arc $a \in \bar{A}$ thus representing the network connectivity benefit per unit cost. Arcs are then ranked in descending order of φ_a (in the following we refer to φ_a as φ_{ij}).

A first feasible defense strategy can then be constructed. We introduce the following additional notation:

- $\overline{N}_t$ = set of non-disrupted nodes at each iteration t, defined as $N \backslash N_t$ where N_t is the set of the optimal disrupted nodes obtained by solving AP at each iteration t
- $\bar{A}_0$ = set $\bar{A}$ ordered by descending values of φ_{ij}
- $\bar{A}_t$ = subset of $\bar{A}$ at iteration t where arcs are ordered by descending values of φ_{ij} and (i, j) is such that $i, j \in \overline{N}_t$
- $\boldsymbol{Z}^{\boldsymbol{g}}$ = greedy protection plan
- C^g = cost of the greedy solution $\boldsymbol{Z}^{\boldsymbol{g}}$
- $found$ = boolean variable identifying if an arc to build the protection strategy has been found
- obj^g = objective value of AP corresponding to the greedy solution $\boldsymbol{Z}^{\boldsymbol{g}}$, i.e., $obj^g = AP(\boldsymbol{Z}^{\boldsymbol{g}})$

The greedy constructive (GC) procedure provides a first feasible protection plan by adding arcs ranked according to φ_{ij}. The procedure terminates when no more arcs can be added without violating the defender budget constraint. The pseudo-code of the GC procedure is reported in Figure 6.

Algorithm2 ***GC procedure***

$\boldsymbol{Z^g} \leftarrow \emptyset, C^g = 0$

$k = 0$

for $(i, j) \in \bar{A}_0$ **do**

$Z^g_{ij} = 1, C^g = C^g + c_{ij}$

if $k < r$

$k = k + 1$

end if

else exit for

end for

$found = true$

while $(found)$ **do**

Solve $AP(\boldsymbol{Z^g})$ to get z_{AP}

$found = false$

for $(i, j) \in \bar{A}_t$ **do**

if $C^g + c_{ij} \leq B$

$found = true, Z^g_{ij} = 1, C^g = C^g + c_{ij}, obj^g = z_{AP}$

if $found = false$

exit for

end if

end for

end while

return $(\boldsymbol{Z^g}, C^g, obj^g)$

Figure 6. Pseudo-code of the GC procedure

3.2.2.2 Local search

This phase of GCLS aims at exploring the neighbourhood of the solution obtained from the greedy constructive algorithm. Two swap policies have been identified that define the neighbourhood: a *one-to-one* swap policy (i.e., LS1: for one arc that is removed, only one arc is swapped in) and a *two-to-two* swap policy (i.e., LS2: for two arcs that are removed, only two arcs are swapped in). The following additional notation is introduced:

- $\bar{A}_{T-1} = \bar{A}_t$ where $t = T - 1$ and T is the last iteration of the greedy constructive algorithm
- $\boldsymbol{Z^{LS}}$ = local search protection plan
- C^{LS} = cost of the local search protection plan $\boldsymbol{Z^{LS}}$.

The local search (LS) procedure analyses the arcs that have been added in the current solution and tries to swap them out. To reduce the computational effort, only those arcs whose φ_{ij} is below a certain threshold φ_{MAX} are considered for the swap. The pseudo-code of the LS procedure implementing the one-to-one swap policy (i.e., LS1) is reported in Figure 7.

Algorithm3 *LS1*

$\boldsymbol{Z^{best}} \leftarrow \boldsymbol{Z^{g}}, C^{best} = C^{g}, obj_{best} = obj^{g}$

  $found\ = true$

  while $(found)$ **do**

    $found\ = false$

    for $(i,j) \in \bar{A}_{T-1}$ **do**

      $\boldsymbol{Z^{LS}} \leftarrow \boldsymbol{Z^{best}}, C^{LS} = C^{best}$

      if $Z_{ij}^{LS} == 1$ **and** $\varphi_{ij} < \varphi_{MAX}$ **then**

      $found = true, Z_{ij}^{LS} = 0$

      $swap1(0, C^{LS} - c_{ij})$

      if $found = false$

      exit for

      end if

    end for

  end while

return $\boldsymbol{Z^{best}}, obj_{best}$

Figure 7. Pseudo-code of the LS1 procedure

The routine $swap$ that appears in the LS examines all the possible combinations of arcs that can be swapped in. Each time a feasible move is identified, the objective value of the new corresponding solution is computed, which is accomplished by solving AP. A threshold φ_{MIN}, similar to φ_{MAX}, is used to reduce the computational effort. Only those arcs whose φ_{ij} is higher than φ_{MIN} are considered to be swapped in. The pseudo-codes of the $swap1$ procedure is reported in Figure 8. Similarly, the pseudo-code of the LS procedure implementing the two-to-two swap policy (i.e., LS2) and the pseudocode of the $swap2$ procedure are reported in Figure 9 and 10, respectively.

Algorithm4 *Swap1*

for $(i,j) \in \bar{A}_{T-1}$ **do**

if $Z_{ij}^{LS} == 0$ **and** $\varphi_{ij} > \varphi_{MIN}$ **and** $C^{LS} + c_{ij} \leq B$ **then**

$Z_{ij}^{LS} = 1$

$Solve\ AP(\boldsymbol{Z^{LS}})$ to get z_{AP}

if $z_{AP} > obj_{best}$ **then**

$\boldsymbol{Z^{best}} \leftarrow \boldsymbol{Z^{LS}}, C^{best} = C^{LS} + c_{ij}, obj_{best} = z_{AP}$

end if

$C^{LS} = C^{LS} + c_{ij}$

$swap1((i,j), C^{LS})$

end if

end for

Figure 8. Pseudo-code for the swap1 procedure

Algorithm5 *LS2*

$\boldsymbol{Z^{best}} \leftarrow \boldsymbol{Z^{g}}, C^{best} = C^{g}, obj_{best} = obj^{g}$

$found\ = true$

while $(found)$ **do**

$found\ = false$

for $(i,j) \in \bar{A}_{T-1}$ **do**

for $(k,l) \in \bar{A}_{T-1}$ **do**

$\boldsymbol{Z^{LS}} \leftarrow \boldsymbol{Z^{best}}, C^{LS} = C^{best}$

if $(Z_{ij}^{LS} == 1$ **and** $\varphi_{ij} < \varphi_{MAX})$ **and** $(Z_{kl}^{LS} == 1$ **and** $\varphi_{kl} < \varphi_{MAX})$ **then**

$found = true, Z_{ij}^{LS} = 0, Z_{kl}^{LS} = 0$

$swap2(0, C^{LS} - c_{ij} - c_{kl})$

if $found = false$

exit for

end if

end for

end for

end while

return $\boldsymbol{Z^{best}}, obj_{best}$

Figure 9. Pseudo-code for the LS2 procedure

Algorithm6 *Swap2*

for $(i,j) \in \bar{A}_{T-1}$ **do**

for $(k,l) \in \bar{A}_{T-1}$ **do**

if $(Z_{ij}^{LS} == 0$ **and** $\varphi_{ij} > \varphi_{MIN}$ **and** $C^{LS} + c_{ij} \leq B)$ **and** $(Z_{kl}^{LS} == 0$ **and** $\varphi_{kl} > \varphi_{MIN}$ **and** $C^{LS} + c_{kl} \leq B)$ **then**

$Z_{ij}^{LS} = 1$ **and** $Z_{kl}^{LS} = 1$

$Solve\ AP(\boldsymbol{Z^{LS}})$ to get z_{AP}

if $z_{AP} > obj_{best}$ **then**

$\boldsymbol{Z^{best}} \leftarrow \boldsymbol{Z^{LS}}, C^{best} = C^{LS} + c_{ij} + c_{kl}, obj_{best} = z_{AP}$

end if

$C^{LS} = C^{LS} + c_{ij} + c_{kl}$

$swap2((i,j),(k,l),C^{LS})$

end if

end for

end for

Figure 10. Pseudo-code for the swap2 procedure

3.3 Experimental Results

In this section, the two solution methodologies (i.e., SVI and GCLS) are tested and compared on real telecommunication networks. Two real networks belonging to the Sterbenz et al. (2010b) repository, which contains different kinds of real telecommunication networks such as national computer, global-scale optical, and international wide-area networks, have been considered for experimentation. Table 2 summarizes the main topological properties of the selected networks, which are undirected: network name (*NETWORK*); number of nodes ($|N|$); number of arcs ($|A|$); minimum, average, and maximum node degree (*MINDEG*, *AVGDEG*, and *MAXDEG*, respectively); and minimum, average, and maximum geographical distance (*MINDIST*, *AVGDIST*, and *MAXDIST*, respectively) measured in kilometers.

Table 2. Summary of the topological features of the case study networks

Network	|N|	|A|	MINDIST	AVGDIST	MAXDIST	MINDEG	AVGDEG	MAXDEG
HiberniaCanada	10	20	22.2	139	364	1	2	3
GtsRomania	19	44	1.2	22.2	50	1	2.32	11

3.3.1 Model parameters settings

The model parameters are generated as follows:

1. The amount of resources needed to disrupt node $k \in N$, d_k, depends on its degree, $DEG(k)$. This assumption is based on the fact that the higher the node degree, the more important the node itself which, consequently, requires more resources to be interdicted (Motter 2004; Yehezkel and Cohen 2012; Lu and Li 2016). Namely, network nodes have been classified in three degree-based categories such as *low*, *medium*, and *high* importance nodes which, respectively, require 2, 4, and 6 units of disruption resources to be fully interdicted. Categories have been identified as follows: low importance nodes are those for which $DEG(k) \in [MINDEG; AVGDEG - (AVGDEG/4)[$; medium importance nodes are those for which $DEG(k) \in [AVGDEG - (AVGDEG/4); AVGDEG + (AVGDEG/4)[$; and high importance nodes are those for which $DEG(k) \in [AVGDEG + (AVGDEG/4); MAXDEG[$. As such, d_k is a non-decreasing step-function of $DEG(k)$.
2. The amount of resources needed to install arc $(i,j) \in \bar{A}$, c_{ij}, depends on its length, $DIST(i,j)$. This assumption is because the bigger the distance among nodes, the more expensive the installation of the arc connecting them (Kahng, Liu and Măandoiu 2002). Namely, potential arcs have been classified in three length-based categories such as *small*, *medium*, and *large* length arcs which, respectively, require 2, 4, and 6 units of the defender budget to be installed. Categories have been identified as follows: small length arcs are those for which $DIST(i,j) \in [MINDIST; AVGDIST - (AVGDIST/2)[$; average length arcs are those for which $DIST(i,j) \in [AVGDIST - (AVGDIST/2); AVGDIST + (AVGDIST/2)[$; and large length arcs are those for which $DIST(i,j) \in [AVGDIST + (AVGDIST/2); MAXDIST[$. As such, c_{ij} is a non-decreasing step-function of $DIST(i,j)$.
3. The interdictor budget, D, is defined as a percentage of P, which is the sum of the resources needed to disrupt all network nodes (i.e., $P = \sum_{k=1}^{|N|} d_k$). Hence, $D = \alpha_1 P$. In our experiments α_1 assumes the following values: 0.05, 0.10, 0.15, 0.20, 0.25, and 0.30. To guarantee D integrality, it has been rounded up to the nearest integer value.
4. The defender budget, B, is defined as a percentage of Q, which is the sum of the costs of all the arcs that can be potentially installed (i.e., $Q = \sum_{(i,j)\in\bar{A}} c_{ij}$). Hence, $B = \alpha_2 Q$ where α_2 assumes the following values: 0.01, 0.02, 0.03, 0.04, and 0.05. To guarantee B integrality, it has been rounded up to the nearest integer value.

3.3.2 Solution methodologies settings

Both SVI and GCLS approaches are implemented using CPLEX 12.6.2 embedded in a C++ program (i.e., CPLEX Callable Libraries deployed through Microsoft Visual Studio Professional 2012). Experiments have been run on a computer with an Intel® Core™ i5-5200U CPU @ 2.20GHz and 8.00 GB of RAM. The SVI algorithm uses CPLEX default parameters while the GCLS parameters have been chosen empirically after a calibration phase. With reference to the greedy construction algorithm, the values of r (i.e., the number of elements to initialize the greedy solution $\boldsymbol{Z^g}$), which depend on both network size (i.e., $|N|$, $|A|$) and defender budget (i.e., B), are chosen as displayed in Table 3.

Table 3. Values of r for different combination of networks and protection budget

	Network	
B	HiberniaCanada	GtsRomania
0.01	2	2
0.02	2	4
0.03	4	4
0.04	4	6
0.05	4	8

The settings of the local search parameters are as follows:

- $\varphi_{MIN} = \left\lfloor max(\varphi_{ij}) - \frac{average(\varphi_{ij})}{4} \right\rfloor$;
- $\varphi_{MAX} = \lceil max(\varphi_{ij}) \rceil$.

3.3.3 HiberniaCanada network results

The HiberniaCanada network is composed of 10 nodes and 20 arcs and connects several points between Canada and US. Table 4 shows the names of the locations corresponding to each node while Figure 11 displays the network itself.

Table 4. HiberniaCanada network – Node details

Network node	Place
1	New York
2	Moncton
3	Edmundston
4	Quebec
5	Montreal
6	Toronto
7	Buffalo
8	Albany
9	Boston Bar
10	Halifax

Figure 11. Hibernia Canada network (adapted from Google Maps)

The SVI algorithm was able to solve all the instances within the given CPU time threshold, in particular, given the reduced dimensions of the HiberniaCanada network, instances were solved in a matter of a few seconds. Table 5 and Table 6 report the objective function values and the CPU time values, respectively, for all the possible combination of α_1 (i.e., interdiction budget) and α_2 (i.e., protection budget) and for the two solution approaches (i.e., SVI decomposition algorithm and GCLS1). Due to the reduced dimensions of the HiberniaCanada network, as it can be appreciated from Figure 11, GCLS2 has not been tested.

Table 5. HiberniaCanada network results – Objective function values

Objective Function												
	α2 = 0.00		α2 = 0.01		α2 = 0.02		α2 = 0.03		α2 = 0.04		α2 = 0.05	
α_1	SVI	GCLS1	SVI	GCLS1	SVI	GCLS1	SVI	GCLS1	SVI	GCLS1	SVI	GCLS1
0.05	72	72	72	72	72	72	72	72	72	72	72	72
0.1	36	36	36	36	56	56	56	56	56	56	56	56
0.15	26	26	26	26	42	42	42	42	42	42	42	42
0.2	18	18	18	18	30	30	32	32	42	42	42	42
0.25	14	14	14	14	18	18	22	22	26	26	26	26
0.3	10	10	10	10	12	12	14	14	16	16	16	16
AVG	29.33	29.33	29.33	29.33	38.33	38.33	39.67	39.67	42.33	42.33	42.33	42.33

Table 6. HiberniaCanada network results – CPU time values

CPU Time												
	α2 = 0.00		α2 = 0.01		α2 = 0.02		α2 = 0.03		α2 = 0.04		α2 = 0.05	
α_1	SVI	GCLS1	SVI	GCLS1	SVI	GCLS1	SVI	GCLS1	SVI	GCLS1	SVI	GCLS1
0.05	0.1	0.0	0.1	0.0	0.1	0.3	0.1	0.4	0.1	0.6	0.2	0.6
0.1	0.2	0.0	0.2	0.0	0.4	0.6	0.4	1.1	0.3	1.4	0.2	1.4
0.15	0.3	0.1	0.3	0.1	0.9	0.6	0.5	1.4	1.1	1.4	1.7	2.1
0.2	0.2	0.1	0.2	0.1	1.1	0.8	1.7	1.6	1.8	1.2	2.3	2.3
0.25	0.1	0.1	0.1	0.1	0.7	1.0	2.1	2.8	3.7	1.7	4.1	2.7
0.3	0.2	0.1	0.2	0.1	0.7	0.9	1.8	2.0	2.3	1.7	2.2	2.1
AVG	0.2	0.1	0.2	0.1	0.7	0.7	1.1	1.5	1.6	1.3	1.8	1.9

Several observations can be drawn from the analysis of Table 5. Results are first commented based on the outcome of the SVI algorithm. For example, for α_1 = 0.1, when α_2 rises from 0.01 to 0.02, the value of network connectivity improves by around 56% (from 36 to 56). Similarly, for α_1 = 0.15, when α_2 increases from 0.01 to 0.02, the value of network connectivity improves by around 62% (from 26 to 42). Further examples where, for a fixed interdiction budget level, an improvement in network connectivity can be appreciated across different levels of protection resources are described as follows:

- for α_1 = 0.2, the value of network connectivity increases by nearly 67% (from 18 to 30), 78% (from 18 to 32), and 133% (from 18 to 42) when α_2 rises from 0.01 to 0.02, 0.03, and 0.04, respectively;
- for α_1 = 0.25, the value of network connectivity improves by around 29% (from 14 to 18), 57% (from 14 to 22), and 86% (from 14 to 26) when α_2 rises from 0.01 to 0.02, 0.03, and 0.04, respectively;
- for α_1 = 0.3, the value of network connectivity increases by nearly 20% (from 10 to 12), 40% (from 10 to 14), and 60% (from 10 to 16) when α_2 rises from 0.01 to 0.02, 0.03, and 0.04, respectively.

The same results can be appreciated from the application of GCLS1. Further observations can be drawn from a computational perspective. From the analysis of Table 6, looking at specific single instances, it can be said that SVI and GCLS1 have comparable CPU times (i.e., matter of a few seconds) and, in majority of the cases, SVI solve instances to optimality faster than GCLS1 however, there are some cases where GCLS1 is faster than SVI.

Figure 12 displays the value of network connectivity for each interdiction budget level across the different levels of protection resources (results are reported based on the SVI decomposition algorithm).

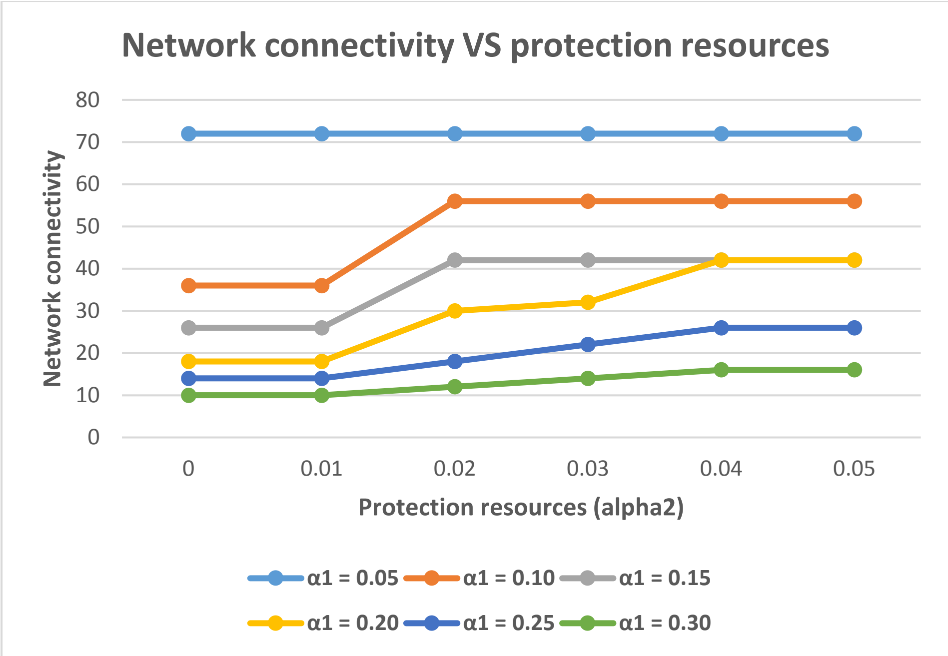

Figure 12. HiberniaCanada network results – Network connectivity VS protection resources

Figure 12 allows to appreciate the importance of deploying protection resources to increase network connectivity under disruptive circumstances. In fact, in absence of any kind of protection (i.e., α_2 = 0), the higher the interdiction budget level, the higher the loss in network connectivity. In particular, network connectivity drops by around 50% (from 72 to 36), 64% (from 72 to 26), 75% (from 72 to 18), 81% (from 72 to 14), and 86% (from 72 to 10) when α_1 raises from 0.05 to 0.1, 0.15, 0.2, 0.25, and 0.3, respectively. However, it can be observed that an investment of 2% of the total protection budget already allows to improve network connectivity. In fact, if solutions are compared for α_2 = 0 and α_2 = 0.02, there is an increase in network connectivity by around 56% (from 36 to 56), 62% (from 26 to 42), 67% (from 18 to 30), 29% (from 14 to 18), and 20% (from 10 to 12) when α_1 is equal to 0.1, 0.15, 0.2, 0.25, and 0.3, respectively. Further improvements can be appreciated for higher amounts of protection resources.

Overall, in the specific case of the HiberniaCanada network, it can be stated that the SVI performs best, in terms of both objective function values and CPU time values however, in the absence of this exact method, GCLS1 is able to find the optimal solution for each problem instance with CPU times comparable to those of SVI. Hence, GCLS1 seems to be a promising heuristic method.

3.3.4 GtsRomania network results

The GtsRomania network is composed of 19 nodes and 44 arcs and connects several points within Romania. Table 7 shows the names of the locations corresponding to each node while Figure 13 displays the network itself.

