OPTIMIZING PRE-EARTHQUAKE MITIGATION MEASURES TO IMPROVE THE EFFICIENCY OF EVACUATION OPERATIONS

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Abstract

In order to reduce human losses and minimize social and economic disruption caused by large-scale earthquakes, effective planning and operational decisions need to be made by responsible agencies and institutions across all pre- and post-disaster stages. Despite the volume and variety of Earthquake Operations Management (EOM) studies employing Operational Research (OR) methodologies, the development of widely applicable methodologies and frameworks emerges as a key insight in need of greater attention.

The first purpose of this dissertation is to highlight and discuss main lines of research involving the use of OR techniques applied specifically to earthquakes disasters. In the light of this purpose, this dissertation reveals the current research gaps in existing OR methodologies in the context of EOM and provides a roadmap for future research by a comprehensive review study. Throughout, we precisely categorize studies based on the disaster stage(s) being dealt with, methodology(ies) applied, and specific planning/operational problem type. We also provide details about the extent of stakeholder involvement and information relating to case studies. Some important considerations are examined relating to realism, comprehensiveness, practicality, and user-friendliness that have been taken from the various problem definitions and solution methodologies described in the literature. Therefore, this dissertation provides important insights on enhancing the realism and applicability of the solution methodologies.

This thesis secondly aims at providing an integrated modelling approach that incorporates mitigation and response stage operations. The key issue is to select optimally the roadway links to be strengthened in a road network by considering their effect on the response stage operations. Given the critical importance of connectivity between affected areas and critical response facilities (i.e., hospitals, fire stations, relief logistics centres) for disaster response operations, as well as the need to improve accessibility as a precautionary measure through link strengthening investments, this dissertation is expected to make a significant contribution to the disaster logistics literature by providing an efficient and practical method to optimize these mitigation decisions.

a Capacitated Network Strengthening Problem (CNSP), which involves optimizing pre-disaster mitigation decisions to strengthen road network links structurally to maximize the efficiency of post-earthquake evacuation operations, is formulated as a two-stage stochastic program. Existing studies that integrate decision making for mitigation and response stage operations include lack of consideration regarding post-earthquake resource availability (i.e., service capacity of hospitals). We take into account the service capacities of supplier facilities so that people can receive timely and necessary medical care. Existing studies have also used overly simplistic assumptions about infrastructure damage levels, operability/survivability of network links and the effectiveness of protection. In this study, operability basically depends on mitigation efforts, earthquake characteristics, and structure features.

Due to the multi-objective structure of the CNSP, multi-objective approaches are first discussed to decide the best approach to solve the model. Second, the Sample Average Approximation (SAA) method is used to reduce the scenario set to a manageable size. The SAA procedure can be applied to solve the stochastic programs with a large number of scenarios, by which good solutions could be provided. Then, a heuristic algorithm based on the Greedy Randomized Adaptive Search Procedure (GRASP) is proposed to solve larger instances. By focusing on earthquakes, the necessary input parameters for the proposed model and solution approach are generated in a realistic setting. Computational experiments are conducted based on generated real-life data and instances adapted from the literature, both to demonstrate the use of the methods and to derive insights for decision authorities.

Acknowledgment

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Research Declaration

This section reports the papers that have been published and will be submitted and the conference talks that have been given during the doctoral activity.

Journal Papers (Published and Ongoing)

Coban B., Scaparra M.P., O'Hanley J.R., (2021). Use of OR in earthquake operations management: A review of the literature and roadmap for future research, International Journal of Disaster Risk Reduction 65, 102539. – Chapter 2

On-going research paper: Coban B., Scaparra M.P., O'Hanley J.R., (2022). Optimizing pre-earthquake mitigation measures to improve the efficiency of evacuation operations – (It will be a summary form of Chapter 3, 4, 5, and 6). In preparation.

The plan is to submit the second paper to the journal Omega in May 2022.

Conference Talks

Coban B., Scaparra M.P., Integrating mitigation and response operations for earthquake operations management. 30th European Conference on Operational Research, 23-26 June 2019, Dublin Ireland - Chapter 2, 3 contain elements of this talk.

Coban B., Scaparra M.P., Optimizing pre-earthquake mitigation measures to improve the efficiency of evacuation operations, The OR Society, OR61 Annual Conference, 3-5 September 2019, Canterbury UK- Chapter 3, 5, and 6 contains elements of this presentation.

Coban B., Scaparra M.P., Network Improvement Problem to improve the efficiency of post-earthquake evacuation operations, International Disaster and Humanitarian Aid Congress, 9-11 February 2022, Istanbul Turkey- Chapter 3, 4, 5, and 6 contains elements of this presentation.

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List of Abbreviations

AA	Affected Areas
ABM	Agent-Based Model
AI	Artificial Intelligence
ATC	Applied Technology Council
BD	Benders Decomposition
CNSP	Capacitated Network Strengthening Problem
CW	Central Warehouses
DA	Decomposition Algorithm
DM	Debris Management
DOM	Disaster Operations Management
EOM	Earthquake Operations Management
ERC	Emergency Response Center
EEWS	Earthquake Early Warning Systems
ES	External Suppliers
FIR	Facility And Infrastructure Restoration
FEMA	US Federal Emergency Management Agency
FHWA	US Federal roadway Administration
GRASP	Greedy Randomized Adaptive Search Procedure
IFRC	International Federation of Red Cross and Red Crescent Societies
IMM	Istanbul Metropolitan Municipality
INFORMS	The Institute for Operations Research and The Management Sciences
IP	Integer Programming
JICA	Japan International Cooperation Agency
GA	Genetic Algorithm
GAP	Generalized Assignment Problem
GIS	Geographical Information System
LCC	Local Collection Centres
LOS	Level of Service
LS	Local Search
M	Mitigation
MCS	Monte Carlo Simulation
MCDM	Multi-Criteria Decision Making
MIF	Multi-Period Interdiction Problem with Fortification
MILP	Mixed-Integer Linear Programming
MS	Management Science
NGO	Nongovernmental Organizations
NSP	Network Strengtening Problem
OCHA	UN Office For the Coordination of Humanitarian Affairs
OR	Operations Research
PGA	Peak Ground Acceleration

PSOA	Particle Swarm Optimization Algorithm
UAV	Unmanned Aerial Vehicle
UD	Unmet Demand
UN	United Nations
P	Preparedness
P/RP	Pre-Positioning/Resource Planning
PP	Protection Planning
RC	Recovery
RD	Relief Distribution
RDC	Relief Distribution Centres
RS	Response
RVA	Reliability And Vulnerability Analysis
SAA	Sample Average Approximation
SD	System Dynamics
SR	Search And Rescue
TA	Tabu Algorithm
TFHA	Turkish Federal roadway Administration
VSM	Viable System Model

1. Introduction

This chapter defines the general context for this dissertation, identifies the issues that have been researched, introduces the research topics that have been addressed, discusses the contributions to knowledge that have been made, and, ultimately, outlines the structure of this dissertation.

1.1. Research Background

Globally, geophysical disasters – primarily earthquakes – lead annually to the death of thousands of people, dislocate millions, and cause significant damage to buildings, roads, and other infrastructure. Between 2009 and 2020, there have been approximately 1800 large earthquakes (magnitude 6 or greater on the Richter scale) and nearly 366,000 fatalities caused by earthquakes across the globe (see Figure 1), more than all other natural disasters put together [1]. Information about the most devastating earthquakes during this period is presented in Table 1.

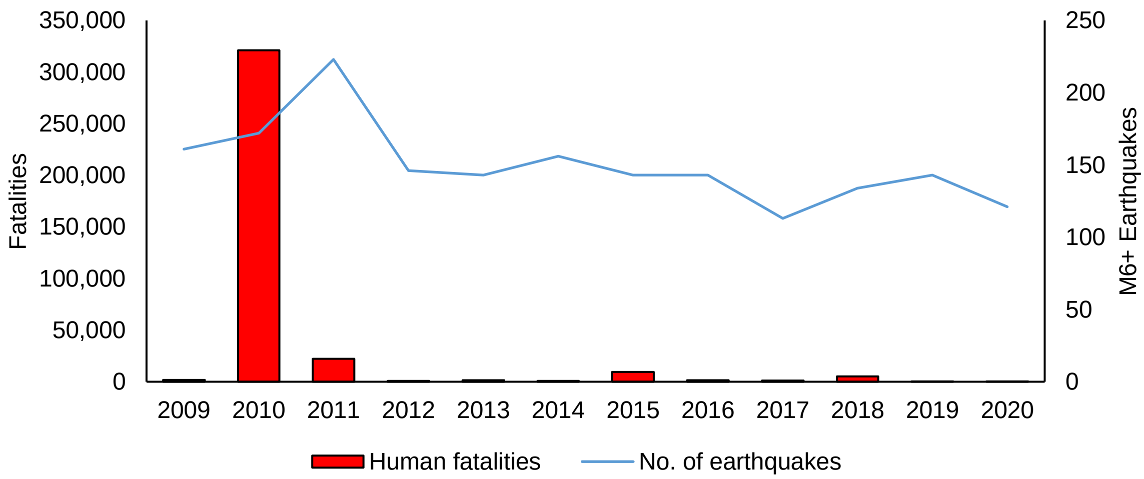

Figure 1. High magnitude earthquake occurrence and human fatalities 2009 to 2020 based on data from the Centre for Research on the Epidemiology of Disasters [1]

Recent earthquake disasters have affected many parts of the world from Asia to the America Although a number of regions and countries are particularly prone to earthquakes, fatalities and other impacts can be highly variable depending on a range of factors such as geological conditions (i.e., presence of active faults and seismic vulnerability), earthquake characteristics (i.e., magnitude, focal depth, and epicentre location), area affected (i.e., city or region), level of development (i.e., physical conditions of building and transportation networks), and preparedness level (i.e., early warning system and risk management measures) [2–5].

Table 1. Most devastating earthquakes 2009-2020

Event	Fatalities	Magnitude	Location
2008 Sichuan earthquake	87,587	7.9	China
2010 Haiti earthquake	316,000	7.0	Haiti
2011 Tōhoku earthquake and tsunami	20,896	9.1	Japan
2015 Nepal earthquake	8,964	7.8	Nepal
2018 Sulawesi earthquake and tsunami	4,340	7.5	Indonesia

Strategic and systematic mitigation actions can significantly reduce vulnerabilities to earthquake damage. For example, two major earthquakes – the 2004 Indian Ocean tsunami and the 2010 Haiti earthquake – both lead to hundreds of thousands of deaths, while a similar scale earthquake in New Zealand in 2010 affected 300,000 people but killed no one due to strict building codes and high level of preparedness [6]. Another example is the most recent disaster in September 2018, the 7.5 magnitude earthquake and subsequent tsunami that hit Palu and Donggala in central Sulawesi, Indonesia. While the number of deaths was comparatively small (4,340), the earthquake ended up displacing over 200,000 people and destroyed or damaged over 40,000 homes [7] as a result of power and communications lines being cut, which led to many residents not receiving tsunami warning messages. This disaster highlights the costs of not implementing a more sophisticated early warning system.

‘Disaster Management’ is defined by The International Federation of Red Cross and Red Crescent Societies (IFRC) as:

> “the organization and management of resources and responsibilities for dealing with all humanitarian aspects of emergency situations under four stages: mitigation and preparedness for pre-disaster operations to decrease the negative influences as far as possible, and response and recovery for post-disaster activities in order to lessen the impact of disasters” [8].

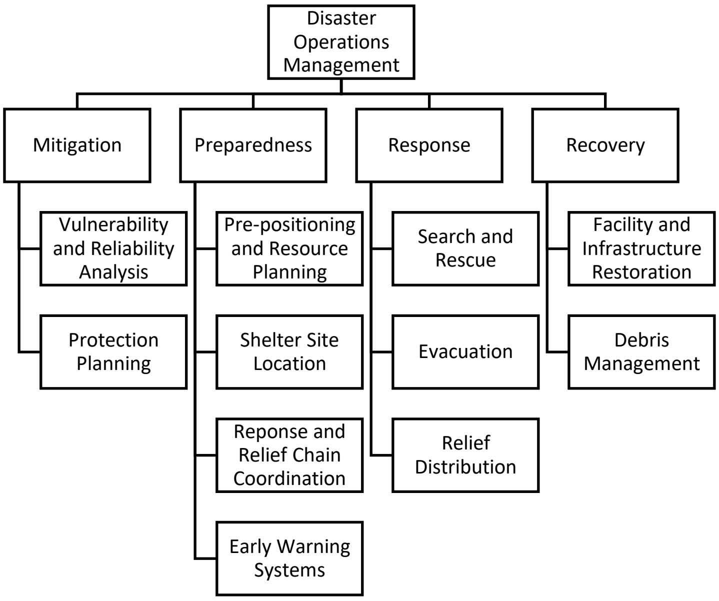

Figure 2. Disaster operations management stages and typical problems addressed in the OR literature

Disaster Operations Management (DOM) involves four distinct stages. The first two focus on pre-disaster issues, the latter two deal with post-disaster measures [9]. *Mitigation* or prevention (stage 1) involves understanding what vulnerability to hazards exist along with protection measures to reduce risk and increase resilience. *Preparedness* (stage 2) assesses plans to save lives and organize response operations prior to a disaster occurring. The main aim is to reach a satisfactory level of readiness to respond to an emergency through development of programs that strengthen the technical and managerial capacity of governments, organizations, and communities (i.e., early warning systems and pre-position of supplies). *Response* operations (stage 3) aim to provide timely assistance to victims, relief, and evacuation of the affected population to a safe zone. *Recovery* (stage 4) takes place after an emergency and is primarily concerned with activities to remove debris, rebuild damaged buildings, and repair essential infrastructure. Figure 2 displays the four DOM stages and typical problems addressed in each stage.

In order to minimize loss of life and social/economic disruption caused by earthquakes, effective planning at all stages of disaster management (i.e., mitigation, preparedness, response, recovery) is required. One analytical approach is the use of operations research (OR) techniques, which can help government agencies and nongovernmental organizations (NGOs) to develop sound and effective procedures and optimize the use of limited resources. The Institute for Operations Research and the Management Sciences (INFORMS) defines OR as:

> “proven scientific, mathematical processes that enable organizations to turn complex challenges into substantial opportunities by transforming data into information, and information into insights that save lives, money and solve problems.” [10]

OR encompasses a variety of quantitative and analytical methods for systematic decision making such as mathematical programming, simulation, and decision analysis. OR techniques have been successfully applied in various real-world application areas like supply chain management, logistics, transportation, healthcare, telecommunication, energy production and distribution, and disaster management. In the context of disaster management, a number of different OR based approaches have been proposed in the literature to find solutions to complex problems arising in different disaster management stages.

Along with pre-earthquake preparedness, an effective response strategy can also drastically reduce human end economic losses [11,12]. Ineffectual management of the Haitian government enormously compounded the impact of the 2010 Haiti earthquake (magnitude 7). After 48-72 hours, chances of finding survivors rapidly decrease. The Haitian government, however, failed to take any decisive action during this crucial phase of the emergency. International organizations quickly mobilized in response, but even this was hampered by the availability of a single-runway airport with a limited capacity and severe damage to the maritime port. As a result, it took several days for the population to start receiving vital supplies [13]. By comparison, in the case of the much larger 2010 Chile earthquake (magnitude 8.8), the Chilean government had in place detailed plans for responding quickly to such an event. Because of the government’s effective control over the situation, the impact of the disaster was greatly reduced (525 victims) and there was almost no need for international assistance [13].

The aftermath of an earthquake, roadway networks play an essential role in transportation systems because food, shelter, medical supplies, and first responders must be transferred swiftly and timely from supply facilities to affected areas. As an example, in the 1976 Tangshan earthquake and the 1995 Hanshin earthquake in Japan, first-day survivors were 81% and 80% percent, respectively, before dropping to 33.7 % and 36.8 % the next day [14]. Despite an abundance of goods, victims of the 2010 Haiti earthquake were unable to receive relief aids for a long time due to serious damage to the road network [15]. Following the 2011 Japan earthquake and tsunami, around three-fourths of the region's roadways were inoperable, causing emergency response activities to be hampered [16]. These experiences reveal the fact that the authorities should focus on the structural strengthening of roadway components, especially for high-risk regions. Due to the limited budget, the key issue is prioritizing the vulnerable components of roadways considering the locations and inherited risk based on the presence of fault-lines.

The first purpose of this thesis is to highlight and discuss main lines of research involving the use of OR techniques applied specifically to earthquake disasters. As part of this dissertation, existing research gaps are highlighted, and accordingly a roadmap is proposed to guide future work and enhance the real-world applicability of OR to earthquake operations management.

This thesis secondly aims at providing an integrated modelling approach which combines the mitigation and response stage operations. The key issue is optimizing the decision-making in selecting the roadway links to be strengthen by considering their effect on the response stage operations, as it is described in a more in-depth way in Chapter 3. Given the importance of connectivity between the affected areas and critical response facilities (i.e., hospitals) for disaster response operations, as well as the need to improve accessibility as a precautionary measure through link strengthening investments, this dissertation is expected to make a significant contribution to the disaster logistics literature by providing an efficient and practical method to optimize these mitigation decisions.

1.2. Research Topics and Motivations

This dissertation has two main parts: (1) an extensive review study of earthquake operations management (EOM) papers published between 2009-2020 (see Chapter 2); (2) a methodological study introducing a Capacitated Network Strengthening Problem (CNSP) which involves optimizing pre-disaster mitigation decisions to strengthen road network links structurally to maximize the efficiency of post-earthquake evacuation operations. Within the scope of the CNSP, a two-stage stochastic program is formulated (see Chapter 3); solution methodologies including multi-objective solution approaches, Sample Average Approximation, and a GRASP-based heuristic algorithm to solve the CNSP are developed (see Chapter 4); finally, two case studies are implemented involving input data generations in a realistic setting (see Chapter 5) and computational experiments based on the case studies are discussed (see Chapter 6).

This dissertation first aims at revealing the current research gaps in existing OR methodologies in the context of EOM and providing a roadmap for future research by a comprehensive review study. OR provides a powerful array of tools for effective and efficient decision making in EOM. However, despite the volume and variety of EOM studies employing OR methods, the development of widely applicable methodologies and frameworks emerges as a key insight in need of greater attention. We examine some important considerations relating to realism, comprehensiveness, practicality, and user-friendliness that have been taken from the various problem definitions and solution methodologies described in the literature. Therefore, this review provides important insights on enhancing the realism and applicability of the solution methodologies. The motivations assisting the need to address these specific topics are the following:

- Each type of disaster has certain features that make it different from others, there is a requirement to tailor conceptualization to specific disasters. Earthquakes and tsunamis may share some similarities with hurricanes and volcanic eruptions when it comes to relief distribution, but they are nonetheless very different from other disasters like landslides, tornados, and wildfires, which are frequently more localized and tend to occur in specific seasons or following certain triggering events (i.e., heavy rain for landslides, lighting for wildfires). For instance, in the case of floods, evacuation has a very strong time element due to how rising waters dynamically impact different areas and eliminate certain escape routes. For earthquakes, the problem is very different – one is often dealing with a much larger scale problem involving large numbers of injured and more random blockage of routes due to rubble. In addition, earthquakes are rather distinct from other disasters given the higher likelihood of secondary disasters (i.e., aftershocks) and the often large number of injured involved. Apart from relief distribution, one type of response stage operations, there are also search and rescue (here earthquakes stand apart from other disasters) and evacuation (again very different for earthquakes due to the typically large numbers of injured, the accessibility on the roads, and the strong interlink with shelter site location).

- Various DOM reviews have highlighted the importance of developing disaster specific models. Given that earthquakes impact a substantially larger number of people globally than any other disaster, it was surprising that there were no reviews dedicated to specifically earthquakes. The aim is addressing this gap in the EOM literature. The conducted review also highlights facets of mitigation, preparedness, response, and recovery operations that are specific to earthquakes to help make it clearer regarding the ways EOM studies employing OR methods have addressed these.

In line with the highlighted research gaps in the conducted review, an integrated model for optimizing pre-earthquake mitigation measures to improve the efficiency of evacuation operations is proposed. We attempt to optimize investment/protection strategies to enhance the resilience of road network components against earthquakes integrated by evacuation allocation decisions in post-earthquake conditions. The motivations behind the need to address these specific topics are as follows:

- Developing realistic methodologies for EOM problems is often constrained by proper consideration of how different DOM stages interact with one another. The vast majority of OR based EOM studies (189 out of 211) were published in the previous 11 years focus on only one disaster stage.

- Given interdependencies among EOM stages, greater effectiveness and efficiencies can often be achieved through integrated planning of various pre- and post-disaster activities. A few studies have examined problems that integrate the mitigation and response stages. However, to the best of our knowledge, there is no single study that investigates the implications of protection planning decisions on post-disaster response actions that considers capacitated suppliers. The proposed model identifies the mitigation decisions to strengthen roadway components considering their impacts on a post-disaster transport network accessibility between the critical capacitated supply and demand points. In this problem, critical supply and demand points refer to emergency response centres (ERCs) (i.e., hospitals, ports, hubs) and affected areas (i.e., evacuation zones), respectively. Finally, the model decides the set of mitigation strategies to be applied by simultaneously considering the operability of road components depending on the applied strategies and then the distribution of the affected people to the ERCs which have limited-service capacity as is the case in reality.

- One of the critical issues is to estimate whether the links are operational/survivable in the aftermath of an earthquake. Existing studies mostly have adopted a binary approach to define post-disaster link damage states (i.e., facilities and road links can be in one of two states: either fully operational/functional or not) and the effectiveness of protection (i.e., protection entirely prevents all damage to facilities/road links). In addition to the structural features of links, the operability should be estimated by taking into account the region in which links are located, as well as earthquake-related features (e.g., epicentre) which have a significant impact on the link's operability. Although protection efforts enhance network links resilience against earthquakes, they cannot guarantee that there will be no damage at all. The degree/type of protection efforts is also critical. One of the key purposes of this study is to address the need for more realistic approaches that take into account a variety of factors related to the impact of protection.

1.3. Research Contributions

As mentioned in Section 1.2, firstly we exclusively review the papers addressing EOM or those that use an earthquake case study to analyse ways of modelling or conceptualizing decision-making problems. This review is published in the International Journal of Disaster Risk Reduction (IJDRR) [17]. IJDRR publishes fundamental and practical research, critical reviews, policy papers, and case studies, with a special emphasis on multi-disciplinary research aimed at mitigating the impact of natural, technological, social, and intentional disasters.

1.3.1. Research contributions related to the published EOM review paper

1) We present a general overview of the OR literature dealing with EOM.

    - To the best of our knowledge, this review is the first attempt at investigating the use of OR techniques specifically for EOM.

2) We provide an in-depth discussion of the ways in which OR has been applied to enhance EOM and the common types of methodologies used.

   - As we limited our review to studies dealing with earthquake-oriented problem definitions or those involving the use of earthquake disaster case studies, our review stands apart from the other DOM review papers. Throughout, we precisely categorize studies based on the disaster stage(s) being dealt with, methodology(ies) applied, and specific planning/operational problem type. We also provide details about the extent of stakeholder involvement and information relating to case studies (i.e., type of infrastructure network examined, if any, and whether real or randomly generated data were used (see in Appendix C).

3) We highlight some important research gaps of existing OR models and approaches and a roadmap for future research.

   - Based on our extensive analysis, we have identified current gaps in the field and outlined a roadmap for future research to enhance the real-world applicability of OR methods applied to EOM in particular and potentially to DOM more generally.

1.3.2. Research contributions related to the proposed modelling approach

As previously mentioned, the second part of the dissertation puts forward an integrated model for optimizing pre-earthquake mitigation measures to improve the efficiency of evacuation operations. In this model, we aim at selecting protection planning strategies for links in a roadway network to assure short and reliable paths between demand points (incident areas) and ERCs. The contributions of the second part of the dissertation are twofold: contributions related to the problem definition and model formulation (1); and contributions related to solution methodologies and case study implementations (2, 3, and 4). These are described below.

1) We propose an integrated protection and evacuation planning model involving realistic assumptions: i) capacitated suppliers; ii) different mitigation strategies with various impacts on resilience per link; iii) focus on enhancing resilience levels of links instead of an approach which guarantee that the link will be undamaged/operational. The model provides effective evacuation allocations of the affected people who need emergency medical care and ensures that only operational roads are used when transporting evacuees to the ERCs. Besides, we take into account the service capacities of ERCs so that people can receive timely and necessary medical care. Our model differs from previous studies in several ways:

   - Existing studies, which integrate decision making for mitigation and response stage operations, include lack of consideration regarding post-earthquake resource availability (i.e., service capacity of hospitals). In these studies, the objective is to assess the accessibility level of the roadway network; therefore, it is assumed that the supply points are uncapacitated.

   - As mentioned in Section 1.2, existing studies have also overly simplistic assumptions about infrastructure damage (i.e., facilities and road links can be in one of two states: either fully operational or not) and the effectiveness of protection (i.e., protection entirely prevents all damage to facilities/road links) (see Section 3.2). In this study, operability basically depends on mitigation efforts, earthquake characteristics, and structure features. In contrast with the existing literature, depending on the initial conditions of links, we consider multiple protection options for each link. In the proposed model, we define resilience levels to estimate survival states of links and assume that protection measures can improve the resilience levels of network links; however, they cannot guarantee that the link will be operational. We use a threshold value that designates operability condition for each link, and it is assumed that experts would provide this threshold value by considering seismic capacity, location of the link, and predicted traffic conditions at that moment. We believe that this approach is more realistic in terms of estimating survival states and assessing protection strategies.

2) Methodologically, the CNSP is challenging since it is formulated as a two-stage stochastic program: the first-stage investment decisions alter the network accessibility that affects the second stage decisions and the objective function. We first use the Sample Average Approximation (SAA) method to reduce the scenario set to a manageable size. The SAA procedure can be applied to solve the stochastic programs with a large number of scenarios, by which good solutions could be provided. Then, a heuristic algorithm based on the Greedy Randomized Adaptive Search Procedure (GRASP) is proposed to solve the larger instances.