Table 7. GtsRomania network – Node details

Network node	Place
1	Craiova
2	Plaiesti
3	Brasov
4	Targoviste
5	Constanta
6	Bucarest
7	Galati
8	Focsani
9	Targu,Mures
10	Timisoara
11	Sibiu
12	Iasi
13	Piatra,Neamt
14	Bacau
15	Deva
16	Cluj
17	Oradea
18	Bors
19	Arad

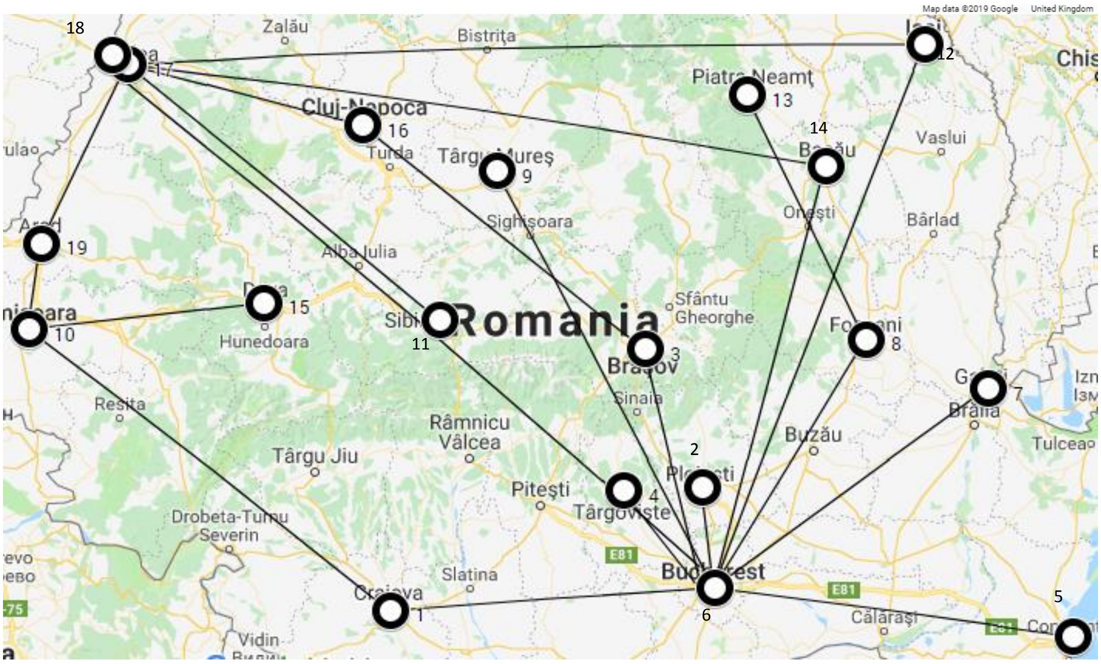

Figure 13. GtsRomania network (adapted from Google Maps)

The SVI algorithm was not able to solve all the instances within the given CPU time threshold set equal to 28800 seconds (i.e., 8 hours), while GCLS1 and GCLS2 were able to obtain a solution in fewer time, and in particular, GCLS2 was able to match the solution found by SVI in 8 hours in matters of minutes. Given the larger network dimensions, compared to those of the HiberniaCanada, an upper bound on the max number of iterations was set for both GCLS1 and GCLS2. This upper bound (i.e, *MAXITER*) has been identified based on combinations of α_1 and α_2. Table 8 and Table 9 reports the objective function values and the CPU time values, respectively, for all the possible combinations of α_1 and α_2 and for the three solution approaches (SVI, GCLS1, and GCLS2), respectively. Given that the GtsRomania network is larger than the HiberniaCanada network, also GCLS2 has been tested.

Table 8. GtsRomania network results – Objective function values

	Objective Function																	
	α2 = 0.00			α2 = 0.01			α2 = 0.02			α2 = 0.03			α2 = 0.04			α2 = 0.05		
α_1	SVI	GCLS1	GCLS2	SVI	GCLS1	GCLS2	SVI	GCLS1	GCLS2	SVI	GCLS1	GCLS2	SVI	GCLS1	GCLS2	SVI	GCLS1	GCLS2
0.05	272	272	272	272	272	272	272	272	272	272	272	272	272	272	272	272	272	272
0.1	112	112	112	210	210	210	240	240	240	240	240	240	240	240	240	240	240	240
0.15	50	50	50	116	116	116	182	162	182	182	182	182	182	182	182	182	182	182
0.2	16	16	16	72	72	72	132	110	132	138	134	134	156	156	156	156	156	156
0.25	8	8	8	24	24	22	42	42	42	58	62	62	72	78	78	76	78	78
0.3	2	2	2	10	10	10	20	20	20	28	24	28	32	30	32	48	32	32
AVG	76.7	76.7	76.7	117.3	117.3	117.0	148.0	141.0	148.0	153.0	152.3	153.0	159.0	159.7	160.0	162.3	160.0	160.0

Table 9. GtsRomania network results – CPU time values

	CPU Time																	
	α2 = 0.00			α2 = 0.01			α2 = 0.02			α2 = 0.03			α2 = 0.04			α2 = 0.05		
α_1	SVI	GCLS1	GCLS2	SVI	GCLS1	GCLS2	SVI	GCLS1	GCLS2	SVI	GCLS1	GCLS2	SVI	GCLS1	GCLS2	SVI	GCLS1	GCLS2
0.05	1.1	0.6	0.6	1.5	29.8	81.4	1.0	47.6	272.3	0.8	46.8	15.6	0.9	38.8	16.7	1.1	21.7	24.3
0.1	1.1	0.7	0.7	67.0	22.2	166.7	46.5	61.4	604.7	10.0	110.7	26.8	9.3	98.9	26.5	11.0	21.7	147.3
0.15	0.9	0.5	0.5	137.1	35.3	219.3	958.1	30.9	711.6	954.8	107.4	60.0	351.7	108.4	165.8	123.7	36.3	148.4
0.2	0.8	0.2	0.2	517.5	22.6	273.6	28800*	24.6	406.8	28800*	64.9	806.3	9326.4	67.9	1572.5	905.8	30.5	171.1
0.25	0.6	0.2	0.2	183.5	39.3	229.8	28800*	53.9	756.8	28800*	38.9	836.6	28800*	43.0	1167.5	28800*	17.3	142.6
0.3	0.6	0.1	0.1	79.6	18.3	265.6	20236.6	54.3	692.0	28800*	27.6	575.9	28800*	31.1	771.4	28800*	26.5	148.2
AVG	0.8	0.4	0.4	164.4	27.9	206.1	13140.4	45.4	574.0	14560.9	66.0	386.9	11214.7	64.7	620.1	9773.6	25.7	130.3

Legend: * = not solved to optimality within the pre-fixed time limit of 28800 seconds

Several observations can be drawn from the analysis of Table 8. Results are first commented based on the outcome of the SVI algorithm. Examples where, for a fixed interdiction budget level, an improvement in network connectivity can be appreciated across different levels of protection resources are described as follows:

- for α_1 = 0.1, the value of network connectivity increases by nearly 88% (from 112 to 210) and 114% (from 112 to 240) when α_2 rises from 0 to 0.01, and 0.02, respectively;
- for α_1 = 0.15, the value of network connectivity improves by around 132% (from 50 to 116) and 264% (from 50 to 182) when α_2 increases from 0 to 0.01, and 0.02, respectively;
- for α_1 = 0.2, the value of network connectivity increases by nearly 350% (from 16 to 72), 725% (from 16 to 132), 763% (from 16 to 138), and 875% (from 16 to 156) when α_2 rises from 0 to 0.01, 0.02, 0.03, and 0.04, respectively;
- for α_1 = 0.25, the value of network connectivity improves by around 200% (from 8 to 24), 425% (from 8 to 42), 625% (from 8 to 58), 800% (from 8 to 72), and 850% (from 8 to 76) when α_2 increases from 0 to 0.01 0.02, 0.03, 0.04, and 0.05, respectively;
- for α_1 = 0.3, the value of network connectivity increases by nearly 400% (from 2 to 10), 900% (from 2 to 20), 1300% (from 2 to 28), 1500% (from 2 to 32)and 2300% (from 2 to 48), when α_2 rises from 0 to 0.01 0.02, 0.03, 0.04, and 0.05, respectively.

Slightly different results can be observed from the application of GCLS1 and GCLS2. Specifically, GCLS1 is not able to obtain the same objective value returned by SVI in 9 cases out of 36 (i.e., for α_2 = 0.02, when α_1 = 0.15 and 0.2; for α_2 = 0.03, when α_1 = 0.2, 0.25 and 0.3; and for α_2 = 0.04 and 0.05, when α_1 = 0.25 and 0.3), while GCLS2 fails to do so in three cases (i.e., for α_2 = 0.01, when α_1 = 0.25; for α_2 = 0.03, when α_1 = 0.2; and for α_2 = 0.05, when α_1 = 0.3). Figure 14 displays the value of network connectivity for each interdiction budget level across the different levels of protection resources (results are reported based on the SVI decomposition algorithm).

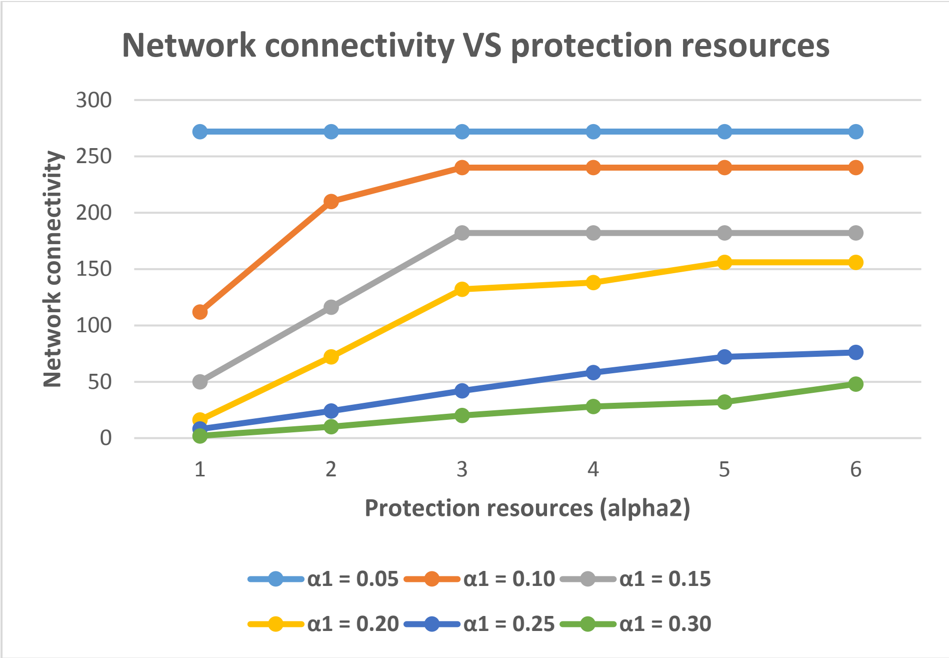

Figure 14. GtsRomania network results – Network connectivity VS protection resources

Figure 14 allows to appreciate the importance of deploying protection resources to increase network connectivity under disruptive circumstances. In fact, in absence of any kind of protection (i.e., α_2 = 0), the higher the interdiction budget level, the higher the loss in network connectivity. In particular, network connectivity drops by around 59% (from 272 to 112), 82% (from 272 to 50), 94% (from 272 to 16), 97% (from 272 to 8), and 99% (from 272 to 2) when α_1 raises from 0.05 to 0.1, 0.15, 0.2, 0.25, and 0.3, respectively. However, it can be observed that an investment of 1% of the total protection budget already allows to improve network connectivity. In fact, if solutions are compared for α_2 = 0 and α_2 = 0.01, there is an increase in network connectivity by around 88% (from 112 to 210), 132% (from 50 to 116), 350% (from 16 to 72), 200% (from 8 to 24), and 400% (from 2 to 10) when α_1 is equal to 0.1, 0.15, 0.2, 0.25, and 0.3, respectively. Further improvements can be appreciated for higher amounts of protection resources.

From the analysis of Table 9, it seems that GCLS2 performs better than GCLS1. In particular, despite for "simple instances" (i.e., α_1 = 0.05 and 0.10 whichever α_2 is) GCLS2 finds the same objective function value of SVI but in longer time, when it comes to instances that have not been solved to optimality, GCLS2 is able to match the objective function value found by SVI in matter of minutes. On the other side, GCLS1 looks inefficient. Although sometimes it matches the objective function values by SVI even in shorter time than GCLS2, the number of instances whose objective function value does not match the one of SVI is higher as well as the gap between the obtained solutions (as it can be observed from Table 8). Figure 15 displays the interdiction budget level-average values of CPU time across different level of protection resources for the three solution approaches (these figures are explicitly reported in correspondence of row *AVG* of Table 9).

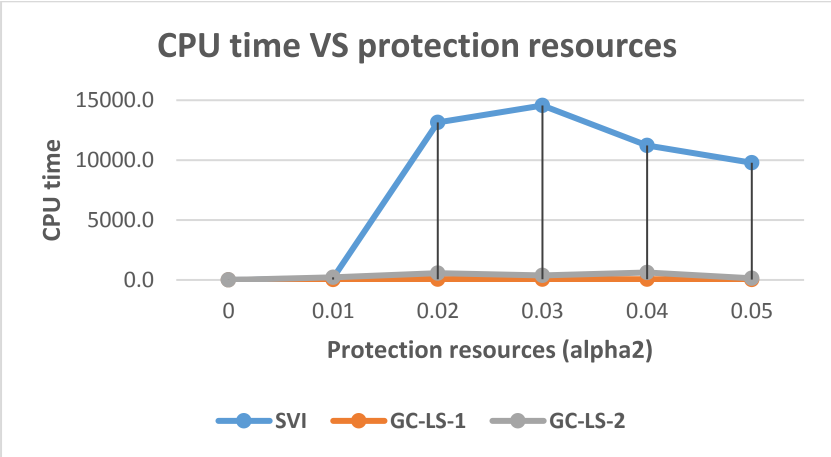

Figure 15. GtsRomania network results – CPU time VS protection resources

Figure 15 reports that, on average, for α_2 = 0.02, 0.03, 0.04, and 0.05, GCLS1 (in orange) and GCLS2 (in grey) are faster than SVI (blue), in fact, the three solution methods require: 45, 574 and 13140.4 seconds when α_2 = 0.02; 66, 386.9, and 14560.9 seconds when α_2 = 0.03; 64.7, 620.1 and 11241.7 seconds when α_2 = 0.04; and 25.7, 130.3, and 9773.6 seconds when α_2 = 0.05, respectively.

Overall, in the specific case of the GtsRomania network, it can be stated that the SVI finds difficulties in closing many instances hence, the need for a heuristic approach is more evident. In particular, GCLS2 performs better than GCLS1 in terms of objective function values, while the inverse phenomenon can be observed when it comes to computational performance. However, based on the obtained results, GCLS2 seems like the most promising method to solve larger instances.

Finally, in order to provide an idea on how, for a fixed interdiction budget level, different solutions (in terms of network connectivity, disrupted nodes and added arcs) are obtained in correspondence of different amount of protection resources, Figure 16, 17, and 18 report the solutions obtained for the GtsRomania network through the application of the SVI algorithm when α_1 = 0.20 and α_2 = 0.01, 0.03, and 0.05, respectively.

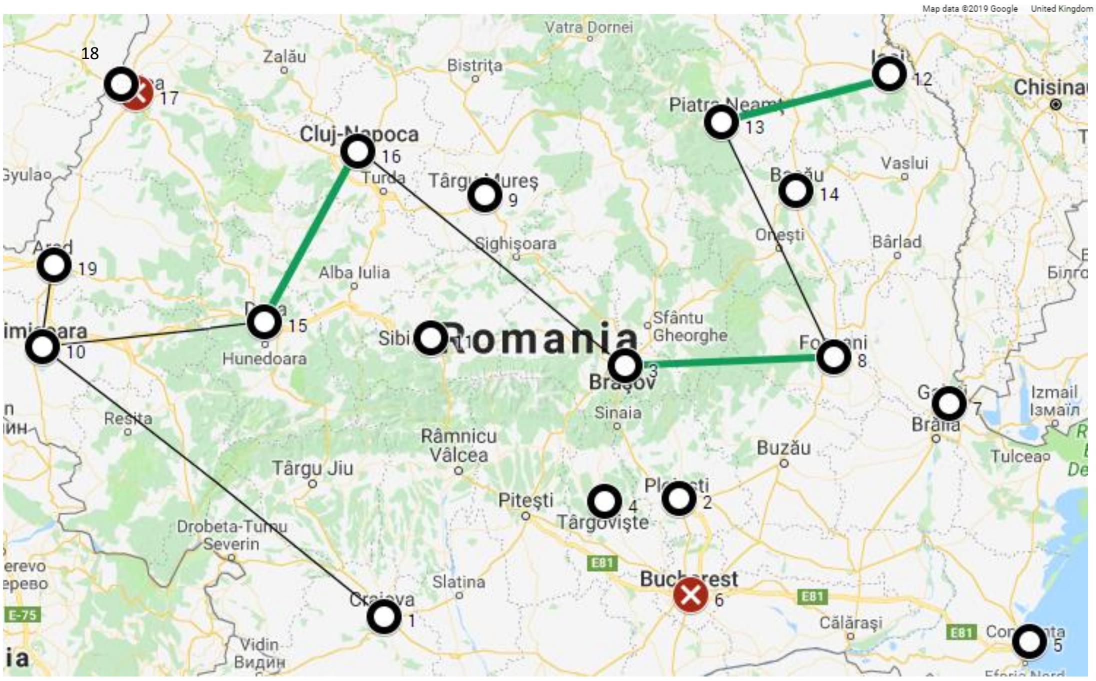

Figure 16. GtsRomania network results - CNDPF solution for α_1 = 0.20 and α_2 = 0.01

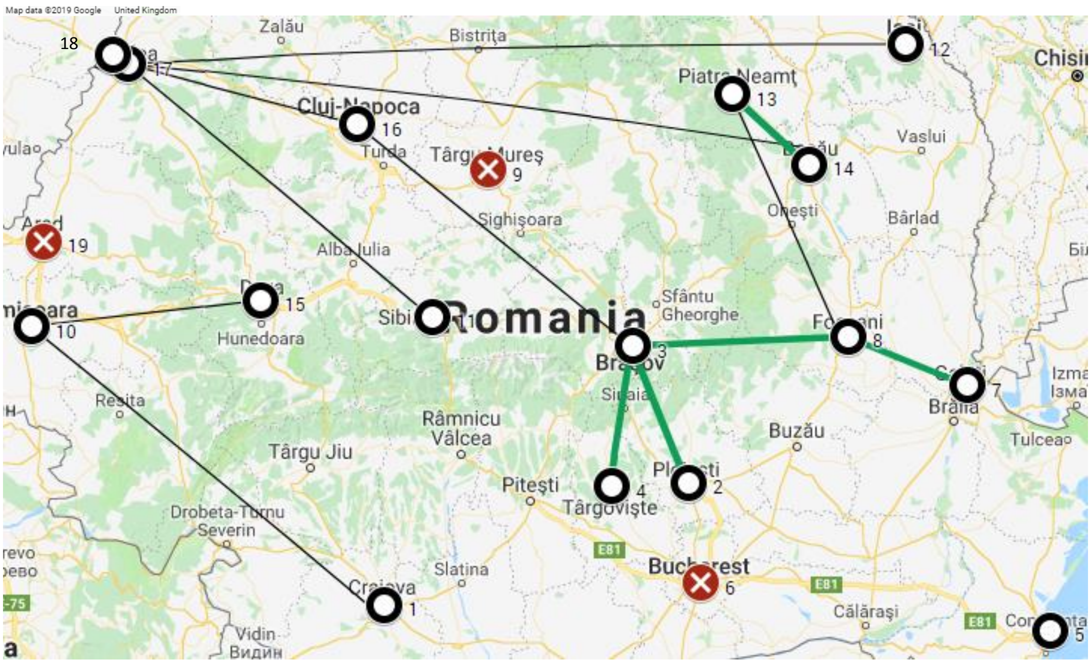

Figure 17. GtsRomania network results - CNDPF solution for α_1 = 0.20 and α_2 = 0.03

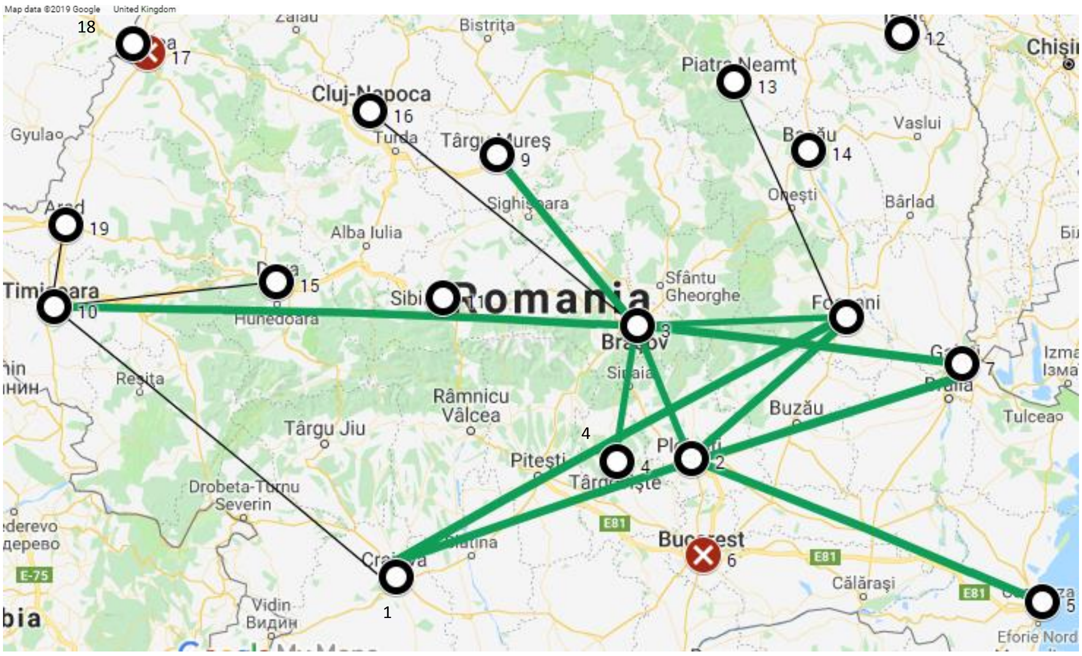

Figure 18. GtsRomania network results - CNDPF solution for α_1 = 0.20 and α_2 = 0.05

Network nodes and arcs are identified with black round shapes and black straight lines, respectively, while network nodes that have been disrupted and arcs that have been added are represented by red crossed round shapes and green straight lines, respectively. From the combined analysis of Figure 16, 17, and 18, it can be observed that different nodes have been disrupted in the three reported solution: 6 and 17 in Figure 16 and 18 while 6, 9 and 19 in Figure 17. The disruption of different nodes is paired with different arcs being selected for addition: (3,8), (12,13), and (15,16) in Figure 16; (2,3), (3,4), (3,8), (7,8), (8,19), (9,16), and (13,14) in Figure 17; and (1,7), (1,8), (2,3), (2,4), (2,5), (2,8), (3,4), (3,7), (3,9), and (3,10) in Figure 18. Also, given that more protection resources correspond to more arcs that can be added, this has led to appreciate an increase in network connectivity from 72 (α_1 = 0.20 and α_2 = 0.01, Figure 16) to 138 (α_1 = 0.20 and α_2 = 0.03, Figure 17) to 156 (α_1 = 0.20 and α_2 = 0.05, Figure 18).

3.4 Conclusions

This chapter has introduced a novel bi-level program (CNDPF) to optimize CII protection by integrating network vulnerability assessment, resource allocation strategies and design operations. To the best of my knowledge, this is the first bi-level program devised for CIIP. In particular, the upper level models the infrastructure owner whose objective is to maximize the network connectivity, resulting from worst-case disruptions due to a generic interdictor modelled at the lower level, by increasing system redundancy through the installation of additional arcs. CNDPF differs significantly from bi-level programs that have been developed for other kinds of CI. As a matter of fact, different infrastructures yield to different targets to be considered. For example, while a railway system aims at maximizing the amount of passenger flow despite malicious attacks, telecommunications networks prioritize network connectivity so as to guarantee its basic functioning. From a modelling perspective, differences can also be appreciated in terms of adopted constraints: while bi-level programs for railway infrastructure protection entail flow conservation and/or shortest path constraints, CNDPF accounts for connectivity conservation constraints. The CNDPF has been solved through a SVI decomposition approach and a heuristic approach (GCLS). In particular, the heuristic approach has been tested according to two different swap policies thus yielding to two different algorithms (GCLS1 and GCLS2). Computational results have been reported for real communication networks and for different levels of both disaster magnitude and protection resources. Experimentation has proven that SVI is a quite successful exact method however, it can encounter difficulties when problem dimensions increase, which motivates the need to develop an alternative (or auxiliary) heuristic approach. GCLS1 has proven to be more successful on a small network while GCLS2 has proven to perform better on a larger network. Nevertheless, results have reported that a reasonable expenditure of protection resources can yield to a significant improvement in the network connectivity.

However, CNDPF is not exempt from limitations based on its underpinning assumptions. For example, CNDPF is a deterministic model because assumes that both interdiction (i.e., how costly to disrupt a node is) and protection (i.e., how costly to build an additional arc is) resources are known. However, both interdiction and protection resources could be uncertain and based on the probability of success of the attack/defense strategy thus requiring a stochastic programming formulation. Another assumption that could be revised and lead to different models is the one related to the adopted objective function. In fact, currently, the defender aims at maximizing the network connectivity while minimizing the damage inflicted by the attacker. Nevertheless, the objective of the defender could be to minimize the protection investment expenditure while guaranteeing a minimum connectivity threshold. Hence, despite the successful and encouraging results so far obtained, enhancements of CNDPF from a modeling perspective could be considered.

4 Optimizing shelter location and evacuation routing operations: the critical issues

This chapter focuses on two specific operations of the DOM response phase: *shelter location* and *evacuation routing*. Specifically, this chapter aims at identifying the central issues that should be addressed in a comprehensive shelter location/evacuation routing model. This is achieved by: (1) analysing existing DM surveys, (2) reviewing optimization models tackling shelter location and evacuation routing operations, either separately or in an integrated manner, (3) performing a critical analysis of existing papers combining shelter location and evacuation routing, concurrently with the responses of their authors, and (4) comparing the findings of the analysis of the papers (i.e., (3)) with the findings of the existing DM surveys (i.e., (1)). The chapter concludes with a discussion on the emergent challenges of shelter location and evacuation routing in optimization and outlines a roadmap for future research.

4.1 Analysis of existing Disaster Management surveys

Operations Research, and optimization in particular, has been applied to DM 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 optimization techniques as reported in the surveys by (Simpson and Hancock 2009; Caunhye, Nie and Pokharel 2012; Galindo and Batta 2013; Hoyos, Morales and Akhavan-Tabatabaei 2015; Özdamar and Ertem 2015; Bayram 2016). In the following, these seven surveys are briefly reviewed, which deal with either DM 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. The 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. 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) are also excluded. The seven surveys are reviewed in chronological order. A summary of the main issues can be found in Table 10.

Table 10. 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 DM	**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)	Optimization for emergency logistics	**Outlets**: TRE, EJOR, MS (mostly) **Timeframe**: 1976-2011	Review of optimization 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 behavior
Galindo and Batta (2013)	OR/MS applied to DM	**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

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.

Table 10. Survey Review Summary (Continued)

Survey	Research Area	Journal Outlets and Timeframe	State-of-the-art	Future Research Directions
Hoyos, Morales and Akhavan-Tabatabaei (2015)	OR applied to DM	**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 optimization 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)	Optimization models for large scale evacuation planning	**Outlets**: OR/MS, DM, behavioral sciences, and engineering-based outlets; models mostly from TRB **Timeframe**: 1952-2016	Review on traffic assignment models, evacuation modelling, and behavioral studies	Inclusion of human behavior 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.

Altay and Green (2006) provide a literature survey of OR/MS applied to DM 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 optimization 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: optimization 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. Optimization 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 behavior in post-disaster environments need to be addressed, for example by using robust optimization 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 DM 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 optimization 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 DM 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 behavior 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 optimization models more realistic and implementable. These include: better modelling of human behavior; 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.

4.2 Optimization for shelter location and evacuation routing

Within the DM context, optimization 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. 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 19.

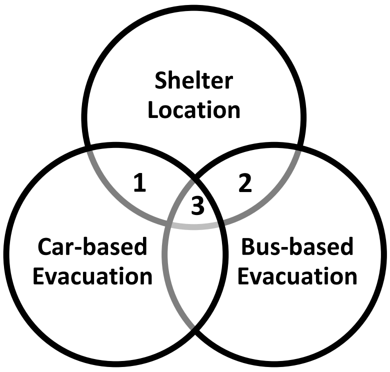

Figure 19. Combination of shelter location and evacuation routing problems

As noted in (Caunhye, Nie and Pokharel 2012), only a few optimization 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 19). 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 optimization model and they apply it to the Logan network, Utah (USA).

Alçada-Almeida et al. (2009) develop a multi-objective optimization model for fire disasters. The objectives to be minimized are: (1) total traveling 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 optimization 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 behavior. The authors apply the proposed optimization 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 (problem categories 2 and 3, Figure 19). An in-depth analysis of recent combined shelter location and evacuation routing models developed from 2012 onwards is subject of investigation and will be discussed next.

4.3 Emergent challenges in optimizing shelter location and evacuation routing

In this section, a brief overview of all the existing recent articles, which will be referred to as case studies, is provided. A structured analysis of the case studies will be then presented, which also includes a discussion of the responses of the authors to an ad-hoc questionnaire.

4.3.1 Case studies overview

The 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 optimizing the location decisions and including two additional criteria in the objective function. The objectives to be minimized are: (1) total traveling 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 traveling 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 optimization 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 behavior 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 my knowledge, this is the only paper to address shelter location, car-, and bus-based evacuation into a combined optimization model, called the Comprehensive Evacuation Problem (CEP). 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 optimization 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 optimization 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 traveling 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 optimizing 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 method. Results are presented for both test and realistic case studies, such as the Istanbul European and Istanbul Anatolian networks under earthquake circumstances.

Table 11 briefly summarises the main features of shelter location, car-based evacuation, bus-based evacuation as separate problems as well as shelter location and car-based evacuation, shelter location and bus-based evacuation and shelter location together with both car-based and bus-based evacuations as combined problems in terms of objectives, constraints and case studies.

Table 11. Features of shelter location, car-based evacuation, bus-based evacuation as separate problems as well as shelter location and car-based evacuation, shelter location and bus-based evacuation and shelter location together with both car-based and bus-based evacuation as combined problems

Problem	Objectives	Constraints	Case Studies
Shelter Location	Total Evacuation Time (Sherali, Carter and Hobeika 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, Carter and Hobeika 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, Carter and Hobeika 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 Traveling 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; Goerigk, Deghdak and T'Kindt 2015) Bushfire (Shahparvari et al. 2017; Shahparvari, Abbasi and Chhetri 2017; Shahparvari and Abbasi 2017)

Table 11. Features of shelter location, car-based evacuation, bus-based evacuation as separate problems as well as shelter location and car-based evacuation, shelter location and bus-based evacuation and shelter location together with both car-based and bus-based evacuation as combined problems (Continued)

Problem	Objectives	Constraints	Case Studies
Shelter Location and Car-based Evacuation	Total Evacuation Time (Kongsomsaksakul, Yang and Chen 2005; Alçada-Almeida et al. 2009; Ng, Park and Waller 2010; Li et al. 2011, Li et al. 2012), Total Number of Shelters (Coutinho-Rodrigues, Tralhão and Alçada-Almeida 2012) Total Risk (Alçada-Almeida et al. 2009; Coutinho-Rodrigues, Tralhão and Alçada-Almeida 2012), Total Shelter Opening Cost (Heßler and Hamacher 2016), Total Travel Distance (Kongsomsaksakul, Yang and Chen 2005; Alçada-Almeida et al. 2009; Ng, Park and Waller 2010; Coutinho-Rodrigues, Tralhão and Alçada-Almeida 2012; Bayram, Tansel and Yaman 2015; Gama, Santos and Scaparra 2016; Bayram and Yaman 2017)	Flow Conservation (Kongsomsaksakul, Yang and Chen 2005; Heßler and Hamacher 2016), Maximum/Minimum Number of Evacuees for Shelter Opening (Alçada-Almeida et al. 2009; Coutinho-Rodrigues, Tralhão and Alçada-Almeida 2012), Number of Shelters (Alçada-Almeida et al. 2009; Li et al. 2011, Li et al. 2012; Coutinho-Rodrigues, Tralhão and Alçada-Almeida 2012; Bayram, Tansel and Yaman 2015; Gama, Santos and Scaparra 2016; Bayram and Yaman 2017), Shelter Utilization (Kılcı, Kara and Bozkaya 2015)	Bomb disposal (Heßler and Hamacher 2016), Earthquakes (Bayram, Tansel and Yaman 2015; Kılcı, Kara and Bozkaya 2015; Bayram and Yaman 2017), Fires (Alçada-Almeida et al. 2009; Coutinho-Rodrigues, Tralhão and Alçada-Almeida 2012); Floods (Kongsomsaksakul, Yang and Chen 2005; Gama, Santos and Scaparra 2016), Hurricanes (Li et al. 2011; Li et al. 2012)
Shelter Location and Bus-based Evacuation	Total Number of Evacuees (Shahparvari et al. 2016), Total Resources (Shahparvari et al. 2016)	Shelter Capacity Expansion (Shahparvari et al. 2016), Total Number of Rescue Vehicles (Shahparvari et al. 2016)	Bushfires (Shahparvari et al. 2016)
Shelter Location, Car-based Evacuation and Bus-based Evacuation	Total Evacuation Time (Goerigk, Deghdak and Heßler 2014), Total Number of Shelters (Goerigk, Deghdak and Heßler 2014), Total Risk (Goerigk, Deghdak and Heßler 2014)	Flow Conservation (Goerigk, Deghdak and Heßler 2014), Shelter Capacity (Goerigk, Deghdak and Heßler 2014), Vehicle Capacity (Goerigk, Deghdak and Heßler 2014)	Bomb disposal (Goerigk, Deghdak and Heßler 2014), Earthquakes (Goerigk, Deghdak and Heßler 2014)

4.3.2 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 (CM)*, *model coding (MC)*, *experimentation (E)*, and *implementation (I)* (Robinson 2014).

Several issues have been identified for each block of the optimization lifecycle for shelter location and evacuation routing. Aspects belonging to the *conceptual modelling* phase include: *stakeholder involvement*; *data collection*; *evacuee categories*, *behavior 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 the analysis, has been structured into four main blocks that mimic the four phases of the optimization 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 a non-profit organization member, an academic and one of the authors of the existing papers. The pilot phase helped structure the final questionnaire that can be found in Table 12.

Table 12. 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?

Table 12. Questionnaire (Continued)

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 optimization model multi-period (e.g., developed over time intervals)?
Q20	Is the optimization 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?

Table 12. Questionnaire (Continued)

	Further Questions (FQ) Block
Q30	What is the main contribution of your paper: a) Theoretical/Methodological/Technical contribution to optimization 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?

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 optimization at the present time, which can be grouped as follows: *stakeholder involvement*, *evacuation modes*, *clear definition of modelling inputs*, *evacuee behavior*, *system behavior*, and *methodology*. Each of these is discussed next. A summary of the results emerging from the analysis and the author questionnaire responses can be found in Table 13.

4.3.2.1 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 optimization 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, p. 13). 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.

Table 13. 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	-	-	✓	✓	✓	-	-	-	-	-	✓	✓	-	-	-	✓	-	-

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

Table 13. Insights achieved through critical analysis of the existing papers (left column) and questionnaire responses of their authors (right column) (Continued)

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

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 TRC 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 optimization 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 optimization modelling rather than practically to the field of DM (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, the analysis seems to suggest that lack of stakeholder involvement leads to missed opportunities for primary data collection, which in turn leads to the development of realistic, as opposed to real, case studies and eventually to lack of real implementation of optimization models.

4.3.2.2 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, Tansel 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 optimization models.

4.3.2.3 Clear definition of modelling inputs and parameters

As observed in (Galindo and Batta 2013), a major drawback of many DOM optimization models is that the assumptions about the inputs for such models are often unclear, limited or unrealistic. This observation was confirmed in the 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. Seven 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 the 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., non-profit organizations). Hence, it should be clearly defined who is supplying the vehicles given that, if different parties are doing so, a further level of coordination may be required and it should be captured within an optimization model.

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

4.3.2.4 Evacuee behavior

In the analysis of evacuee behavior, five dimensions have been identified to affect the way people evacuate during an emergency (Figure 20): *time of day* (Q8), *route diversion* (Q9), *evacuee demographics* (Q10), *route preference* (Q9), and *warning signals* (Q9). These are explored in turn next.

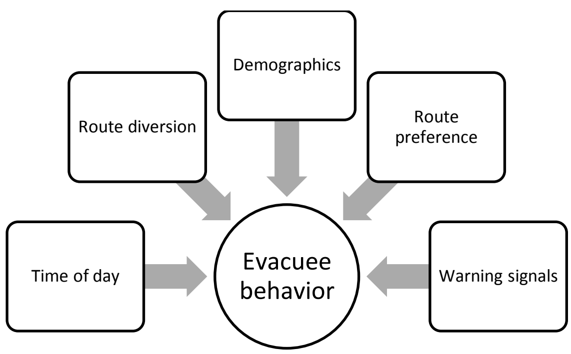

Figure 20. Evacuee behavior aspects of an evacuation process

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 behavior. Despite their relevance, these elements have not been addressed in the 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 traveling time. This approach is based on the assumption that such a behavior 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*).

Among the nine case studies, only three explicitly take into account the evacuee route preference, by using a dynamic UE 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 the 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, the analysis shows that evacuee behavior 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.

4.3.2.5 System behavior

The analysis of the system behavior 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 the first chapter, section 1.2.2, three categories of shelters can be considered, all providing different services. All the models in the 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 traveling 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 optimization 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 traveling 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 this chapter, section 4.1. The models of the nine case studies use the following objectives as *performance criteria*: expected unmet shelter demand and expected total network traveling 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 traveling 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 behavior 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.

4.3.2.6 Methodology

Different modelling techniques and solution methodologies are deployed in optimization. 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 models* (Q21) bi-level program 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 optimization 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 optimization 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, the 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.

4.4 Discussion and roadmap for future research

The nine case studies (Section 4.3.1) encompass different aspects of shelter location and evacuation routing operations. Through their analysis, various challenges that optimization should tackle to embed more realism into future models have been identified so that they can be used to inform decision making in real disaster situations. Further research directions are now outlined: some of them confirm gaps identified in previous surveys (Section 4.1) while others newly stem from the analysis of the nine case studies.

4.4.1 Stakeholder involvement

Five surveys explored in section 4.1 (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 optimization modelling that involves engaging with stakeholders to enable the actual implementation of optimization models (e.g., arrangements for a future evacuation plan). The case studies analysed in this 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 DM 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 my knowledge, PSMs have not yet been proposed to tackle evacuation planning issues, offering new research opportunities. Optimization 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).

4.4.2 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). The 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 the analysis is that optimization researchers have so far neglected to account for *assisted evacuation* and *multimodal evacuation*. *Assisted evacuation*, as mentioned in chapter 1, section 1.2.2, 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 traveler 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 optimization 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 optimization 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.

4.4.3 Clear definition of modeling 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 optimization models are needed, as already pointed out in the survey by Galindo and Batta (2013). The 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 optimization models. In order to provide more realistic modelling assumptions, the 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 traveling times, needs to be clearly understood and reliably modelled by using probabilistic analysis, statistics methods and social science studies.

4.4.4 Evacuee behavior

Two surveys (Caunhye, Nie and Pokharel 2012; Bayram 2016) advocate the integration of human behavior in optimization models. Human behavior, in fact, adds an additional layer to the uncertainty characterising evacuation processes and should therefore be addressed, for example through the use of robust optimization (Caunhye, Nie and Pokharel 2012). The analysis of human behavior has been broken down into five main aspects: *time of day, route diversion, evacuee demographics*, *route preference*, and *warning signals*. The 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 my knowledge, in the broad field of optimization, few studies, which do not belong to the 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 Behavior", which is a simulation tool that combines household behavior and traffic assignment issues. This may suggest to put forward a combination of optimization and simulation for evacuation planning where optimization 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 behavioral 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 behavior 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 optimization 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 optimization 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 optimization 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 optimizes the issuance of warning signals across several hurricane scenarios while the lower level evaluates both cost and risk associated with the emerging strategy.

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 Behavioral OR (BOR). For example, social media platforms could be deployed to manage vehicle procurement so 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 behavior* 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 behavior is an output, rather than an input, for warning signals and could be considered in future optimization research. Hence, the thorough examination of social media data through machine learning, artificial intelligence and/or statistics-based techniques and ABS could be deployed 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 behavior 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 behavior poses significant challenges: it requires advanced tools to collect and analyse data and expertise in other disciplines (e.g., social sciences, machine learning, and psychology). It results in highly complex mathematical models that may be difficult to solve thus requiring novel and cutting-edge solution methodologies. However, the inclusion of behavioral aspects would result in models that are more reliable and more likely to be used in real disaster situations.

4.4.5 System behavior

System behavior 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). The 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 DM 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 optimization. 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.

4.4.6 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). The 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, the analysis reveals that optimization 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, the final suggestion is to aim for *interdisciplinarity*.

4.5 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. The most recent optimisation models tackling shelter location and evacuation routing problems in an integrated manner have been critically analysed. Through the analysis of these state of the art models, the current challenges emerging in this research area have been identified and a roadmap for future research has been outlined.

The analysis confirms some of the findings of previous DM-specific 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 this 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.

The ultimate scope of this dissertation is to detail the current state-of-the-art in the optimization field for shelter location and evacuation routing so as to identify current challenges and outline a roadmap for future research. This could be paired with an analysis of the current state-of-practice by reviewing decision-making requirements and current best practices in the field as offered by several disaster emergency institutions such the Federal Emergency Management Agency (FEMA) in the US. The above vision is quite ambitious and requires an interdisciplinary approach towards shelter location and evacuation routing operations. However, a novel scenario-based flow-location-allocation-routing model is introduced in Chapter 5, which aims at filling some of the aforementioned gaps such as: modeling of infrastructure disruptions, realistic modelling assumptions, combination of different evacuee categories, inclusion of route preference, and adoption of equity-based approaches.

5. An integrated user-system approach for shelter location and evacuation routing

This chapter presents a novel scenario-based mixed-integer program which integrates shelter location, self-evacuation and supported-evacuation decisions, namely the *Scenario-Indexed Shelter Location and Evacuation Routing (SISLER)* problem. To the best of my knowledge, only Goerigk, Deghdak and Heßler (2014) have so far produced an optimization model tackling the aforementioned three aspects together. However, the approach hereby adopted is different, as it will be clarified in the following. The model is solved through a Branch-and-Cut algorithm of an off-the-shelf software, enriched with valid inequalities adapted from the literature. Computational results are reported for both testbed instances and a realistic case study.

5.1 The Scenario-Indexed Shelter Location and Evacuation Routing problem

The ultimate goal of SISLER is to tackle some of the current challenges in the shelter location and evacuation routing field that have emerged in the analysis carried out in Chapter 4. As a remainder, the challenges have been grouped into five macro-categories: (1) *stakeholder involvement*, (2) *evacuation modes*, (3) *clear definition of modeling inputs and parameters*, (4) *evacuee behavior*, and (5) *system behavior*. In particular, SISLER contributes to knowledge by attempting to address gaps regarding categories (2), (4) and (5).

Firstly, SISLER combines shelter location with two different types of evacuation, i.e., car-based evacuation and bus-based evacuation, thus addressing the need to consider different evacuation modes in a combined way (challenge belonging to category (2)). To the best of my knowledge, only another paper has recently attempted to consider the aforementioned three aspects together Goerigk, Deghdak and Heßler (2014), which has been described in section 4.3.1.