3) As a contribution to the practice, we describe how the suggested methodologies can be utilized in pre-disaster planning and mitigation and demonstrate a sample application using two case studies. By focusing on earthquakes, we demonstrate the inclusion of technical aspects and the generation of the necessary input parameters for the proposed model and solution approach in a realistic setting.

4) Two case studies, based on a simplified and a detailed Istanbul roadway network, are conducted for an anticipated earthquake scenarios in Istanbul to provide practical insights to authorities. Computational experiments are conducted based on generated real-life data and instances or adapted from the literature, both to demonstrate the use of the methods and to derive insights for decision authorities. Case study applications contain two main parts: (1) the input generation and (2) the computational study.

   - We conduct two case studies by using a simplified and detailed real roadway network. Particularly, the data instance generation process is quite elaborate and involves using two different algorithms (the *k*-shortest path and the *p*-dispersion algorithms) for path generation. Each parameter value is generated well-grounded based on realistic perspectives. For instance, in estimating the link's resilience levels, a previously used method is adapted for the detailed network. This method considers the seismic intensity and magnitude of the earthquake, the seismic risk factor depending on links' coordination and epicentre of the earthquake and the earthquake vulnerability score based on the structures' features. Additionally, different mitigation strategies for each link have been generated and it is assumed that the more costly ones are more effective in terms of enhancing resiliency. Likewise, there may not be the same number of options for each structure type and, therefore, an approach is adopted that strategies should be varied for a structure that is known to show less resilience against a possible earthquake. The used method, which considers the cost-impact relationship for mitigation projects, is a novel approach in this field.

- The Japan International Cooperation Agency's (JICA) report proposes four earthquake scenarios which were created based on historical earthquakes and North Anatolian fault line. We conduct the case study implementations for an earthquake having a magnitude of 7.7, which is identified as the worst-case scenario in the JICA report. Some parameters (i.e., the seismic risk levels of links, casualty demand) are estimated based on the epicentre and magnitude of the anticipated earthquake in the JICA report. Thus, we use real earthquake data and information from government agency documents to analyse the solutions of our model in realistic earthquake scenarios.

1.4. Outline

The remainder of this dissertation is organized as follows.

Chapter 2 provides a review on earthquake operations management (EOM) to highlight and discuss main lines of research involving the use of OR techniques applied specifically to earthquakes disasters. As part of the review, we identify existing research gaps and propose a roadmap to guide future work and enhance the real-world applicability of OR to earthquake operations management. The identified gaps and future research recommendations are summarized in Chapter 2.

Chapter 3 introduces the Capacitated Network Strengthening Problem (CNSP) which integrates selecting mitigation strategies and evacuation allocation planning, describes the detailed problem statement with the problem assumptions and the model formulation which is a novel two-stage stochastic program for the CNSP.

Chapter 4 provides the proposed solution approaches. The multi-objective approaches are discussed to decide the best approach to solve the CNSP due to the model's multi-objective structure. The Sample Average Approximation (SAA), which is frequently employed to solve large scale stochastic optimization problems, is proposed to solve the proposed model. Finally, a GRASP-based heuristic algorithm is developed to conduct analysis on the larger networks.

Chapter 5 presents the input data generations for the case study implementations such as defining network components, estimating resilience levels of links, generating alternative routes connecting demand-supplier nodes, and scenario generation. Two case studies (the simplified and detailed networks) are developed using Istanbul roadway network datasets. The two data sets are generated using two geographical information system (GIS) programs: ArcGIS and GoogleMaps.

Chapter 6 discusses the findings of the analysis. These include a comparison of the multi-objective approaches and a discussion of the results generated by the SAA procedure for the simplified network. An analysis of the results obtained by the proposed heuristic algorithm on the simplified network is also included. The chapter concludes with an investigation of the results obtained by using the GRASP-based heuristic algorithm on the detailed network and a discussion of the managerial insights that can be derived from the solution analysis.

Finally, Chapter 7 offers some concluding remarks and an outline of future research directions.

2. Use of OR in earthquake operations management: A review of the literature and roadmap for future research

In this chapter, we provide a comprehensive review which addresses earthquake operations management (EOM) or those that use an earthquake case study to analyse ways of modelling or conceptualizing decision-making problems.

In this review, we focus on how pre- and post-earthquake operations have been tackled and streamlined by using OR methodologies. Post- and pre-disaster planning may require specific approaches depending on the type of natural disaster. For instance, evacuation operations for disasters with little or no warning, such as earthquakes and nuclear accidents, begin immediately after the disaster, whereas short-notice disasters, like hurricanes and floods, typically provide a lead time of 24-72 hours for evacuation to occur [18]. In the case of earthquakes, which are near impossible to predict accurately, they may affect a wide area and often have compounding effects that lead to a series of disasters. Such issues need be taken into account when prioritizing post-earthquake operations. Required medical aid can also vary greatly depending on the type of disaster. Injuries tends to be more severe in earthquakes and include crushed limbs and spinal cord injuries requiring both emergency care and longer-term rehabilitation. It is widely agreed that disaster operations management (DOM) should be tailored to specific disasters, so as to capture the unique characteristics of each disaster type. . For this reason, this work only focuses on earthquakes, and we exclusively review papers addressing EOM or those that use an earthquake case study to analyse ways of modelling or conceptualizing decision-making problems.

OR techniques have been applied to deal with DOM problems since the early 1980s [19]. The OR literature on disaster operations and humanitarian supply chain management is considerable, as evidenced by the number of recent survey papers published between 2015 and 2020 [18,20–35]. Published survey papers that we examined are summarized in Table 2.

Table 2. Summary of reviewed disaster operations management papers

Survey Article	Stage*	Focus†	Review Period
Bayram [18]	Rs	Optimization models for evacuation planning	1952-2016
Galindo and Batta [20]	All	OR/MS literature related to DOM	2005-2010
Hoyos et al. [21]	All	OR techniques with stochastic components	2006-2012
Özdamar and Ertem [22]	Rs + Rc	Integration of OR with information systems and enabling technologies	1993-2014
Çelik [23]	Rc	Network restoration and recovery operations	2000-2016
Amideo et al. [24]	Rs	Shelter location and evacuation routing	2013-2018
Gupta et al. [25]	All	OR/MS literature related to DOM	1957-2014
Zheng et al. [26]	All	Evolutionary algorithms applied to disaster relief operations	1996–2014
Habib et al. [27]	All	Humanitarian supply chain management	2005-2015
Gutjahr and Nolz [28]	All	Multi-criteria optimization for disaster aid operations	2007-2015
Balcik et al. [29]	P + Rs	Humanitarian inventory planning and management	2006–2016
Zhou et al. [30]	All	Emergency decision support systems	2000-2016
Boonmee et al. [31]	P + Rs	Optimization models for facility location planning	1964-2016
Behl and Dutta [32]	M + P + Rs	Humanitarian supply chain management	2011-2017
Sabbaghtorkan et al. [33]	P	Prepositioning of assets and supplies	2000-2018
Kovacs and Mosthtari [34]	All	Applied methodologies in humanitarian operations	2006-2018
Farahani et al. [35]	Rs	Casualty management	1977-2019

* M: Mitigation, P: Preparedness, Rs: Response, Rc: Recovery.

† OR: Operations Research, MS: Management Science.

The contribution of this review is multi-fold. First, we present a general overview of the OR literature dealing with DOM. Second, we provide an in-depth discussion the ways in which OR has been applied to enhance EOM and the common types of methodologies used. Third, we highlight some important research gaps of existing OR models and approaches and a roadmap for future research. A key insight of our review is the necessity of adopting a multidisciplinary approach to EOM that includes OR.

The remainder of this chapter is organized as follows. Section 2.1 gives a general overview the role of OR in DOM by carrying out a meta-analysis of recent survey reviews. In Section 2.2, we review how EOM is addressed in the OR literature. Section 2.3 provides a classification and analysis of reviewed reviews. A roadmap for future research directions and some concluding remarks are outlined in Section 2.4 and 2.5, respectively.

2.1. Literature Review Methodology and Summary

In the remainder of this study, we review studies that apply OR methods to address problems in EOM. We use a broad definition of OR, which includes mathematical programming, heuristics and metaheuristics, decision analysis, machine learning and artificial intelligence (AI), Soft OR, and expert systems. "Mathematical programming" or optimization aims at finding the most efficient (i.e., guaranteed best) allocation of limited resources in order to maximize or minimize some objective (i.e., total cost) subject to a set of constrains that limit which actions can be taken [36]. "Heuristics and metaheuristics" (hereafter heuristics) are algorithms which apply a series of rules (typically iterative) to quickly find approximate solutions to large and/or complex optimization problems [37]. Heuristics are called for when an exact approach cannot be used or would require an excessive amount of time to solve. "Decision analysis" includes a number of quantitative and graphical methods for identifying the best option among a defined (usually small) set of alternatives for complex or risky decision problems based on one or more evaluation criteria [38]. "Simulation" involves representing a real-world system (normally over time) using logic, mathematics, and computers for the purposes of predicting system behaviour (possibly stochastic) or evaluating performance of different plans for improving the system [39]. The main types of simulation include Monte Carlo simulation, discrete event simulation, system dynamics, and agent based modelling. "Stochastic modelling" is the application of probability theory to represent and predict the outcomes of stochastic processes [39]. "AI", in relation to OR, includes a broad class of approaches designed to enable computer systems to automatically perform tasks that would normally require human intelligence, such as information processing, pattern recognition, and decision making [40]. "Machine learning," a subclass of AI, include a wide range of mathematical models/algorithms which are trained to find patterns in data in order to make predictions or decisions [41]. "Soft OR" includes a variety of problem structuring and stakeholder facilitation methods to help frame messy, ill-defined, and complex problems in rigorous but non-mathematical way [42]. Soft OR primarily aims at promoting learning and shared understanding of a systems as opposed to specific 'solution.' Game theory studies situations involving conflict and cooperation "Game theory" is a branch of mathematics concerned with the analysis of strategies to competitive situations in which the payoff a participant receives depends on both his/her actions and the actions of other players [43]. Finally, "expert systems" are computer system that emulate the decision making ability of a human expert [44]. They are usually designed to solve complex problems by reasoning about facts and assertions, mainly with if-then rules rather than through procedural code.

We systematically reviewed the literature that included one or more of the following sets of keywords: 1) “earthquake’’, ‘‘disaster*’’, “catastroph*, “humanitarian logistic*”, or “emergency” and 2) “*modelling”, “*programming”, “optimization”, “decision theory”, “multi-criteria decision”, “multi-criteria analysis”, “problem structuring method”, “system thinking”, “Soft OR”, “agent based simulation”, “Monte Carlo simulation”, “discrete event simulation”, “system dynamics”, “expert systems”, “artificial intelligence”, “neural network”, “stochastic modelling”, “stochastic model”, “probabilistic model”, “game theory”, “heuristic” or “metaheuristic” and spelling variations (i.e., British English spellings). We limited the time interval for the review to 2009-20 and used Scopus databases covering various large publishers such as Elsevier, Springer, Taylor & Francis, and IEEE. Selection of articles was based on two main criteria; (i) whether a paper applied one or more OR techniques to DOM decision making and (ii) whether it specifically addressed EOM or did not necessarily focus on earthquakes but did have a case study involving earthquakes. After further manual processing, 211 papers, which satisfied these criteria, were finally selected.

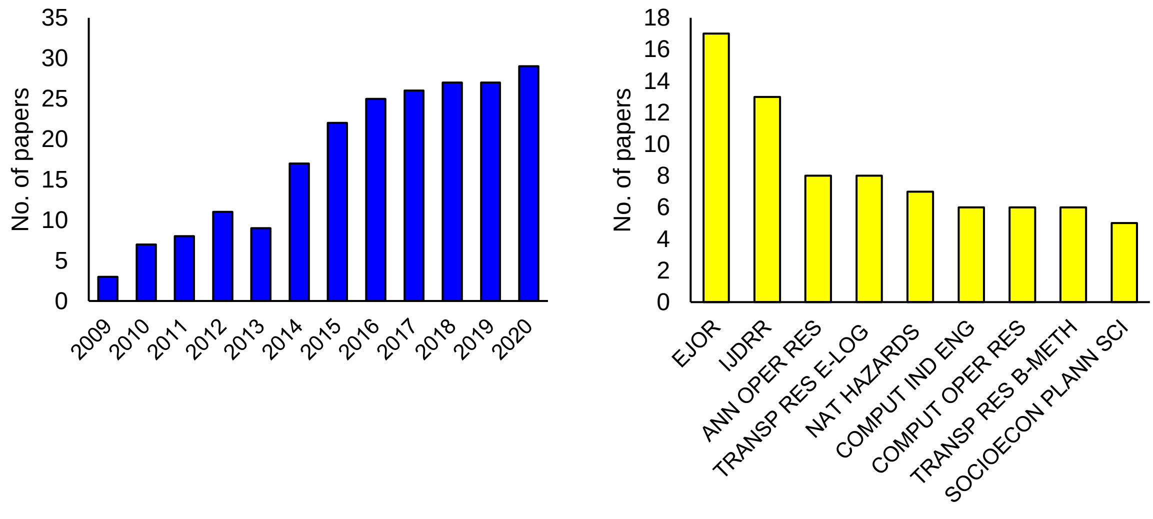

Figure 3. Number of OR papers applied to EOM by year (a) and by journal with five or more such papers (b*)*

Figure 3 shows the number of articles published between 2009 and 2020 on OR applied to EOM and the journals that published five or more such papers. The top two journals in terms of number of publications are European Journal of Operational Research (EJOR), which publishes both theoretical and applied research in OR, and International Journal of Disaster Risk Reduction (IJDRR), which covers a broad set of disciplines aimed at reducing the impact of natural, technological, and social disasters. A general observation is that many of the published EOM studies appear in OR focused journals (not unsurprising) and have bias towards transportation and other infrastructure related problems. Interestingly, more specialized journals in fields like seismology, engineering, and geography, which were included in our literature search, rarely publish OR based studies on EOM, hence why they do not appear in Figure 3b.

Table 3. Summary statistics of EOM disaster stages addressed in the literature

Disaster Stage(s)	No. of papers	Proportion (%)
Mitigation	41	19.4
Preparedness	62	29.4
Response	66	31.3
Recovery	20	9.5
Integrated Stages	22	10.4
Mitigation & Preparedness	1	4.5
Mitigation & Response	2	9.1
Mitigation & Recovery	1	4.5
Mitigation, Preparedness & Response	1	4.5
Preparedness & Response	9	40.9
Preparedness, Response & Recovery	1	4.5
Response & Recovery	7	31.8

Statistics for reviewed papers are given in Tables 3 and 4. Of the 211 papers reviewed, the preparedness and response stages have received similar amounts of attention (29-31%), while mitigation has received comparatively less attention (19%), and recovery the least attention (9%). The vast majority of research (90%) has focused on a single disaster stage as opposed to the integration of operations from multiple stages (10%), which has generally appeared only more recently. Integration of either preparedness and response (41%) or response and recovery (32%) has received considerably more attention than any of the other combinations. In addition, not a single study addresses decision making in all four stages; usually only two stages are considered and only two studies consider three stages. As evident from Table 4, heuristics are the most frequently utilized OR method (33%), followed by mathematical programming (29%), simulation (11%), machine learning (10%), and decision analysis (3%). Few studies have involved the use of multiple methods (9%).

Table 4. Summary statistics of OR methodologies used in EOM

Methodology	No. of papers	Proportion (%)
Heuristic	70	33.2
Mathematical programming	62	29.4
Simulation	24	11.4
Machine learning	21	10.0
Decision analysis	7	3.3
Soft OR	2	0.9
Expert system	2	0.9
AI	2	0.9
Game theory	1	0.5
Stochastic modelling	1	0.5
Multiple methods	19	9.0

2.2. Literature Review Classification and Analysis

In the following subsections, we provide an in-depth analysis of the literature using the categorization shown in Figure 2. Within each category, we discuss each disaster stage in turn and the methodologies used to address them. Studies that address the integration of two DOM stages are reviewed and categorized in the final subsection. For the most used OR methods in each category, tables and figures are provided to gather additional insights.

2.2.1. Mitigation Stage

The mitigation stage involves strategic decision making to enhance the condition of buildings and critical infrastructure networks (i.e., electricity generation and distribution, transportation, water supply, telecommunication, hospitals, and fire stations). Primary mitigation measures include earthquake-resistant constructive, building retrofit, and upgrading components of critical infrastructure systems to make them resistant to seismic activity or/and ground motion. In comparison to other types of natural disasters, features specific to earthquake mitigation include the enormity of the challenge due to the extent of human habitation concentrated in seismically active areas, the relatively high cost to implement mitigation measures (to a large number structures spread over large areas), the typically long recurrence time (decades or more) between sizable quakes and, as a result, the greater amount of lead time to plan and take pre-emptive action.

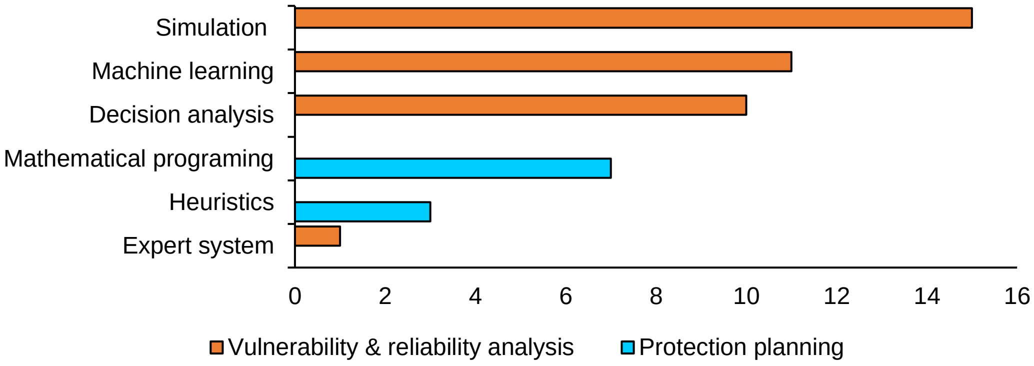

Figure 4. Methodologies used in mitigation problems

Mitigation problems can be divided into two main categories: 1) reliability and vulnerability analysis, which involves, for instance, estimating damage levels of infrastructure components (i.e., whether a road segment is operational or not) and 2) protection planning to reduce vulnerabilities and risks to critical infrastructure. A summary of OR methodologies applied to solve mitigation problems is shown in Figure 4. Three methodologies – simulation, decision analysis, and machine learning – have been used the most (36 papers) among the 41 reviewed papers. Expert systems, mathematical programming, and heuristics, in contrast, have been applied far less (11 papers). Other methodologies, such as Soft OR, game theory, and stochastic modelling, appear not to have been used at all to address mitigation problems. As is clear from Figure 4, reliability and vulnerability analysis has drawn the most attention, while comparatively little has focused on protection planning. Table 5 provides a detailed breakdown of studies in each category by problem type and methodologies used.

Table 5. Details of the types of problems addressed and methodologies used in the mitigation stage

Problem	Method	References*
Vulnerability and reliability analysis		
Seismic reliability analysis	Simulation	[45–56]
	Machine learning	[57]
Seismic hazard mapping	Decision analysis	[58–63]
	Machine learning	[63]
Building vulnerability analysis	Simulation	[64,65]
	Machine learning	[66–71]
	Decision analysis	[69,70,72,73]
Fatality estimation	Simulation	[65]
	Machine learning	[74,75]
Earthquake characteristics prediction	Expert system	[76]
	Machine learning	[77]
Protection planning		
Fortification of infrastructure networks and buildings	Mathematical programming	[51,78–83]
	Heuristic	[84–86]

* References highlighted in bold incorporate more than one methodology and/or address multiple problem types.

2.2.1.1. Vulnerability and Reliability Analysis

Vulnerability and reliability are especially important when examining the operability of buildings and critical infrastructure. Murray and Grubesic [87] state: "*While reliability focuses on the possibility of maintaining the performance of critical infrastructure elements, vulnerability focuses on the potential for disrupting critical infrastructure elements or degrading them to a point when performance is diminished.*" Both vulnerability and reliability and are important for the continuity of critical infrastructure operations.

Seismic reliability analysis of critical infrastructure plays an essential role in the mitigation stage. The primary aim is to compute a measure of reliability given failure probabilities for an individual component of a system or for the system as a whole. Simulation is the most used OR method in this category. Details of simulation models reviewed are provided in Table 6. Simulation models have been used to estimate earthquake induced failure probabilities of system components, damage levels caused by interruptions to system operations, and reliability/vulnerability measures. Examples include reservoir storage of hydropower systems [56], substations in electric power grids [47], energy pipelines [55], water supply systems

[45,53], and transportation networks [49,51,52,54]. In addition to specific types of infrastructure, simulation has been used to evaluate the susceptibility to landslides caused by earthquakes and heavy rainfall for regions of a large urban area [46,50]. Monte Carlo simulation appears to be the main simulation paradigm used for seismic reliability analysis, though there are a couple examples of system dynamics [45,56] and a very recent one using agent based modelling [48]. Besides simulation, Nabian and Meidani [57] investigate the use of deep neural networks, a machine learning method, for seismic reliability analysis. They use a case study of the California transportation network to demonstrate the effectiveness of the proposed method for accelerating earthquake reliability analysis.

Table 6. Details of simulation models for reliability and vulnerability analysis

Reference	Model Type*	Outputs/Findings
Bagheri et al. (2010) [45]	SD	Failure probability for water supply systems
Sun and Chen (2010) [46] Sun et al. (2011) [50]	MCS	Failure probability of earthquake-induced landslides
Li et al. (2019) [47]	MCS	Failure probability of power systems
Feng et al. (2020) [48]	ABM	Traffic flow characteristics
Günneç & Salman (2011) [49]	MCS	Reliability measures for networks
Chang et al. (2012) [51]	MCS	Earthquake intensity at each bridge location
Gertsbakh & Shpungin (2012) [52]	MCS	Failure probabilities for links in a network
Jin & Wang (2012) [53]	MCS	Seismic risk of water supply systems
Mohaymany et al. (2012) [54]	MCS	Connectivity and reliability measures for networks
Dadfar et al. (2018) [55]	MCS	Vulnerability functions for energy pipelines
King et al. (2017) [56]	SD	System disturbances and failure states for hydropower systems
Ahmad et al. (2012) [64]	MCS	Damage levels of structures
Akpabot et al. (2018) [65]	MCS	Damage levels for buildings and casualty levels

* MCS: Monte Carlo simulation, SD: system dynamics, ABM: agent based model.

For studies on seismic hazard mapping the preferred approach is multi-criteria decision making (MCDM), a class of decision analysis techniques, implemented in a geographical information system (GIS). Examples of GIS-based MCDM include the generation of seismic physical vulnerability maps [46,47,53] and tsunami risk maps [60].

For building vulnerability analysis (i.e., analysis of individual buildings as opposed to infrastructure networks or urban/residential areas), machine learning is the most frequently used method for estimating risk/damage levels based on various independent variables like structure type, constructive quality, built area, and occupancy level [66,74]. Neural networks have been developed to inform post-earthquake activity planning by evaluating building collapse ratios using optical and satellite data [68] and to construct a composite social, economic, environmental, and physical vulnerability index for seismically prone regions [69]. Simulation has also been used to estimate damage levels for bridges and buildings [64,65].

Another key strand of reliability and vulnerability analysis is estimating human fatalities and determining the distribution of casualties. One such study is Akpabot et al. [65], who address how to predict the post-earthquake status of buildings (collapsed or not) and casualty levels using Monte Carlo simulation. Another is Gul and Guneri [75], who apply a neural network to estimate casualty proportions based on earthquake occurrence time, earthquake magnitude, and population density. Aghamohammadi et al. [74] assume that damage levels for buildings are known in advance and apply a neural network to estimate casualty levels considering the same inputs as Gul and Guneri [75] along with damage levels.

Finally, earthquake characteristics prediction (i.e., magnitude, depth, location, probability of occurrence, seismic energy release) has been carried out using both machine learning techniques [77] and expert systems [76]. The study by Ikram and Qamar [76] is interesting for trying to predict subsequent earthquakes based on most recent earthquake attributes, such as a defined range, depth, and location, and for validating their approach using real-life earthquake data.

2.1.2.2. Protection Planning

This subsection covers studies on protection planning for strategic pre-earthquake mitigation. Note that all of the studies reviewed employ either mathematical programming or heuristics to decide which infrastructure to fortify or upgrade in order to minimize system vulnerability or maximize reliability/resilience. Details are provided in Table 7. The majority of work has focused on protection of links in transportation networks in order to optimize one or more objectives such as maximizing post-earthquake connectivity [79,84], minimizing travel cost [79,80,85], minimizing investment/retrofitting cost [54,80,81,85], minimizing unsatisfied demand [80,85], and maximizing evacuation capacity [51]. Only a few studies have additionally or exclusively looked at retrofitting buildings [81,82,85]. Liberatore et al. [82], for example, decide which hospitals to fortify in order to minimize maximum reduction in medical service capacity (i.e., unmet demand) and patient assignment costs in the presence of propagating failures.