Secondly, SISLER challenges Goerigk, Deghdak and Heßler (2014)'s assumption related to the adoption of a SO approach where a planning authority is in charge of shelter location, car-based evacuation, and bus-based evacuation decisions. In fact, it may be argued that this assumption is not very realistic, unless paramilitary circumstances are in place, given that self-evacuees will always attempt to travel the shortest available route. This is the reason why SISLER assumes that all self-evacuees, even the furthest ones, are able to reach a shelter within a traveling time threshold and, based on how strict or loose this threshold is (i.e., how much self-evacuees are willing to travel either a shorter or lengthier route), they are free to decide which path to take. On the other side, the system planner is in charge of opening shelter sites and arranging supported-evacuation. This assumption allows to tackle challenges belonging to both categories (4) and (5). In fact, self-evacuee willingness to travel either shorter or lengthier routes allows to account for evacuee behavior (4) while, imposing that all self-evacuees, despite their position, are able to reach a shelter within a traveling time threshold, attempts to address equity issues, which are system behavior-related challenges (5).

Thirdly, SISLER deploys scenario-based programming, which is a modeling technique that has already been successfully deployed within the disaster management field (e.g., emergency relief supply pre-positioning (Rawls and Turnquist (2010)) as well as in the specific shelter location and evacuation routing research area (Li et al. (2012), as described in Section 4.3.1). It may be argued that, during disaster response, given that the disaster has occurred, the specific scenario to deal with is known. However, within a restricted time frame to put into action an evacuation plan, it is fundamental to know in advance how to proceed. Therefore, under uncertain circumstances and based on disaster-specific historical data of the areas under consideration, a scenario-based formulation is an efficient tool to obtain a solution that is robust across different disastrous conditions. In particular, the scenario-based formulation of SISLER allows to account for road network infrastructure disruptions in a direct way, as to be detailed in the following (Section 5.1.1), which is another system behavior-related challenge (5). On the contrary, Goerigk, Deghdak and Heßler (2014) provide a multi-objective formulation where the evacuation time, the number of shelters to be opened, and the risk exposure of the evacuees are combined. The risk exposure of the evacuees may address infrastructure disruptions indirectly however, it does not allow to provide a trustworthy solution across different possible disastrous circumstances.

5.1.1 Model assumptions

The assumptions underpinning the SISLER problem are as follows.

1. Both self-evacuation and supported-evacuation are considered, the reason being to address both the majority of the evacuees (i.e., those who can autonomously drive a vehicle) as well as the remaining minority (e.g., the elderly, the medically-homebound, etc.).

2. Self-evacuation involves people evacuating with their own vehicles towards a shelter (people moving towards other destinations are not considered). In the following, this type of evacuation is also referred to as evacuation mode (a) or car-based evacuation.
3. Supported-evacuation is arranged by public authorities and relies on buses which are stored and dispatched from a depot. In the following, this type of evacuation is also referred to as evacuation mode (b) or bus-based evacuation.
4. The area affected by the disaster is divided in different evacuation zones. Both self-evacuation and supported-evacuation start at the centroid of each zone. In fact, prior to plan for the evacuation of a certain area, a process named zoning is carried out, which divides the region under study in different zones. Then, for each zone, the point where all evacuees are assumed to depart for evacuation is identified, namely the centroid.
5. The proposed model is deterministic hence, for each zone, the number of self-evacuees and supported-evacuees (i.e., evacuation demand) is known.
6. Both shelters and buses have a limited capacity. In fact, when planning for shelters, the amount of space available to each evacuee as well as to vehicles taking them to safe sites should be accounted for (guidelines can be found from agencies such as the Turkish Red Crescent (Kılcı, Kara and Bozkaya 2015)). Similarly, buses have limited space to be allocated that needs to be considered.
7. Split delivery of supported-evacuees is possible (more than one bus may collect people from the same area and bring them to different shelters). However, all self-evacuees from the same zone go to the same shelter. From a practical point of view, in fact, it would be difficult to direct self-evacuees to different shelters.
8. The objective is to minimize the completion time of the supported-evacuation.
9. Self-evacuees use the shortest available path to reach their assigned shelters. To guarantee an egalitarian allocation, even the furthest group of self-evacuees must be able to reach a shelter site within a given traveling time threshold.
10. Contraflow lane reversal (Murray-Tuite and Wolshon 2013) has been assumed on the network arcs whose destination node is a shelter site, which means that those arcs can be traveled only in one direction (i.e., towards the shelter). This is an approach that has been already adopted in various evacuation processes in the US (Brachman and Church 2009).

11. Each bus performs a single trip to collect evacuees from the evacuation zones, the reason being that a flood-like disaster has been considered while designing this model. When a flood strikes, there is a central zone that gets affected and then the disaster starts to propagate in the neighboring areas. Hence, from an evacuation perspective, once a bus has departed from the depot, it collects the evacuees, takes them to a shelter and stops there, without returning to the dangerously affected area.
12. Several disruption scenarios are considered, which differ in terms of road network arc availability, and each scenario occurs with a given probability. In particular, scenarios of increasing disaster magnitude have been considered, such as small-scale, medium-scale and large-scale disruption circumstances, so as to account for disaster propagation. Nevertheless, different type of scenarios could be considered.

5.1.2 Model formulation

[4]The SISLER problem can be described as follows.

Sets and indices

$G(N, A)$: directed network

N: set of network nodes

N_a ($N_a \subseteq N$): set of zones where evacuation mode (a) starts, indexed by i

N_b ($N_b \subseteq N$): set of zones where evacuation mode (b) starts, indexed by i, where $N_a \cap N_b \neq \emptyset$ hence, some zones may have both evacuations (mode (a) and (b)) occurring

N_s ($N_s \subseteq N$) : set of potential shelter sites, indexed by j

D: set of network disruption scenarios, indexed by d

A: set of network arcs

A_d ($A_d \subseteq A$): set of available arcs under disruption scenario d

K: set of buses stored and dispatched from a depot node o ($o \in N$), indexed by k

Parameters

q_i^a: expected number of mode (a) evacuees in zone $i \in N_a$

[4] For the sake of clarity, the reader is informed that the mathematical notations hereby introduced are for this specific chapter and do not relate with those introduced in other chapters of this dissertation.

q_i^b: expected number of mode (b) evacuees in zone $i \in N_b$

C_j: capacity of a shelter at site j

r_j: amount of resources to set up a shelter at site j

R: total amount of available resources

B_k: capacity of bus k

τ_{lm}^d: traveling time from node l to node m in scenario d (for bus-based evacuation)

t_{ij}^d: shortest traveling time from zone $i \in N_a$ to site j in scenario d (for car-based evacuation)

T^d: self-evacuees traveling time threshold in scenario d

p_d: probability of occurrence of scenario d

α: parameter representing the car-based evacuees willingness to travel, $\alpha \in [0,1]$

Decision variables

γ_d: bus-based evacuation maximum completion time in scenario d

g_{lm}^{kd}: number of evacuees who travel from node l to node m with bus k in scenario d

v_i^{kd}: number of evacuees who start evacuation at node $i \in N_b$ with bus k in scenario d

w_j^{kd}: number of evacuees who end evacuation at site j with bus k in scenario d

x_{ij}^d: 1 if the evacuees in zone $i \in N_a$ are assigned to shelter j in scenario d, 0 otherwise

z_{lm}^{kd}: 1 if bus k travels from node l to node m in scenario d, 0 otherwise

y_j: 1 if a shelter is opened at site j, 0 otherwise

The mathematical formulation of SISLER is the following.

$$[\text{SISLER}]\ min \sum_{d\in D} p_d\, \gamma_d \tag{33}$$

s.t.

$$\gamma_d \geq \sum_{(l,m)\in A_d} \tau_{lm}^{d} z_{lm}^{kd} \qquad \forall\, k \in K, d \in D \tag{34}$$

$$\sum_{m:(o,m)\in A_d} z_{om}^{kd} \leq 1 \qquad \forall\, k \in K, d \in D \tag{35}$$

$$v_m^{kd} + \sum_{l:(l,m)\in A_d} g_{lm}^{kd} = w_m^{kd} + \sum_{l:(m,l)\in A_d} g_{ml}^{kd} \qquad \forall\, m \in N, k \in K, d \in D \tag{36}$$

$$\sum_{l:(l,m)\in A_d} z_{lm}^{kd} - \sum_{l:(m,l)\in A_d} z_{ml}^{kd} = 0 \qquad \forall\, m \in N\backslash(o \cup N_s),\ k \in K, d \in D \tag{37}$$

$$g_{lm}^{kd} \leq B_k z_{lm}^{kd} \qquad \forall\, (l,m) \in A_d, k \in K, d \in D \tag{38}$$

$$\sum_{k\in K} v_i^{kd} = q_i^b \qquad \forall\, i \in N_b, k \in K, d \in D \tag{39}$$

$$v_l^{kd} = 0 \qquad \forall\, l \in N\backslash N_b, k \in K, d \in D \tag{40}$$

$$w_l^{kd} = 0 \qquad \forall\, l \in N\backslash N_s, k \in K, d \in D \tag{41}$$

$$\sum_{j\in N_s} x_{ij}^{d} = 1 \qquad \forall\, i \in N_a, d \in D \tag{42}$$

$$\sum_{j\in N_s} t_{ij}^{d} x_{ij}^{d} \leq (1+\alpha)T^d \qquad \forall\, i \in N_a, d \in D \tag{43}$$

$$\sum_{i\in N_a} q_i^a x_{ij}^d + \sum_{k\in K} w_j^{kd} \leq C_j y_j \qquad \forall\, j \in N_s, d \in D \tag{44}$$

$$\sum_{j\in N_s} r_j y_j \leq R \tag{45}$$

$$\gamma_d \geq 0 \qquad \forall\, d \in D \tag{46}$$

$$g_{lm}^{kd} \geq 0 \qquad \forall\, (l,m) \in A_d, k \in K, d \in D \tag{47}$$

$$v_l^{kd} \geq 0 \qquad \forall\, l \in N, k \in K, d \in D \tag{48}$$

$$w_l^{kd} \geq 0 \qquad \forall\, l \in N, k \in K, d \in D \tag{49}$$

$$x_{ij}^{d} \in \{0,1\} \qquad \forall\, i \in N_a, j \in N_s, d \in D \tag{50}$$

$$z_{lm}^{kd} \in \{0,1\} \qquad \forall\, (l,m) \in A_d, k \in K, d \in D \tag{51}$$

$$y_j \in \{0,1\} \qquad \forall\, j \in N_s \tag{52}$$

The objective function (33) minimizes the expected bus-based evacuation maximum completion time over the different network scenarios. Constraints (34) guarantee that γ_d is the completion time (i.e., the longest bus route) in scenario d. Constraints (35) – (41) model the bus-based evacuation. For each bus k and scenario d, constraints (35) ensure that each bus departs from the depot o (if it departs); constraints (36) and (37) are flow conservation constraints; constraints (38) impose that people travel an arc only if a bus, whose capacity cannot be exceeded, serves that arc; constraints (39) guarantee that all the people of zone $i \in N_b$ evacuate to some shelter; constraints (40) and (41) state that evacuation starts only at nodes $i \in N_b$ and ends at shelter sites $j \in N_s$, respectively. Constraints (42) and (43) model the car-based evacuation. For each scenario d, constraints (42) ensure that every evacuation zone $i \in N_a$ is assigned to exactly one shelter, while constraints (43) ensure that the evacuation time for cars does not exceed a given threshold. Constraints (44) link together both self-evacuation and supported-evacuation variables by imposing that the shelter capacity cannot be exceeded, while constraint (45) states that the total amount of resources available to set up shelters cannot be exceeded. Constraints (46) – (52) are non-negativity and binary constraints.

Note that SISLER's objective can yield multiple optimal solutions, some of which are inefficient from the car-based evacuation perspective. To guarantee an efficient allocation of self-evacuees to shelters, a lexicographic objective function is deployed by adding a second term (car-based evacuation total duration time across all the scenarios) to the objective (33) (as adopted by Bish (2011)). In particular, the lexicographic objective formulation is the following:

$$min \sum_{d \in D} p_d \left(\gamma_d + \frac{1}{L} \Theta_d\right) \tag{53}$$

where $\Theta_d = \sum_{i \in N_a} \sum_{N_s} t_{ij}^d x_{ij}^d$ is the total car-based evacuation duration time for scenario $d \in D$, and $L = 2 \sum_{d \in D} T^d$ is a lexicographic constant which ensures that the supported-evacuation maximum completion time dominates the self-evacuation total duration time.

An interesting feature of SISLER is that it allows decision planners to identify a trade-off between self-evacuation and supported-evacuation oriented solutions, by changing a parameter which represents the route length that car-based evacuees are willing to accept. This permits to balance the bus-based evacuation completion time objective and the car-based evacuation equity requirement. Figure 21 displays an example.

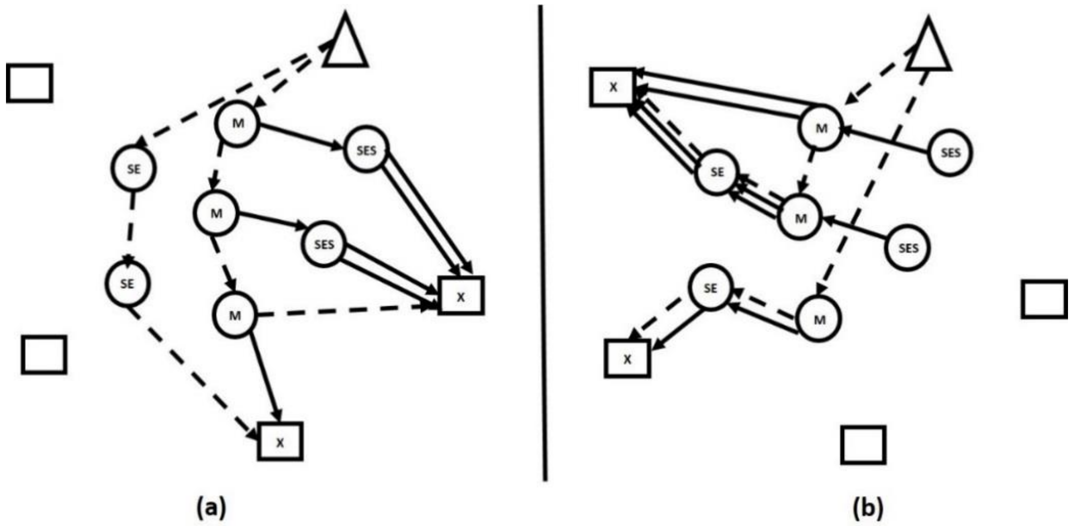

Figure 21. Self-evacuation oriented solution (a) and supported-evacuation oriented solution (b)

In Figure 21, triangle, square, and round shapes represent, respectively, the depot, candidate shelter sites, and evacuation zone centroids. Selected shelters are marked with a cross and centroids are identified with the acronyms of the evacuees departing from there (i.e., SES = Self-Evacuees who move towards a Shelter, SE = Supported Evacuees who move towards a shelter, and M = mixed demand, which is a combination of SES and SE). Normal and dashed arrow lines represent, respectively, SES assignments and SE routes. A tighter threshold (a) favours self-evacuation by inducing the opening of shelters close to self-evacuees or mixed evacuation zones; if the threshold becomes looser (b), the supported-evacuation maximum completion time decreases while the self-evacuation total duration time increases.

5.2 Solution Methodology

SISLER has been solved through a *Branch-and-Cut* approach of an off-the-shelf software, which has been enriched with valid inequalities adapted from the literature.

Branch-and-Cut approaches are exact methods that have been largely applied to solve various integer programming (IP) problems (Mitchell 2002). A Branch-and-Cut approach is the combination of two other well-known IP solution methods: the *Branch-and-Bound* and the *Cutting Plane* methods. A Branch-and-Cut approach consists of designing a Branch-and-Bound algorithm where at each node of the decision tree some cuts are generated so to obtain either an integer solution or a bound improvement. Then, once the efficacy of these cuts decreases, no additional cuts are generated and the branching phase starts. In particular, a Branch-and-Cut approach allows to overcome some of the drawbacks of the two aforementioned methods (i.e., the Branch-and-Bound and the Cutting Plane methods). Compared to a pure Branch-and-Bound approach, the Branch-and-Cut provides a (dynamic) strengthening of the model formulation. On the other side, compared to a pure Cutting Plane method, the branching phase allows to overcome the "tailing off" status (i.e., a long series of iterations where cuts are added without a significant improvement of the current model formulation).

Inequalities that are generated can be valid either *locally* or *globally*. *Locally* means that cuts are valid only in correspondence of the specific node of the decision tree (as well as its descendants) where they have been added. On the other side, *globally* means that inequalities are valid throughout the entire decision tree. In this case, it is possible to store all the cuts that have been generated into a data structure that takes the name of *pool of constraints*. Given the initial model formulation, when a new node of the decision tree is generated, the branching conditions are imposed and the linear relaxation is computed. A solution is obtained which, if fractional, prompts the search for constraints that have been violated which are then added to the current formulation. Then, the linear relaxation is solved again until all the constraints within the pool are satisfied. If the obtained solution is still fractional, either new procedures are implemented to find new global cuts or the branching phase starts; otherwise, if the solution is integer and all the constraints are not violated, the solution is optimal. Hence, the two key components of a Branch-and-Cut algorithm are:

- the *pool of constraints*, which stores all the cuts that are globally valid, and
- the *separation procedures*, which allow to identify inequalities that are violated in correspondence of the current linear relaxation solution.

The design of efficient *separation procedures* is a crucial point of a Branch-and-Cut approach. They can either be *general purpose*, which means that they are applicable to any generic IP, or *ad-hoc*, which means that they are implemented for a specific class of problems.

5.2.1 Valid inequalities for SISLER

Valid inequalities for SISLER have been identified based on the sub-problems SISLER is composed of which are: the *Bus Evacuation Problem (BEP)*, the *Capacitated Facility Location Problem (CFLP)*, and the *Multi-Commodity Flow Problem (MCFP)*.

Firstly, the literature on the BEP is little given that this problem has been introduced fairly recently (Bish 2011). However, the BEP is related to the well-known Vehicle Routing Problem (VRP). The routing aspect of SISLER is not pure given that the buses, once they start the journey from the depot, stop at a shelter destination without returning to the depot. This is motivated by the fact that SISLER is a static model and, as such, the evacuation occurs within a unique period where buses drop supported-evacuees at shelter sites. Moreover, even in case of a dynamic model, it would be safer to assume that buses do not return to the depots but just to some of the evacuation nodes (in fact, bus depots were subject to flooding in the aftermath of Hurricane Katrina in 2005 (Bish (2011)). Given the usage of buses, the following round-up constraints (Boccia et al. 2018) are introduced for SISLER

$$\sum_{m:(o,m)\in A_d} \sum_{k\in K} z_{om}^{kd} \geq \left\lceil \frac{\sum_{i\in N_b} q_i^b}{B_k} \right\rceil \qquad \forall\, d \in D \qquad (54)$$

which impose a lower bound on the number of buses that can be used for each scenario, having assumed that $B_k = B \;\; \forall\, k \in K$.

Secondly, the literature on inequalities for the CFLP (Leung and Magnanti 1989; Klose and Drexl 2005) presents three main categories of inequalities:

- *Aggregated Capacity Constraints (ACC)* such as

$$\sum_{j\in N_s} C_j y_j \geq \left\lceil \sum_{i\in N_a} q_i^a + \sum_{i\in N_b} q_i^b \right\rceil \qquad (55)$$

  which, given facilities with equal capacity restrictions (i.e., $C_j = C \;\; \forall\, j \in N_s$), impose a lower-bound on the number of facilities that should be opened.

- *Residual Capacity (RC)* constraints such as

$$\sum_{i\in N_a} q_i^a\, x_{ij}^d + \sum_{k\in K} w_j^{kd} - RC \sum_{j\in N_s} y_j \leq \sum_{i\in N_a} q_i^a + \\ + \sum_{i\in N_b} q_i^b - RC \left\lceil \frac{\sum_{i\in N_a} q_i^a + \sum_{i\in N_b} q_i^b}{C_j} \right\rceil \qquad \forall\, j \in N_{s,} d \in D \qquad (56)$$

where $1 \leq RC \leq C$, having assumed $C_j = C \;\; \forall\, j \in N_s$. These constraints identify the customer demand that the last available facility should satisfy. In the case of SISLER, evacuees are seen as customers (hence, evacuee demand as customer demand), and shelters as facilities.

- *Variable Upper Bounds (VUB)* constraints such as

$$x_{ij}^{d} \leq y_j \qquad \forall\, i \in N_a, j \in N_s, d \in D \tag{57}$$

which require that a customer can be assigned to a facility only if the facility is open. For SISLER, it means that self-evacuees move towards a shelter site in a certain scenario only if the shelter has been opened.

Finally, the literature for the MCFP presents various inequalities however, those which could be easily deployed for SISLER are the *Strong Inequalities (SI)* introduced by Chouman, Crainic and Gendron (2009) for the Multi-Commodity Capacitated Fixed-Charge Network Design (MCND) problem, which is based on the MCFP. The concept underpinning this set of constraints is the following: if a network arc is deployed, then the amount of flow of a certain commodity traversing that arc should be less than or equal to the demand of the commodity itself. This set of constraints, given that the two categories of evacuees (i.e., self-evacuees and supported-evacuees) can be seen as two different commodities, has been adopted and used for supported-evacuees. The adapted valid inequalities are the following:

$$v_i^{kd} \leq q_i^b \sum_{m:(i,m)\in A_d} z_{im}^{kd} \qquad \forall\, i \in N_b, k \in K, d \in D \tag{58}$$

Specifically, for each scenario d, the amount of supported-evacuees leaving evacuation zone $i \in N_b$ with bus k should not exceed the total evacuation demand of that zone and travel only an arc (i, m) which is available.

Among all the aforementioned valid inequalities, (54) and (58) have demonstrated to yield an improvement in the value of the linear relaxation of SISLER, when considered separately or in combination, while the remaining valid inequalities did not affect the value of the linear relaxation of SISLER. Therefore, (54) and (58) have been embedded as valid inequalities at the root node of the decision tree within the IBM ILOG CPLEX 12.6 Branch-and-Cut framework.

It has been possible to appreciate which are the cuts that CPLEX adopts to solve SISLER instances and in which amount (based on average values): *flow cover cuts* (61%), *mixed integer rounding (MIR) cuts* (25%), *lift-and-project cuts* (8%), *implied bound cuts* (3%), *cover and Gomory fractional cuts* (both at 1%), and *clique, zero-half, and GUB cuts* (that together constitute 1%). The in-depth description of the aforementioned cuts is out of the scope of this dissertation and the interested reader can start referring to CPLEX User's Manual (CPLEX), and then proceed with relevant branch-and-cut literature (Mitchell 2002). However, an interesting observation can be drawn on the first two categories of cuts added by CPLEX (i.e., flow cover and MIR cuts, which represent the majority of the cuts) and the nature of SISLER. In fact, flow cover cuts are defined based on constraints containing continuous variables whose upper bound varies between zero and a positive value according to the corresponding binary variables, while MIR cuts are produced by imposing integer rounding on the coefficient of integer decisional variables as well as the corresponding right-hand side constraint. This is in line with the flow problem component of SISLER, which contribute to model the bus-based evacuation.

5.3 Experimental Results

SISLER is a mixed-integer linear programming (MILP) model which was implemented using IBM ILOG OPL modeling language and solved with the Branch-and-Cut algorithm of the solver CPLEX, version 12.6, enriched with additional valid inequalities, as described in Section 5.2.1, on a computer with an Intel® Core™ i5-5200U CPU @ 2.20GHz and 8.00 GB of RAM.

5.3.1 Testbed instances generation

Two testbed instances of different density have been deployed to test SISLER: one of 25 nodes and 56 arcs (25X56) and another one of 25 nodes and 165 arcs (25X165). Both instances have been generated as follows. A 100x100 square study area like the one displayed in Figure 22 has been considered, where the black area represents the central zone of the disaster (i.e., where the disaster starts), the grey area the region where the disaster can propagate, and the white area the safety zone (i.e., the disaster cannot reach that area).

The coordinates of evacuation zones, transshipment nodes, and shelter sites were generated at random in the black, light grey, and white areas, respectively.

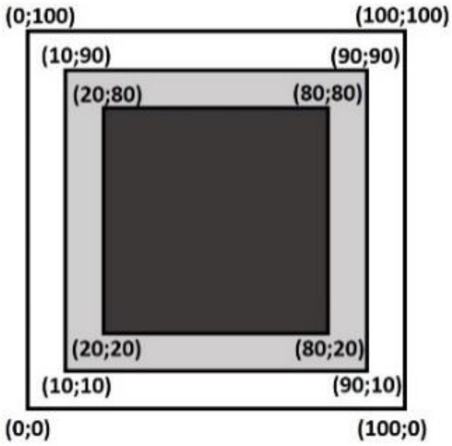

Figure 22. Study area

Specifically, evacuation zones where only self-evacuation occurs account for 25% of the network nodes (i.e., 6 nodes), evacuation zones where only supported-evacuation occurs account for 15% of the network nodes (i.e., 4 nodes), evacuation zones where both self-evacuation and supported-evacuation occur account for 15% of the network nodes (i.e., 4 nodes), pure transshipment nodes account for 15% of the network nodes (i.e., 4 nodes), shelter sites account for the remaining 25% of the network nodes (i.e., 6 nodes), and the remaining 5% of the network nodes constitutes the depot node. Arcs were also generated at random and Euclidean distances were used as a proxy for traveling times. In accordance with the contraflow lane reversal assumption, it has been assumed that arcs from transshipment nodes to candidate shelter sites can be traveled only in one direction (i.e., towards the shelter). Three scenarios have been considered: (1) a *small disruption scenario*, where all network arcs are available, (2) a *medium disruption scenario*, where some network arcs connecting evacuation nodes (i.e., within the black area), accounting for 20% of the network arcs, have been affected by the disaster, and (3) a *large disruption scenario* where some arcs connecting evacuation and transshipment nodes (i.e., from the black to the grey area), accounting for 10% of the network arcs, have been disrupted in addition to the arcs already inoperable in the medium scenario. Arcs to be disrupted were decided at random however, when advancing from the medium to the large scenario, within a level of proximity. This choice of scenarios has been motivated having in mind a specific disaster such as flooding where the off-set of the disaster occurs in certain points of networks and then propagates from there within a certain degree of proximity.

Results are reported for two cases: where only one of the three scenarios is considered (i.e., single scenario instances) and where all the three scenarios are together (i.e., combined scenario instances).

In terms of model parameters, the following settings have been adopted.

1. Evacuation demand (measured in numbers of households) was assumed to be a random integer uniformly distributed between 50 and 550, as in (Gama, Santos and Scaparra 2016).
2. A homogeneous bus fleet was assumed (i.e., $B_k = B \ \forall \, k \in K$) and the number of buses was computed as the round-up ratio [total bus-based evacuation demand/bus capacity], :

$$number\ of\ buses = \left\lceil \frac{\sum_{i \in N_b} q_i^b}{B} \right\rceil.$$

3. Shelter capacities were computed as reported by Gama, Santos and Scaparra (2016), based on (Lorena and Senne 2004), as the round-up ratio [total evacuation demand/maximum number of shelters that can be opened]:

$$C_j = \left\lceil \frac{\sum_{i \in N_a} q_i^a + \sum_{i \in N_b} q_i^b}{p * \beta} \right\rceil$$

   where, more specifically, p is the maximum number of shelters that can be opened based on the budget constraint (45) and β is a weighting parameter set equal to 0.8. Shelter capacities are assumed to be the same for each shelter (i.e., $C_j = C \ \forall \, j \in N_s$).
4. For each scenario and car-based evacuation zone, the shortest traveling time and the time threshold were computed in a pre-processing phase. Self-evacuee shortest travelling times for each scenario (i.e., t_{ij}^d) were computed through a shortest path algorithm, while the self-evacuee traveling time threshold for each scenario (i.e., T^d) was computed through an auxiliary capacitated p-center model. In particular, the p-center model aims at minimizing the self-evacuee maximum traveling time to reach shelter sites. In this case, shelter capacities are

still computed as based on (Lorena and Senne 2004) however, only the total self-evacuee evacuation demand is considered (i.e., $\sum_{i \in N_a} q_i^a$) to compute the reduced shelter capacity.

5. A decreasing probability distribution was used to combine the three different scenarios ($p_1 = 0.5, p_2 = 0.3$, and $p_3 = 0.2$). This choice is based on the assumption that a large-scale disastrous circumstance (i.e., scenario 3) is less likely than a medium-scale one (i.e., scenario 2), which in turn is less likely than a small-scale disruption leaving transport links unaffected (i.e., scenario 1).

5.3.1.1 Computational results for the 25x56 network

The network with 25 nodes and 56 arcs was used as a proof of concept to demonstrate the validity of the problem and to preliminary test the SISLER formulation. Given its dimensions, even without adding the inequalities found for SISLER, both single and combined scenario instances were solved in a matter of few seconds.

The results for the 25x56 network are displayed in Table 14, 15, 16 and 17 for the small, medium, large scenarios, and their combination, respectively. The tables report the bus-based evacuation maximum completion time, the car-based evacuation total duration time, and the open shelters for different values of α ranging from 0 to 1 (note that the potential shelter sites for the 25x56 network are nodes 19, 20, 21, 22, 23, and 24).

Table 14. Computational results for the 25x56 network – Scenario 1 (Small)

Scenario 1 (Small)			
α	Bus-based evacuation maximum completion time	Car-based evacuation total duration time	Open shelters
0	212	282	{19,20,23,24}
0.1	212	282	{19,20,23,24}
0.2	143	301	{19,21,23,24}
0.3	143	301	{19,21,23,24}
0.4	143	301	{19,21,23,24}
0.5	138	323	{19,22,23,24}
0.6	138	323	{19,22,23,24}
0.7	138	323	{19,22,23,24}
0.8	138	323	{19,22,23,24}
0.9	138	323	{19,22,23,24}
1	138	323	{19,22,23,24}

Table 15. Computational results for the 25x56 network – Scenario 2 (Medium)

Scenario 2 (Medium)			
α	Bus-based evacuation maximum completion time	Car-based evacuation total duration time	Open shelters
0	175	347	{19,21,23,24}
0.1	175	347	{19,21,23,24}
0.2	175	347	{19,21,23,24}
0.3	175	347	{19,21,23,24}
0.4	175	347	{19,21,23,24}
0.5	168	427	{20,22,23,24}
0.6	168	427	{20,22,23,24}
0.7	168	427	{20,22,23,24}
0.8	168	421	{19,20,22,24}
0.9	168	421	{19,20,22,24}
1	168	421	{19,20,22,24}

Table 16. Computational results for the 25x56 network – Scenario 3 (Large)

Scenario 3 (Large)			
α	Bus-based evacuation maximum completion time	Car-based evacuation total duration time	Open shelters
0	211	447	{19,20,22,24}
0.1	211	447	{19,20,22,24}
0.2	211	447	{19,20,22,24}
0.3	211	447	{19,20,22,24}
0.4	211	447	{19,20,22,24}
0.5	211	447	{19,20,22,24}
0.6	211	447	{19,20,22,24}
0.7	211	447	{19,20,22,24}
0.8	211	447	{19,20,22,24}
0.9	211	447	{19,20,22,24}
1	211	447	{19,20,22,24}

Table 17. Computational results for the 25x56 network – All Scenarios (Mix)

	All Scenarios (Mix)		
α	Bus-based evacuation maximum completion time	Car-based evacuation total duration time	Open shelters
0	216	322.4	{19,20,23,24}
0.1	216	322.4	{19,20,23,24}
0.2	166.2	361.2	{20,21,23,24}
0.3	166.2	361.2	{20,21,23,24}
0.4	166.2	361.2	{20,21,23,24}
0.5	161.6	415.2	{20,22,23,24}
0.6	161.6	415.2	{20,22,23,24}
0.7	161.6	415.2	{20,22,23,24}
0.8	161.6	415.2	{20,22,23,24}
0.9	161.6	415.2	{20,22,23,24}
1	161.6	415.2	{20,22,23,24}

From the analysis of the tables, it is possible to infer the trade-off between the bus-based evacuation maximum completion time and the car-based evacuation total duration time.

For example, in the small scenario (i.e., Table 14) when α increases from 0.1 to 0.2, the supported-evacuation maximum completion time drops by nearly 33% (from 212 to 143), while the self-evacuation total duration time increases by around 7% (from 282 to 301), which also implies a change in the shelter location decisions (from node 20 to node 21). Another change in both evacuation times and shelter locations can be observed when α rises from 0.4 to 0.5. In this case, the bus-based evacuation maximum completion time decreases by nearly 3% (from 143 to 138), while the car-based evacuation total duration time raises by around 7% (from 301 to 323), and node 22 is open instead of node 21. A visual representation of the trade-off between the bus-based evacuation maximum completion time and the car-based evacuation total duration time when α varies between 0 and 1 for the small scenario is displayed in Figure 23.

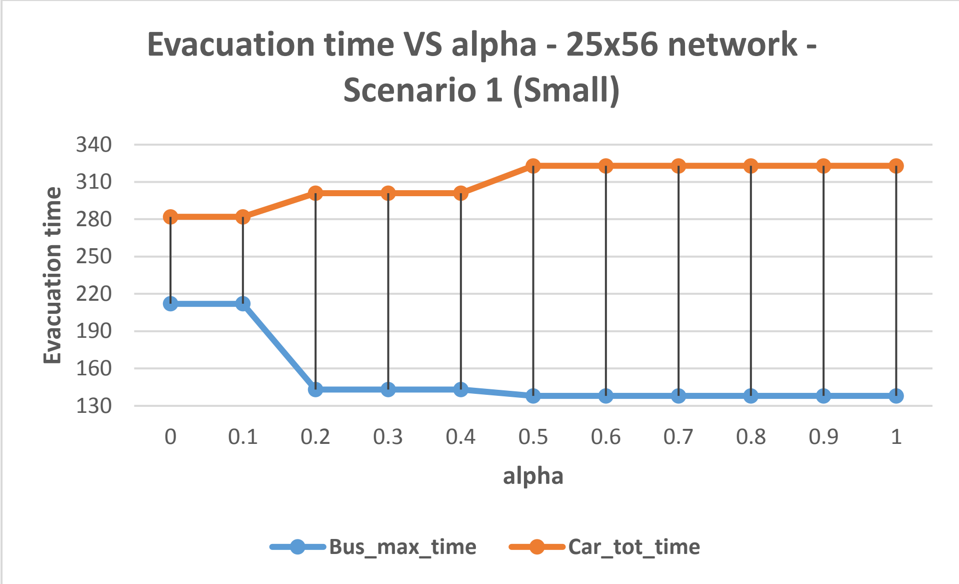

Figure 23. Evacuation times trade-off for different values of α – 25x56 network – Scenario 1 (Small)

Other examples can be appreciated from the analysis of the medium scenario (i.e., Table 15). When α increases from 0.4 to 0.5, the supported-evacuation maximum completion time drops by nearly 4% (from 175 to 168), while the self-evacuation total duration time increases by around 23% (from 347 to 427), leading to a shift in shelter location decisions (two nodes are changed among four, specifically, nodes 20 and 22 are preferred over nodes 19 and 21). Conversely, when α rises from 0.7 to 0.8, the bus-based evacuation time does not change however, the car-based evacuation completion time decreases by nearly 1% (from 427 to 421) and there is a change in shelter location decisions (from node 20 to node 19). This is motivated by the fact that the more α increases, the more the self-evacuation traveling time threshold becomes looser, thus allowing allocations that were infeasible for lower values of α. A visual representation of the trade-off between the bus-based evacuation maximum completion time and the car-based evacuation total duration time when α varies between 0 and 1 for the medium scenario is displayed in Figure 24.

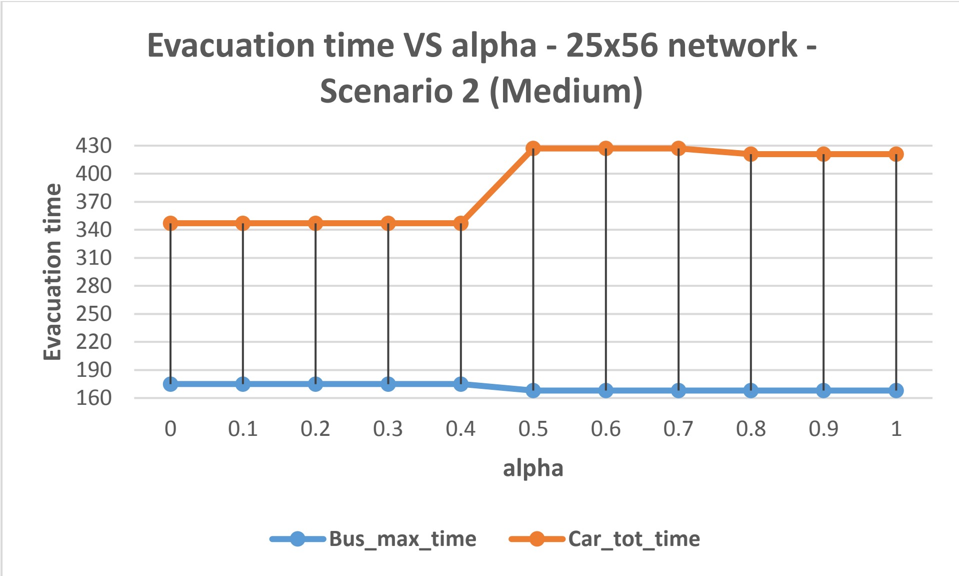

Figure 24. Evacuation times trade-off for different values of α – 25x56 network – Scenario 2 (Medium)

Differently from the small and medium scenarios, no trade-off between the bus-based evacuation maximum completion time and the car-based evacuation total duration time can be appreciated for the large scenario (i.e., Table 16). In this case, the solution is always the same, irrespective of the value of α. However, the trade-off can still be observed when combining the three scenarios (i.e., Table 17). In fact, when α increases from 0.1 to 0.2, the supported-evacuation maximum completion time drops by nearly 23% (from 216 to 166.2), while the self-evacuation total duration time rises by around 12% (from 322.4 to 361.2), and this implies a change in the shelter location decisions (from node 19 to node 21). Another change in both evacuation times and shelter locations can be appreciated when α raises from 0.4 to 0.5. In this case, the bus-based evacuation maximum completion time decreases by nearly 3% (from 166.2 to 161.6), while the car-based evacuation total duration time rises by around 15% (from 361.2 to 415.2), and node 22 is opened instead of node 21. A visual representation of the trade-off between the bus-based evacuation maximum completion time and the car-based evacuation total duration time when α varies between 0 and 1 for the combined scenario is displayed in Figure 25.

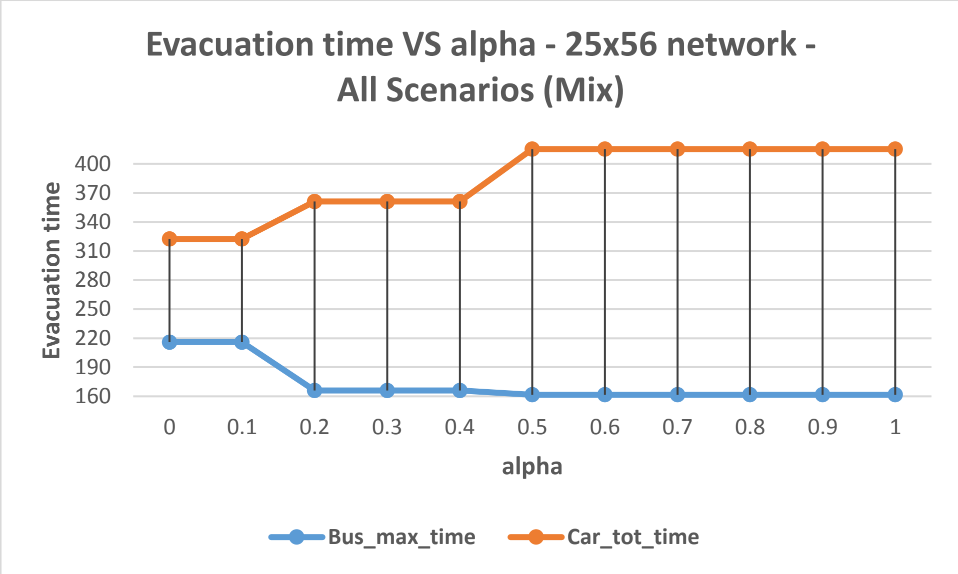

Figure 25. Evacuation times trade-off for different values of α – 25x56 network – All Scenarios (Mix)

Moreover, the comparison of the results across all the tables highlights the importance of considering multiple scenarios. The solutions found when all the three scenarios are taken into account can differ quite significantly from the solutions obtained for a single scenario. For example, the optimal set of shelters in the solution obtained when α = 0.2, 0.3 and 0.4, which is composed of nodes 20, 21, 23, and 24, is different from the optimal set selected in the single scenario instances for the same values of α (i.e., 19, 21, 23, and 24 for both the small and medium scenarios and 19, 20, 22, and 24 for the large scenario), and so are the bus routes and self-evacuee to shelter allocations.

Table 18 reports the values of the linear relaxation of SISLER without any inequality (*LR*), with the addition of inequalities (54) (*LR+BUS*), with the addition of inequalities (58) (*LR+FLOW*), and with the addition of both inequalities (54) and (58) (*LR+BUS+FLOW*) for the small (*S*), medium (*M*), large (*L*) scenarios, and their combination (*MIX*), respectively.

Table 18. Computational results for the 25x56 network – Linear relaxation values

Scenario	LR	LR+BUS	LR+FLOW	LR+BUS+FLOW
S	103.83	111.83	113.9	120.83
M	113.18	121.98	137.9	145.9
L	117.98	132.38	141.7	153.57
MIX	109.47	118.99	126.66	134.9

From the analysis of the table, it is possible to appreciate the improvement in the value of the linear relaxation of SISLER due to the addition of the inequalities. The presence of inequalities (54), (58), and their combination increases, respectively, the value of the linear relaxation by around: 8% (from 103.83 to 111.83), 10% (from 103.83 to 113.9), and 16% (from 103.83 to 120.83) in the small scenario; 8% (from 113.18 to 121.98), 22% (from 113.18 to 137.9), and 29% (from 113.18 to 145.9) in the medium scenario; 12% (from 117.98 to 132.38), 20% (from 117.98 to 141.7), and 30% (from 117.98 to 153.57) in the large scenario; and 9% (from 109.47 to 118.99), 16% (from 109.47 to 126.66), and 23% (from 109.47 to 134.9) in the combined scenario. The value of the linear relaxation is the same whichever value of α hence, it seems that the choice of α is not relevant to this matter. Usually, an improvement in the value of the linear relaxation allows to solve instances in a shorter amount of time. As mentioned previously, it was not possible to appreciate these benefits of the additional inequalities in terms of computational performance on the 25x56 network. However, the positive contribution of the additional inequalities will be demonstrated through the analysis of the experimental results of the 25x165 network, specifically when it comes to combined scenario instances.

5.3.1.2 Computational results for the 25x165 network

Following the same scheme for instance generation, computational results are now reported for a more dense network with 25 nodes and 165 arcs. In particular, it is demonstrated how the inclusion of the ad-hoc inequalities within the IBM ILOG CPLEX Branch-and-Cut framework makes a clear difference and allows to always obtain an integer solution, which would have not been possible otherwise, within the pre-fixed computational time limit set equal to 3600 seconds. The reason for this tight time limit is due to the fact that, in order to effectively deploy SISLER during the DOM response phase, it has to provide solutions in a reasonable amount of time.