Table 7. Summary of protection planning studies

Reference	Decisions	Objective(s)	Case Study
Chang et al. (2012) [51]	Bridge retrofit standards	Maximize post-disaster network evacuation capacity given a limited budget	Memphis, Tennessee, USA
Mohaymany et al. (2012) [78]	Transport links to invest in	Minimize investment cost to satisfy connectivity reliability and travel time reliability requirements	Sioux Falls, South Dakota, USA
Peeta et al. (2010) [79]	Road links to retrofit	Maximize post-disaster connectivity and minimize traversal cost between origin and destination nodes given a limited budget	Istanbul, Turkey
Lu et al. (2018) [80]	Bridge retrofit standards	Minimize retrofitting cost, expected transport cost, transport cost risk, and unsatisfied demand	Sioux Falls, South Dakota, USA
Zolfaghari & Peyghaleh (2015) [81]	Building retrofit standards	Minimize mitigation expenditures and future reconstructive expenditures	Tehran, Iran
Liberatore et al. (2012) [82]	Hospitals to retrofit	Minimize cost of assigning patients to hospitals and unmet demand	L'Aquila, Italy
Aydin (2020) [83]	Location of recycling and landfill areas for processing debris from end-of-life buildings	Minimize recycling and landfill area set-up cost, cost of debris transport and processing and maximize revenue of recovered materials	Istanbul, Turkey
Chu & Chen (2016) [84]	Road links to retrofit	Maximize connectivity reliability for roadway networks	-
Döyen & Aras (2019) [85]	Building retrofit standards and road links to retrofit	Minimize building and road link retrofit costs, expected transport costs and unsatisfied demand for relief	Istanbul, Turkey
Edrisi & Askari (2019) [86]	Road links to expand and stabilize	Minimize travel time and expected fatalities	Sioux Falls, South Dakota, USA

As is typical with these studies, the authors first analyse the computational performance of their proposed model or solution approach and then apply it to a case study based on real-world data. The aim here is to show how the model is capable of capturing all crucial network information and how the solution methodology generates robust solutions in acceptable computation time. As seen in Table 7, some use case studies of transportation networks located in seismically active areas. In addition, there are multi-methodology approaches combining two methodologies, such as simulation for estimating parameters related to vulnerability and reliability (i.e., damage state scenarios based on structural characteristics) and a mathematical programming model for optimizing protection decisions [51,54].

2.2.2. Preparedness Stage

The preparedness stage, the most studied of the four disaster stages in EOM, includes plans and preparations made in advance of an earthquake, such as logistical readiness to deal with adverse impacts of earthquakes, the development of response mechanisms and procedures, rehearsals, the development of long-term and short-term strategies, public education, and the implementation of early warning systems. The problems associated with the preparedness stage can be categorized as: 1) relief pre-positioning and resource planning (i.e., locating distribution centres, stocking relief supplies, emergency medical care staffing); 2) shelter site location; 3) emergency response and relief chain coordination; and 4) early warning systems. While preparedness is crucial for any type of natural disaster, the severity of damage caused by earthquakes and, crucially, the often complete lack of advanced warning about when and where an earthquake will strike (i.e., essentially instantaneous for earthquakes and minutes for tsunamis versus days for hurricanes, wildfires, and volcanic activity), underscore the importance and benefits of preparedness.

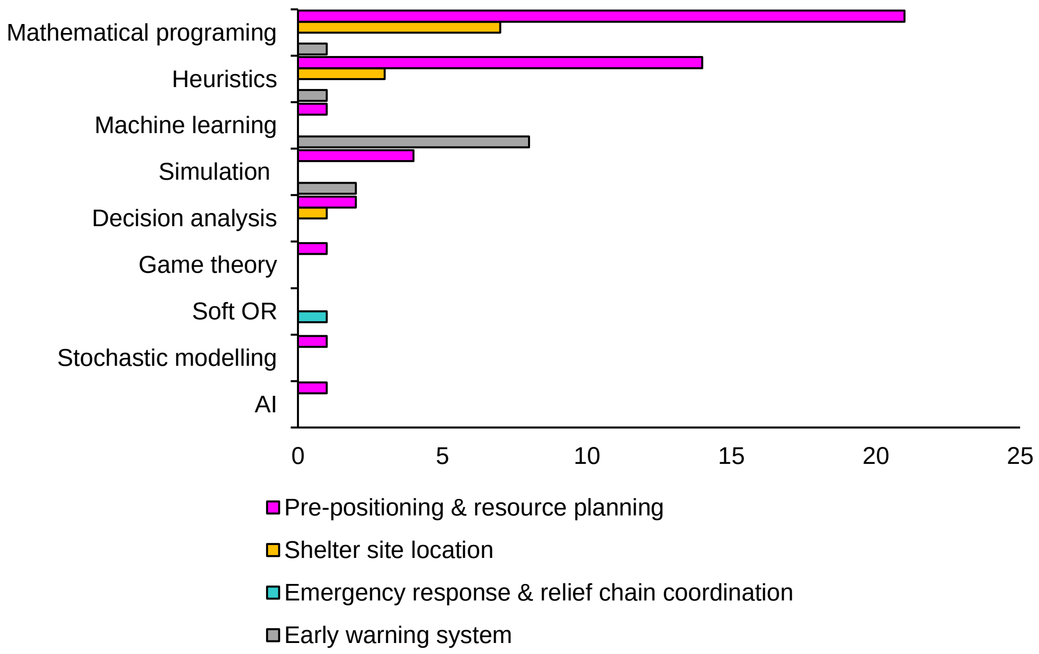

Figure 5. Methodologies used in preparedness problems

A summary of problem types and the OR methodologies used is preparedness planning is shown in Figure 5. Relief pre-positioning and resource planning is the most addressed problem type, accounting for 40 of the 62 studies. The other three categories, shelter site location, relief chain coordination, and early warning systems, have received significantly less attention, with 11, 1, and 12 studies, respectively. In terms of methodologies, unlike with the mitigation stage, nearly all methodologies, apart from expert systems, have been used to analyse and solve problems in this stage. However, mathematical programming and heuristics are by far the dominate techniques, having been applied in 46 (74%) of the 62 studies. Table 8 gives a detailed breakdown of preparedness related studies based on problem type and methodology used.

Table 8. Details of the types of problems addressed and methodologies used in the preparedness stage.

Problem	**Method**	**References***
Relief pre-positioning and resource planning		
Pre-positioning distribution centres	Mathematical programming	[88–104]
	Heuristic	[105–117]
	Decision analysis	[94,110]
	Game theory	[118]
	AI	[95]
Pre-positioning medical centres	Mathematical programming	[119]
Relief inventory management	Mathematical programming	[90,92–96,100–104,113,120–122]
	Heuristic	[106–108,112–116]
	AI	[95]
	Simulation	[120]
	Stochastic modelling	[123]
Staff planning	Simulation	[124–126]
	Machine learning	[126]
	Heuristic	[127]
Shelter site location		
	Mathematical programming	[98,128–133]
	Heuristic	[134–136]
	Decision analysis	[131]
Emergency response & relief chain coordination		
	Soft OR	[137]
Early warning system		
Earthquake/tsunami prediction and notification	Machine learning	[138–145]
	Simulation	[146,147]
Sensor location	Mathematical programming	[148]
	Heuristic	[149]

* References highlighted in bold incorporate more than one methodology and/or address multiple problem types.

2.2.2.1. *Relief Pre-Positioning and Resource Planning*

This category includes problems related to pre-positioning relief distribution centres (RDCs), medical centres, relief inventory management, and staff planning. RDCs play an indispensable role in relief logistics by receiving and consolidating relief supplies (i.e., food, water, clothing, temporary shelters, and medication) and then distributing them to affected populations. Strategic pre-positioning of RDCs prior to an earthquake can significantly affect the performance of the subsequent disaster response (i.e., in terms of response time, accessibility, and equity) [99]. Resource planning, meanwhile, plays a crucial role in the preparedness stage through effective stockpiling of supplies and determining staff requirements in order to avoid shortages, which could pose severe risks to human life if they were to occur. For clarity, most of the studies included here typically model aspects of the response stage (i.e., relief distribution), but do so only in a very simplified way for the purposes of determining where best to locate RDCs in order to satisfy anticipated demand for relief. Only if more complex decisions involving, for example, scheduling of rescue teams or loading and routing of relief, are the models considered integrated (i.e., preparedness and response, see Section 2.5).

Mathematical programming and heuristics are far and away the most commonly used approaches, comprising 35 (85%) of the 41 studies addressing relief pre-positioning and resource planning (see Table 8). Table 9 presents details of these studies, including the types of decisions and objectives considered. As can be seen, the most common objectives in pre-positioning RDCs and resource planning include the minimization of cost, transportation time, and demand shortages. In terms of cost components, some studies focus on fixed and variable operating costs (i.e., constructive of facilities and the procurement and holding of supplies) and or transportation costs (i.e., [100,103,112]), while others separately or additionally consider social costs (i.e., fatalities and deprivation cost) [91,113]. Minimization of transport time usually refers to distances/travel time between RDCs and local distribution points (i.e., [88,100,109]). Most of the studies reviewed consider distribution of multiple commodities but do not give specifics. One study looks specifically at medical supply distribution to hospitals [90]and a couple at blood distribution [95,96].

Table 9. Details of mathematical programming and heuristic approaches for relief pre-positioning and resource planning problems

Problem	Decisions	Objective(s)	References*
Pre-positioning distribution centres	Locations of distribution centres	Minimize cost	[95,96,98,103]
		Minimize distance	[110]
		Minimize transport time	[109,111]
		Maximize coverage	[105]
		Minimize cost and transport time	[88,112]
		Minimize cost and shortages	[89,94,100,102]
		Minimize transport time and shortages	[90,104]
		Minimize cost and shortages and maximize equity	[115]
		Minimize cost and maximize equity and reliability	[106]
	Locations and capacities of distribution centres	Maximize accessibility	[99]
		Minimize cost and shortages	[101,108]
		Minimize cost and victim travel time	[114]
		Minimize cost and fatalities	[91,113]
		Minimize cost and maximize equity	[93,107]
		Minimize cost, transport time and shortages	[116]
		Minimize cost, victim travel time and shortages	[97]
		Minimize cost, transport time and shortages and maximize equity	[92]
Pre-positioning medical centres	Location and capacity of medical centres	Minimize travel time, underachievement of target waiting time, unused capacity and set-up time	[119]
Relief inventory management	Inventory levels of relief supplies	Minimize cost	[95,96,103]
		Minimize cost and shortages	[94,100–102,108]
		Minimize cost and transport time	[112]
		Minimize cost and victim travel time	[150]
		Minimize cost and fatalities	[91,113]
		Minimize transport time and shortages	[90,104]
		Minimize cost and maximize equity	[93,107]
		Minimize cost and shortages and maximize equity	[115]
		Minimize cost, transport time and shortages	[116]
		Minimize cost and maximize equity and reliability	[106]
		Minimize cost, transport time and shortages and maximize equity	[92]
		Maximize probability of satisfied demand	[120]
		Maximize min. covered demand	[121]
		Minimize cost and shortages and maximize lives saved	[122]
Staff planning	Staffing levels	Maximize expected number of functional operating rooms and minimize expected travel distance	[127]

* References highlighted in bold address multiple problem types.

As highlighted by the Sphere Standards [151], RDCs should be established where they are safe and most convenient for affected populations. In addition, principles of equity should be considered to ensure every affected person receives equal opportunity to obtain relief. This highlights the importance of including accessibility and fairness as problem objectives. Some studies consider ease of access from affected areas to relief distribution points and accordingly maximize equitable access [99]. More recent studies consider equitable allocation of relief to affected areas and local distribution points, in other words, fair relief distribution [92,93,106].

It is worth noting that a majority of studies adopt a multi-faceted approach that considers multiple objectives and multiple types of decisions, including locating RDCs and determining their inventory levels. For example, Tofighi et al. [116] optimize four objectives: (i) minimization of fixed and variable costs associated with setting up central warehouses and RDCs and holding relief, (ii) minimization of total and (iii) minimization of maximum time to ship relief from central warehouses to affected areas via RDCs, and (iv) minimization of a weighted combination of relief shortages and unused relief. Paul and Wang [91] meanwhile, not only consider decisions about the locations, capacities, and inventory levels of RDCs but also the risk of damage to RDCs and how potential loss of supplies may impact relief allocation decisions.

In additional to mathematical programming and heuristic approaches, a few other methodologies have been applied to relief pre-positioning and resource planning. For instance, system dynamics was used by Wu et al. [120] to inform relief inventory planning, including stock holding and replenishment decisions, and by Xu et al. [124] to find best ratio of medical staff to rescue workers. Discrete event simulation has also been applied to assess the benefits of having an emergency plan in place as well as increasing staff and/or emergency room capacity [125]. A game theoretic approach is employed by Bell et al. [118] for locating RDCs in degradable road networks. Stochastic modelling has been used to find optimal reordering policies for relief goods given uncertainty about demand and lead-time [123]. Lastly, Bayesian belief networks (AI) was used by Chen and Wang [95] to model uncertainty about earthquake locations/intensity and number of injuries in need of blood when deciding about blood stocking levels.

2.2.2.2. Shelter Site Location

After a large earthquake, buildings may be damaged or destroyed and a large number (possibly hundreds of thousands) of people may become homeless. Affected residents will need to move to designated emergency housing termed shelters until the disaster recovery process is completed. Accordingly, pre-determined shelter areas should be strategically located, taking into account site suitability and access to relief supplies. Shelter areas must also be located within a reasonable distance from earthquake affected areas, accessible by safe travel routes, and provisioned with or close to essential services (i.e., medical care). It should be clear that identifying optimal locations for shelters is a complex problem. In all, we found ten studies on shelter site location specifically looking at earthquakes. All employ mathematical programming or heuristics.

A variety of factors have been considered when locating shelters. Bayram et al. [129], for example, focus on minimizing total evacuation time assuming evacuees travel to their nearest shelters via shortest or near shortest paths. Kınay et al. [133] instead locate shelters to maximize minimum site suitability based on criteria proposed by the Turkish Red Crescent, including distance to healthcare institutions, electrical infrastructure, and sanitary systems and terrain characteristics. Bayram and Yaman [130] apply a two-stage stochastic programming approach to incorporate uncertainty about evacuation demand and disruption to road and shelter site capacities. Hu et al. [135] employ particle swarm optimization, a metaheuristic approach, to locate shelters at minimum cost subject to capacity and distance constraints. Trivedi and Singh [131] propose a model for optimizing shelter sites based on victim travel distance, distance to relief and health centres, unmet demand, number of shelters, site risk (vulnerability to earthquakes, floods, landslides), and degree of public ownership. Other interesting aspects addressed in shelter location include risks associated with travelling to and remaining at shelters [128] and changes in both population size and spatial distribution [134] of those needing shelter.

2.2.2.3. Emergency Response and Relief Chain Coordination

Coordination and cooperation between emergency response and relief organizations (i.e., government agencies, emergency services, humanitarian organizations) is essential for responding in a timely and appropriate manner to earthquake disasters. Emergency response and relief chain coordination problems focus on the importance of effective and flexible structures that enhance interoperability, communication, and synchronized response of multiple EOM stakeholders to minimize human and economic losses in the aftermath of an earthquake.

Despite the importance of multi-agency coordination, we found only one study dealing with the topic. Specifically, Preece et al. [137] model the complex interactions involved with stakeholder communication. The authors examine how application of the viable system model (VSM), a Soft OR method, can help identify key shortcomings and opportunities in communication systems. Using a case study of the Great Hanshin-Awaji Earthquake in 1995, they demonstrate the utility of VSM structures to facilitate communication and coordination during a disaster.

2.2.2.4. Early Warning Systems

Earthquake early warning systems (EEWSs) form an essential part of the preparedness stage by providing timely and relevant information immediately following an earthquake. Effective EEWSs can help significantly to save lives and reduce damage. Two main problem types are discussed here: earthquake/tsunami prediction and notification and earthquake/tsunami sensor location.

Table 10. Details of studies addressing early warning systems

Topic	Method	References
Earthquake location/magnitude prediction	Machine learning	[138,140]
Tsunami wave height prediction	Machine learning	[139,141]
Reduction of false alarm rates	Machine learning	[142–144]
Earthquake detection	Machine learning	[145]
Early warning lead time and reliability estimation	Simulation	[146]
Ground motion prediction	Simulation	[147]
Seismometer/tsunameter location	Mathematical programming	[148]
	Heuristic	[149]

As seen in Table 10, machine learning is the most commonly used approach in EEWS prediction and performance, comprising 8 (67%) of the 12 studies reviewed here. An example application of machine learning is to reduce false alarms by rapidly and reliably discriminating real earthquake signals from other signals [142–144]. This is critical to improving the performance of EEWSs, as excessive false alarm rates cant impose a heavy cost in terms of service loss, undue panic, and diminishing confidence in EEWSs. Machine learning has also been used for initial detection of earthquakes from siesmic sensor data [142–144], advanced prediction of the location and magnitude of earthquakes [138,140], real-time classifcation of near- versus far-source earthquakes, and tsunami wave height estimation [139,141].

Somewhat surprisingly, only a couple examples of simulation being applied in EEWS were found in the literature. Wang et al. [147], for example, propose a Monte Carlo simulation approach to predict peak ground motion quickly and precisely given limited seismic data. Information about ground motion is crucial in early warning systems because a region's peak ground motion provides an indication of the scale of the potential disaster in terms of building damage and threat to life. Meanwhile, Oliveria et al. [146] use Monte Carlo simulation to estimate amount "lead time" between when an early warning is received and the earthquake arrives and the potential costs of false alarms from an end-user standpoint.

Similarly, mathematical programming and heuristics have found only limited used in EEWS design. Oth et al. [149] propose the use of a genetic algorithm to optimize the location and calibration (trigger thresholds) of seismic sensors for a regional EEWS. Mulia et al. [148] investigate the use of dimensionality reduction techniques to identify an initial set of sensor locations for detecting multiple large-magnitude tsunami sources and then apply optimization to minimize forecasting error by removing redundant measurement locations.

2.2.3. Response Stage

In the aftermath of an earthquake, the primary concerns in the response stage are providing first-aid and rescuing trapped survivals, determining temporary shelter site locations, evacuating the affected population to safe zones, shelters, and medical centres, and providing emergency relief to victims. What often makes response so critical in the case of earthquakes versus other natural disasters is the scale of the problem. Whereas other types of natural disasters tend to be more localized and affect a smaller population, earthquakes can cause damage over wide areas (hundreds of thousands of square miles), resulting in enormous damage to properties and infrastructure (tens of billions of dollars), and lead to enormous casualties both in terms of number (hundreds of thousands of dead and injured) and severity. With this in mind, we focus on three main problem types within the earthquake response stage: 1) search and rescue; 2) evacuation; and 3) relief distribution. A summary of the problem types and the OR methodologies used to solve response stage problems is provided in Table 11.

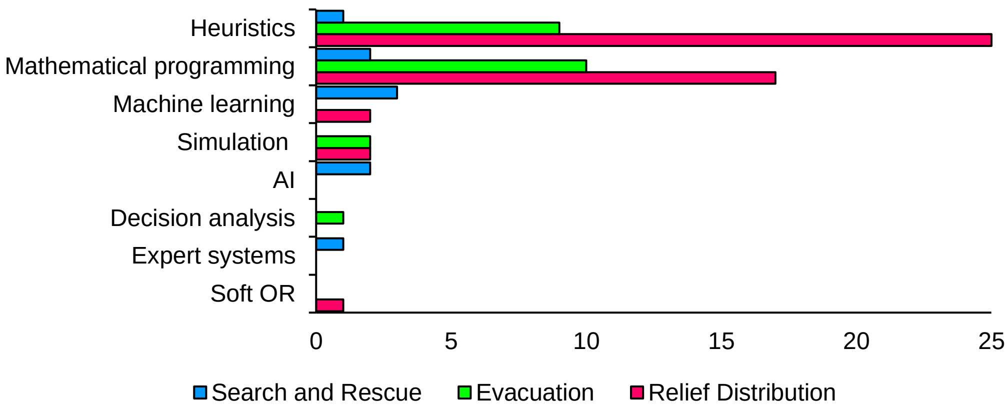

Figure 6. Methodologies used in response problems

As can be seen, relief distribution problems have received the most interest among the three problem types. A handful of studies address the integration of relief distribution and evacuation. Two methodologies – mathematical programming and heuristics – dominate (used 56 times) among the 66 response stage studies. Interestingly, simulation, which is used frequently in pre-earthquake stages (mitigation and preparedness), has rarely been used in post-earthquake response problems.

Table 11. Details of the types of problems addressed and methodologies used in the response stage

Problem	Method	References*
Search and rescue		
Rapid damage assessment	Machine learning	[152,153]
	Expert system	[154]
	Heuristic	[155]
Rescue operations	Mathematical programming	[156,157]
	Machine learning	[158]
	Expert system	[154]
	AI	[159,160]
Evacuation		
Routing and allocation	Mathematical programming	[161–170]
	Heuristic	[166,171–178]
	Simulation	[166]
	Decision analysis	[174]
Human behaviour	Simulation	[179]
Relief distribution		
Relief logistics	Mathematical programming	[161–165,180–191]
	Heuristic	[177,178,192–214]
	Simulation	[191,215]
	Machine learning	[163]
	Decision analysis	[191]
	Soft OR	[216]
Road damage assessment	Machine learning	[217]

* References highlighted in bold incorporate more than one methodology and/or address multiple problem types.

2.2.3.1. Search and Rescue

Search and rescue, the response stage category least examined in the literature, includes problems related to rapid damage assessment and rescue operations. Rapid damage assessment aims to inform first responders and other operations personnel about the damage status of buildings and infrastructure following an earthquake. Rescue operations involve the deployment of specially trained rescue teams to provide first-aid and free survivors from rubble. Table 12 provides details of studies in this category, including the systems/tools developed, their aims, OR methods used, and case study applications.

Table 12. Details of studies addressing search and rescue problems

Reference	System/tool	Aim	Method	Case Study
Bai et al. (2017) [152]	Remote sensing	Building damage mapping	Machine learning	-
Kim et al. (2020) [153]	Seismic loss assessment	Sensor location for near real-time assessment of building damage	Machine learning	-
Schweier & Markus (2009) [154]	Information system	Support onsite search and rescue teams and building inspectors	Expert system	-
Chu et al. (2015) [155]	Participant selection	Selection of volunteers for collection of crowdsourcing data	Heuristic	2010 Haiti earthquake
Chu & Zhong (2015) [156]	Medical rescue team assignment	Maximize number of saved casualties	Mathematical programming	2008 Sichuan earthquake
Ahmadi et al. (2020) [157]	Scheduling/routing of rescue teams	Maximize min. demand coverage	Mathematical programming	Tehran, Iran
Chaudhuri & Bose (2020) [158]	Smart infrastructure image classifier	Identification of survivors in debris	Machine learning	2011 Tōhoku and 2012 Emilia earthquakes
Zheng et al. (2015) [159]	Rescue wings	Monitor and analyse the status of identified victims	AI	2013 Ya'an earthquake
Liu et al. (2016) [160]	Rescue team task assignment	Plan search and rescue operations given uncertain road damage	AI	2014 Ludian earthquake

Detecting the damage status of buildings quickly and accurately is vital to improving response times of rescue operations. Bai et al. [152] use a machine learning framework to compare the performance of using post-event remote sensing data versus multi-temporal images for estimating building damage ratios. Building damage ratio information is particularly useful for determining where damage is concentrated across a city or area and to efficiently concentrate response efforts. Schweier and Markus [154] develop two different integrated information systems involving the use of expert systems to inform both rescue operations and building damage assessment. The first generates advice for onsite search rescue teams about suitable procedures and equipment to use at a particular building collapse, while the second aids inspectors in determining whether a building is safe to use after an earthquake Accurate identification and classification of victims after an earthquake is crucial for improving rescue and evacuation efficiency. Chu and Zhong [156], meanwhile, propose a mathematical programming model for assigning medical rescue teams to affected areas in the very early stage after an earthquake to maximize the expected number of casualties that can be saved. Zheng et al. [159] describe a web-based system to classify potential earthquake victims according to priority of need based on profile data, vital signs, location, and environmental conditions. Finally, Chu et al. [155] propose a model and solution approach for making effective use of crowd sourcing information by selecting volunteers to explore earthquake affected areas given the benefits and cost of deploying them.

2.2.3.2. Evacuation

Evacuation normally takes place during initial phase of the response stage to transfer the injured to medical centres and those in immediate danger or made homeless due to an earthquake to safe zones and temporary shelters [18]. Evacuation is the second most addressed problem in the response stage, comprising 19 of the 67 studies. The main decision making issues include the allocation of evacuees to medical facilities, integration of evacuee planning and location of temporary shelters following an earthquake, and investigation of the role of human behaviour on evacuation operations.

Among studies using mathematical programming and heuristics, two basic decision frameworks have been considered: routing and allocation of affected people to safe zones by minimizing travel distance or evacuation time [171,175], sometimes in combination post-disaster shelter site location [77,82,89], and recovery of injured and transfer to medical centres to minimize loss of life [162,163,166,168,174]. Forcael et al. [171], for example, find that optimized evacuation routes result in shorter evacuation times from tsunami prone areas based on validation from live evacuation drills. Chen et al. [172] investigate how GIS and global positioning system (GPS) technologies can be combined with heuristic methods to support evacuation decisions by identifying in real-time the location of people in need of evacuation and optimal paths (based on length and reliability) for emergency recuse teams to reach them. Rakes et al. [175] propose a model and solution approach for allocating individual families to temporary housing units. Unlike most other studies, they consider each family's educational and healthcare support needs when making assignments. Kilci et al. [169] consider jointly where to locate shelters and allocate victims to shelters taking into account accessibility to critical infrastructure, terrain characteristics, and public ownership of shelter sites. Ozbay et al. [176] present a multi-stage approach for (i) locating shelter sites after an earthquake but before demand is known; (ii) allocating evacuees to their nearest shelters once demand is known; (iii) the need to open additional shelters due aftershocks creating more demand for shelters. Meanwhile, Mills et al. [166] consider patient survival rates and service times for different types of traumatic injuries when making ambulance and medical facility allocation decisions in order to maximize the expected number of survivors. Both Oksuz and Satoglu [168] and Liu

[174] look at where to locate temporary medical centres (aka field hospitals) to deal with the evacuation and treatment of mass casualties.

Among the few studies using simulation is Liu et al. [179], who develop an agent based model to examine how building damage and human behaviour interact when people attempt to evacuate a building. A key aim of theirs is to understand how exit flow rates from buildings can be increased through better building design and the development of improved evacuation strategies. Mills et al. [166] also use a discrete event simulation approach but primarily as a way of assessing the performance of proposed heuristics that use limited up-to-date information when making dynamic ambulance assignments.