Results are displayed in Table 19, 20, 21 and 22 for the small, medium, large scenarios, and their combination, respectively. The tables report the CPU time spent at the root node in seconds (*Time at the root node*) and the total CPU time spent to solve an instance in seconds (*Total CPU time*) without any inequality (*I*), with the addition of inequalities (54) (*I+BUS*), with the addition of inequalities (58) (*I+FLOW*), and with the addition of both inequalities (54) and (58) (*I+BUS+FLOW*) for different values of α ranging from 0 to 1. The tables also report the solution details in terms of bus-based evacuation maximum completion time (*Bus max time*), the car-based evacuation total duration time (*Car tot time*) and the open shelters (note that the potential shelter sites for the 25x165 network are nodes 19, 20, 21, 22, 23, and 24) for all the different values of α.

Table 19. Computational results for the 25x165 network – Scenario 1 (Small)

Scenario 1 (Small)											
	I		I+BUS		I+FLOW		I+BUS+FLOW		Solution details		
α	Time at root node	Total CPU time	Time at root node	Total CPU time	Time at root node	Total CPU time	Time at root node	Total CPU time	Bus max time	Car tot time	Open shelters
0	2.17	120.28	3.20	22.23	1.53	144	1.17	27.22	133	402	{20,21,24}
0.1	2.90	20.28	4.15	13.28	1.56	108.5	1.59	23.24	132	407	{20,23,24}
0.2	1.70	18.22	2.25	44.73	1.31	28.39	1.00	28.27	132	407	{20,23,24}
0.3	2.40	90.26	2.46	43.35	1.28	40.83	1.20	34.45	132	407	{20,23,24}
0.4	2.11	16.04	2.56	17.72	1.45	25.49	1.04	22.11	132	407	{20,23,24}
0.5	2.56	75.75	1.86	81.79	1.31	134.88	1.67	23.17	132	407	{20,23,24}
0.6	2.07	57.6	1.84	33.74	1.28	30.11	1.62	37.21	132	407	{20,23,24}
0.7	2.04	11.61	1.61	18.39	1.64	33.82	1.22	26.57	132	407	{20,23,24}
0.8	2.37	12.23	1.29	27.24	1.47	37.28	1.06	23.6	132	407	{20,23,24}
0.9	1.62	15.79	2.17	12.39	1.69	33.17	1.51	39.42	132	407	{20,23,24}
1	2.06	16.05	1.76	12.51	1.56	34.62	1.75	43.41	132	407	{20,23,24}
AVG	2.2	41.3	2.3	29.8	1.46	59.2	1.4	29.9	132.1	406.6	N/A

Table 20. Computational results for the 25x165 network – Scenario 2 (Medium)

Scenario 2 (Medium)											
	I		I+BUS		I+FLOW		I+BUS+FLOW		Solution details		
α	Time at root node	Total CPU time	Time at root node	Total CPU time	Time at root node	Total CPU time	Time at root node	Total CPU time	Bus max time	Car tot time	Open shelters
0	6.26	7.79	3.63	4.34	0.84	2.04	0.95	12.85	133	402	{20,21,24}
0.1	3.54	5.73	4.24	8.35	1.16	5.12	1.28	7.24	133	401	{20,23,24}
0.2	3.28	5.93	2.01	5.3	1.14	3.68	1.08	1.7	133	401	{20,23,24}
0.3	2.11	3.95	2.76	3.17	1.33	4.84	0.80	1.73	133	401	{20,23,24}
0.4	2.18	2.53	1.82	4.87	0.83	9.2	1.22	5.41	133	401	{20,23,24}
0.5	1.73	3.77	1.89	10.45	1.15	4.59	1.04	7.13	133	401	{20,23,24}
0.6	1.19	3.65	2.06	6.54	0.73	5.07	0.56	1.39	133	401	{20,23,24}
0.7	1.90	2.59	1.87	3.57	1.11	10.97	0.83	3.39	133	401	{20,23,24}
0.8	1.54	3.52	1.67	5.26	0.84	6.71	0.55	1.47	133	401	{20,23,24}
0.9	0.84	1.76	0.76	3.04	0.81	13.73	0.73	5.29	133	401	{20,23,24}
1	0.91	1.67	0.76	2.34	0.97	13.46	0.79	6.01	133	401	{20,23,24}
AVG	2.3	3.9	2.1	5.2	1.0	7.2	0.9	4.9	133.0	401.1	N/A

Table 21. Computational results for the 25x165 network – Scenario 3 (Large)

	Scenario 3 (Large)										
	I		I+BUS		I+FLOW		I+BUS+FLOW		Solution details		
α	Time at root node	Total CPU time	Time at root node	Total CPU time	Time at root node	Total CPU time	Time at root node	Total CPU time	Bus max time	Car tot time	Open shelters
0	4.88	5.57	4.90	5.41	2.45	6.69	1.00	6.3	139	409	{20,22,24}
0.1	4.66	9.7	5.80	13.62	2.40	3.43	1.51	3.2	137	416	{22,23,24}
0.2	1.81	3.01	1.97	9.84	1.04	5.97	0.81	5.91	133	420	{20,21,24}
0.3	3.81	5.48	1.89	3.2	1.00	8.61	0.73	8.75	133	420	{20,21,24}
0.4	2.21	4.57	1.36	9.48	0.73	27.71	0.84	6.33	133	420	{20,21,24}
0.5	2.04	4.45	0.89	5.66	1.16	42.89	0.64	7.08	133	420	{20,21,24}
0.6	1.45	36.57	1.48	9.58	0.83	13.48	0.75	7.69	133	420	{20,21,24}
0.7	1.12	6.99	1.01	12.64	0.69	49.37	1.67	6.36	133	420	{20,21,24}
0.8	1.69	7.29	1.45	7.83	0.98	9.11	0.94	14.88	133	420	{20,21,24}
0.9	1.86	8.02	0.97	8.85	1.00	24.48	0.42	17.14	133	420	{20,21,24}
1	1.14	20.23	1.00	26.16	1.11	10.31	0.50	6.54	133	420	{20,21,24}
AVG	2.4	10.2	2.1	10.2	1.2	18.4	0.9	8.2	133.9	418.6	N/A

Table 22. Computational results for the 25x165 network – All Scenarios (Mix)

	All Scenarios (Mix)										
	I		I+BUS		I+FLOW		I+BUS+FLOW		Solution details		
α	Time at root node	Total CPU time	Time at root node	Total CPU time	Time at root node	Total CPU time	Time at root node	Total CPU time	Bus max time	Car tot time	Open shelters
0	-	-	-	-	-	-	-	-	-	-	-
0.1	4.04	3600*	5.41	3600*	2.06	143.69	2.18	522.67	135	395.3	{22,23,24}
0.2	3.32	3600*	4.04	3600*	3.06	623.74	2.50	474.41	132.5	411.2	{20,23,24}
0.3	3.60	3600*	2.93	3600*	3.38	736.04	2.54	2769.05	132.5	411.2	{20,23,24}
0.4	3.32	3600*	4.74	3408	3.11	3600*	2.31	282.14	132.5	411.2	{20,23,24}
0.5	3.09	3600*	3.12	3600*	3.95	947.85	2.89	1922.12	132.5	411.2	{20,23,24}
0.6	3.84	3600*	4.15	3600*	2.80	630.01	2.68	855.87	132.5	411.2	{20,23,24}
0.7	3.32	3600*	3.21	3600*	3.34	1194.53	2.25	253.8	132.5	411.2	{20,23,24}
0.8	3.14	3600*	3.56	3600*	2.42	1707.12	2.28	534.18	132.5	411.2	{20,23,24}
0.9	5.23	3600*	5.04	3600*	2.96	2409.87	2.34	418.72	132.5	411.2	{20,23,24}
1	3.48	3600*	3.20	3600*	3.31	3600*	2.62	440.56	132.5	411.2	{20,23,24}
AVG	3.6	3600	3.9	3580.8	3	1559.3	2.5	847.4	132.8	409.6	N/A

Legend: - = No solution has been found; * = Instance not been solved to optimality within the pre-fixed time limit of 3600 seconds; N/A = Not Applicable

Similarly to the 25x56 network, it is possible to infer the trade-off between the bus-based evacuation maximum completion time and the car-based evacuation total duration time. For example, in the small scenario (i.e., Table 19) when α increases from 0 to 0.1, the supported-evacuation maximum completion time drops by nearly 1% (from 133 to 132), while the self-evacuation total duration time increases by around 1% (from 402 to 407). This entails a change in the shelter location decisions where node 23 is open instead of node 21. A visual representation of the trade-off between the bus-based evacuation maximum completion time and the car-based evacuation total duration time when α varies between 0 and 1 for the small scenario is displayed in Figure 26.

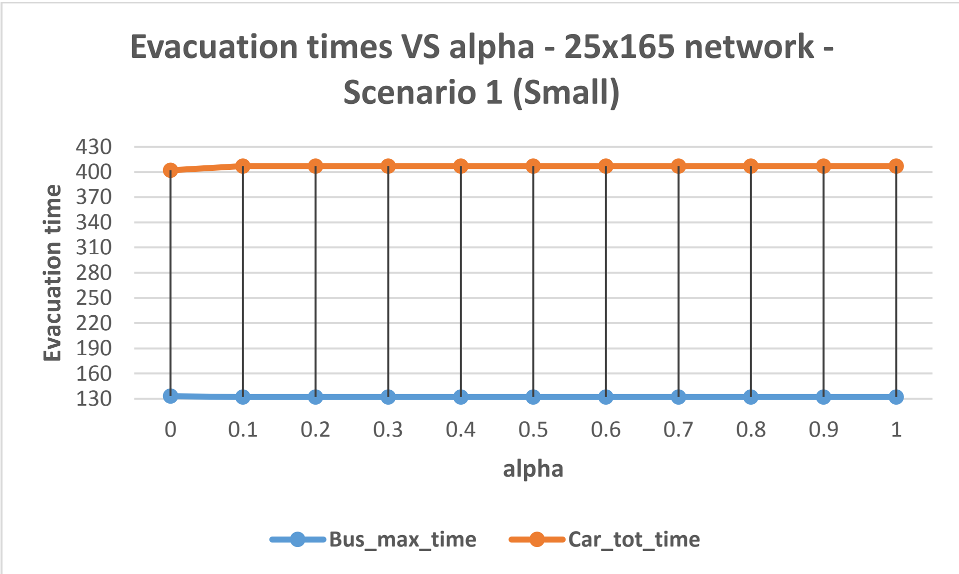

Figure 26. Evacuation times trade-off for different values of α – 25x165 network – Scenario 1 (Small)

Another example can be appreciated from the analysis of the medium scenario (i.e., Table 20). When α increases from 0 to 0.1, the bus-based evacuation maximum completion time does not change however, the car-based evacuation total duration time decreases slightly (from 402 to 401). This is motivated by the fact that the more α increases, the more the self-evacuation traveling time threshold becomes looser, thus allowing allocations that were infeasible for lower values of α. This also entails a change in the shelter location decisions where node 23 is open instead of node 21.

Further examples emerge in the analysis of the large scenario (i.e., Table 21). When α increases from 0 to 0.1, the supported-evacuation maximum completion time drops by nearly 1% (from 139 to 137), while the self-evacuation total duration time increases by around 2% (from 409 to 416), and there is a change in shelter locations (from node 20 to node 23). Another change in both evacuation times and shelter sites can be observed when α rises from 0.1 to 0.2. In this case, the bus-based evacuation maximum completion time decreases by nearly 3% (from 137 to 133), while the car-based evacuation total duration time raises by around 1% (from 416 to 420), and the optimal set of shelter locations changes from 22, 23, and 24 to 20, 21, and 24. A visual representation of the trade-off between the bus-based evacuation maximum completion time and the car-based evacuation total duration time when α varies between 0 and 1 for the large scenario is displayed in Figure 27.

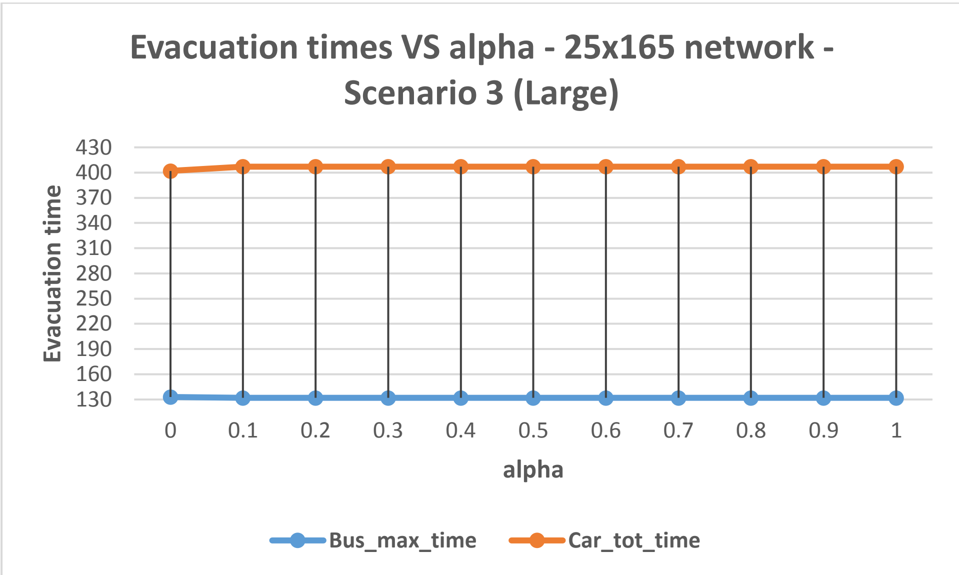

Figure 27. Evacuation times trade-off for different values of α – 25x165 network – Scenario 3 (Large)

Finally, the trade-off can also be inferred when the three scenarios are combined together (i.e., Table 22). In fact, when α rises from 0.1 to 0.2, the supported-evacuation maximum completion time decreases by around 2% (from 135 to 132.5), while the car-based evacuation total duration time rises by nearly 4% (from 395.3 to 411.2), and node 20 is opened instead of node 22. A visual representation of the trade-off between the bus-based evacuation maximum completion time and the car-based evacuation total duration time when α varies between 0 and 1 for the combined scenario is displayed in Figure 28.

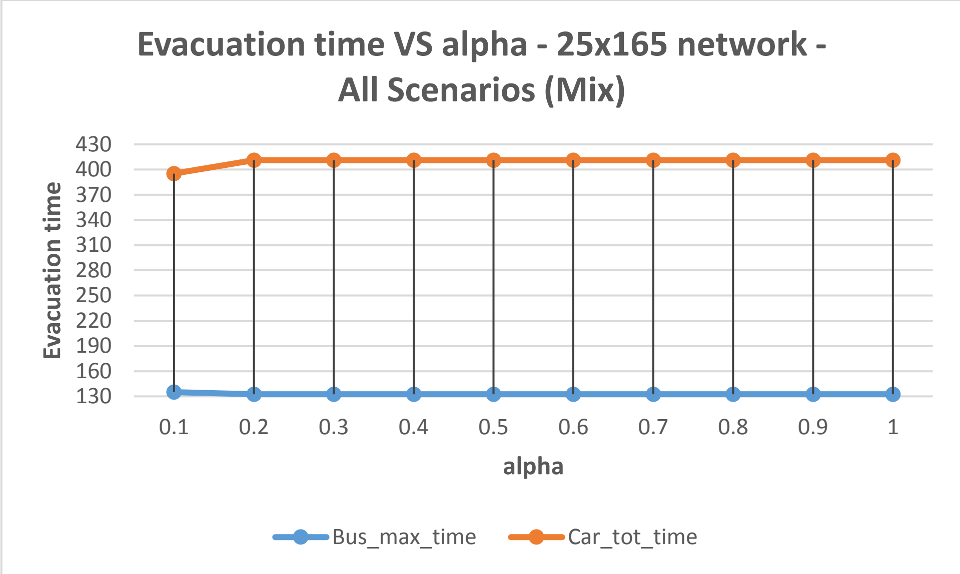

Figure 28. Evacuation times trade-off for different values of α – 25x165 network – All Scenarios (Mix)

Table 23 reports the values of the linear relaxation of SISLER without any inequality (*LR*), with the addition of inequalities (54) (*LR+BUS*), with the addition of inequalities (58) (*LR+FLOW*), and with the addition of both inequalities (54) and (58) (*LR+BUS+FLOW*) for the small (*S*), medium (*M*), large scenarios (*L*), and their combination (*MIX*), respectively.

Table 23. Computational results for the 25x165 network – Linear relaxation values

Scenario	LR	LR+BUS	LR+FLOW	LR+BUS+FLOW
S	64.86	68.36	86.86	90.30
M	64.86	68.36	95.36	98.61
L	64.86	68.36	95.36	98.61
MIX	64.86	68.36	91.11	94.46

Further observations can be drawn from the combined analysis of Tables 19, 20, 21, 22, and 23 that concern the value of the linear relaxation of SISLER, the total CPU time spent to solve an instance, and the number of instances that have not been solved to optimality within the pre-fixed time limit (this applies exclusively to combined scenario instances). Table 23 shows that the addition of inequalities (54), (58), as well as their combination, leads to an improvement of the value of the linear relaxation of SISLER by around, respectively: 5% (from 64.86 to 68.36), 34% (from 64.86 to 86.86), and 39% (from 64.86 to 90.30) in the small scenario; 5% (from 64.86 to 68.36), 47% (from 64.86 to 95.36), and 52% (from 64.86 to 98.61) in both the medium and large scenarios; and 5% (from 64.86 to 68.36), 40% (from 64.86 to 91.11), and 46% (from 64.86 to 94.46) in the combined scenario. These values are correlated to the time spent at the root node as well as the total CPU time spent to solve an instance and, specifically in case of combined scenario instances (i.e., Table 22), to the number of instances that have been solved within the pre-fixed time limit of 3600 seconds. The presence of additional inequalities entails an increase in the time spent at the root node by around 8% (from 3.6 to 3.9) when adding inequalities (54), while a decrease by nearly 16% (from 3.6 to 3) when adding inequalities (58), and 32% (from 3.6 to 2.5) for their combination, based on average computed values (*AVG*). On the other side, the total CPU time decreases by around 3% (from 3600 to 3508.8), 57% (from 3600 to 1559.3), and 76% (from 3600 to 847.4) for inequalities (54), (58), and their combination, respectively, based on average computed values (*AVG*). These results are in line with the increase in the value of the linear relaxation previously reported. Furthermore, the presence of inequalities allows to solve instances to optimality within the pre-fixed time limit and to reduce the average gap for those that were not solved to optimality, as displayed in Table 24. In particular, Table 24 reports the lower bound value (*LB*), the upper bound value (*UB*), which is the best found integer, and the resulting gap (*GAP*) for combined scenario instances without any inequality (*I*), with the addition of inequalities (54) (*I+BUS*), with the addition of inequalities (58) (*I+FLOW*), and with the addition of both inequalities (54) and (58) (*I+BUS+FLOW*) when α varies from 0 to 1.

Table 24. Computational results for the 25x165 network – All Scenarios (Mix) – Gap analysis

	I			I+BUS			I+FLOW			I+BUS+FLOW		
α	LB	UB	GAP	LB	UB	GAP	LB	UB	GAP	LB	UB	GAP
0	-	-	-	-	-	-	-	-	-	-	-	-
0.1	131.54	137	3.99%	131.17	137	4.26%	135	135	0%	135	135	0%
0.2	113.09	133	14.97%	129.14	133	2.90%	132.5	132.5	0%	132.5	132.5	0%
0.3	126.63	133	4.79%	123.94	133	6.81%	132.5	132.5	0%	132.5	132.5	0%
0.4	123.99	133	6.77%	132.5	132.5	0%	132.24	132.5	0.20%	132.5	132.5	0%
0.5	132.5	133	0.38%	123.64	133	7.04%	132.5	132.5	0%	132.5	132.5	0%
0.6	123.04	133	7.49%	132.5	133	0.38%	132.5	132.5	0%	132.5	132.5	0%
0.7	125.13	133	5.92%	127.87	133	3.86%	132.5	132.5	0%	132.5	132.5	0%
0.8	125.43	133	5.69%	129.13	133	2.91%	132.5	132.5	0%	132.5	132.5	0%
0.9	128.54	133	3.35%	130.83	133	1.63%	132.5	132.5	0%	132.5	132.5	0%
1	128.74	133	3.20%	126.54	133	4.86%	130	132.5	1.89%	132.5	132.5	0%
AVG	125.86	133.4	5.65%	128.73	133.35	3.46%	132.474	132.75	0.21%	132.75	132.75	0

Legend: - = No solution has been found; N/A = Not Applicable

The addition of inequalities (54), which yield the lowest increase of the linear relaxation value, did not allow to solve any of the combined scenario instance to optimality. Conversely, the addition of inequalities (58), to which corresponds a higher increase of the linear relaxation value, allowed to close to optimality eight out of ten combined scenario instances. Finally, the combination of inequalities (54) and (58), to which corresponds the best improvement in the value of the linear relaxation, yield to close to optimality all the combined scenario instances. Moreover, a decrease in the average gap by around 39% (from 5.65% to 3.46%) and 96% (from 5.65% to 0.21%) can be appreciated for inequalities (54) and (58), respectively.

5.3.2 Case study: Sioux Falls network

5.3.2.1 Case study description

In addition to testbed instances, SISLER has also been tested on a realistic case study, which is the Sioux Falls network (network data are available at Transportation Network, which is a network repository for transportation research (Transportation Network for Research Core Team)). The Sioux Falls network has been quite used in the transportation literature, including evacuation planning studies (Ng, Park and Waller 2010). The network is composed of 24 nodes and 76 arcs and it is displayed in Figure 29.