2.2.3.2. Relief Distribution

the immediate aftermath of an earthquake, supply chains and logistics operations need to be rapidly organized to transport and distribute significant quantities of relief to affected areas taking into account an initial assessment of demand and post-disaster conditions (i.e., functionality of the transportation network). Logistics steps typically involve receiving and consolidating relief supplies from external suppliers (ESs) at large central warehouses (CWs) located outside the affected zone (aka "hot" zone"), distributing relief from CWs to RDCs located in the hot zone, and then redistributing relief from RDCs to local relief distribution points within affected areas (AAs), which may include shelters, spot recue areas, hospitals, and individual residential areas. Sometimes CWs do not constitute a distinct element of the logistics network (either because CWs are not required or CWs also serve as RDCs), in which case it is assumed that relief supplies move directly from ESs to RDCs.

As seen from Table 11, mathematical programming and heuristics stand out as the dominate methods for addressing relief distribution problems, making up 42 of the 45 studies in this category. An overview of these studies, including logistics activities, number of relief goods, and mode of transportation, is provided in Table 13 with further details provided in an Appendix A. A majority (27 out of 42) focus exclusively on distribution between RDCs and AAs; only a handful consider supply side logistics by including distribution from CWs (i.e., [187,193,198,199]) to RDCs. A few recent papers have looked at even more complex multi-echelon relief supply chains involving (i) distribution among ESs, CWs, RDCs, and AAs [189] and (ii) blood donation at local collection centres (LCCs), transfer to testing laboratories or regional blood centres (~CWs), and on to local blood centres (~RDCs) and regional/local hospitals (~AAs) [163,181]. In addition, a majority of papers consider (i) multiple commodities (25 out of 42), as opposed to distribution of a single generic commodity, and (ii) multi-modal transport (27 out of 42) using a heterogeneous set of vehicles with different capacities and travel speeds, rather than with a fleet of identical vehicles. Vehicle types considered range from maritime ships [183] to road vehicles (i.e., [182,186,197,198]) through to helicopters [177,185,199]. In a few cases, submodels capture variants of vehicle routing problems in which capacitated vehicles complete tours to one or more AAs from a designated RDC (i.e.,[190,194,195,208]) or travel to AAs while resupplying at different RDCs (i.e., [161,197]). Note that less than half (17 out of 42) simultaneously consider multiple commodities and multi-modal transport.

Table 13. Summary of mathematical programming and heuristic approaches for relief distribution problems

Logistics activities	No. of Goods	Mode of transport	References
RDC-RDC	Multi	Multi	[188]
RDC-AA	Single	Single	[178,192,196,197,201,203,204]
		Multi	[183,187,196,202,204,205]
	Multi	Single	[194,195,207,213]
		Multi	[161,164,180,185,186,198,203,206,208]
CW-RDC-AA	Multi	Single	[189,213]
		Multi	[191,198]
ES-RDC-AA	Single	Multi	[162]
	Multi	Single	[165]
		Multi	[177,183,212]
ES-CW-RDC-AA	Multi	Single	[189]
LCC-CW-RDC-AA	Single	Multi	[163,181]

Further analysis reveals that nearly all mathematical programming and heuristic studies for relief distribution adopt a multi-objective framework to capture different, possibly conflicting logistics performance indicators. Typical objectives and variations thereof include: minimizing the cost of transporting relief (i.e., [177,185,205,208], minimizing response time (i.e., [183,186,193,197]), minimizing unmet demand (i.e., [161,180,190,203]), and maximizing route reliability (i.e., [183,194,204,208]). Additionally, most of the studies, except five, apply their modelling framework to a case study, usually involving an historical earthquake. For example, Wang et al. [211] consider a multi-model transport fleet for distributing multiple commodities between RDCs and AAs to minimize both total cost and maximum time to distribute relief and maximize the minimum reliability of routes used by vehicles and then apply their approach to the 2008 Wenchuan earthquake. Vitoriano et al. [182], meanwhile, only consider a single commodity but optimize no less than six different objectives (minimization of transport cost, maximum time to deliver relief, unmet demand, and maximize unmet demand and maximization of route link reliability and security), using a case study of the 2010 Haiti earthquake as a demonstration. More recent work has combined relief distribution with evacuation to shelters and or transport of injured to medical facilities [162–164,178].

Four other methods besides mathematical programming and heuristics have been applied to relief distribution. This includes: (i) a system dynamic model to analyse a relief distribution system built for the Longmen Shan fault, China, where many destructive earthquakes have occurred [215]; (ii) Soft OR for developing a conceptual model of post-disaster survivor perception-attitude-resilience relationships to inform emergency logistics operations in a way that takes into account perspectives of both government planners and the psychology of affected populations; (iii) machine learning (neural networks) for designing an efficient blood supply chain [163] and predict the structural status of road links when deploying relief [217]; and (iv) decision analysis to assess performance of relief distribution based on demand coverage, logistics costs, and response time [191].

2.2.4. Recovery Stage

During recovery, the fourth stage of EOM, the overall aim is to return an affected community to normal after a major quake. Recovery begins right after the emergency. In the short-term, recovery is an extension of the response stage that deals with the restoration of basic services in the days and weeks after a disaster. In the long-term, recovery focuses on restoring economic activity and community wellbeing by rebuilding damaged facilities and housing, which can take years.

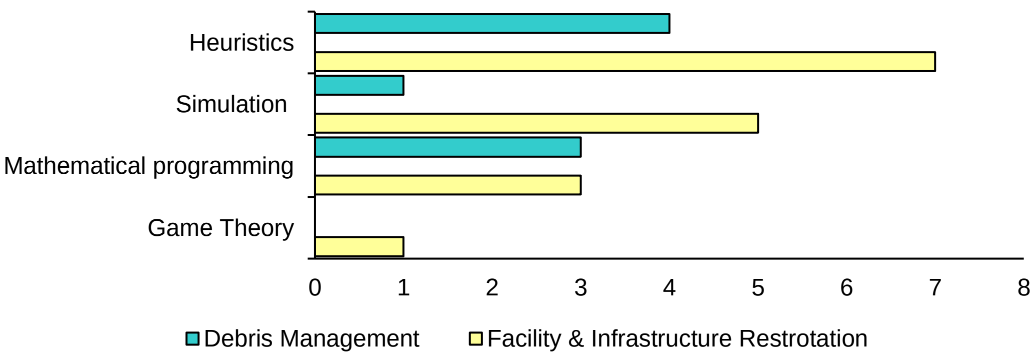

Figure 7. Methodologies used in recovery problems

In view of this, we consider two basic types of recovery operations: 1) debris management and 2) facility and infrastructure restoration. Debris management is initially concerned with quickly clearing debris from impacted urban areas and roads, thereby allowing rescue, evacuation, and relief distribution operations to proceed more efficiently [218]. Later on, debris needs to be collected and processed. Debris removal management after large-scale earthquakes can be one of the most complicated and time consuming activities of post-disaster operations. Facility and infrastructure restoration focuses on planning operations involved with repair and rebuilding of damaged buildings and critical infrastructure networks like water, electricity, and road transportation. This includes prioritization of buildings and infrastructure components and scheduling of restoration work teams based on criticality and the need to provide maximum network functionality. Like with response stage problems, the sheer scale of both debris management and facility and infrastructure restoration operations involved with earthquakes sets them apart from other types of natural disasters.

Table 14. Details of the types of problems addressed and methodologies used in the recovery stage

Problem	Method	References*
Debris management		
Debris clearance, collection and processing	Mathematical programming	[218–220]
	Heuristic	[218,221–223]
	Simulation	[224]
Facility and infrastructure restoration		
Planning repair work	Mathematical programming	[225–227]
	Heuristic	[228–234]
	Simulation	[224,225,235–237]
	Game theory	[227]

* References highlighted in bold incorporate more than one methodology and/or address multiple problem types.

Recovery problems have received significantly less attention than the other stages with only 20 studies reviewed. A summary of OR methodologies used for both problem types is shown in Figure 7. As can be seen, only four OR methods have been applied in recovery stage problems. Similar to the preparedness and response stages, mathematical programming and heuristics are the most frequently used OR methods. A limited number use simulation alone or in combination with mathematical programming and heuristics, while one study combines mathematical programming with game theory. Additional details about recovery problems are given in Table 14.

2.2.4.1. Debris Management

Given limited resources, efficient and effective planning of debris clearance to improve connectivity between relief demand and supply is vital during disaster response. There are a few studies addressing debris clearance and relief distribution problems in an integrated manner, but details of these studies are given in Section 2.5. In this section, we only discuss studies that deal exclusively with debris clearance, collection, and processing operations.

Mathematical programming and heuristic methods for debris management have considered a number of different objectives, such as maximizing road network accessibility by minimizing the time to reopen a predefined set of travel paths [219], minimizing the time to clear debris from a road network and restore full connectivity [218], minimizing the time to clear debris from a road network while maximizing connectivity between all origin and destination pairs over time [221] and minimizing a combination of logistics costs involved with processing debris (i.e., transporting, sorting, storage, and disposal of debris), environmental and operational risks from exposure to contaminated debris, and the psychological costs imposed on victims and residents from the waiting time to remove debris [220]. Apart from these, a system dynamics model was used by Hwang et al. [224] to adopt a more holistic perspective to recovery operations, including debris removal. A key finding is that consideration of the interdependencies among multiple recovery operations can lead to better understanding of the overall recover process and development of more effective recovery strategies.

2.2.4.2. Facility and Infrastructure Restoration

Problems dealing with the repair and rebuilding of facilities and critical infrastructure networks (i.e., road transportation, water, gas, and electricity networks) damaged by earthquakes mainly focus on resource allocation and scheduling/routing of emergency repair crews. Here, typical aims are to restore full functionality of infrastructure networks as quickly as possible following an earthquake, minimizing the number of people without service during repair, and minimizing reconstructive costs. A variety of different aspects of this basic problem have been considered, mostly involving the use of mathematical programming and heuristics (10 out of 13).

For example, González et al. [225] consider a set of interdependent water, gas, and power networks and apply both mathematical programming and simulation to minimize repair and supply shortage costs by coordinating repair of multiple, different network elements collocated in the same area. Meanwhile, Nozhati et al. [228] employ approximate dynamic programming (a hybrid mathematical programming and heuristic approach) to minimize the time to restore electricity to a specified fraction of the population, while maximizing the number of people with electricity service over time. In a series of papers, Yan, Shih, and colleagues explore the application of time-space network flow models and heuristic solution methodologies for scheduling the deployment of road repair crews in order to minimize the time of road repair operations [229,230] and distribution of essential supplies (i.e., fuel, machines, food) to repair crews at least cost [231,232]. Different problem variants include the need to adjust original schedules following demand and supply perturbations (i.e., aftershocks causing additional damage and additional repair crews being mobilized) and consideration of multiple vehicle types combined with stochastic travel times. Luna et al. [236] examine the use discrete event simulation to model the restoration time of a water distribution network under different seismic scenarios and help inform resource allocation planning. Besides repair of critical infrastructure networks, Gosavi et al. [237] address damage containment and restoration of urban areas using discrete even simulation. Longman and Miles [235] also use discrete event simulation to predict timelines for rebuilding damaged housing and inform resource requirements (i.e., inspectors and constructive workers) following the 2015 Nepal earthquake.

2.2.5. Integrated Stages

Given interdependencies among EOM stages, greater effectiveness and efficiencies can often be achieved through integrated planning of various pre- and post-disaster activities. The majority of research, however, has focused on a single EOM stage. Relatively few studies (22 out of 211) have combined problems from different EOM stages in an integrative fashion. Integrated disaster management is clearly recognized as a key gap in the literature that needs be addressed moving forward. Figure 8 shows the different methods used in the integration of different EOM stages. As with most single stage studies, mathematical programming and heuristics are the most frequently used OR methods, accounting for no less than 19 (86%) of the 22 studies.

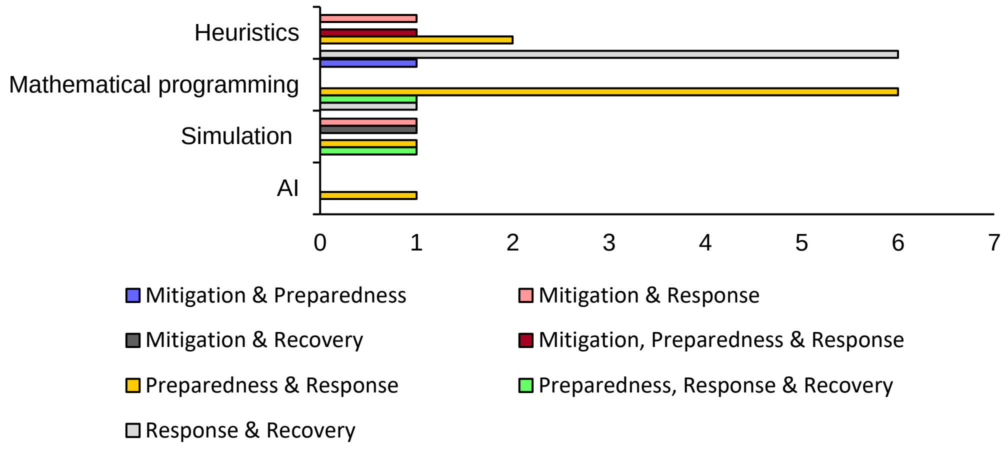

Figure 8. Methodologies used in integrated stages of EOM

Table 15 provides a breakdown of the problems addressed and methodologies used in the integration of EOM stages. The two most frequent combination of stages are preparedness and response (9 out of 22) and response and recovery (7 out of 22). Only two studies combine three stages, namely (i) mitigation, preparedness, and response and (ii) preparedness, response, and recovery. As can be seen from Table 15, studies combining preparedness and response have looked at relief pre-positioning and resource planning problems together with either evacuation of victims or the distribution of relief to affected areas. Integrated response and recovery planning, meanwhile, has focused mainly on how facility and infrastructure restoration (i.e., road networks) can more effectively support relief distribution operations. Table 16 present further details of integrated EOM studies involving the application of mathematical programming and heuristic methods, including the types of decisions and objectives considered.

A total of 9 studies have looked specifically at how preparedness positively impacts on response. A general observation is that many of the papers reviewed investigate inherent trade-offs between greater investment in locating RDCs and or stockpiling relief and lower penalties as measured by demand shortages, response time, number of people evacuated, etc. Typically, multi-objective frameworks are adopted to capture the multitude of planning goals that often at play. Salman and Gül [238], for instance, propose a model for locating field hospitals and determining the number of ambulances needed to minimize travel and waiting times of casualties. Regarding relief distribution, Mete and Zabinsky [239] optimize the location, capacity, and inventory levels of RDCs at minimum cost in order to reduce the transport time of and unmet demand for medical supplies. Of note, they incorporate operational level decisions about vehicle loading and routing when devising an optimal relief distribution plan.

Sitting of RDCs and relief distribution combined with vehicle routing has been considered by other authors as well [240,241]. In a few cases, studies RDC location has also been combined with evacuation [242,243]. Apart from mathematical programming and heuristic methods, Sahebjamnia et al. [244] develop a sophisticated hybrid simulation and AI decision support system for prepositioning RDCs and managing the allocation and distribution of relief by a humanitarian relief chain. Three main performance indicators – set-up/transport cost, relief shortages/excess, and response time – are used to evaluate tradeoffs of alternative relief chain configurations under different disaster scenarios, make iterative improvements, and finally make recommendations about the best configuration for any given post-disaster state.

Table 15. Details of the types of problems addressed and methodologies used in integrated stages of EOM

Stages	Problems*	Method(s)	References
Mitigation & Preparedness	PP & P/RP	Mathematical programming	[245]
Mitigation & Response	PP & RD	Heuristic	[246]
	RVA & SR	Simulation	[247]
Mitigation & Recovery	RVA & FIR	Simulation	[248]
Mitigation, Preparedness & Response	PP, P/RP & RD	Heuristic	[249]
Preparedness & Response	P/RP & E	Mathematical programming	[238,242]
	P/RP & RD	Mathematical programming	[239,250,251]
		Heuristic	[240,241]
		Simulation & AI	[244]
	P/RP, E & RD	Mathematical programming	[243]
Preparedness, Response & Recovery	P/RP, RD & FIR	Mathematical programming & simulation	[252]
Response & Recovery	RD & DM	Heuristic	[253]
	RD & FIR	Mathematical programming	[254]
		Heuristic	[255–259]

* PP: Protection Planning, P/RP: Pre-positioning and/or Resource Planning, RD: Relief Distribution, RVA: Reliability and Vulnerability Analysis, SR: Search and Rescue, FIR: Facility and Infrastructure Restoration, E: Evacuation, DM: Debris Management.

Relatively fewer studies have looked at combining both pre-disaster stages (1 study) or both post-disaster stages (8 studies). All have employed mathematical programming or heuristic methods. Hu et al. [245] examine the problem of reinforcing RDCs and roads (mitigation) as well as setting relief inventory levels (preparedness) in order to minimize total cost (protection plus relief procurement, holding, and transport), deaths, and demand shortages. Integration of response and recovery has been considered by a number of authors. For example, Çelik et al. [253] develop a heuristic for optimizing the clearance of road debris (recovery) and the distribution of relief from RDCs to AAs (response) over time. Meanwhile, various studies, including Yan and Shih [256], and Li and Teo [254], have looked at variations of how repair of damaged road links (recovery) can better support relief distribution (response) by reducing response time and increasing demand satisfaction, among other goals.

Table 16. Details of mathematical programming and heuristic approaches for integrated stages of EOM

Stages*	Decision(s)	Objective(s)	References
M+P	Reinforcement of buildings, reinforcement of the road network and relief inventory levels	Minimize building reinforcement, road network reinforcement, procurement, and expected transport/holding costs, transport time, shortages and deaths	[245]
M+Rs	Road link protection and distribution of relief items	Minimize expected weighted average distances between supply and demand points	[246]
M+P+Rs	Building retrofits, road link protection, capacity of emergency aid and distribution of relief items	Minimize lives at risk and maximize number of people saved	[249]
P+Rs	Location of field hospitals, number and allocation of ambulances and transport of casualties by ambulances	Minimize casualty travel and waiting times	[238]
	Location of medical supply centres and transfer points, allocation of medical supplies and transport of injured to hospitals via transfer points	Minimize transportation time of injured and supplies and minimize set-up, transport and response time violation costs	[242]
	Location and inventory levels of distribution centres and distribution of relief through a network	Minimize set-up, procurement and transport costs, unused inventory and unmet demand	[250]
	Location, capacity and inventory levels of distribution centres and distribution of relief by vehicle routing	Minimize set-up costs, transport time and unmet demand	[239]
	Location, capacity and inventory levels of distribution centres and distribution of relief by vehicle routing	Minimize max. weighted unmet demand, transport time and set-up, procurement, transportation, inventory holding shortage costs	[251]
	Location of distribution centres and distribution of relief by vehicle routing	Minimize transport time, unmet demand and set-up costs	[240]
	Location of distribution centres and distribution of relief by UAV trip assignments	Minimize transport time of UAVs and travel time of people	[241]
	Location and inventory levels of distribution centres, allocation of rescue vehicles and relief and transport of injured to medical facilities by vehicle trip assignment	Minimized set-up, operational, transport and holding costs, cost variability, unmet demand and unrecovered injuries	[243]
P+Rs+Rc	Location and capacity of distribution centres, restoration equipment inventory levels, distribution of relief through a network and repair of damaged road links	Minimize set-up, restoration equipment procurement and expected transport costs and unmet demand	[252]
Rs+Rc	Debris clearance from roads and distribution of relief	Maximize satisfied demand for relief	[253]
	Repair of damaged road links and distribution of relief through a network	Maximize satisfied demand, security and reliability and minimize max. delivery time	[254]
		Minimize delivery time	[255]
		Minimize delivery time and time to repair	[256]
	Repair of damaged road links and accessibility of affected areas from distribution centres	Minimize time to reach affected areas	[257]
	Repair of damaged road points and distribution of relief through a network	Maximize cumulative accessibility and min. satisfied demand	[258]
	Repair of damaged road links and distribution of relief by vehicle routing	Minimize set-up, transport and road repair costs and response time and maximize route reliability	[259]

* M: Mitigation, P: Preparedness, Rs: Response, Rc: Recovery.

2.3. Roadmap for Future Research

As should be clear from our review, OR provides a powerful array of tools for effective and efficient decision making in EOM. However, despite the volume and variety of EOM studies employing OR methods, the development of widely applicable modelling frameworks emerges as a key shortcoming in need of greater attention. As noted in previous surveys, applicability is critical in the field EOM owing to how any real-world decisions ultimately translate into direct impacts on communities and individuals. Below we examine some important considerations relating to realism, comprehensiveness, practicality, and user-friendliness that have been taken from the various problem definitions and solution methodologies described in the literature. Figure 9 summarizes these features as they relate to the development of applicable EOM planning frameworks. Our hope is that this will prove useful to informing future lines of research and continued advancement of the field.

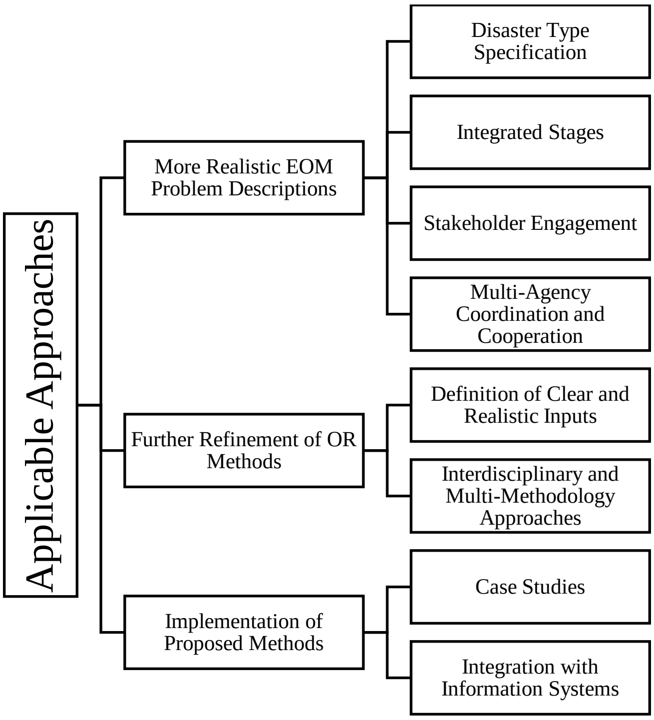

Figure 9. Key features for developing more applicable EOM methods

2.3.1. More Realistic EOM Problem Descriptions

As evident from our literature review and previous reviews [18,20,21,24], a vast amount of research has been carried out in the past decades on the use of OR methods for EOM. We point out, however, that most studies have analysed problem from a methodological and or theoretical perspective as opposed to real-world applicability and use. Frequently, studies fail to develop problem representations that are familiar to practitioners, instead opting to define novel problem formulations that differ greatly from practical and realistic ways of doings things. For OR methods to achieve greater applicability in EOM, it is essential that problem definitions be well-grounded in reality and context. To this end, we provide some recommendations that may serve to enhance the realism and, therefore, applicability of OR methods in EOM through better problem identification and specification, greater stakeholder involvement, further integration of different disaster stages, and enhancement of multi-agency coordination and cooperation.

2.3.1.1. Disaster Type Specification

DOM reviews thus far have not really touched on which specific disaster types may be more or less favourable to real-world application of OR methodologies. This is somewhat surprising, since in practice, disaster risk assessment and planning is usually performed separately (i.e., using software like Hazus [260]) for tsunamis, earthquakes, floods, hurricanes, and other disaster types. Contrary to this, we observed that only 138 of 211 studies in our review present a problem definition expressly focused on earthquakes and EOM decision making (see Appendix B). In only a few studies were emergency operations and stakeholder roles defined by field experts [131,215]. Interestingly, studies addressing reliability and vulnerability analysis and integrated disaster management have gone the furthest in terms of using earthquake-oriented problem specifications. Other EOM problem areas, however, tend to be more generic and theory-oriented and potentially less useful in real-world planning. We would argue that specifying which disaster type is being addressed would translate into greater transparency and precision in terms the problem that is being addressed and, in turn, lead to the development of more realistic and applicable models.

With regard to EOM, the frequent neglect to identify a specific disaster type is perhaps one reason why problem descriptions usually ignore two key features of large earthquakes, namely the potential for and need to contend with 1) cascading or secondary effects [261] and 2) subsequent disasters caused by aftershocks [162,185]. Cascading events can occur as an indirect result of a major quake. For instance, an earthquake that ruptures gas supply pipelines can result in fires and explosions that dramatically increase urban damage and risk to life [262]. Other examples of secondary effects from earthquakes include landslides that occur long after the event following heavy rainfall, flooding caused by breached dams and levees, and even the triggering of volcanic eruptions. In the case of earthquakes, which normally strike with no warning and affect a large area, the potential for cascading effects is often magnified in comparison other types of disasters. Aftershocks, meanwhile, are common following a large quake and not only can cause significant damage days or even weeks later, but can seriously hamper response and recovery operations. The 2011 Tōhoku (aka Great East Japan Earthquake), for example, caused extensive damage and left over 20,000 people dead. This was in large part because it was a compound disaster involving earthquakes, a tsunami, and a nuclear accident that widely impacted the whole nation [263]. As noted by Marano et al. [264], over 20% of deaths attributed to earthquakes over the past 40 years were a result of secondary causes (i.e., landslide, liquefaction, tsunami, and fire).

2.3.1.2. Integrated Stages

Besides a lack of disaster type specification, realism of EOM studies is often constrained by proper consideration of how different DOM stages interact with one another. Like other reviews, we found that the vast majority of OR based EOM studies (189 out of 211) published in the previous 11 years focus on only one disaster stage as opposed to the integration of multiple stages. The latter group has mostly appeared in the literature fairly recently. In this subsection, we identify a number of aspects of EOM that could be aptly addressed through integration of different DOM stages.