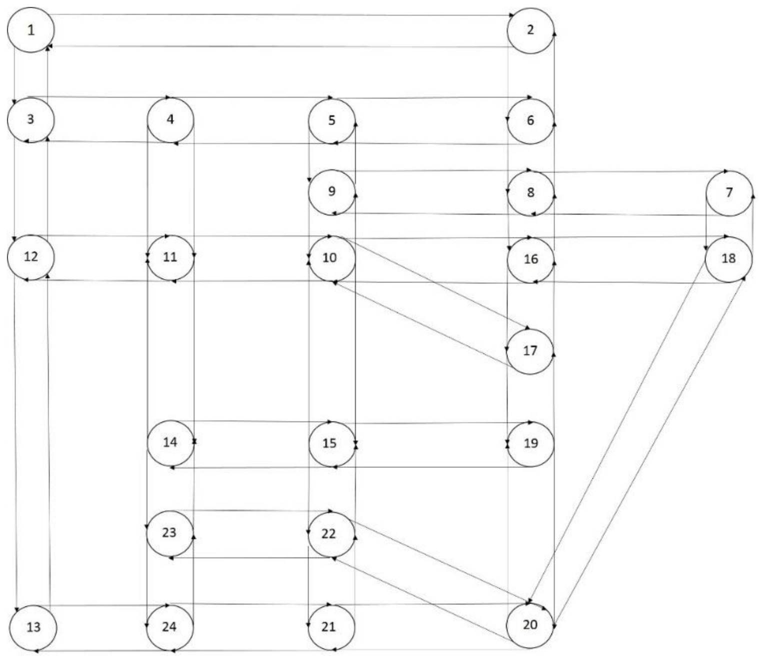

Figure 29. Sioux Falls Network (adapted from Transportation Network for Research Core Team)

For experimentation purposes: node 4, 7, 8, 14, 19, and 21 are assumed to be car-based evacuation only zones; node 3, 9, 15, and 22 are assumed to be bus-based evacuation only zones; node 5, 11, 16, and 23 are assumed to be mixed-evacuation zones (i.e., both car-based and bus-based evacuations can occur); node 1, 2, 13, 18, and 20 are assumed to be candidate shelter sites; node 12 is assumed to be the depot; and the remaining network nodes are assumed to be pure transshipment nodes. Note that, based on SISLER assumptions, arcs whose final destination is a candidate shelter location are travelled only towards the shelter (hence, the arc that is travelled in the opposite direction is not considered) and, given that buses are not returning to the depot, all the network arcs originally having node 12 as a terminal point have been discarded. This has led to a reduced version of the Sioux Falls network with 24 nodes and 58 arcs, as reported in Figure 30.

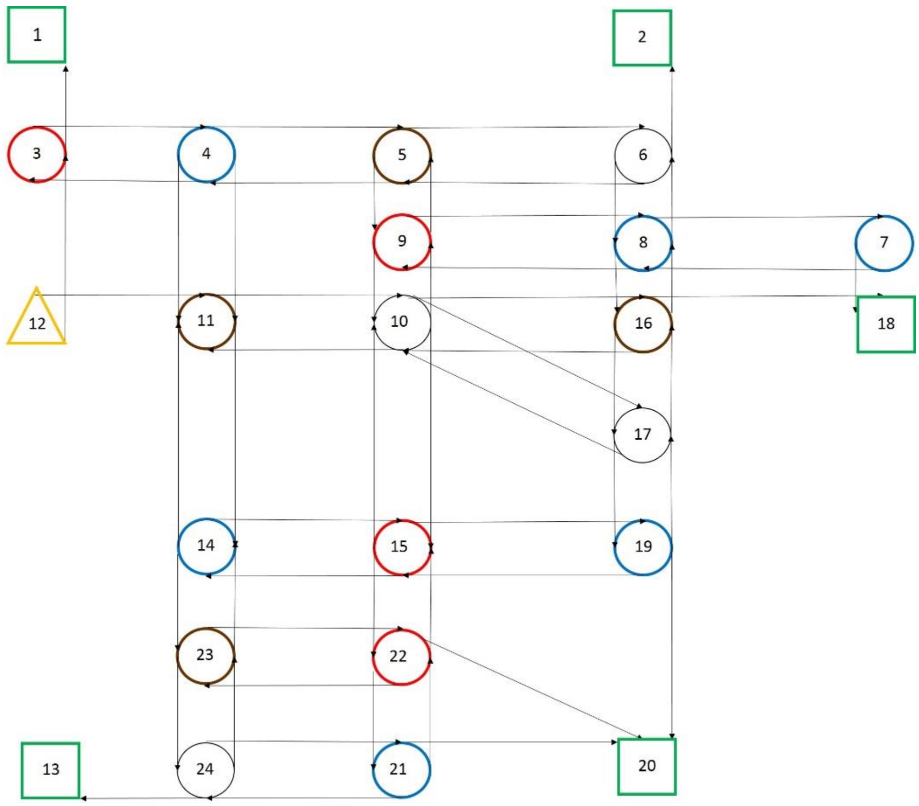

Figure 30. Sioux Falls network under SISLER assumptions – Scenario 1 (Small)

Network nodes are categorized in Figure 30 as follows: blue, red, and brown round shapes represent car-based only, bus- based only, and mixed-evacuation demand zones, respectively; green square shapes are shelter candidate locations; and the yellow triangle is the depot.

Evacuation demand and traveling times have been computed based on the Sioux Falls network data that have been found (Transportation Networks). Model parameter settings (e.g., bus fleet, number of buses, shelter capacity, self-evacuees traveling time threshold, and scenario probability distribution) are computed exactly as described for the testbed instances. The three different scenarios have been designed as follows: for the small scenario (Scenario 1), it is assumed that all network arcs are available, which is the network displayed in Figure 30; for the medium scenario (Scenario 2), it is assumed that arcs (4,5), (5,4), (8,16), (14,15), (15,14), and (16,8) are disrupted; and for the large scenario (Scenario 3), it is assumed that arcs (10,11), (10,17), (11,10), (17,10), (21,24), and (24,21) are disaster-affected, in addition to the arcs already unavailable in the medium scenario. Figure 31 and Figure 32 display the Sioux Falls network under Scenario 2 and Scenario 3 circumstances, respectively.

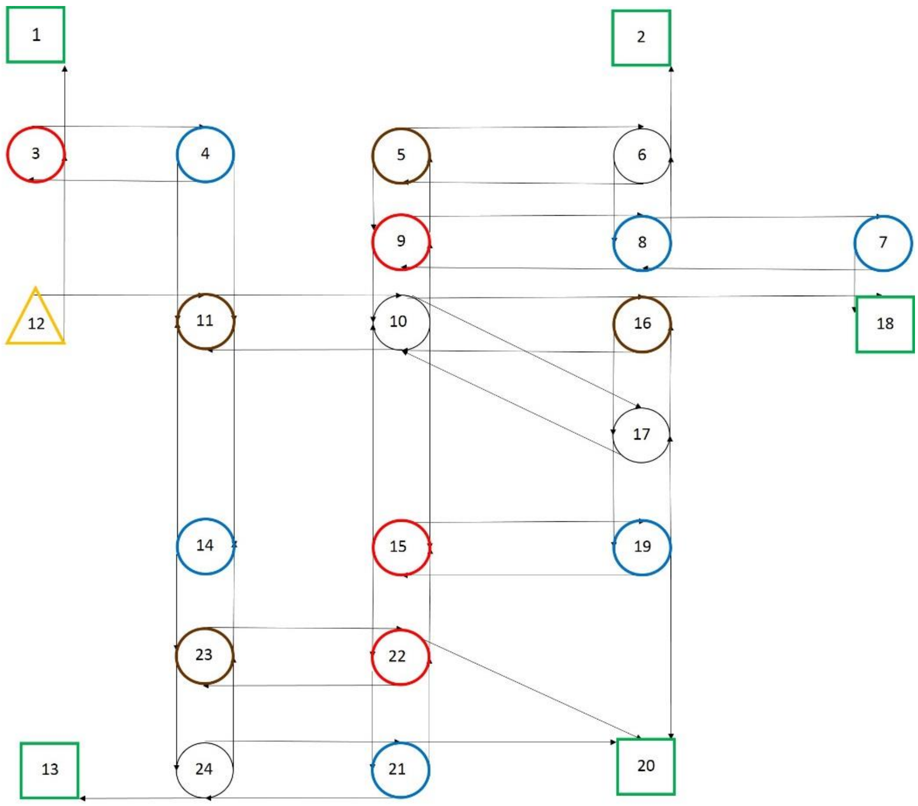

Figure 31. Sioux Falls network under SISLER assumptions – Scenario 2 (Medium)

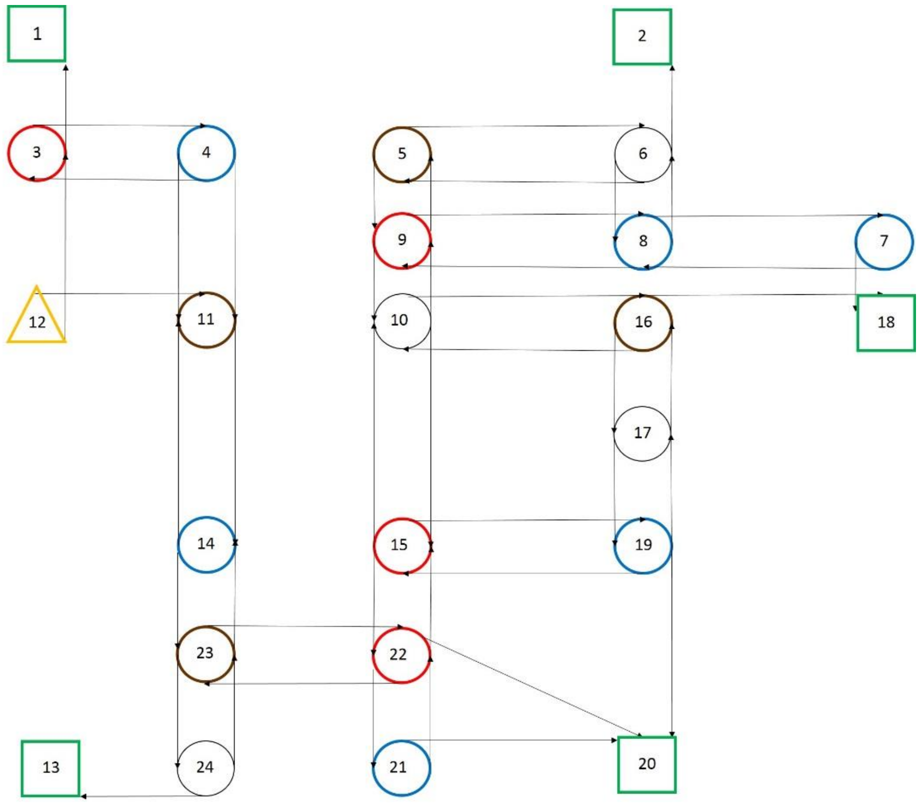

Figure 32. Sioux Falls network under SISLER assumptions – Scenario 3 (Large)

5.3.2.2 Computational results

The results for the Sioux Falls network are displayed in Table 25, 26, 27, and 28 for the small, medium, large scenarios, and their combination, respectively. The tables report the bus-based evacuation maximum completion time, the car-based evacuation total duration time and the open shelters for different values of α ranging from 0 to 1 (remember that the potential shelter sites for the Sioux Falls network are nodes 1, 2, 13, 18, and 20).

Table 25. Computational results for the Sioux Falls network – Scenario 1 (Small)

Scenario 1 (Small)			
α	Bus-based evacuation max completion time	Car-based evacuation total time	Open Shelters
0	25	83	{2,18,20]
0.1	25	83	{2,18,20}
0.2	25	74	{13,18,20}
0.3	25	74	{13,18,20}
0.4	25	74	{13,18,20}
0.5	25	74	{13,18,20}
0.6	25	74	{13,18,20}
0.7	25	74	{13,18,20}
0.8	25	74	{13,18,20}
0.9	25	74	{13,18,20}
1	25	74	{13,18,20}

Table 26. Computational results for the Sioux Falls network – Scenario 2 (Medium)

Scenario 2 (Medium)			
α	Bus-based evacuation max completion time	Car-based evacuation total time	Open Shelters
0	41	75	{1,18,20}
0.1	41	75	{1,18,20}
0.2	41	75	{1,18,20}
0.3	31	79	{13,18,20}
0.4	31	79	{13,18,20}
0.5	31	79	{13,18,20}
0.6	31	79	{13,18,20}
0.7	31	79	{13,18,20}
0.8	31	79	{13,18,20}
0.9	31	79	{13,18,20}
1	31	79	{13,18,20}

Table 27. Computational results for the Sioux Falls network – Scenario 3 (Large)

Scenario 3 (Large)			
α	Bus-based evacuation max completion time	Car-based evacuation total time	Open Shelters
0	44	88	{1,2,20}
0.1	44	88	{1,2,20}
0.2	44	88	{1,2,20}
0.3	44	88	{1,2,20}
0.4	44	88	{1,2,20}
0.5	44	88	{2,13,18}
0.6	44	88	{2,13,18}
0.7	44	88	{1,2,20}
0.8	44	88	{2,13,18}
0.9	44	88	{2,13,18}
1	44	88	{2,13,18}

From the analysis of the tables, it is possible to infer the trade-off between the bus-based evacuation maximum completion time and the car-based evacuation total duration time.

For example, in the small scenario (i.e., Table 25) when α increases from 0.1 to 0.2, the supported-evacuation maximum completion time does not change while the self-evacuation total duration time reduces by around 11% (from 83 to 74). This is motivated by the fact that the more α increases, the more the self-evacuation traveling time threshold becomes looser, thus allowing allocations that were infeasible for lower values of α and, in this specific case, it also implies a change in the shelter location decisions (from node 2 to node 13). A change in both evacuation times and shelter locations can be observed from the analysis of the medium scenario (i.e., Table 26). When α increases from 0.2 to 0.3, the bus-based evacuation maximum completion time drops by nearly 23% (from 41 to 31), while the car-based evacuation total duration time increases by around 5% (from 75 to 79), leading to a shift in shelter location decisions (node 13 is opened instead of node 1). A visual representation of the trade-off between the bus-based evacuation maximum completion time and the car-based evacuation total duration time when α varies between 0 and 1 for the medium scenario is displayed in Figure 33.

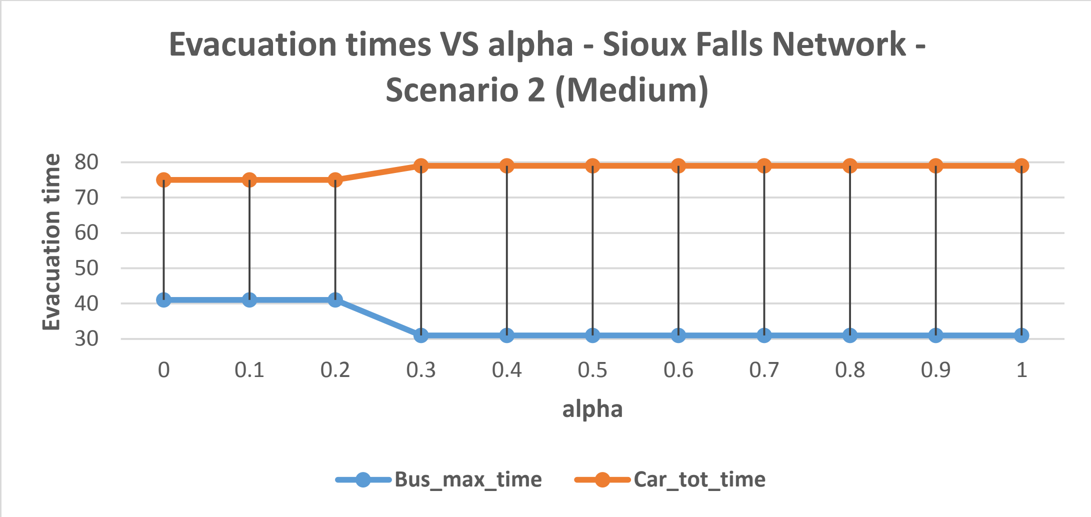

Figure 33. Evacuation times trade-off for different values of α – Sioux Falls network – Scenario 2 (Medium)

Moreover, regarding the large scenario (i.e., Table 27), neither the supported-evacuation maximum completion time nor the self-evacuation total duration time change however, there are some changes in the shelter location decisions (e.g., when α increases from 0.4 to 0.5). The reason for this can be the presence of multiple optimal solutions. In fact, the objective function considers the supported-evacuation maximum completion time and the self-evacuation total duration time in its lexicographic form however, the shelter location decisional variables are not present in the objective function.

Single scenario instances were solved in matter of few seconds. Results of combined scenario instances are reported in Table 28. The table reports the CPU time spent at the root node in seconds (*Time at the root node*) and the total CPU time spent to solve an instance in seconds (*Total CPU time*) under four different circumstances which are without any inequality (*I*), with the addition of inequalities (54) (*I+BUS*), with the addition of inequalities (58) (*I+FLOW*), and with the addition of both inequalities (54) and (58) (*I+BUS+FLOW*) for different values of α ranging from 0 to 1. The tables also report the solution details in terms of bus-based evacuation maximum completion time (*Bus max time*), the car-based evacuation total duration time (*Car tot time*) and the open shelters for all the different values of α.

Table 28. Computational results for the Sioux Falls network – All Scenarios (Mix)

All Scenarios (Mix)											
	I		I+BUS		I+FLOW		I+BUS+FLOW		Solution details		
α	Time at root node	Total CPU time	Time at root node	Total CPU time	Time at root node	Total CPU time	Time at root node	Total CPU time	Bus max time	Car tot time	Open shelters
0	1.25	949.75	1.28	800.71	1.58	2099.81	1.39	267.28	36	73	{1,18,20}
0.1	1.20	3002.2	1.29	2797.32	1.76	783.81	1.45	826.6	36	73	{1,18,20}
0.2	1.20	344.19	1.26	512.7	1.69	638.98	2.06	817.54	36	73	{1,18,20}
0.3	1.09	105.19	1.11	65.26	1.78	94.71	1.97	52.88	33	75.4	{1,18,20}
0.4	1.23	66.69	1.36	60.79	1.95	58.41	1.70	141.8	31	81.9	{1,18,20}
0.5	1.01	337.77	1.34	130.96	1.53	401.61	1.33	349.96	31	76.9	{13,18,20}
0.6	1.31	175.19	1.29	186.03	1.34	595.89	1.42	433.37	31	76.9	{13,18,20}
0.7	1.34	369.83	1.11	214.92	1.64	229.43	1.39	433.64	30.6	83.1	{2,18,20}
0.8	1.11	229.73	1.14	119.47	1.67	144.77	1.62	80.09	30.6	83.1	{2,18,20}
0.9	1.00	143.32	1.19	401.25	1.39	92.56	1.37	326.09	30.6	83.1	{2,18,20}
1	1.19	338.47	1.08	233.19	1.68	128.5	1.53	75.49	30.6	83.1	{2,18,20}
AVG	1.17	551.12	1.22	502.05	1.64	478.95	1.58	345.85	32.4	78.4	N/A

From the analysis of Table 28, it is possible to infer the trade-off between the bus-based evacuation maximum completion time and the car-based evacuation total duration time. For example, when α increases from 0.2 to 0.3, the supported-evacuation maximum completion time drops by around 8% (from 36 to 33) while the self-evacuation total duration time increases by around 3% (from 73 to 75.4) however, this does not entail a change in shelter location decisions. Another example can be observed when α rises from 0.3 to 0.4, in fact, the bus-based evacuation maximum completion time decreases by around 6% (from 33 to 31) while the car-based evacuation total duration time increases by around 1% (from 75.4 to 76.9). Differently, when α increases from 0.4 to 0.5, there is no change in bus-based evacuation maximum completion time however, the car-based evacuation total duration time drops by around 6% (from 81.9 to 76.9). This is motivated by the fact that the more α increases, the looser is the self-evacuation traveling time threshold thus allowing self-evacuees to shelter allocation that were not allowed for previous values of α. Moreover, this leads to a change in the shelter location decisions, in fact, node 13 is opened instead of node 1. A further example of trade-off between bus-based evacuation and car-based evacuation that does also require a shift in shelter location decisions can be appreciated when α rises from 0.6 to 0.7, where the supported-evacuation maximum completion time drops by around 1% (from 31 to 30.6) while the self-evacuation total duration time increases by around 8% (from 76.9 to 83.1), and node 2 is opened instead of node 13. A visual representation of the trade-off between the bus-based evacuation maximum completion time and the car-based evacuation total duration time when α varies between 0 and 1 for the combined scenario is displayed in Figure 34.