Tasks associated with recovery and mitigation partially overlap. Better understanding of the connections between protection strategies and damage states that result in lower recovery costs of a system is a key research theme that warrants greater consideration in decision modelling frameworks. Conversely, recovery can also be catalyst for mitigation. The motto ‘Build Back Better’, often heard in recent years, advocates the adoption of integrated disaster risk reduction measures into physical infrastructure restoration work following a disaster in order to enhance resilience of and minimize future risks to people, livelihoods, and the environment [263]. Despite the clear links between mitigation and recovery, we found only one study by Cho and Park [248] addressing this combination of DOM stages. Analysis of the trade-offs between investing in infrastructure protection and the associated economic and social costs of disruption and recovery is a clear gap in the literature.

Notably, recent work has examined problems that intersect with the mitigation and response stages. This includes the use of heuristics to optimize building/road link protection and post-disaster relief distribution [246,249] and simulation to assess vulnerabilities to urban infrastructure and search and rescue effectiveness [247]. Invariably, simplifications need to be made with any model. Nonetheless, identified drawbacks with existing mitigation and response studies include lack of consideration regarding post-earthquake resource availability (i.e., personnel, vehicles, relief supplies) and potential reduction of resources due to earthquake damage, as well as overly simplistic assumptions about infrastructure damage (i.e., facilities and road links can be in one of two states: either fully operational or not) and the effectiveness of protection (i.e., protection entirely prevents all damage to facilities/road links). From a modelling perspective, incorporating protection-damage functions, in particular, is no easy task. However, future work on this aspect might take inspiration from Chang et al. [51], among others, who looked at using Monte Carlo simulation to better understand how for various bridge retrofit standards, uncertainty about earthquake intensity and bridge structural damage affected bridge traffic-carrying capacity based on established bridge fragility and damage-functionality relationships.

Although relief pre-positioning and resource planning (preparedness) combined with relief distribution (response) has received relatively more attention than other types of integrated planning (see Table 15), additional lines of research within this area remain. Most researchers have concentrated on the impact of locating RDCs, while sometimes also considering decisions about capacity and inventory levels, on relief distribution effectiveness. However, to our knowledge, no studies have looked at simultaneously positioning RDCs, setting relief inventory levels, and locating shelter sites with relief distribution. Further research might address this gap as well as factor in the interplay between shelter site location and evacuation time/distance.

Blocked roads and paths to affected areas are frequent in the aftermath of an earthquake. While some research has dealt with debris clearance to reestablish relief supply lines (see Table 15), there is an evident lack of research focused on how debris removal allows for evacuation from affected areas. Additionally, none have incorporated stochastic elements related to debris amount or resource requirements for clearance/repair. Finally, no research that we are aware of has combined preparedness and recovery, for example RDC location and resource planning considering likely road infrastructure damage and speed of debris clearance on relief distribution performance.

We acknowledge that from a modelling standpoint, development of integrated models often involves much a higher degree of complexity that can pose a serious challenge in terms of substantially increased computational time requirements. Nevertheless, greater use of integrated modelling can provide clear benefits (i.e., greater realism, enhanced coordination, more efficient use of limited resources) and issues related to solution time can at least partially be addressed by developing multiple inter-linked models and solving them in stages or using heuristics and approximation methods to solve realistically sized problem instances in reasonable computational time.

2.3.1.3. Stakeholder Engagement

There is broad recognition that in order to achieve buy-in and a measurable improvement in EOM performance, all key stakeholders need to be involved both in implementation and problem identification and modelling (not necessarily fine-grain details but at least general structure) [154,167,191,215]. Lack of stakeholder involvement in model conceptualization and development often leads to more theoretical and less realistic problem definitions, case studies that provide limited insights, and ultimately low likelihood of proposed methods ever being implemented [23].

To help understand the prevalence of stakeholder involvement in academic studies, the articles we reviewed were assigned one of three categories: 1) no involvement; 2) partial involvement (i.e., providing data and or general advice for case studies, including review and verification of model inputs); and 3) significant involvement (i.e., direct participation of an agency, NGO, or institution in the conceptualization and development of the modelling approach). Findings are detailed in Appendix B. Regrettably, despite the large body of EOM research reviewed, we found that only 19 (8%) of the 211 studies had significant stakeholder involvement and just 64 (25%) had even partial stakeholder involvement.

Focusing on studies that had "significant" stakeholder involvement, these can be further subdivided into various distinct groups. One group worked in close collaboration and co-design of the study through use of participatory approaches (i.e., interviews and workshops) to inform model conceptualization from the very beginning [88,208]. A second group engaged with stakeholders, mainly through interviews with emergency department personnel and EOM planners, to seek advice about specific issues relating to emergency response operations [125] or as part of defining qualitative or quantitative evaluation criteria (a.k.a. key performance indicators) of their decision support models [69,72,73,131]. Finally, a third group mainly looked at post-disaster psychological metrics of local residents directly impacted by large-scale earthquakes based on interviews and questionnaires [215,216]. Only one study addressed a problem proposed by EOM practitioners themselves [115]. Although the level of stakeholder involvement does vary somewhat, a general observation about the afore mentioned studies (in comparison to those with no or partial stakeholder involvement) is that their assumptions and model features tend to show a greater degree of realism aimed at meeting the specific needs of EOM practitioners.

To sum up, our analysis reveals that stakeholder involvement is for the most part an important but neglected aspect of OR studies applied to EOM, especially in the initial problem identification stage. Failure to identify earthquakes as the key focus of DOM research and involve EOM stakeholders from the start has resulted in modelling approaches that lack realism and real-world application by practitioners. Greater use of problem structuring (i.e., hierarchical process modelling) and other Soft OR methods as part of facilitated workshops involving one or more stakeholders, we would suggest, would go a long way toward addressing this shortcoming. Such approaches are commonly used in healthcare settings [265,266] when dealing with complex and unstructured problems and or where they may be multiple groups of stakeholders with potentially conflicting views about a problem. EOM shares much in common with healthcare and would likely benefit by adopting Soft OR conceptual frameworks. This is not to say that Soft OR should be the preferred or only approach to EOM, but simply that it should be used much more frequently as the starting point for subsequent Hard OR approaches (i.e., mathematical programming and heuristics) to ensure that they are well-grounded within a stakeholder perspective.

2.3.1.4. Multi-Agency Coordination and Cooperation

As noted by various authors, cooperation and coordination among multiple outside relief agencies and local and national government agencies is crucial to efficient EOM [20,265]. For example, in the case of the Indonesia Tsunami in 2018, foreign and local humanitarian organizations, including the Red Cross, other NGOs, and the United Nations (UN), were all in close communication with the Indonesian government to provide rapid support to the affected area of Sulawesi [268]. Foreign militaries actively participated in relief aid distribution with an average of 15-20 flights per day to the city of Palu. Supporting this effort was the UN Office for the Coordination of Humanitarian Affairs (OCHA), which assisted with information sharing and coordination of relief aid shipments. Similar to OCHA, the EU’s Emergency

Response Coordination Centre is responsible for collecting and analyses real-time information, devising response plans, and coordinating the EU's disaster response efforts by matching offers of assistance to the needs of the disaster-stricken country [269].

In spite of the importance of multi-agency coordination and cooperation in real-world planning, surprisingly little research involving OR methods has been devoted to this subject. We found only one study focused specifically on emergency response and relief chain coordination [137] (preparedness) and a second that applies a sophisticated bi-level optimization framework to the problem of coordinating multiple, independent countries and aid agencies in relief distribution (response) [183]. Clearly, future research needs redress this gap in the literature.

2.3.2. Further Refinement of OR Methods

After defining a realistic and holistic problem description, ideally supported by stakeholder involvement, the next step should be the development of modelling frameworks and solution methodologies based on clearly defined model inputs (i.e., data, decision variables, and objectives or performance criteria). Depending on the specific problem and needs of decision makers, multi-methodology and interdisciplinary approaches may be called for. Below, we elaborate on these points.

2.3.2.1. Definition of Clear and Realistic Inputs

Lack of a clear problem description and assumptions has been highlighted by other DOM reviews [20,23]. Here we delve into this topic for the specific case of earthquake disasters, emphasizing the need to define clear and realistic inputs for various EOM problems.

While reliability and vulnerability analysis has been successfully applied to a wide range of different types of infrastructure (see Table 6), including electricity grids [47,55], energy pipelines [55], water supply systems [49,51], and transportation networks [103,114], protection planning models have mainly focused on transportation networks (i.e., road links and bridges) [79,80] and occasionally buildings [81,82] (see Table 7). Often times, in the case of road network protection, rather abstract representations of the transport infrastructure have been applied without going into detail regarding the individual components of the network that can suffer damage (i.e., nodes, links, and pathways), the possibility some component are composed of multiple elements, the type of damage that can be sustained by different components, the degree of susceptibility to damage of each component, and what specific options are available to mitigate against damage. For instance, the literature is rather vague about what constitutes a road link. If a particular section of road has an intervening bridge or tunnel, then by any normal standard it should be decomposed into three links even if there are no road junctions along the way. Further, little or no consideration is given to the causes and likelihood of link failures; is it due to say landslide blockage versus fracture, buckling, or subsidence? Finally, in most models there is no explicit consideration of what a protection action constitutes or its effectiveness in preventing damage [85,246].

Based on the above assessment, we offer two recommendations. The first is that there is a clear need to address protection of critical infrastructure networks besides just transport. Different infrastructure networks face unique risks from earthquakes and have very different types of protection strategies that can be practically implemented. It would be worthwhile to elucidate these differences and develop bespoke models for different infrastructure types. The second recommendation, regardless of the type of infrastructure network being considered, is that protection models should be combined more frequently with a preliminary reliability and vulnerability analysis, especially when it comes to case studies. We envision that reliability and vulnerability assessment models could form the basis for producing inputs to a protection model, including a detailed assessment of failure modes and probabilities and development of concrete protection strategies that are properly costed out and understood in terms of their physical/operational effects of damage prevention.

Turning now to the preparedness stage, while there is a fair amount of research on relief pre-positioning and resource planning, various limitations are evident based on our review of existing models. For one, a fair number of studies considered stocking of multiple commodities but do not give any specifics. It is not at all clear if non-perishable or perishable goods are involved or some combination thereof. For perishable goods, holding time (which is not usually considered) as well as transport time (which often is considered) becomes a key factor. Only a few studies relief pre-positioning and resource planning have looked at inventory holding and stock replenishment policies [103,120,123], which directly influence holding time. Additionally, with few exceptions (i.e., [92,100]), RDC location and inventory planning problems focus exclusively on relief distribution between RDCs and AAs, without considering supply from external suppliers or central warehouses. What is more, little or no mention of transport mode and vehicle availability is made in the literature on relief pre-positioning and resource planning.

A similar set of critiques apply to relief distribution models (response stage), except that multi-modal transport and vehicle resources are often considered. Looking specifically at provision of emergency medical services, only limited work has dealt with duty allocation and scheduling [156,196], even though this is crucial factor in determining the number of earthquake victims that can be saved. Further research could also look at medical team composition (i.e., number of nurses, doctors, and first aid workers) depending on estimated casualty amounts.

Evacuation planning, another response stage problem, has usually been based on defining routes to predetermined safe zones [128,171]. In practice, however, safe areas may need to be designated after an earthquake occurs, depending on the location of the epicentre, its magnitude, and damage to roads and buildings. Future work in this area needs to address the stochastic nature of earthquakes and the imperative of having contingent evacuation plans based on a range of different scenarios. Amideo et al. [24] emphasize paying greater attention to mass-transit-based evacuation and multi-modal evacuation approaches in DOM, which also applies to EOM.

2.3.2.2. Interdisciplinary and Multi-Methodology Approaches

A number of authors have pointed out the need for using interdisciplinary approaches in DOM. Amideo et al. [24], for example, suggest that use of techniques and concepts from different relevant disciplines would provide a more realistic frameworks for shelter location and evacuation routing. Hoyos et al. [21] provide some general recommendations about combining optimization with probabilistic or stochastic methods. Here, we aim to highlight how a multi-methodology approach, in particular handling of information using multiple techniques and different disciplines, would help facilitate a more open and systematic decision making process.

In the wider mitigation planning literature, the survival and damage levels of road networks and other infrastructure is typically determined by distance from epicentres or fault lines. In OR studies, however, few attempts have been made to accurately estimate post-disaster network failures as part of protection planning. Based on our review, Monte Carlo simulation is the most frequently used method to estimate infrastructure failure probabilities [51,54], though other techniques like Bayesian networks have also been applied [246]. In many cases, however, it is not clear how these probabilities relate to the geophysical properties of quakes (including epicentre distance, magnitude, and wave type) and infrastructure vulnerabilities.

Further research on infrastructure fortification would benefit from a multi-methodology approach combining optimization with seismic risk assessment and engineering in addition to simulation. Here, various techniques used in the field of seismology, including machine learning, might prove particularly useful in estimating damage levels [66,74] and human losses [75] based on key variables like structure type, constructive quality, built area, and occupancy level. Subsequent application of simulation to assess key uncertainties combined with earthquake engineering to specify feasible fortification/retrofit alternatives [272,273] could form the basis for developing more holistic and realistic mathematical programming or heuristic methods to efficiently allocate limited protection resources. Similar to protection planning type studies, greater use of forecasting methods from the seismology (i.e., for estimating the intensity and frequency of quakes) would significantly enhance the rigor of relief pre-positioning and resource planning models. A good example is a study by Battarra et al. [121]. While the mathematical programming model they present is fairly simplistic, their work is notable for adopting a multi-disciplinary approach to disaster preparedness, specifically the allocation of relief supplies among RDCs.

Finally, better understanding of human behavioural responses would also greatly improve the realism of OR models, especially as part of response operations. Amideo et al. [24], for example, categorize evacuee behaviour based on five different dimensions that have an impact on evacuation effectiveness during an emergency: time of day, route diversions, demographics, route preference, and warning signals. One of their key findings is that time of day and demographics play a critical role in route diversion choice and, in turn, potential delays during an evacuation. In the case of EOM, however, only one study by Liu et al. [179] explicitly address aspects of human behaviour during evacuation. Similar to Amideo et al. [24], they find that mean evacuation time from buildings can be underestimated by at least 20% if social behaviours are not accounted for. We highlight this gap in EOM and suggest that future research should incorporate behavioural OR [274] and Soft OR [42] techniques to analyse individual and group responses as part of multi-methodology response planning.

2.3.3. Implementation of Proposed Methods

In the final stage of developing EOM methods applicable to real-world problems, it is important to consider: 1) validation via the use of case studies and 2) the frequently need to integrate information systems to support real-time data acquisition and multi-agency coordination. Below we discuss these two key point in further detail.

2.3.3.1. Case Studies

Most studies we looked applied their modelling and solution framework to a real or semi-realistic case study (see Appendix C) to demonstrate the utility of their proposed approach and derive new insights to support policy making and planning. This was typically carried out in two steps – first the generation of inputs to highlight data requirements and show how the proposed framework can be applied in practice and second a set of computational experiments to generate baseline results and carry out further what-if or sensitivity analysis. Here, we focus on the data generation phase and the common limitations of earthquake scenario development.

The generation of problem data can sometimes be laborious and require the use of specialized GIS software, like ArcGIS and GoogleMaps. For other types of data, discussions and interviews with expert stakeholders (discussed in Section 2.5.1.2) are sometimes required. More often than not, simplified versions of infrastructure systems (i.e., transport networks and water supply systems) are developed from secondary data sources or based on randomly generated data (see Appendix C). Consequently, even when GIS tools are used to develop a network representation, they may not involve a high degree of detail (i.e., individual road segments and buildings). In addition, demand nodes are typically represented by whole cities or even provinces with level of demand proportional to population size (i.e., [111,185,245]). Resources, however, are sometimes defined in aggregate terms (i.e., total supply), instead of being distributed among individual locations with defined distances to demand nodes (i.e., [219,253]). Based on this we make a few seemingly obvious recommendations. These are particularly pertinent to protection planning, relief pre-positioning, shelter site location, evacuation, relief distribution, and recovery stage problems. Where possible, real network data of sufficient detail for planning purposed should be used. Linked to this, demand should generally be defined at district or neighbourhood level for large cities and by towns/communities when working at the scale of provinces. Finally, supply nodes and supply amounts should nearly always be included, ideally based on information provided by local authorities, to give a more realistic picture of how resources can be most effectively allocated.

Besides basic network configuration and resource availability data, case studies must also invariably incorporate information about the anticipated impacts of an earthquake (i.e., casualties, infrastructure damage, traffic conditions). Our analysis shows that disaster scenario development is mainly informed by two sources: 1) government and NGO technical reports and 2) software platforms (see Appendix C). Reports from agencies like the Japan International Cooperation Agency [275,276] often provide detailed analysis of likely earthquake occurrences and post-earthquake conditions, including predicted magnitudes, rupture locations and lengths [105,246], classification of at risk roadway components [218], and casualty rates and associated evacuation demand [130]. Software like Hazus [260] are also useful in forecasting the number of displaced households [194], the number of critically injured [166,194], and infrastructure damage levels [165]. Depending on the disaster stage and type of model, either the most probable scenario is examined [72,131,222] or multiple scenarios (that vary in terms of earthquake position/magnitude, time of occurrence, etc.) are considered in an effort to find sufficiently robust solutions [88,130,241]. We do not have any major critiques about how disaster scenarios are developed in the case studies we reviewed except to say that greater attention should be paid to properly assigning probabilities to each scenario when multiple scenarios are included. This mainly applies to mitigation and preparedness stage problems. Not infrequently, scenarios are given equal chance of occurrence. Clearly, more scientific approaches are needed, perhaps involving interdisciplinary methods.

2.3.3.2. Integration with Information Systems

In the context of EOM, information systems are invaluable for providing accurate data to all relevant actors and area experts involved in both pre-disaster mitigation and preparedness planning and post-disaster response and recovery activities. Usually, information systems are implemented using a combination of GIS software, remote sensing data, government databases, and other modern information technology systems. Such systems greatly enhance the decision making-process of EOM, including but not limited to relief chain coordination, search and rescue, evacuation, relief distribution, and debris clearance through better knowledge of where damage to buildings and infrastructure and location and needs of affected people. As with other reviews [20,21,23], we affirm the critical need for the development and deployment of user-friendly information systems in EOM, as well as the potential of OR methods to enhance the capabilities of such systems.

Especially important to enhancing the efficiency of humanitarian relief operations and guiding investment in preemptive measures to reduce earthquake risks is the availability of accurate real- and near real-time data. In more developed areas of the world, national- or regional-level earthquake information systems have been created, which provide access to real- and near real-time data for various types of analyses. An example of a near real-time system is Hazus, developed and maintained by the US Federal Emergency Management Agency (FEMA). Hazus integrates geographic and other types of data into a GIS-based software platform to estimate direct and indirect losses from hazards, including earthquakes [277]. A notable real-time data information system is Turkey's Rapid Earthquake Response System, which can estimate damage to facilities and the roadway network across Istanbul following an earthquake through collection of data from pre-installed seismic sensors [218]. In the absence of centrally managed earthquake information systems, as is common in many least economically developed countries, open-source, online platforms that make use of Volunteered Geographic Information (VGI) have sometimes been relied up by government agencies and NGOs. Following the 2010 Haiti earthquake, for example, OpenStreetMap volunteers from around the world used satellite images to map the outlines of streets and buildings in the Port-au-Prince area. This effort was further supported by on-the-ground volunteers in Haiti who upload additional information using portable GPS devices [278]. We note that decentralized online and VGI systems like one used in Haiti are, in comparison to a centralized information system, less prone to being knocked out as a result of a large quake.

We observe that a number of OR studies in the EOM literature have made use of outputs from near real-time information systems as part of case studies, typically when defining earthquake scenarios and estimating damage and casualty levels (i.e., [166,190,251]). A key difficulty potentially inhibiting wider integration of real- and near real-time data into OR based decision support tools may be the considerable amount of data processing required to translate data contained in an information system into a format that can be readily inputted into an OR model. More importantly, vital pieces of information needed by OR models are often missing or incomplete (i.e., due to inability to assess on-the-ground conditions), which invariably impacts the quality and usefulness of OR model outputs. In the worst case, data gaps can render solutions infeasible (i.e., when a bridge is shown to be intact from satellite images but no longer capable of bearing vehicles above a critical weight). This is especially concerning when deriving solutions for early stage response. There have been some attempts to address this. Yagci Sokat et al. [217], for example, propose a framework to estimate incomplete information on the status of a network following a disaster. Although promising, a significant amount of time for manual collection and data transformation is still needed. Future studies could consider automating these processes to quickly provide essential data in an appropriate format that can be used by OR planning tools. Additionally, future research might look at new approaches for incorporating real-time data provided by UAVs, as well as social media or other user-generated data. Great use of UAVs in EOM would help to eliminate uncertainties about post-earthquake states by providing information to first responders and relief organization about which structures have been affected, the extent of damage, estimated numbers of people affected, the passability of roads, and so on, thus improving damage assessment, search and rescue, evacuation, relief distribution, and restoration activities. Similarly, social media data may be useful for quickly identifying the needs of victims and improving situational awareness of emergency response and relief efforts. However, given obvious concerns about the accuracy of such data, there is a clear need for formal frameworks to determine the best way of integrating social-media with more conventional data sources [204]. Finally, future research might look to move beyond the traditional paradigm of having a separate information system that subsequently feeds into standalone OR models for carrying out analyses. We believe there is enormous potential for greater integration of OR methods into real- and near real-time earthquake data information systems, either directly through collaboration with government agencies and NGOs or possibly by developing add-on modules for more widely used systems (i.e., OpenStreetMap).

2.4. Conclusions

To the best of our knowledge, this review is the first attempt at investigating the use of OR techniques specifically for EOM. Given that we limited our review to studies dealing with earthquake-oriented problem definitions or those involving the use of earthquake disaster case studies, our review stands apart from past and recent DOM review papers. Throughout, we have taken care to precisely categorize studies based on the disaster stage(s) being dealt with, methodology(ies) applied, and specific planning/operational problem type. We also provide details about the extent of stakeholder involvement and information relating to case studies (i.e., type of infrastructure network examined, if any, and whether real or randomly generated data were used). Basic findings are that most research has focused on a single EOM disaster stage, with preparedness and response problems receiving by far the most attention. More recent work has begun to look at the integration of two or more disaster stages. In terms of modelling and solution methodology, mathematical programming and heuristics are by far the most widely used for most problem types, though there are exceptions. Finally, most studies have little or no stakeholder involvement.

3. A model for optimizing pre-earthquake mitigation measures to improve the efficiency of evacuation operations

This chapter presents a novel two-stage stochastic program for a network strengthening problem, called the *Capacitated Network Strengthening Problem* (CNSP), which integrates mitigating strategies' selection and evacuation allocation planning. The CNSP mainly identifies the mitigation decisions for the roadway components considering their impacts on a post-disaster transport network accessibility between the critical supply and demand points. In this problem, critical supply and demand points refer to emergency response centres (ERCs) (i.e., hospitals) and affected areas (i.e., evacuation zones), respectively. The proposed model determines how to allocate demand (those in need of emergency medical care in the demand points) considering the network accessibility and supplier capacities by minimizing total unmet demand and travel distance. Unmet demand refers to the number of people who need medical care but cannot be transferred from affected areas to ERCs due to road conditions and/or capacity constraints.

The remainder of this chapter is organized as follows. In Section 3.1, we give a brief introduction related to the problem background. Related work in the literature is given in Section 3.2. The problem description and the proposed integrated model formulation are presented in Section 3.3.

3.1. Introduction

Strategic and systematic mitigation actions can significantly reduce vulnerabilities to earthquake damage. Efficient mitigation strategies can minimise the impact of earthquake damage by reinforcing vulnerable components of transportation networks (bridges, tunnels, etc.) before they are likely to be disrupted. In comparison to other types of natural disasters, features specific to earthquake mitigation include human habitation concentrated in seismically active areas, high cost of implementing mitigation measures (too many structures spread over large areas), long recurrence time (decades or more) between sizable quakes and, as a result, the amount of lead time to plan and take pre-emptive action.

Decision-making during mitigation action planning must be conducted analytically and in a systematic manner while also considering the potential impacts of these decisions on the post-earthquake situation. Typically, authorities are faced with the pre-disaster mitigation problem of deciding which links in the network should be structurally strengthened against the risk of earthquakes to ensure that the links are less likely to fail after an earthquake, and thereby improve network accessibility. As resources for pre-disaster operations are limited and strengthening the entire transportation network is not financially viable, it is crucial that mitigation investments are optimised to achieve maximum post-disaster response efficiency.

For vulnerable components of critical infrastructures, the mitigating philosophy should either be that the structure is designed to have no damage/only minor damage which is repairable or that the structure can sustain some controlled structural damage so as to prevent collapse that can block accessibility. Damaged roads directly affect the delivery of time-sensitive response operations after an earthquake (i.e., providing first-aid and rescuing trapped survivals, evacuating the affected population to safe zones and medical centres, and providing emergency relief to victims). For example, despite the abundance of supplies, victims of the 2010 Haiti earthquake could not receive relief items for a long period since the damage caused to the road network severely hampered transportation activities [279]. The subsequent tsunami caused extensive damage to roads and bridges, resulting in the paralysis of land transportation. Moreover, due to road destruction in Aceh After the 2004 Asian Tsunami, the long distance between hospitals and the patient transfer centres, and the time spent handling victims, it took longer than usual (>1 hour) to transfer patients to hospitals [280].

Roadways may become inoperable in the event of an earthquake. Earthquakes can cause cracks and deformations in roads obstructing the transportation. The collapse of roadside buildings, viaducts, bridges, and pedestrian overpasses on a roadway may halt traffic on that road. Transportation functionality may be measured as relative to accessibility, travel time, flow reliability, and traffic interruptions [279]. In practice, Level of Service (LOS) is a measurement (threshold) which is used to qualitatively describe the operating conditions of a roadway based on factors such as speed, travel time, delay, and safety [279]. On the basis of the LOS definition, we use a threshold value that designates operability condition for each link and it is assumed that experts would provide this threshold value by considering seismic capacity, location of the link, and predicted traffic conditions at that moment. We focus on accessibility on the network rather than traffic conditions at the time. In the proposed model, operability depends on mitigation efforts, earthquake characteristics (i.e., peak ground acceleration (PGA) level which measures how intensive the ground shakes in a given geographic area, epicentre location, etc.), and structural features.

Within the context of this problem, several mitigation strategies can be adopted, including strengthening the structure using cross braces and other reinforcements; using damping or structural isolation systems to prevent rigid structural components from banging into each other, which is a leading cause of earthquake damage; incorporating dampers that can absorb some of the forces that result from a seismic activity [281]. These strategies can be implemented with an aim to increase seismic resilience of vulnerable links and subsequently improve the post-earthquake survival status of roads. Seismic risk assessment for transportation infrastructure can guide the estimation processes of how the various components of a road network would be affected by seismic activity depending on hazard characteristics and initial resilience conditions of infrastructures. In practice, a structure's response to seismic activity is estimated by the seismic assessment techniques using specific parameters such as seismic capacity, weaker sections/components and mode of failure [282]. In this study, we call *resilience* the ability to maintain transportation functionality in various levels in a network/roadway component.

Selection of mitigation strategies requires the evaluation of the available options according to performance objectives. These objectives consist of providing a service level known as "operational" guaranteeing the occupation or the immediate use of the structure after a seismic event by reducing post-earthquake damage [279]. In practice, to assess the mitigation efforts, analytical and/or experimental techniques (i.e., quasi-static cyclic load testing techniques, shake table testing and pseudo-dynamic testing) are used to test and validate the system performance of structures against any earthquake occurrence [283]. In practice, the determination and design of applicable retrofit strategies requires preliminary assessment and detailed evaluation processes. For example, the ATC-6-2, developed by Applied Technology Council (ATC) in collaboration with the US Federal Highway Administration (FHWA), is a widely used preliminary assessment method for thoroughly analysing an existing bridge and potential retrofitting options for the most frequent seismic deficiencies. In this ATC 6-2 scoring method, three factors, which are vulnerability (bearing type, superstructure skew angle, minimum support length), seismicity (the geology and geotechnical surroundings of the structure), and structural importance (daily average traffic, the physical size of the structure, the population surrounding the structure, its usage), are considered to define the bridge/viaducts' vulnerability scores [284]. Therefore, in the proposed formulation, we assume that the impacts of mitigation strategies on resilience levels of infrastructures against a particular earthquake scenario can numerically be assessed by the analytical and/or experimental techniques. Post-earthquake survival states of network links are dependent on the current resilience levels with/without mitigation efforts in a particular earthquake scenario. Then, alternative short and reliable routes between critical supply (i.e., ERCs) and demand points (i.e., evacuation zones) are identified to measure network-wide accessibility.

Emergency Response Centres (ERCs) including hospitals and temporary medical centres (could be built in airports and hubs) have an important role in serving casualties and preventing loss of lives after natural disasters. The disaster victims who need medical care should be transported from incident areas to ERCs through the road network after an earthquake. Each ERC has a limited-service capacity depending on the number of patients being currently served and the limited medical staff. Realistically, if the issue is that of evacuating injured people who need immediate medical care, it would undoubtedly be necessary to consider the ERCs. Besides road availability, ERCs have service capacities, and this should be considered in the casualty transportation. In the proposed model, we attempt to allocate people who need medical care by considering service capacity and road conditions.

People, who are injured and in need of medical care, urgently need to be transferred from earthquake zones to medical care facilities. The information about which roads are operational for transportation after an earthquake is known by public authorities. If the injured people transfer takes place without considering the service load of hospitals, the patients will have to be transferred to other centres for emergency treatment. For example, after the 2004 Asian earthquake and tsunami, the nearest hospital was unable to service many injured persons evacuated from the impacted areas, therefore these people had to be relocated to various hospitals that were 40-50 kms away [285].

This research problem aims to optimize investment/protection strategies to enhance the resilience of components in a road network against earthquakes by considering evacuation allocation in post-earthquake conditions. Protection planning strategies are identified for specific road components in a roadway network for the purpose of ensuring short and reliable routes between demand points (incident areas) and ERCs.

We propose a two-stage stochastic programming model that combines mitigation planning to strengthen road network resilience against failure in the aftermath of an earthquake and post-disaster evacuation planning. Therefore, we seek to address decision-making issues while selecting investment strategies to mitigate and enhance the resilience of road networks against earthquakes. The model decides the set of mitigation strategies to be applied by simultaneously considering the operability of links depending on the applied strategies and then the distribution of the affected people to the ERCs which have limited-service capacity.

Let us summarise the proposed problem's contributions as two primary points:

- We present a model of integrated protection and evacuation planning based on realistic assumptions: i) capacitated suppliers, ii) including various mitigation projects per link with varying impacts on resilience, iii) focused on improving resilience levels of links rather than an approach that guarantees the link will be undamaged/operational.

- The approach ensures that only operable roadways are used to transport evacuees to ERCs and offers effective evacuation allocations of affected people. Furthermore, we consider the service capacities of medical facilities to ensure that individuals receive timely and essential medical care.

3.2. Related Work

To reduce the risk of inaccessibility between affected zones and ERCs, the weakest components of transportation infrastructures whose failure would have the greatest impact on accessibility should be identified and protected in the pre-disaster. Some of links in transportation networks should be selected to invest for enhancing their resilience against disasters to provide the best post-disaster response efficiency with respect to the limited protection budget.

We review the studies which address the protection/investment planning to strengthen the links on transportation networks. Pre-disaster protection planning problems aim at selecting the links of the network to retrofit so that the chosen links are less likely to collapse/fail after a disaster, and therefore the network accessibility improves [246].

The first approach is addressing only pre-disaster mitigation decisions (selecting the links to be invested/strengthened) with the objective of maximizing transportation network connectivity/accessibility in post-disaster. Peeta et al. [79] introduce a two-stage stochastic programming model for an investment problem to protect roadway networks affected by earthquakes with the objective of maximizing the post-disaster connectivity and minimizing traversal costs between multiple origin and destination (O–D) nodes. The planning problem only seeks connectivity between various O-D pairs and hence focuses on incapacitated supplier capacities and road conditions.

Another approach is addressing to increase the link capacities by the retrofitting efforts. Link capacities refer to traffic capacity related to travel time. Du and Peeta [286] provide a bilevel stochastic model that, rather than evaluating a single disaster scenario, evaluates many disaster situations. The model includes retrofitting options that not only ensure connectivity but also increase traffic capacity while lowering retrofitting costs. Hence, the model also considers partial investment options for link retrofitting rather than full or no-retrofitting so that the links can be strengthened at different levels. Another consideration for pre-disaster mitigation problems is improving link capacities. Mohaymany et al. [54] propose an optimization framework to identify link strengthening decisions using three post-disaster link survival statuses: normal, deteriorated, and failed. The link capacities are defined by a discrete performance function reflecting the occurrence probability corresponding to these survival stages. Furthermore, they assume that only one level of retrofitting improves the performance of each link. The reliability metrics are generated using a Monte-Carlo simulation method, and the problem is solved using a genetic algorithm.

Some work investigates the trade-off between protection planning and post-disaster stage effort, implying that efficient protection planning attempts to reduce the requirement for additional post-disaster activities effort. There are several variations of transportation network protection problems that consider the impact on the response stage operations. Some researchers apply two-stage models where the first stage decisions indicate the assignments of retrofit strategies and the second stage simultaneously seeks response stage decisions. Lu et al. [80] formulate a mean-risk two-stage stochastic MINLP model, in which the first-stage decisions determine the optimal allocation of retrofit strategies for bridges, whereas the second-stage decisions focus on post-disaster traffic assignment. Contrary to the majority of work in this area, they include multiple damage states and multiple retrofit strategies where binary decision variables are used to indicate whether a specific strategy/investment project is selected for a bridge. The mean-risk two-stage stochastic programming model is formulated as a non-convex MINLP, wherein the travel cost for bridge links is a non-convex nonlinear function of retrofit decisions. To solve the model, they propose a decomposition method based on the Benders Decomposition (BD). They apply a case study based on the benchmark Sioux Falls network.

Another work on the integration of protection planning and post-disaster stage operations is by Yucel et al. [246], who optimise the expected post-disaster network accessibility by pre-disaster structural improvements to selected network components by considering correlated link failures. They represent the dependency model using a Bayesian network and estimate the probability of any network scenario, given the conditional probabilities defined by the Bayesian network. They present a two-stage stochastic program in which a network accessibility measure is optimized with the objective of maximizing accessibility measures. For combining retrofitting planning for both links and buildings, Doyen and Aras [85] address additionally retrofitting decisions for buildings and links in the first stage and tackle relief distribution decisions in the second stage. Similarly, Edrissi et al. [249] integrate three main problems in their formulation: mitigating the impact of the disaster by renovating risky buildings, strengthening vulnerable links in the roadway network, and allocating/locating emergency aid levels.

Some work assumes that the number of fatalities will be reduced by enhancing link capacities or decreasing failure probabilities, which will result in less travel time for providing relief item allocations or allowing rescue teams to save more people. Edrissi et al. [279] focus on investing in retrofitting critical transportation links with the objective of maximizing the retrofitted critical links that have high failure probabilities. They also aim at minimising the death toll correlating immediate relief item allocations. A heuristic algorithm is proposed to solve real size problems and this method only considers the network scenarios in which a specified number of links may fail. Edrisi and Askari [86] propose a protection planning problem which allocates a protection budget for mitigation strategies such as capacity expansion and post-disaster stabilisation for transportation network links. To solve the budget allocation problem, a bi-level optimisation procedure is introduced where the total travel time and the total number of casualties are minimised in the objective function. The model assumes that the number of fatalities reduce by improving capacity and resilience of links owing to the reduction in travel time for the rescue teams leading to the rescue of more people. The first sub-problem level allocates an available budget to pre-disaster capacity expansion while the second decides the level of stabilisation of each link. A Particle Swarm Optimization (PSO) algorithm is proposed to solve the optimisation problem.

A few works in the literature consider the impacts of investment/strengthening actions on recovery operations (e.g., reconstructive or repair) in protection planning problems. Liu et al. [287] present a two-stage stochastic programming model to improve the resilience of roadway bridges with the objective of minimising expected cost and risk. They also assume that the impact of retrofit is quantified as savings in reconstructive and travel delay costs. In another similar work, Miller-Hooks et al. [288] posit that taking mitigation actions can reduce the implementation time of recovery actions. In their model, the first stage includes decisions on pre-disaster protection planning actions that would be taken prior to disaster scenario. The second stage seeks the decisions on the selection of post-disaster recovery actions to be taken in the aftermath of disruption, assuming that the impact of the disaster on arc capacities and traversal times is known. They solve the model with L-shaped method with Monte Carlo sampling.

Protection planning studies address similar problem definitions, however, the assessment approaches of accessibility differ. These differences have an essential role in terms of practicality. For instance, two conditions are used to assess accessibility: the surviving states of links (i.e., intact or collapsed, operational or non-operational) and the impact of protection techniques on roadways (protected/non-protected). One of the critical issues is to estimate whether the links are operable/survivable aftermath of an earthquake. Most studies in literature have adopted a binary approach to define post-disaster link damage states (e.g., undamaged or collapsed, operational or non-operational). Instead of using binary representations (operational/non-operational) for the surviving states of links, some research has used various measures (i.e., link capacity, travel time reliability) to assess the post-disaster conditions in addressing network protection planning problems. Besides, different approaches of assessing impacts of mitigation actions on the link seismic capacity/survival probability/structural conditions have been adopted in the literature. Table 17 summarises the assumptions used in related studies, such as link survivability states, assessment of impacts (how to assess/measure the effects of mitigation efforts on operability/functionality of links), identified mitigation options (single or multiple) for each link, and incapacitated/capacitated suppliers.

Table 17. Details of related studies

Study	Assumptions: Surviving states	*Assessment of mitigation impacts*	*Mitigation choice per link*	*Suppliers*	Solution Method	Case Studies
Mohaymany et al. (2012) [78]	Link capacity mode (normal, degraded, failed)	-	Single	U	GA	The Sioux Fall (N,E): (24,76)
Peeta et al. (2010) [79]	Binary (Functional/Not)	-	Single	U	SAA	Istanbul roadway network (N,E): (25, 30)
Lu et al. (2018) [80]	Link capacity	Expansion on link capacity	Multiple	U	BD	The Sioux Fall (N,E): (24,76)
Edrisi and Askari (2019) [86]	Binary (Stabilized /Not)	Expansion on link capacity	Single	U	PSOA	The Sioux Fall (N,E): (24,76)
Yücel et al. (2018) [246]	Binary (Functional/Not)	-	Single	U	TA	Istanbul roadway network (N,E): (60, 83)
Edrissi et al. (2015) [279]	Transportation time changes	Reduction in failure probability	Continuous [0,1]	U	HA	Tehran city (N,E): Not Specified
Du and Peeta (2014) [286]	Transportation time changes	Reduction in failure probability	Multiple	U	DA	The Sioux Fall (N,E): (24,76)
Liu et al. (2009) [287]	Binary (Damaged, not)	-	Single	U	BD	The Sioux Fall (N,E): (24,76)
Miller-Hooks et al. (2012) [288]	Link capacity	Expansion on link capacity	Multiple	U	L-Shaped DA	Double-Stack Container Network (N,E): (8,46)
Faturechi and Miller-Hooks (2014) [289]	Link capacity	Expansion on link capacity	Multiple	U	DA	Random generated (N,E): (6,16)
Current research	**Resilience level and survivability threshold dependent**	**Increase in resilience levels**	**Multiple**	**C**	**SAA and GRASP**	**Istanbul highway network (N,E): (60, 83) and (N,E): (349,689)**

* U: Uncapacitated, C: Capacitated

*DA: Decomposition Algorithm, BD: Benders Decomposition, GA: Genetic Algorithm, TA: Tabu Algorithm, PSOA: Particle Swarm Optimization Algorithm, GRASP: Greedy, SAA: Sample Average Approximation, (N,E): (Number of nodes, Number of links)

Some studies [80,86,288,289] have assessed mitigation activities as a factor to improve the pre-estimated link capacities in the aftermath of an earthquake relative to travel time. For instance, Edrissi et al. [279] use an LSO measurement to assess post-earthquake status based on travel time. If the effect of damage status on travel time is not considered in a defined problem, there are two assumptions in deciding whether a link is operational or not. First, if the link is strengthened, that link will be operational in post-earthquake. Second, a survival probability or risk level is assigned to a link depending on the features such as the region where they are located and the risky structures they contain, and post-earthquake operability is decided based on these values. For example, Yücel et al. [246] define a survival probability for each link and these survival probabilities can be increased by the investments. If a link is not mitigated, it is assumed that a link fails or not based on a generated vector which contains a random number for each link from a uniform distribution between 0 and 1. If a link's survival probability is less than that random number, the link will be operational and remain connected. If a link is mitigated, then the survival probability is set to 98%.

Operability/Functionality is the most commonly used metric for describing system resilience [290]. In this study, we refer *resilience* to the ability to maintain transportation functionality in various levels in a network/ roadway component, therefore a link's resilience level is one of the factors which affect operability. Post-earthquake damage states of roadway links would change due to the level of seismic actions and periodic strengthening [291]. Additionally, a link would be operational for transportation even if it has a minor/slight damage. In the proposed model, we define resilience levels to estimate survival states of links, and we assume that the protection operations can improve the resilience levels of network links; however, they cannot guarantee that there will be no damage at all. Hence, we assume that estimated post-earthquake survival states of network links depend on the resilience level for a particular earthquake scenario (each link has a unique threshold value to be operational for each scenario). We believe that this approach is more realistic in terms of estimating survival states and assessment of protection strategies.

As it is typical with these studies, authors first analyse the computational performance of their proposed model or solution approach and then apply it to a case study based on real-world data. Here, the aim is to show how the model can capture all crucial network information and how the solution methodology generates robust solutions in acceptable computation times. As seen in Table 17, the majority of authors use the well-known hypothetical Sioux network data which is commonly used in transportation research. Conversely, in some studies, instances in case studies are generated from the transportation networks of historical earthquake areas/risky regions. We conduct two case studies by using a simplified and detailed Istanbul roadway network, the realistic input generation methods and case study implementation are explained in Section 5, in detail.

We review the previous work which address protection/investment planning to strengthen the links on transportation networks. While most of the work focuses on optimising post-disaster accessibility/connectivity by deciding which infrastructure to fortify or upgrade in order to minimise system vulnerability or maximise reliability/resilience, a few of them involve post-earthquake operational decisions in addition to these mitigation decisions. These problems addressed so far in the literature differ from ours in two aspects: i.) we assume that mitigation strategies increase the resilience level by applying mitigation projects and each link has a threshold to be operational, which is determined considering earthquake characteristics and structural conditions; ii.) our goal is to provide access to people who may require medical care in the aftermath of an earthquake in the shortest possible time and also we take service capacity of suppliers into account. This is the first attempt to address the protection and evacuation planning in an integrated manner by maximising the efficiency in post-earthquake evacuation operations (minimising the unmet demand and travel time simultaneously) considering the capacitated ERCs.

3.3. Problem Statement and Model Formulation

This section starts by providing the problem statement with model assumptions and then moves on to the mathematical formulation.

3.3.1. Problem Statement

We propose a two-stage stochastic programming model which combines protection and evacuation planning decisions. An investment problem, which we call the *Capacitated Network Strengthening Problem* (CNSP), is introduced, and formulated as a two-stage stochastic program in which the objective is to minimize both unmet evacuation demand and travel distance.

The model identifies the link strengthening decisions in the first-stage. In the second stage, our model decides on the allocation of evacuation demand to emergency response facilities in the network considering post-earthquake road conditions. The idea is to identify a protection plan not only to swiftly evacuate injured people from the affected areas to an emergency response facility, but also to ensure that they promptly receive health care. Therefore, we take into account facility capacities in the problem context. The proposed model has two main objectives including minimizing unmet evacuation demand (the primary objective) and evacuation time (the secondary objective).

The main aim of our study is not to solve a detailed evacuation planning problem but to investigate the trade-off between protection planning and response activities considering the effect of mitigation decisions on post-disaster actions. This model examines this problem at a strategic level and considers an integrated approach which combines pre-earthquake protection planning and a simplified version of post-earthquake evacuation plan.

The road network is represented by an undirected connected graph $G = (N, E)$ where N is the set of nodes including possible affected regions denoted by I and current medical facilities (suppliers) denoted by J, N=$I \cup J$ and E is the set of links, specifically links connecting demand and supplier nodes. The highly populated residential areas, emergency response facilities and junction points are represented by nodes on the roadway system. We assume that all possible routes are known in advance and the set of routes between demand node $i \in I$ and supplier node $j \in J$ is denoted by R_{ij}. Travel distances are defined by l_r for $r \in R$ and l_{max}^{i} is the longest length of the routes which connects demand node $i \in I$ and the supplier nodes. Each demand (affected area) node $i \in I$ has a unique evacuation demand, denoted by d_i. This input parameter is estimated by considering the population affected in an anticipated disaster scenario.

The CNSP specifically concentrates on enhancing the resilience of vulnerable road components (bridge/viaducts) against large-scale earthquakes by considering the connectivity/accessibility of a road network. In this study, we call resilience the ability of a link to maintain transportation accessibility. For each link $e \in E$, we denote by ρ_e its initial resilience level, i.e. its resilience level without the implementation of any mitigation project.

Mitigation strategies are implemented to upgrade resilience levels of vulnerable links and subsequently improve the post-earthquake survival status of roads. We define a set of mitigation projects denoted by P. Each mitigation project $p \in P$ has an associated cost c_p. The total cost of the selected protection projects cannot exceed a limited protection budget B.

We assume that the impact of the mitigation projects on the resilience level of a link can numerically be assessed and that there are different mitigating options (projects) that can be implemented on one link, with different impacts on the link resilience levels. We also assume that each mitigation project only affects one link and that only one mitigation project can be implemented on each link. This is a realistic assumption when considering mitigation measures for earthquakes, such as the retrofit of infrastructure components. Different retrofit projects with different impacts can be considered to strengthen a component, but only one of them can be implemented. We define a parameter δ_{pe} that represents the amount of improvement in resilience level of a link $e \epsilon E$ when a mitigation project $p \in P$ is implemented. After the mitigation decisions, the resilience levels should be updated by adding the corresponding improvement by the chosen project. The resulting resilience levels are referred to as the ultimate resilience levels in the formulation. In summary, the ultimate resilience level of a link depends on its initial resilience level and on the selection of the mitigation project affecting that link.

A threshold value that designates operability condition for each link is used in the formulation, and it is assumed that experts would estimate this threshold value by considering seismic capacity and location of the link. A link may be mitigated to varied degrees but may still be inoperable after the earthquake due to the risk it carries. The operability status of each link, which is called survival status of a link in this model, depends on its ultimate resilience level and the survivability threshold. Each link has a unique threshold value. If a link's ultimate resilience level is greater than or equal to the survivability threshold for that link, that link will be operational, i.e., available for transportation. We define network scenarios denoted by Ω , indexed by s. In each scenario, survivability threshold value for each link is denoted by $\beta_e(s)$ for link $e \in E$ in scenario s. All second-stage decision variables are scenario-dependent.

The operability status of each link, which represent the link availability for transportation, is captured by a binary variable, which takes value 1 if the link is operational and 0 otherwise. Uncertainties like unknown survivability conditions are captured through the use of a finite number of network scenarios. In this model, we include discrete scenarios which refer to uncertain survival threshold sets for links. This approach defines a minimum resilience level for each link to be operational. Let the random vector ξ describe the uncertain survivability threshold values. Each realization ξ(s) define network operability scenarios with $prob(\xi)$ which is the probability distribution of uncertain parameters.

As mentioned above, this model investigates the defined problem at a strategic level and uses a simplified post-earthquake evacuation planning problem to inform protection planning decisions. With regard to evacuation decisions, the model determines how to allocate demand (those in need of emergency medical care) to emergency response facilities considering their capacities and travel distance. However, it does not incorporate other operational aspects related to the availability of transfer vehicles and complex routing decisions. Regarding demand allocations from same demand points to different emergency response facilities, split delivery of evacuees is possible.

3.3.2. Model Formulation

Before presenting the model formulation, we summarize the notation for sets, parameters, and decision variables:

<u>Sets</u>

I = *Set of demand nodes, indexed by i*

J = *Set of supplier nodes, indexed by j*

P = *Set of mitigation projects indexed by p, p'*

E = *Set of links, indexed by e*

R_{ij} = *Set of the routes connecting demand node i and supplier node j, indexed by r*

E_r = *Set of links in route r*

Ω = *Set of scenarios, indexed by s*

<u>Parameters</u>

$B = Budget\ for\ protection\ planning$

$c_p = Cost\ of\ project\ p$

$$\tau_{pe} = \begin{cases} 1, if\ project\ p\ \in P\ affects\ \ link\ \ e \\ 0, otherwise \end{cases}$$

$\rho_e = Initial\ resilience\ level\ of\ link\ e$

$\delta_{pe} = Improvement\ in\ resilience\ level\ of\ link\ e\ if\ project\ \ p$

$is\ implemented$

$\beta_e(s) = Survivability\ threshold\ for\ link\ e\ in\ scenario\ s$

$q_j = Service\ capacity\ of\ facility\ j$

$d_i = Demand\ at\ node\ i$

$l_r = Travel\ distance\ of\ route\ \ r$

$l^i_{max} = \ Maximum\ travel\ distance\ of\ route\ which\ connects\ demand\ node\ i$

$M = \ Big\ value$

<u>First-stage decision variables</u>

$$y_p = \begin{cases} 1, if\ mitigation\ project\ p\ is\ implemented \\ 0, otherwise \end{cases}$$

<u>Second-stage decision variables</u>

$$x_{ijr}(s) = \begin{cases} 1, if\ people\ in\ demand\ node\ \ i\ are\ assigned\ to\ facility \\ \qquad j\ \ using\ route\ \ r\ in\ scenario\ s \\ 0, otherwise \end{cases}$$

$z_{ijr}(s) = Number\ of\ people\ in\ demand\ node\ i\ allocated\ to\ facility\ j\ using\ route\ r\ in$

$scenario\ s$

$v_e(s) = Ultimate\ resilience\ level\ of\ link\ e\ in\ scenario\ s$

$$o_e(s) = \begin{cases} 1, if\ link\ e\ is\ operational\ in\ scenario\ s \\ 0, otherwise \end{cases}$$

$u_i(s) = Unmet\ demand\ at\ node\ i\ in\ scenario\ s$

We formulate the CNSP, as a two-stage stochastic program, in which the objective is to minimize both unmet demand and travel distance over all possible scenarios. The two-stage stochastic programming (TS-SP) model provides the best decision about the selected protection strategies and the allocations of injured people to emergency response facilities.

The objective function of the first stage is to minimize the expected value of the objective functions defined in the second stage, $E_{prob}[Q(y, \xi(\mathrm{s}))]$. Note that we assume that the probability distribution is known, and the expectation of the second-stage cost function is taken with respect to this probability distribution. For simplicity of notation, we use a weight notation for both objective functions. Weights are chosen in a way which guarantees that minimizing total unmet demand is the primary objective and minimizing total travel distance for a given unmet demand value is the secondary objective. Further discussion about this is carried out in the next chapter.