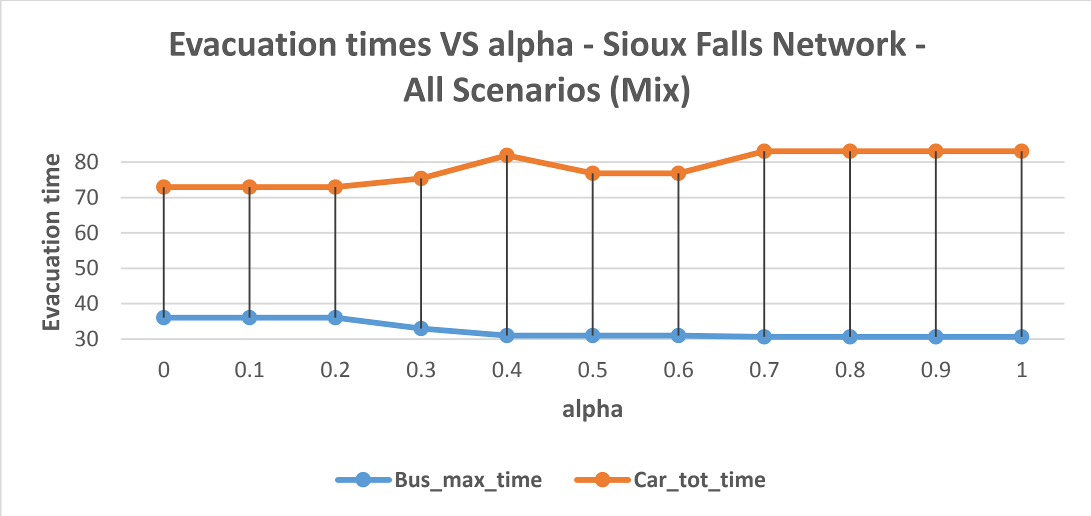

Figure 34. Evacuation times trade-off for different values of α – Sioux Falls network – All Scenarios (Mix)

Moreover, the comparison of the results across all the tables highlights the importance of considering multiple scenarios. In fact, the solutions found when all the three scenarios are taken into account can differ quite significantly from the solutions obtained for a single scenario. For example, the optimal set of shelters in the solution obtained when α = 0.7, 0.8, 0.9, and 1, which is composed of nodes 2, 18, and 20, is different from the optimal set selected in each individual scenario for the same values of α (i.e., 13, 18, and 20 for both the small and medium scenarios and 2, 13, and 18 for the large scenario), and so are the bus routes and self-evacuee to shelter allocations.

Table 29 reports the values of the linear relaxation of SISLER without any inequality (*LR*), with the addition of inequalities (54) (*LR+BUS*), with the addition of inequalities (58) (*LR+FLOW*), and with the addition of both inequalities (54) and (58) (*LR+BUS+FLOW*) for the small (*S*), medium (*M*), large scenarios (*L*), and their combination (*MIX*), respectively.

Table 29. Computational results for the Sioux Falls network – Linear relaxation values

Scenario	LR	LR+BUS	LR+FLOW	LR+BUS+FLOW
S	19.31	19.31	19.57	19.57
M	19.82	19.82	20.09	20.09
L	24.42	24.42	24.68	24.68
MIX	20.48	20.48	20.75	20.75

Further observations can be drawn from the combined analysis of Tables 28 and 29 from a computational perspective. A slight improvement in the value of the linear relaxation of SISLER can be appreciated due to the addition of the inequalities. The presence of inequalities (54) does not yield any improvement while inequalities (58) increase the value of the linear relaxation by around 1% in each single scenario (from 19.31 to 19.57 in the small scenario, from 19.82 to 20.09 in the medium scenario, and from 24.42 to 24.68 in the large scenario). The combination of inequalities (54) and (58) does not produce any improvement. The reason for this result may be due to either the specific network under consideration or the scenario settings. The presence of additional inequalities entails an increase in the time spent at the root node by around 3% (from 1.17 to 1.22), 39% (from 1.17 to 1.64), and 33% (from 1.17 to 1.58), for inequalities (54), (58), and their combination, respectively, based on average computed values (AVG). Inversely, the total CPU time decreases by around 9% (from 551.12 to 502.05), 13% (from 551.12 to 478.95), and 37% (from 551.12 to 345.85) for inequalities (54), (58), and their combination, respectively, also based on average computed values (AVG). This is in line with the increase in the value of the linear relaxation (from 20.48 to 20.75) that can be appreciated for both inequalities (58) and combination of both (54) and (58). Hence, this demonstrates the positive contribution deriving from additional inequalities. Obviously, there are some instances for specific values of α, where the addition of inequalities may actually delay the completion of an instance however, the above statements hold on average terms, and single instances should be studied separately for each network.

5.4 Conclusions

This chapter has introduced a novel scenario-based mixed-integer program to optimize shelter location and evacuation routing decisions simultaneously. In particular, to the best of my knowledge, this is the second model that attempts to address together shelter location, car-based evacuation, and bus-based evacuation. The model integrates both user and system perspectives, in fact, the former is still in charge of his routes and the latter arranges shelter sites and evacuation for special-needs populations. Trade-off solutions between the two perspectives can be appreciated through the willingness of self-evacuees to travel paths that are lengthier than their shortest ones. The model has been solved through a Branch-and-Cut algorithm of an off-the-shelf software which has been enriched with additional inequalities based on the study of the literature of related problems. Experimentation has been carried out on both testbed instances and a realistic case study. Results have shown user-system trade-off solutions and have also highlighted the importance of considering different disruption scenarios. In fact, in some cases, the solution obtained for combined scenarios can be quite different from the solutions of the related single scenario instances. Moreover, it has been proven that the addition of further inequalities has positively contributed to the model solution from a computational perspective. In fact, for the larger testbed network, it has allowed to solve instances within the pre-fixed time limit and has sped up the total CPU time needed to close instances on an average basis (this has been appreciated also for the realistic case study). Hence, the obtained results demonstrate that the approach is able to find robust and efficient evacuation plans, thus providing local governments and emergency planners with a valuable decision support tool.

Nevertheless, SISLER is not exempt from limitations based on its underpinning assumptions. Firstly, SISLER is a deterministic model because assumes that the evacuation demand is known. However, evacuees may not be willing to leave their own houses despite warning signals thus requiring adjustments to the evaluation of the evacuation demand. This shortcoming may be tackled through the development of a formulation based on robust programming so as to account for uncertainties in the evacuation demand. Secondly, SISLER, is a static model and, given that disasters are intrinsically dynamic, a further research step would be to develop a time-dependent formulation so as to account for several aspects: disaster propagation (whichever the choice of disruption scenarios), traffic evolution (so as to include also congestion), and resources availability (both in terms of shelters to be equipped and vehicles to be used). Thirdly, the usage of the Euclidean distance as a proxy for travelling times may not be correctly representative of a real network. From a mathematical perspective, the Euclidean distance is a norm 2 while the Manhattan distance is a norm 1: in order to account for real-like distances, a norm between 1 and 2 shall be used. Finally, from a computational perspective, SISLER has been tested on networks whose node cardinality is around 25 and whose arc cardinality ranges from 56 to 165; also, only three possible scenarios have been considered (i.e., small-like disruption, medium-like disruption, and large-like disruption). With these settings, the proposed Branch-and-Cut approach with additional inequalities has proven to be successful however, an increase in the number of disruption scenarios and/or network dimensions will require the development of new ad-hoc cuts (to be identified through polyhedral theory) and/or to devise other approaches (such as applying Benders decomposition or deploying some forms of relaxation to obtain bounds to speed up the resolution process). Hence, despite the successful and encouraging results so far obtained, enhancements of SISLER from both a modeling and an algorithmic perspectives will have to be considered in order to increase its potential as a realistic model and its application to larger real-life networks (i.e., scalability).

6. Conclusions

This chapter summarizes the contributions of this dissertation and offers some further research directions towards the two research fields this doctoral activity has dealt with: critical information infrastructure protection and shelter location and evacuation routing.

6.1 Research summary

This dissertation has focused on operations belonging to the mitigation and response phases of the DOM. In particular, on the mitigation side, the attention has been devoted to the field of *critical information infrastructure protection*, while, on the response side, two key evacuation planning operations have been investigated, *shelter location and evacuation routing*.

Within the *CIIP* context, the following research questions have been answered: CIIP.1) what are the most critical elements of a system that, if disrupted, would interrupt or significantly degrade the system's normal functioning; CIIP.2) how can such an interruption be prevented or mitigated by resource allocation plans aimed at hardening system elements; and CIIP.3) is it possible and worthwhile to design and establish infrastructures that are intrinsically able to resist service failure when a disruptive event occurs? Questions CIIP.1), CIIP.2), and CIIP.3) have been answered by reviewing *survivability-oriented interdiction*, *resource allocation strategy*, and *survivable design models*. From the review process, it has emerged that resource allocation strategy models to protect CII constitute a research area so far overlooked. Hence, the focus has then be narrowed to the resource allocation strategy models category, and a survey of multi-level programs that have been developed for protecting other CI (i.e., *supply chains*, *transportation systems*, and *utility networks*) has been produced so to identify some aspects that could be adapted for CIIP. Moreover, a novel bi-level program, namely the *Critical Node Detection Problem with Fortification (CNDPF)* problem, has been introduced. In particular, the ultimate goal is to minimize the negative impact on network connectivity due to worst-case disruptions, affecting the system nodes, through mitigation strategies finalized at the installation of additional network arcs. A SVI decomposition method and a Greedy Constructive Local Search (GCLS) approach have been developed to solve the model. Two real telecommunication networks (Sterbenz et al., 2010b) have been used to test the model and the corresponding solution methodologies. Experimental results have proven that the SVI decomposition algorithm is a quite successful exact method however, it can encounter difficulties when problem dimensions increase, which motivates the need to develop an alternative (or auxiliary) heuristic approach. The Greedy Constructive and Local Search heuristic with a one-to-one swap policy (GCLS1) has proven to be a valid alternative to the SVI decomposition algorithm when applied to a small network, while The Greedy Constructive and Local Search heuristic with a two-to-two swap policy (GCLS2) has performed satisfyingly on a larger network, and proved to be better than GCLS1. Nevertheless, results have highlighted that a reasonable expenditure of protection resources can yield significant improvements in the network connectivity.

Within the *shelter location* and *evacuation routing* context, the following research questions have been answered: SLER.1) what are the current challenges emerging in the shelter location and evacuation routing field from an optimization-based perspective; SLER.2) when planning for efficient evacuation plans: how many shelters should be opened and where should they be located, how should self-evacuation be addressed in the planning framework, and how should supported-evacuation be organized in order to assist people belonging to sensitive categories (e.g., disabled, elderly)? Question SLER.1) has been answered by reviewing specific optimization-based disaster management surveys and critically analysing the most recent optimization models tackling the two aforementioned problems in an integrated manner. Through the analysis of these state of the art models, the current challenges emerging in this research area have been identified. These include: *stakeholder involvement*, *evacuation modes*, *clear definition of modelling inputs*, *evacuee behavior*, *system behavior*, and *methodology*. In addition, a roadmap for future research has been outlined. Furthermore, based on some of the identified challenges, question SLER.2) has been answered by defining a novel scenario-based location-allocation-routing model to optimize evacuation planning decisions. The proposed model, called the *Scenario-Indexed Shelter Location and Evacuation Routing (SISLER)* model, integrates shelter location and evacuation routing decisions, while considering both a user perspective (self-evacuation) and a system perspective (supported-evacuation). It also addresses the uncertainty of the infrastructure availability after a disaster by optimizing evacuation plans across several disruption scenarios. It has been demonstrated that the model can be used to identify user-system trade-off solutions on both testbed instances and a realistic case study. Experimentation has also highlighted the importance of considering different disruption scenarios.

6.2 Further research directions

6.2.1 Critical Information Infrastructure Protection

The research on CIIP issues aimed at hedging against potential physical attacks is still evolving. The demand for such work has been prompted by disasters of diverse nature, with 9/11 being a seminal one.

On a general note, the survivability optimization models that have been reviewed in this dissertation are basic models that can be extended in a number of ways. For example, interdiction and protection models could be extended to tackle both physical and logical survivability issues by incorporating routing and arc capacity assignment decisions. In addition, most of the optimization models developed so far are deterministic. However, failures and disruptions are random events, often difficult to predict. The probabilistic behavior of complex CII under disruptions would be better modelled by using stochastic models, including uncertain parameters (e.g., uncertainty on arc/node availability, extent of a disruption, etc.). Alternatively, the uncertainty characterizing disruptions could be captured in scenario-based models which incorporate robustness measures for the identification of solutions which perform well across different disruption scenarios. Future models could even combine the optimization of protection and restoration strategies in a unified framework so as to distribute resources efficiently across the different stages of the DOM cycle (protection plans belong to the pre-disaster stage while recovery plans refer to the post-disaster stage). Other resource allocation models could consider identifying trade-off investments in physical protection and cyber-security to mitigate the impact of both physical and logical attacks. The models discussed in this dissertation have been solved by using a variety of optimization algorithms, including exact methods (e.g., decomposition) and heuristics (e.g., evolutionary algorithms). The development of more complex models, such as stochastic, bi-level and multi-objective models, would necessarily require additional research into the development of more sophisticated solution techniques, possibly integrating exact and heuristic methodologies into a hybrid heuristic framework. Another possible line of research could be to investigate hyper-heuristics, which can be defined as learning mechanisms that either choose or generate heuristics to solve complex combinatorial problems and whose final aim is to find the best sequence of heuristics to be used rather than solving the problem just with one method (Burke et al. 2013).

On a more specific level, critical information infrastructure protection can be achieved through the optimal allocation of protective resources among system components.

Alternatively, CIIP can be achieved through network design operations (i.e., network extension aimed at increasing system redundancy). The CNDPF belongs to the latter category. Some possible research directions are described as follows. Firstly, from a modeling perspective, the option of partial interdiction as proposed by (Aksen, Akca and Aras 2014) could be considered. Partial interdiction means that the disruption of a network node does not necessarily imply its total inoperability. This could be eventually linked with the concept of level of service or recovery time, as introduced by Losada, Scaparra and O'Hanley (2012). The CNDPF has been formulated as a deterministic bi-level program however, given that the failure of a system component is an uncertain event, a stochastic version could be defined (Liberatore, Scaparra and Daskin 2011; Losada et al. 2012). To this end, a probability could be associated to the failure of a specific network node. Moreover, it would also be interesting to incorporate different interdiction models at the lower level, as those described in (Faramondi et al. 2017; Faramondi et al. 2018). These include: the β-Vertex Disruptor problem, which aims at identifying the smallest set of network nodes whose removal would degrade the network connectivity to a pre-fixed level, or the Cardinality Constrained Critical Node Detection Problem (CC-CNP), which aims at identifying the smallest set of network nodes to be disrupted so that the size of the largest connected component is within a predefined acceptance threshold. Secondly, from a methodological perspective, alternative swap policies for the local search phase (e.g., one-to-many) in combination with different ordering (e.g., increasing rather than decreasing) for the greedy constructive procedure could be investigated for GCLS. Moreover, other different local search-based heuristic approaches could be tested in order to assess how to tackle some of the shortcomings emerged in the application of GCLS. These include Greedy Randomized Adaptive Search Procedure (GRASP), Iterated Greedy Local Search, and Variable Neighborhood Search (VNS). Eventually, these models could also be tested on network with specific topologies (i.e., full mesh, star, etc.) so as to identify any connection between the algorithm suitability and the network topological structure.

Finally, the ultimate challenge when developing optimization approaches for increasing CII survivability is to consider the interdependency among multiple CI and the potential cascading failures across different lifeline systems. As noted by (Sharkey et al. 2015), information sharing and coordination among infrastructures significantly improve the effectiveness of survivability strategies, as opposed to decentralized decision making. However, existing models that address network interdependencies are either overly simplistic or too theoretical. This line of research certainly warrants further investigation.

6.2.2 Shelter location and evacuation routing

Shelter location and evacuation routing, and evacuation planning more in general, is a field which offers plenty of opportunities for both practitioners and researchers, which still requires in-depth investigation given that their combination has not yet been tackled comprehensively.

On a general note, the following issues should be addressed: adoption of Soft OR/PSMs approaches; development of multi-objective, combined, multi-period and stochastic models, along with cutting edge algorithms; clear and realistic modelling assumptions; deployment of information systems and user-friendly GIS-based platforms; primary data collection to embed more realism into optimisation models; combination of different evacuee categories; inclusion of assisted and multi-modal evacuation and issues such as evacuation vehicle procurement; addressing of issues such as time of day, route diversion, evacuee demographics, route preferences, and warning signals to model evacuee behaviour more accurately; adoption of novel equity-based approaches for shelter location and evacuation routing; integration of infrastructure disruption, congestion, and shelter categories into optimisation models; and interdisciplinary research towards shelter location and evacuation routing.

On a more specific level, this dissertation introduced a scenario-based location-allocation-routing model to optimize evacuation planning decisions, namely SISLER. SISLER is still far from being comprehensive and could be further extended to include other complicating aspects, such as a time perspective (through a time-dependent formulation), congestion issues, multiple objectives, demand uncertainties, evacuation modes (i.e., inclusion of SED) and evacuee behavior. Decisions about the timing of evacuation orders and the distribution of relief supplies to shelters could also be integrated into the model. The model needs to be tested on larger networks, for different probability distributions and with different disruption scenarios. Undoubtedly, solving larger problems with many disruption scenarios will require to further improve the solution method that has been proposed (through the definition of ad-hoc valid inequalities and separation procedures), to be eventually paired with ad-hoc heuristic approaches. Moreover, advanced methods for generating realistic scenarios, even in a different way from the one proposed, and solving large-scale stochastic programs (e.g., Sample Average Approximation) should be developed; robust optimization approaches could be adopted to account for evacuation demand uncertainties and different targets (e.g., evacuation time, evacuee risk, network congestion, shelter coverage) could be considered through a multi-objective optimization framework. Furthermore, it could be also investigated how to improve the current lexicographic objective function formulation so as to also account for the optimization of the bus routes directly into the objective function. Obviously, this requires more research into identifying values of the lexicographic constants so that not just the main objective is dominant but the first lexicographic component dominates over the second one.

Hence, the research proposed in this doctoral dissertation has got potential to practically improve mitigation and response operations in Disaster Management and could serve to emergency management decision-makers such as public authorities, NGOs as well as humanitarian operators. Eventually, 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 operations 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 direct 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. This would not only lead to advances in the OR discipline towards the challenging and interdisciplinary nature of DM problems but also help to bridge the gap between the development of optimization tools and their practical application in disaster situations so as to propose novel approaches that are more closely aligned with technology and practice.

7. Research contributions

This section reports the papers that have been published and the conference talks that have been given during the doctoral activity. Some of the produced contributions are part of the thesis (as specified) while others are not included. However, they are listed for completeness in order to provide a detailed summary of the research that has been produced.

7.1 Papers

Esposito Amideo A., Scaparra M.P., Kotiadis K. (2018). Optimising Shelter Location and Evacuation Routing Operations: The Critical Issues. *European Journal of Operational Research* (In press) – Chapter 4

Starita S., **Esposito Amideo A.**, Scaparra M.P. (2018). Assessing Urban Rail Transit Systems Vulnerability: Metrics vs. Interdiction Models. In: *D'Agostino G., Scala A. (eds) Critical Information Infrastructures Security. CRITIS 2017. Lecture Notes in Computer Science*, vol 10707. Springer, Cham. DOI: https://doi.org/10.1007/978-3-319-99843-5_13

Faramondi, L., Oliva, G., Setola, R., Pascucci, F., **Esposito Amideo, A.**, and Scaparra, M. P. (2017). Performance Analysis of Single and Multi-Objective Approaches for the Critical Node Detection Problem. In: *Sforza A., Sterle C. (eds) Optimization and Decision Science: Methodologies and Applications. ODS 2017. Springer Proceedings in Mathematics & Statistics*, vol 217 (pp. 315-324). Springer, Cham. DOI: https://doi.org/10.1007/978-3-319-67308-0_32

Esposito Amideo, A., and Scaparra, M. P. (2017). A Scenario Planning Approach for Shelter Location and Evacuation Routing. In: *Sforza A., Sterle C. (eds) Optimization and Decision Science: Methodologies and Applications. ODS 2017. Springer Proceedings in Mathematics & Statistics*, vol 217 (pp. 567-576). Springer, Cham. DOI: https://doi.org/10.1007/978-3-319-67308-0_57 – Chapter 5 is an extension of this research paper

Esposito Amideo A., Scaparra M.P. (2017). A Synthesis of Optimization Approaches for Tackling Critical Information Infrastructure Survivability. In: *Havarneanu G., Setola R., Nassopoulos H., Wolthusen S. (eds) Critical Information Infrastructures Security. CRITIS 2016. Lecture Notes in Computer Science*, vol 10242 (pp. 75-87). Springer, Cham. DOI: https://doi.org/10.1007/978-3-319-71368-7_7 – Chapter 2 is an extension of this research paper

7.2 Conference Talks

Esposito Amideo, A.*, Scaparra, M. P., Sforza, A., and Sterle C.. Integrating Shelter Location and Evacuation Routing: A Trade-Off between User and System Perspectives. *OR60 "Anniversary" Conference, 11th-13th September 2018, Lancaster, UK.* – Chapter 5 contains elements of this presentation

Esposito Amideo, A.*, Scaparra, M. P., Sforza, A., and Sterle C.. An integrated user-system approach for shelter location and evacuation routing. *7th International Workshop on Freight Transportation and Logistics, Odysseus 2018, 3rd-8th June 2018, Cagliari, ITALY.* – Chapter 5 contains elements of this presentation

Starita, S., **Esposito Amideo, A.***, and Scaparra, M. P.. Assessing Urban Rail Transit Systems Vulnerability: Metrics vs. Interdiction Models. *The 12th International Conference on Critical Information Infrastructures Security, CRITIS2017, 9th-11th October 2017, IMT School for Advanced Studies, Lucca, ITALY.*

Esposito Amideo, A.*, and Scaparra, M. P.. A Scenario Planning Approach for Shelter Location and Evacuation Routing. *International Conference on Optimization and Decision Science, XLVII Annual Meeting of AIRO, ODS 2017, 4th-8th September 2017, Sorrento, Naples, ITALY.* – Chapter 5 contains elements of this presentation

Esposito Amideo, A.*, Scaparra, M. P., and Kotiadis, K.. OR Applied to Shelter Location and Evacuation Routing: Emerging Challenges and Further Research Directions. *Socialising Business Research – Connecting and Advancing Knowledge, 5th-7th June 2017, Kent Business School, University of Kent, Canterbury, UK*. – Chapter 4 contains elements of this presentation

Esposito Amideo, A.*, and Scaparra, M. P.. A Synthesis of Optimization Approaches for Tackling Critical Information Infrastructure Survivability. *The 11th International Conference on Critical Information Infrastructures Security, CRITIS2016, 10th-12th October 2016, UIC Headquarters, Paris, FRANCE.* – Chapter 2 contains elements of this presentation

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