With these notations, TS-SP model for the CNSP is as follows:

TS-SP First stage: $obj_{tssp} = \min E_{prob}[Q(y, \xi(\mathrm{s}))]$ (3.1)

$s.t.$

$$\sum_{p \in P} c_p y_p \leq B \quad (3.2)$$

$$\sum_{p \in P} \tau_{pe} y_p \leq 1 \qquad \forall e \epsilon E \quad (3.3)$$

$$y_p \in \{0,1\} \qquad \forall p \epsilon P \quad (3.4)$$

TS-SP Second stage: (3.5)

$$Q(y, \xi(\mathrm{s})) = \min(weight_1 \textstyle\sum_{i \in I} u_i(s) + weight_2 \sum_{i \in I} \sum_{j \in J} \sum_{r \in R_{ij}} z_{ijr}(s) l_r)$$

$$x_{ijr}(s) \leq o_e(s) \qquad \forall i \ \epsilon\ I, \forall j \ \epsilon\ J, \forall r \ \epsilon\ R_{ij}, \forall e \ \epsilon\ E_r \quad (3.6)$$

$$v_e(s) = \sum_{p \in P} \delta_{pe}(s) y_p + \rho_e \qquad \forall e \ \epsilon\ E \quad (3.7)$$

$$v_e(s) - \beta_e(s) - M o_e(s) \leq 0 \qquad \forall e \ \epsilon\ E \quad (3.8)$$

$$v_e(s) - \beta_e(s) + M(1 - o_e(s)) \geq 0 \qquad \forall e \ \epsilon\ E \quad (3.9)$$

$$z_{ijr}(s) \leq d_i x_{ijr}(s) \qquad \forall i \in I, \forall j \in J, \forall r \in R_{ij} \qquad (3.10)$$

$$\sum_{i \in I} \sum_{r \in R_{ij}} z_{ijr}(s)\, u_i(s) = d_i \qquad \forall i \in I \qquad (3.11)$$

$$\sum_{i \in I} \sum_{r \in R_{ij}} z_{ijr}(s) \leq q_j \qquad \forall j \in J \qquad (3.12)$$

$$x_{ijr}(s) \in \{0,1\} \qquad \forall i \epsilon I, \forall j \epsilon J, \forall r \epsilon R_{ij} \qquad (3.13)$$

$$o_e(s) \in \{0,1\} \qquad \forall e \epsilon E \qquad (3.14)$$

$$z_{ijr}(s) \in \mathbb{Z}^+ \qquad \forall i \epsilon I, \forall j \epsilon J, \forall r \epsilon R_{ij} \qquad (3.15)$$

$$v_e(s) \in \mathbb{Z}^+ \qquad \forall e \epsilon E \qquad (3.16)$$

$$u_i(s) \in \mathbb{Z}^+ \qquad \forall i \epsilon I \qquad (3.17)$$

The first-stage objective function obj_{tssp} is the expected value of second stage objective function. Constraint (3.2) ensures that the budget limit B is not exceeded, and Constraints (3.3) force the model to choose at most one project for each link. Constraints (3.4) is binary restrictions on the protection strategy selection in the first stage of TS-SP model. $Q(y, \xi(s))$ is the objective function of the second stage, it is aimed to maximize the efficiency of evacuation operations in the immediate post-disaster response stage by implementing mitigation projects. Under a specific budget, while our primary objective is minimizing total unmet demand, the secondary objective is minimizing travel distance in evacuation operations. Multi-objective solution approaches are investigated in Section 4.1.

Constraints (3.6) satisfy the condition which is route selection should be done if that route connects associated demand node and supplier node. It also specifies that if one of the links that in route r is not operational in scenario w, this route cannot be used for evacuation so the $x_{ijr}(s)$ variable is forced to be zero. Constraints (3.7) determine the ultimate resilience levels for links according to the chosen projects. We assume that if a link's resilience is lower than the threshold value denoted by $\beta_e(s)$, this means that the link will not be operational for transportation post-earthquakes and the survival status variable denoted by $o_e(s)$ will be 0. This condition is enforced by Constraints (3.8) - (3.9). Constraints (3.10) ensure that if a demand area is not assigned to a supplier node, the number of evacuated people from that demand node to that supplier node should be 0. Constraints (3.11) determine unmet evacuation demand based on the total number of evacuated people and estimated demand for each demand node. Constraints (3.12) shows that the service capacities of facilities limit the evacuation operations. Constraints (3.13), and (3.14) are binary restrictions on connectivity, and accessibility variables. Constraint (3.15), (3.16), and (3.17) ensure the decision variables take on non-negative integer values.

The TS-SP model is hard to solve as it is difficult to evaluate the expected cost of second stage for a given y', i.e., $E_{prob}[Q(y', \xi(s))]$. For this reason, the TS-SP model can be explicitly reformulated by combining two stages together as a scenario-based (SB) model (the deterministic equivalent), which is referred as extensive form. Differently, SB model has the scenario index denoted by s of the set of scenario S for scenario-dependent parameters and decision variables and we keep the weight coefficients here. However, multi-objective solution methodologies are investigated in the following chapter. Let β_e^s denote the survival threshold value for each link e for each scenario s. We assume that the probability that a scenario s occurs is denoted by $prob_s$.

SB model formulation is as follows:

$$min \sum_{s \in S} weight_1 \sum_{i \in I} u_i^s + weight_2 \sum_{i \in I} \sum_{j \in J} \sum_{r \in R_{ij}} z_{ijr}^s l_r \tag{3.18}$$

$st.$

$$\sum_{p \in P} c_p y_p \leq B \tag{3.19}$$

$$\sum_{p \in P} \tau_{pe} y_p \leq 1 \qquad \forall e \in E \tag{3.20}$$

$$x_{ijr}^s \leq o_e^s \qquad \forall i \epsilon I, \forall j \epsilon J, \forall r \epsilon R_{ij}, \forall e \epsilon E_r, \forall s \epsilon S \tag{3.21}$$

$$v_e^s = \sum_{p \in P} \delta_{pe}^s y_p + \rho_e \qquad \forall e \epsilon E, \forall s \epsilon S \tag{3.22}$$

$$v_e^s - \beta_e^s - M o_e^s \leq 0 \qquad \forall e \epsilon E, \forall s \epsilon S \qquad (3.23)$$

$$v_e^s - \beta_e^s + M(1 - o_e^s) \geq 0 \qquad \forall e \epsilon E, \forall s \epsilon S \qquad (3.24)$$

$$z_{ijr}^s \leq d_i x_{ijr}^s \qquad \forall i \epsilon I, \forall j \epsilon J, \forall r \epsilon R_{ij}, \forall s \epsilon S \qquad (3.25)$$

$$\sum_{j \in J} \sum_{r \in R_{ij}} z_{ijr}^s + u_i^s = d_i \qquad \forall i \epsilon I, \forall s \epsilon S \qquad (3.26)$$

$$\sum_{i \in I} \sum_{r \in R_{ij}} z_{ijr}^s \leq q_j \qquad \forall j \epsilon J, \forall s \epsilon S \qquad (3.27)$$

$$y_p \in \{0,1\} \qquad \forall p \epsilon P \qquad (3.28)$$

$$x_{ijr}^s \in \{0,1\} \qquad \forall i \epsilon I, \forall j \epsilon J, \forall r \epsilon R_{ij}, \forall s \epsilon S \qquad (3.29)$$

$$o_e^s \in \{0,1\} \qquad \forall e \epsilon E, \forall s \epsilon S \qquad (3.30)$$

$$z_{ijr}^s \in \mathbb{Z}^+ \qquad \forall i \epsilon I, \forall j \epsilon J, \forall r \epsilon R_{ij}, \forall s \epsilon S \qquad (3.31)$$

$$v_e^s \in \mathbb{Z}^+ \qquad \forall e \epsilon E, \forall s \epsilon S \qquad (3.32)$$

$$u_i^s \in \mathbb{Z}^+ \qquad \forall i \epsilon I, \forall s \epsilon S \qquad (3.33)$$

To fully represent all combinations of survivability thresholds, an exponential number of scenarios are required depending on how many scenarios exist for β_e^s for each link. This condition does not allow directly solving the model with a standard mixed integer programming (MIP) solver, such as CPLEX OPL, for even a small network with all possible scenarios. Hence, it is necessary to develop more efficient algorithms to solve the CNSP exactly or approximately. In the next chapter, the multi-objective approaches will be explored.

3.4. Conclusion

This chapter has introduced a novel two-stage stochastic program TS-SP for the CNSP which integrates selecting mitigation strategies and evacuation allocation planning. To the best of my knowledge, this is the first integrated program which consider the capacitated suppliers. Since the second stage of TS-SP has two objectives such as minimizing unmet demand and travel time, it first requires to be chosen the multi-objective solution approach. To do that, the TS-SP model has been explicitly reformulated by combining two stages together in a scenario-based (SB) model (the deterministic equivalent), which is referred as extensive form.

4. Solution Approach

In this chapter, we describe the different methodologies devised to solve the CNSP model. We first discuss two multi-objective approaches to address the model's multi-objective structure. Sample Average Approximation (SAA), which is frequently employed to solve large scale stochastic optimization problems, is then proposed to solve the SB model described in Chapter 3. Even though SAA reduces the problem size considerably compared to the original problem defined in Chapter 3, it still must solve a two-stage stochastic mixed integer problem which is computationally challenging for large-instances. To conduct analysis on larger networks, finally, we also propose a heuristic algorithm based on the Greedy Randomized Adaptive Search Procedure known as GRASP.

4.1. Multi-objective Solution Approaches

Multi-objective optimization is an important aspect of optimization activities because practically all real-world optimization issues are best suited to being described using multiple conflicting objectives [291]. The multi-objective optimization requires the simultaneous optimization of more than one objective functions [293]. Since the proposed SB model has two main objectives (minimizing the total unmet demand and travel distance), it can be categorised as a multi-objective optimization problem. In this section, the multi objective solution methods are investigated and most appropriate one would be chosen to solve the proposed model.

Multi-objective problems (MOP) are more complex to solve than single-optimization problems (SOP) because there is no single solution; rather, there is a set of acceptable trade-off optimal solutions. This set is known as Pareto front. The concept of domination is used in most multi-objective optimization solution methods. In these methods, two solutions are compared based on whether one dominates the other solution or not. The pareto dominance solution are usually achieved when one objective function cannot increase without reducing the other objective function [294].

Solving MOPs has traditionally consisted of converting all objectives into a single objective function such as the weighted sum method, lexicographic method and ε-constraint method. In the case of the weighted-sum approach, the idea is to assign a weight (depicts the importance/priority of the objective) to each normalized objective function so that the problem is converted to a single objective problem with a scalar objective function [294]. The single objective is then solved subject to the constraints of all the objective functions. Lexicographic method is an effective way for prioritization of various objectives and this method guarantees that improving the objectives with lower priority does not deteriorate the performance of higher priority objectives [296]. In the ε-constraint method, one of the objective functions is optimized using the other objective functions as constraints, incorporating them in the constraint part of the model.

The weighted-sum method has been successfully used to solve a variety of bi-objective models in different application areas, such as traffic assignment [295,296], energy management [297], and hazardous material transportation [298]. On the other hand, the lexicographic method also has been applied to solve a wide range of MOP in a variety of application domains, including road pricing [299], energy [300] and scheduling [301]. Finally, multi-objective optimization problems have been solved by using the ε-constraint method in different research areas such as location-routing [302,303], energy efficiency [304], and job scheduling [305].

These methods, which are utilized as alternatives for one another, have some advantages and disadvantages when compared each other. Using the weighted-sum approach necessitates determining the relative value of the weight coefficients, which generally reflects the relative priority of the objectives. The solution is dependent on the chosen weighting coefficients. However, it is difficult to quantitatively measure the relative importance among the objectives. Therefore, the weighted-sum approach is simple to apply since it has a single objective function; however, it is not guaranteed to produce the complete Pareto front of non-dominated solutions. Similarly, in ε -constraint method, the ε vector must be chosen carefully so that it is within the minimum or maximum values of the individual objective function. With the lexicographic method, the solution is, theoretically, always Pareto optimal because each objective is treated independently [306]. On the other hand, applying this method is computationally expensive since it requires the solution of many single-objective problems to obtain just one solution point.

Although the lexicographic method always provides the pareto optimal solution, the weighted-sum method is both easy to implement and computationally better than the lexicographic method. As mentioned above, the issue is setting the relative values for the weight coefficients and the weights are defined for each objective function to depict the importance of different objectives. Since one unit decrease in u_i^s corresponds to one unit increase z_{ijr}^s at most and $l_r \leq l_{max}^i$ in every condition, while the weight value for the first term u_i^s is 1, the weight value $\frac{1}{l_{max}^i}$ for the second term in the objective function is chosen, which makes $\frac{l_r}{l_{max}^i}$ less than 1 as applied in [307]. This weight value ensures that the minimization of the total unmet demand is the primary objective and travel distance is the secondary objective. Then, the lexicographic method will be used to validate the solutions obtained by the implementations of the weighted-sum method.

In the proposed model regarding the weighted-sum approach, all the objective functions are summed to a single-objective function, as shown in (4.1). We have modified the objective function by adding the secondary objective as follows:

$$min \sum_{s}^{|S|} prob_s \sum_{i}^{|I|} \sum_{j}^{|J|} \sum_{r}^{|R|} (u_i^s + z_{ijr}^s \frac{l_r}{l_{max}^i}) \tag{4.1}$$

The modified model to apply the weighted-sum approach is as follows:

(4.1)

$st.$

(3.19-3.33);

The lexicographic method is used to optimise objectives sequentially by firstly minimising the total unmet demand, and then minimizing total travel distance which is affected by the obtained value of the primary objective. We solve first the model as a single-objective problem with the primary objective which is $min \sum_{s}^{|S|} \sum_{i}^{|I|} u_i^s$. Then, the model is solved with the secondary objective which is $\sum_{s}^{|S|} \sum_{i}^{|I|} \sum_{j}^{|J|} \sum_{r}^{|R|} z_{ijr}^s l_r$ with an added constraint defined as (4.2) in which $\sum_{s}^{|S|} \sum_{i}^{|I|} u{*}_i^s$ is the optimal solution of the first objective function.

$$\sum_{s}^{|S|}\sum_{i}^{|I|} u_i^s \leq \sum_{s}^{|S|}\sum_{i}^{|I|} u^{*s}_i \tag{4.2}$$

In summary, the models are defined to apply the lexicographic method in the following:

First model	Second model
$\min \sum_{s}^{\lvert S\rvert}\sum_{i}^{\lvert I\rvert} prob_s u_i^s$	$\min \sum_{s}^{\lvert S\rvert}\sum_{i}^{\lvert I\rvert}\sum_{j}^{\lvert J\rvert}\sum_{r}^{\lvert R\rvert} prob_s z_{ijr}^s l_r$
$st.$	$st.$
(3.3-3.17);	(3.3-3.17), (4.2);

4.2. Sample Average Approximation (SAA)

The basic idea behind Sample Average Approximation (SAA) is the expected objective value of the stochastic problem can be approximated by the corresponding value of the sampling problem [308]. In this study, we use the well-known SAA method, which is a Monte Carlo simulation-based method to solve stochastic discrete optimization problems. This method has been applied to solve various two-stage stochastic problems such as facility location problem by [308], container repositioning problem in maritime transportation by [309] and facility location and network restoration by [252].

In the SAA method, the expected objective function of a stochastic problem is approximated by a sample average using a random sample of S scenarios. Kleywegt et al. [310] propose a SAA method to solve stochastic programming models with integer decision variables. According to the convergence analysis carried out by [310], solving a SAA problem with a modest sample size yields a reasonable and good approximate solution for the true problem. The true problem, in this case, is the scenario-based model that includes all possible scenarios.

In this study, we follow the SAA scheme presented in [309]. The SAA approach approximates the TS-SP model by the following SAA model. The SAA procedure is described as follows:

Step 1. Generate N independent samples each consisting of S scenarios. Solve the corresponding problem (SAA problem) for each sample:

The SAA problem:

$$\min \frac{1}{S} \sum_{s=1}^{S} Q(y,\ \xi(s))$$

s.t.

(3.2)-(3.4); and (3.6)-(3.17);

Let $obj_n, n = 1, \ldots\ldots, N$, be the corresponding optimal objective value.

Step 2. Compute $\overline{obj_S} = \frac{1}{N}\sum_{n=1}^{N} obj_S^n$. It is well known that the expected value of $\overline{obj_S}$ is less than or equal to the optimal value obj^* of the true problem. Therefore, $\overline{obj_S}$ is a lower bound for the optimal value of the true problem.

Step 3. Choose one of the *N* solutions obtained in Step 1 which is a feasible solution y^n. Generate another independent sample of scenarios S' where $|S'|$ is much bigger than $|S|$. This step involves solution of S' independent second-stage problem. Since y^n is a feasible solution to the true problem, we have $\widehat{obj_{S'}}(y^n) \geq obj^*$. Thus, $\widehat{obj_{S'}}(y^n)$ is an estimate of an upper bound on obj^*. Find an upper bound on the optimal value of the true problem by evaluating the following function:

$$\widehat{obj_{S'}}(y^n) = \frac{1}{S'} \sum_{s=1}^{S'} Q(y^n,\ \xi(s))$$

Step 4. Compute $\widehat{obj_{S'}}(y^n) - \overline{obj_S}$ to estimate the optimality gap of the solution y^n

If the estimated optimality gap is too large, we increase the sample size |*S*| and we repeat steps 1–4. Whenever the estimated gap are sufficiently small or enough iterations are made, we stop the algorithm and report the solution. Using this technique, a near-optimal solution can be obtained by solving the SAA problem with modest number of scenarios.

4.3. Heuristic Algorithm

In this section, we propose a Greedy Randomized Adaptive Search Procedure (GRASP) to be able to solve larger instances of the problem. We also develop a procedure to design evacuation allocations considering total unmet demand and travel distance. In the following subsections, we introduce the details of the proposed methods.

Feo and Resende [311] introduced the GRASP to address the limitations of solely greedy constructive algorithms. It is an iterative technique that builds up a solution at each step by randomly selecting elements from a dynamically built list. GRASP consists of two main procedures, namely constructive and local search. At each iteration of the GRASP, a feasible solution is constructed by applying the constructive phase, followed by the local search procedure in order to search for a locally optimal solution. The pseudo-code and flowchart for the proposed GRASP are provided in Figure 10 and 11 and explained in the following subsections.

GRASP pseudo-code

$bestSolution \leftarrow \emptyset$; $bestObj = \infty$; $iter = 1$
while $iter < MaxIter$ **do**
// Constructive Phase
$Solution_{iter} \leftarrow \emptyset$; $obj_{iter} = \infty$;
$CalculateBenefit(Solution_{iter})$
  while there are candidate projects **do**
  $buildRCL(Solution_{iter})$
  Select randomly a project p' from RCL;
  Add p' to $Solution_{iter}$
  $UpdateOperability(Solution_{iter})$
  $CalculateBenefit(Solution_{iter})$
  end while
$UpdateShortestRoutes(Solution_{iter})$
$CreateAcessibleSupplierList(Solution_{iter})$
$FindEvacuationAllocations(Solution_{iter})$
Save obj_{iter} and $Allocations(Solution_{iter})$ for $Solution_{iter}$
$FindCriticalLinks(Solution_{iter}, CL)$
// Local Phase
$LocalSearch(Solution_{iter}, bestSolution, bestObj, bestAllocations)$
$iter$ ++
end while
return $bestSolution, bestObj, bestAllocations$
end GRASP

Figure 10. Pseudo-code of the proposed GRASP algorithm

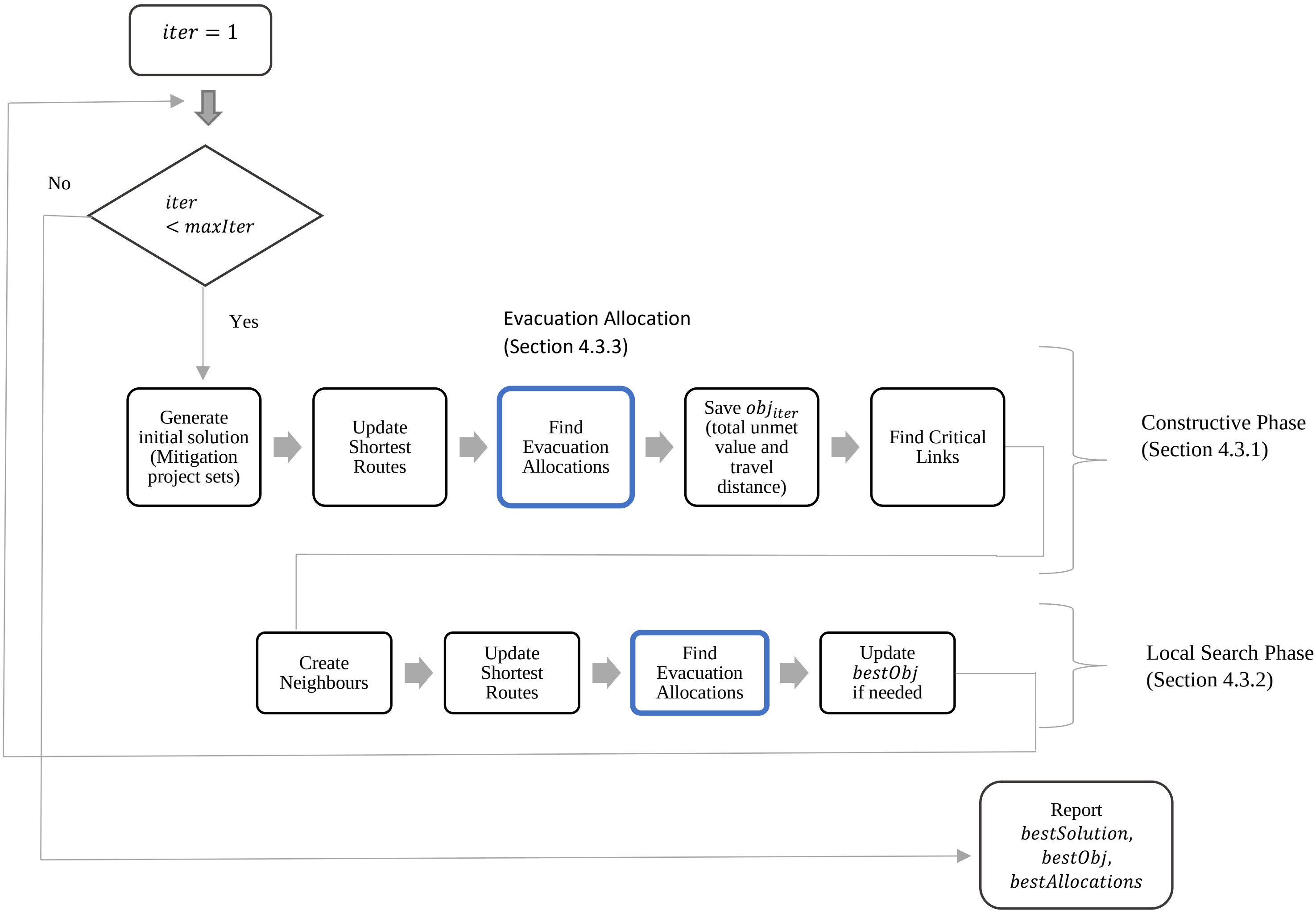

Figure 11. Flowchart for the proposed GRASP

4.3.1. Constructive Phase

For the proposed problem, the constructing phase generates initial solutions. The quality of feasible solutions is defined with respect to the total unmet demand value and travel distance of the corresponding evacuation allocation. In the constructive phase, a set of best candidates (mitigation projects) considering the estimated contribution to the objective function (unmet demand and also travel distance) are stored in a dynamic list. In each iteration, the list is updated according to the benefits for the current network. Once an initial solution (a set of mitigation projects) is generated, evacuation allocations for the associated solution are found by a procedure to be explained in Section 4.3.3. Restricted Candidate List (RCL) is a dynamically built list storing a set of good candidates. RCL is made up of the beneficial mitigation projects to the evacuation planning. The following notations help to explain the constructive phase:

- $benefit_p$: benefit ratio for each $p \in RCL$, which measures the contribution on accessibility between demand-supplier (d-s) pairs if project p is added to the current solution
- $ratio_{is}$: allocation chance measure for each demand node $i \in I$ in scenario $s \in S$ considering the total capacity in accessible suppliers comparatively to total capacity in all suppliers
- c_{min}, c_{max} : minimum and maximum $benefit_p$ $over\ all\ p \in RCL$
- RCL is associated with a threshold parameter $\alpha \in [0,1]$ and formed by all projects which can be feasibly inserted into the partial solution under constructive and whose benefit is superior to the threshold value. Namely, project p' is included in the RCL if $benefit_{p'} \in [c_{max} - \alpha(c_{max} - c_{min}), c_{max}]$.
- $iter$ is the iteration index
- $asup_{is}^{iter}$: list of accessible suppliers to demand node $i \in I$ in scenario $s \in S$ at iteration $iter$
- $acap_{js}^{iter}$: available capacity at supplier $j \in J$ in scenario $s \in S$ at iteration $iter$
- u_{is}^{iter} : unmet demand in demand node $i \in I$ in scenario $s \in S$ at iteration $iter$
- c_p : cost of project $p \in RCL$
- $MaxIter$: The maximum number of iterations
- $Solution_{iter}$, $Allocations(Solution_{iter})$, obj_{iter} : the mitigation project selection, corresponding allocations, and objective values (total unmet demand and travel distance) obtained at iteration $iter$
- CL : stores the critical links for the local search

Some expedients that have been adopted to improve the GRASP algorithm in terms of efficiency are explained in the following. For estimation of the quality of each candidate in the constructive phase, we devise a method to calculate a benefit value for each candidate project considering the impact on accessibility on the current network. This benefit value measures the possible contribution to improve evacuation allocations. For instance, if a project provides access between an isolated demand node and available supplier node, that would be a considerable contribution to the current situation. The GRASP algorithm implementation is explained by the following crucial subroutines:

$buildRCL(Solution_{iter})$ creates a list called Restricted Candidate List (RCL) which stores the set of these good candidates according to the $benefit_p$ value The probabilistic component of the constructive phase is in the random choice of one of the best candidates from this list; therefore, not necessarily the best candidate will be added.

$CalculateBenefit(Solution_{iter})$ updates the $benefit_p$ value obtained by adding project p to $Solution_{iter}$. The constructive of RCL is guided by the benefit ratio $benefit_p$,$p \in RCL$, which measures the contribution on accessibility between demand-supplier (*i-j*) pairs if project p is added to $Solution_{iter}$. This is a sort of alternative way to have an idea how evacuation allocations would be affected, and this way is undoubtedly a less computationally expensive than finding evacuation allocations in every step.

To evaluate projects based on their contribution to the accessibility between *i-j* pairs, we define a ratio which measures the allocation chance considering the total capacity in accessible suppliers comparatively to the total capacity in all suppliers, denoted by $ratio_{is}$ for each demand node i and each scenario $s \in S$ as computed by Equation 4.3 below. If a demand node has no access to any supplier, which means that demand node is fully isolated, $ratio_{is}$ would be equal to 0. On the other hand, if a demand node i has access to at least one supplier, then $ratio_{is} > 0$. As the number of accessible suppliers increases, so does the chance of allocating the needed people. Especially in each iteration of project evaluation, these ratio values would be informative to calculate the benefits on evacuation allocations. The ratio values are separately calculated for each scenario $s \in S$.

$$ratio_{is} = \frac{\sum_{j \in asup_{is}}^{J} q_j}{\sum_{j \in J}^{J} q_j} \qquad \forall s \in S, \forall i \in I \tag{4.3}$$

The routes connect the *i-j* pairs. A mitigation project is applied to increase a link' resilience level, and that link would be operational depending on the scenario so a route or routes may turn into operational once the selected project is applied. Therefore, new accessible *i-j* routes or shorter routes between already connected *i-j* pairs would be added to the existing network. Three different cases may occur:

(1) The newly added route/s allows the connection between demand *i* and supplier *j* (previously not connected), and demand node i was not accessible from any other supplier in scenario $s \in S$ ($ratio_{is} = 0$),

(2) The newly added route/s allows the connection between demand *i* and supplier *j* (previously not connected), and demand node i was accessible from at least one other supplier in scenario $s \in S$ ($ratio_{is} > 0$),

(3) The newly added route is a shorter route connecting demand *i* and supplier *j* (already connected) in scenario $s \in S$.

Namely, let U_{ps}^{1} be the number of newly connected *i-j* pairs where demand *i* did not have access to any other supplier (case 1), U_{ps}^{2} be the number of newly connected *i-j* pairs where demand *i* had already access to at least one other supplier (case 2), U_{ps}^{3} be the number of new shortest routes between already connected *i-j* pairs (case 3) when project $p \in P$ is chosen. Undoubtedly, the biggest impact on network accessibility would be generated by the first case and then respectively be decreased. We give a weight σ to each impact with $\sigma_1 < \sigma_2 < \sigma_3$. If a project does not affect the network operability, adding that project to the current solution would not have any impact on evacuation allocations. At each iteration, we calculate $benefit_p$ using Equation 4.4.

$$benefit_p = \sum_{s=1}^{|S|} prob_s(\sigma_1 U_{ps}^{1} + \sigma_2 U_{ps}^{2} + \sigma_3 U_{ps}^{3}) \tag{4.4}$$

$UpdateOperability(Solution_{iter})$ checks the mitigated links to see if their operability status has changed considering the new resilience levels once the projects in $Solution_{iter}$ are implemented. Accordingly, the operability statuses of the routes with these links are updated.

$UpdateShortestRoutes(Solution_{iter})$ finds the accessible (which means all links on routes are operational) shortest routes for the all *i-j* pairs subject to the operability status of the network links. The possible routes are generated by the *k*-shortest path and *p*-dispersion algorithm (explained in Section 5.2). The routes connecting *i-j* pairs are given to the algorithm as an input so if there is more than one accessible route for a *i-j* pair, it is ensured that the shortest one should be preferred.

$CreateAcessibleSupplierList(Solution_{iter})$ keeps a list consisting of the accessible suppliers for each demand node. The lists should be updated once the shortest routes for all *i-j* pairs are updated by $UpdateShortestRoutes(Solution_{iter})$.

$UpdateRCL(Solution_{iter})$ is used to keep track of the mitigation projects that can be added to $Solution_{iter}$ without violating the budget constraints. This set is updated at each stage so that it contains the most beneficial links for evacuation allocations.

$FindEvacuationAllocations(Solution_{iter})$ is used to find the best allocations regarding the accessible supplier lists for each demand node and available capacities in these suppliers. The best allocations which give the least unmet demand with the minimum travel distance are saved as $Allocations(Solution_{iter})$. The procedure is explained in Section 4.3.3.

$FindCriticalLinks(Solution_{iter}, CL)$ checks the routes connecting unsatisfied demand nodes and available supplier nodes, identifies non-operational links on these routes for $Solution_{iter}$. These non-operational links are referred to as critical links, and the projects which mitigate the critical links are identified and saved in a list referred to critical link list CL for the local search. The idea is to try and reduce the solution space which is explored during the local search; namely, the search to improve the current solution is restricted to a narrower area to increase the algorithm efficiency.

4.3.2. Local Search Phase

The local search procedure is applied to explore the neighbourhood of the initial solution which is produced in the constructive phase. For the neighbour solutions, the evacuation allocations are found by a procedure to be explained in Section 4.3.3. In the GRASP algorithm pseudo-code shown in Figure 10, the local search procedure, denoted by $LocalSearch(Solution_{iter}, bestSolution, bestObj, bestAllocations)$ aims to improve the constructed solution $Solution_{iter}$ by exploring feasible solutions in the neighbourhood. In the following, we explain the neighbour search method, acceptance and stopping criteria for the procedure. The following notation helps to explain the local search phase:

- $bestSolution$, $bestAllocations, bestObj$: refer to the best solution found, corresponding evacuation allocations and objective value including total unmet demand and travel distance
- φ: the number of iterations in the local search
- it: iteration index in the local search
- $Neighbourset_{it}$: a neighbour solution set is produced by $CreateNeighbour(InitialSolution\ , Neighbourset_{it})$
- $Neighbour_n$: refers to the n^th^ neighbour solution in the $Neighbourset_{it}$

We define two different local search methods which are the one-step and multi-steps. The one-step local search generates a new neighbour solution set in each iteration and the best one with the minimum unmet demand is chosen (best-improvement strategy) in each iteration. The multi-steps local search repeats the one-step local search multiple times until the solution is not improving once compared to the $bestObj$. In the multi-steps local search, $bestSolution$ is updated in each step (each step contains φ iterations) and it is used as an initial solution for the next step. The local search procedure uses the following additional subroutine:

$CreateNeighbour\ (InitialSolution\ , Neighbourset_{it})$ checks if the initial solution would be improved by a move operator. The move, which is *remove+insert*, is used to generate the neighbour solutions as a combination of a drop project from the initial solution and add *m* projects from CL considering feasibility, respectively. Considering budget constraint and the cost of the project, which is dropped from the initial solution, *m* could be 1 or more. Feasible neighbours are generated, and the neighbour solutions are stored in $Neighbourset_{it}$ in iteration it.

To select the best local solution in terms of the primary objective function value (total unmet demand), the procedure $FindEvacuationAllocations(Solution_{iter})$ is used to find the evacuation allocation and accordingly the objective function value. CL is updated in each iteration (see $FindCriticalLinks(Solution_{iter}, CL)$) .

GRASP Local Search Pseudo-Code

One Step Local Search	**Multi Steps Local Search**
$bestSolution\ \leftarrow Solution_{iter};\ bestObj = obj_{iter};$	$bestSolution\ \leftarrow Solution_{iter}, bestObj = obj_{iter}$
$InitialSolution\ \leftarrow Solution_{iter}$	$InitialSolution\ \leftarrow Solution_{iter}$
$it = 0$	$check = 1$
while $it < \varphi$ **do**	**while** $check = 1$ **do** // if the best solution is not improving after
$CreateNeighbour\ (InitialSolution\ , Neighbourset_{it})$	φ iterations, *check* will be equal to 0 then the procedure will be
for (each neighbour $Neighbour_n$ in $Neighbourset_{it}$)	terminated.
$UpdateOperability(Neighbour_n)$	$it = 0$
$UpdateShortestRoutes(Neighbour_n)$	$check = 0$
$CreateAcessibleSupplierList(Neighbour_n)$	**while** $it < \varphi$ **do**
$FindEvacuationAllocations(Neighbour_n)$	$CreateNeighbour\ (InitialSolution\ , Neighbourset_{it})$
if $obj_n < bestObj$	**for** (each neighbour $Neighbour_n$ in $Neighbourset_{it}$)
$localObj = obj_n$	$UpdateOperability(Neighbour_n)$
$bestAllocations\ \leftarrow\ Allocations_n$	$UpdateShortestRoutes(Neighbour_n)$
$bestSolution\ \leftarrow Neighbour_n$	$CreateAcessibleSupplierList(Neighbour_n)$
end if	$FindEvacuationAllocations(Neighbour_n)$
end for	**if** $obj_n < bestObj$

it ++

end while

return $bestSolution, bestObj, bestAllocations$;

end GRASP

$localObj = obj_n$

$bestAllocations \leftarrow Allocations_n$

$bestSolution \leftarrow Neighbour_n$

$check = 1$

end if

end for

it ++

end while

if $check = 1$

$FindCriticalLinks(bestSolution, CL)$

$InitialSolution \leftarrow bestSolution$

end if

end while

return $bestSolution, bestObj, bestAllocations$;

end GRASP

Figure 12. Local Search procedure pseudo-code for the proposed GRASP

4.3.3. Evacuation Allocations

The efficiency of the solutions (mitigation project selection) in GRASP is determined by the overall unmet demand and travel distance resulting from the evacuation allocations. We use a two-step procedure to find evacuation allocations based on the current network conditions determined by the mitigation project selection. To begin, we use a greedy strategy (assign to the closest supplier) to generate an initial solution. Second, to improve the initial solutions, we apply an iterative improvement local search procedure. In the next sections, we will discuss these methods in further detail.

4.3.3.1.Initial Solution Generation

We apply a greedy strategy which is to assign each demand node to the closest available and accessible supplier to generate feasible initial solutions for evacuation allocations. The pseudo-code for the proposed greedy strategy is provided in Figure 13 and explained in the following.

In the proposed greedy strategy, demand nodes are assigned to nearest suppliers in an order that demand nodes which do have access to only one supplier come first. After deciding each allocation, the capacity availability for the assigned supplier is updated. Even if a demand node has access to a supplier, it might not be able to be assigned to that supplier due to lack of capacity condition. In this case, allocations are made in order of proximity. If the capacity of the assigned supplier is not entirely sufficient, the current capacity is allocated for that demand node, the unmet demand is updated and then the procedure continues to check the available suppliers in order of proximity (see Figure 13). Once the last demand node is evaluated to be assigned to a supplier, the procedure is terminated.

We keep two lists for each demand node $i \in I$: accessible suppliers denoted by acc_i and available suppliers (which is $acap_j$>0) denoted by ava_i. Once the initial solution is generated $Allocations$, a list denoted by unm is used to store the demand nodes with unmet demand.

```
procedure Initial Allocation Generation
input u_i, acap_j, acc_i, ava_i, unm
Allocations ← ∅, unm ← ∅
Sort demand nodes i ∈ I : ava_i ≠ ∅ (Ascending sort by the number of available suppliers for each demand node)
while (all demand nodes i ∈ I : ava_i ≠ ∅ are checked)
    while (u_i ≠ 0 and ava_i ≠ ∅ )
        Sort suppliers j ∈ ava_i in descending order of distance to demand node i ∈ I
            if (u_i ≤ acap_j)
                Add allocation {i, j, u_i} in Allocations
                u_i = 0
                acap_j = acap_j − u_i
            end if
            if (u_i ≥ acap_j)
                Add allocation {i, j,acap_j} in Allocations
                u_i = u_i − acap_j
                acap_j = 0
                Remove supplier j from ava_i i ∈ I
            end if
    end while
end while
if (u_i > 0)
Add demand node i in unm
end if
return Allocations
end Initial Allocation Generation
```

Figure 13. Greedy strategy pseudo-code

4.3.3.2.Local Search Procedure

This local search procedure uses the initial solutions provided by the greedy strategy and aims at improving the initial solution by searching the neighbourhood. The pseudo-code of the local search procedure is provided in Figure 14. The used neighbourhood search operators, acceptance/termination criterions, and the associated subroutines used in the local procedure are explained in the following.

```
procedure Local Search
input Allocation
UpdatedAllocation ← ∅;
    while (all demand node i ∈ unm are checked)
        if (ava_i ≠ ∅)
            InsertAvailableAllocations(Allocations, UpdatedAllocation)
            Allocation ← UpdatedAllocation
        end if
        if (acc_i ≠ ∅)
            ExchangeAllocations(Allocation, UpdatedAllocation)
        end if
    end while
return UpdatedAllocation
end Local Search
```

Figure 14. Local search procedure

We describe the neighbourhood search strategies used to improve evacuation planning. A new feasible solution (allocations set) is generated by an initial solution and the neighbour solutions are accepted only if a solution provides a better allocation plan with less unmet demand or same unmet demand with less travel distance. There are two search operators called $InsertAvailableAllocations$ and $ExchangeAllocations$ to generate a new (better) neighbour solution. The logic of these two operators is explained in the following. The local search procedure basically terminates when they reach a minimum objective function value where no neighbour has a better objective value. In other words, if the search operators check all the feasible options, the procedure terminates.

The neighbourhood search uses the additional following subroutines:

$InsertAvailableAllocations(Allocations, UpdatedAllocation)$ evaluates if there is any feasible allocation to insert and improve $Allocations$ considering the available suppliers $j \in ava_i$ for demand node $i \in unm$. If a demand node $i \in unm$ has access to an available supplier (which means $ava_i \neq \emptyset$), an allocation between demand node i and supplier node $j \in ava_i$ is inserted in the current allocations. Additionally, if there is more than one available supplier for that demand node, the procedure chooses the supplier considering travel time between demand-supplier nodes until $u_i = 0$ or $ava_i = \emptyset$. $Allocations$ are updated by adding the new allocations and saved as $UpdatedAllocation$. In each *insert* move, the lists $acc_i, ava_i, and\ all_j$ should be updated using $UpdatedAllocation$.

$InsertAvailableAllocations(Allocation,\ UpdatedAllocation)$ simply adds new allocations considering only available suppliers for unsatisfied demand nodes. On the other hand, the second procedure considers potential *remove* + *insert* moves on allocations while taking into account all accessible suppliers. We call this neighbourhood search procedure $ExchangeAllocations(Allocation,\ UpdatedAllocation)$.

$ExchangeAllocations(Allocation,\ UpdatedAllocation)$ considers all accessible suppliers for demand nodes $i \in unm$. There are cases where there is no available capacity at accessible suppliers (which means $ava_i = \emptyset,\ acc_i \neq \emptyset$), because these accessible suppliers serve other demand nodes. Here, the idea is creating available capacity in suppliers $j \in acc_i$ which are accessible but are not able to serve due to insufficient capacity for demand node $i \in unm$. To create capacity on the suppliers $j \in acc_i$, it is necessary to change allocations made to these suppliers.

The operator used in the $ExchangeAllocations$ is *remove+insert.* Specific conditions (swap criteria) should be satisfied to remove an allocation and insert a new one for each demand node $i \in unm$. For $i \in unm,\ \forall j \in acc_i,\ \ \forall i' \in all_j$. There are two main cases under these conditions and the check procedures are named by Exchange Allocation Check-1 and Exchange Allocation Check-2 (see Figure 15 and 16):

- If $ava_{i'} \neq \emptyset$ (meaning that demand node i' has access to other available suppliers rather than *j*), then demand node i' should be allocated to another supplier $j' \in ava_{i'}$ (if there is more than one supplier in $ava_{i'}$, the one with the minimum travel distance should be chosen). In this case, the exisiting allocation between i' and j are removed or updated depending on the the available capacities of the associated suppliers and the new allocation between i' and j' are inserted to the solution as given in Figure 14. Existing allocation between i' and *j* is denoted by $\{i', j,\ \ t\}$ and t represents the number of transferred people from node i' to j.

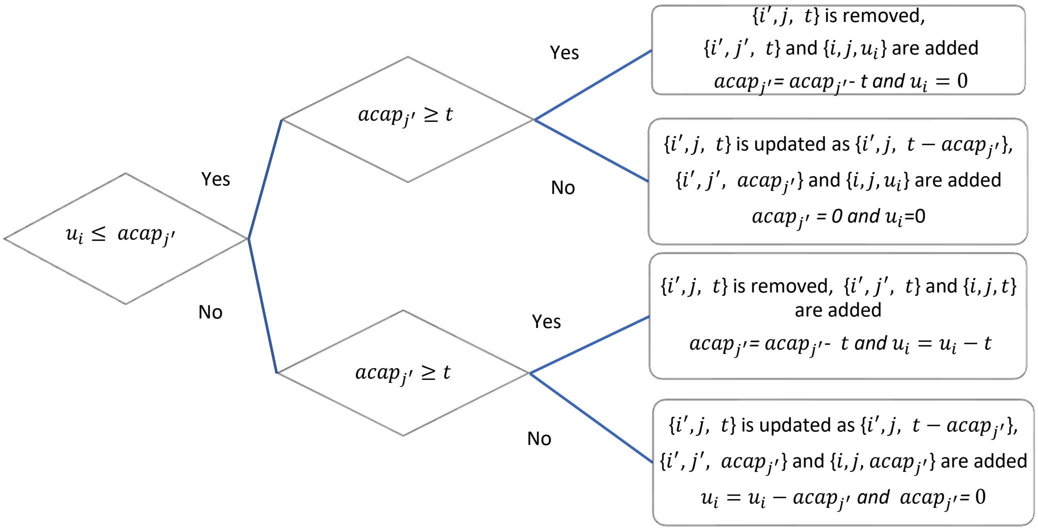

Figure 15. Exchange Allocation Check-1

- If $ava_{i'} = \emptyset\ and\ acc_{i'} \neq \emptyset$ (meaning that demand node i' does access to at least one supplier but not any available supplier), the accessible suppliers $j'' \in acc_{i'}$ for demand node i' should be checked whether some space would be opened by changing allocations. All demand nodes $i'' \in all_{j''}$ are checked to see if $ava_{i''} \neq \emptyset$. If the demand node i'' has access to an available supplier, then demand node i'' should be allocated to the supplier $j''' \in ava_{i''}$ (if there is more than one supplier in $ava_{i''}$,, the one with the minimum travel distance should be chosen). Existing allocation between i'' and j'' is denoted by $\{i'', j'', t^1\}$ and t^1 represents the number of transferred people from node i'' to j''. Another existing allocation between i' and j is denoted by $\{i', j, t^2\}$ and t^2 represents the number of transferred people from node i' to j. Same as the previous case, the corresponding allocations are removed or updated and inserted depending on the associated suppliers and the available capacities of these suppliers as given in Figure 15.

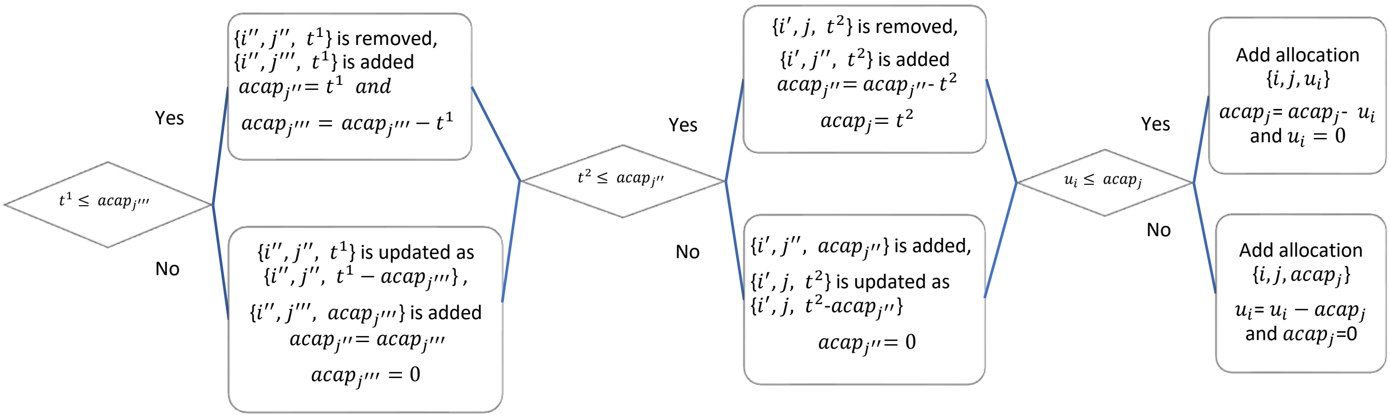

Figure 16. Exchange Allocation Check-2

$Allocations$ are updated by the check procedure given Figure 15 and 16 and saved as $UpdatedAllocation$. Then, the available capacities and unmet demand values are updated regarding $UpdatedAllocation$. In each insert move, the lists $acc_i, ava_i, and\ all_j$ should be updated regarding $UpdatedAllocation$. Figure 17 illustrates the pseudo-code of the exchange allocations operator.

---

procedure Exchange Allocations Operator
input $Allocation$
$UpdatedAllocation \leftarrow Allocation$;
Check if there is any feasible allocation change for demand node $i \in unm$
  while (all accessible suppliers $j \in acc_i$ are checked or $u_i = 0$)
    while (there is demand node $i' \in$ all$_j$ to be checked and $u_i \neq 0$)
      if ($ava_{i'} \neq \emptyset, j' \in ava_{i'}$)
       Update the allocations according to the rule in Exchange Allocation Check-1
       $Allocation \leftarrow UpdatedAllocation$
      end if
      else if ($ava_{i'} = \emptyset$ and $acc_{i'} \neq \emptyset$)
        while (there is accessible supplier $j'' \in acc_{i'}$ to be checked and $u_i \neq 0$)
          while (there is demand node $i'' \in$ all$_{j''}$ to be checked or $u_i \neq 0$)
            if ($ava_{i''} \neq \emptyset, j''' \in ava_{i''}$)
             Update the allocations according to the rule in Exchange Allocation Check-2
             $Allocation \leftarrow UpdatedAllocation$
            end if
          end while
        end while
      end else
    end while
  end while
$Allocation \leftarrow UpdatedAllocation$
return $UpdatedAllocation$
end Exchange Allocation Operator

Figure 17. Exchange Allocations Operator

An illustrative example is provided in the following to explain the neighbourhood search operators in the local search. Figure 18 shows an initial solution for evacuation allocations.

Demand nodes				
No	ava_i	acc_i	d_i	u_i
1	-	{4}	100	100
2	{1,3}	{2}	300	-
3	{3}	{4}	100	-
4	{1}	{2}	100	100
5	{3}	{2,4}	200	-
6	{1}	{2,4}	100	-

Supplier nodes	
No	$acap_j$
1	100
2	-
3	100
4	-

Allocations			
No	i	j	$\#\ of\ people$
1	2	2	300
2	3	3	100
3	5	4	200
4	6	1	100

Figure 18. An example of local search for evacuation allocations (1)

The proposed procedure first evaluates the available suppliers for the demand node with unmet demand and insert a feasible allocations for these demand nodes by $InsertAvailableAllocations(Allocations, UpdatedAllocation)$. Demand node 1 and 4 have unmet demand and demand node 4 has access to an available supplier which is supplier 1. With the *insert* operator, {4, 1, 100} allocation is added to the current solution. Then, the allocations, available capacities and unmet demand are updated as in Figure 19.

Demand node				
No	ava_i	acc_i	d_i	u_i
1	-	{4}	100	100
2	{3}	{2}	300	-
3	{3}	{4}	100	-
4	-	{2}	100	-
5	-	{2,4}	200	-
6	-	{2,4}	100	-

Supplier node	
No	$acap_j$
1	-
2	-
3	100
4	-

Allocations			
No	i	j	$\#\ of\ people$
1	2	2	300
2	3	3	100
3	5	4	200
4	6	1	100
5	4	1	100

Figure 19. An example of local search for evacuation allocations (2)

There is only one demand node has unmet demand in the situation shown in Figure 19. Demand node 1 does not have access to any available supplier. For this reason, the second neighbourhood search operator which is $ExchangeAllocations(Allocation, UpdatedAllocation)$ should be used to see if there is any move that could improve the current solution. Demand node 1 has only access to supplier 4 then the allocations which are made to supplier 4 should be evaluated. Demand node 5 is allocated to supplier 4 and it is checked if demand node 5 can be allocated to any available supplier. Demand node 5 has access to supplier 2 but supplier 2 has no available capacity with the current allocations. In this case, to create available capacity in the supplier 2, the method checks all the allocations which are made to this supplier. Demand node 2 is allocated to supplier 2 although the demand node has access to supplier 3 which has available capacity. {2, 2, 300} is removed and {2, 2, 200} and {2, 3, 100} are added to the current solution. {5, 4, 200} is removed and {5, 4, 100} and {5, 2, 100} allocations are added to the current solution. In this case, with the *remove+insert* operator, Then, the available capacities and unmet demand are updated.

Demand node				
No	ava_i	acc_i	d_i	u_i
1	{4}		100	100
2	-	{2, 3}	300	-
3	-	{3}	100	-
4	-	{2}	100	-
5	{4}	{2}	200	-
6	{4}	{2}	100	-

Supplier node	
No	$acap_j$
1	-
2	-
3	-
4	100

Allocations			
No	i	j	$\# \ of \ people$
1	2	2	200
2	3	3	100
3	5	4	100
4	6	1	100
5	4	1	100
6	2	3	100
7	5	2	100

Figure 20. An example of local search for evacuation allocations (3)

After the last arrangements on the allocations, supplier 4 has available capacity to cover the demand at demand node 1. The last move should be inserting an allocation as {1, 4, 100} so there is no unmet demand, and the procedure is stopped.

4.4. Conclusion

In this chapter, three different solution approaches have been proposed to solve the CNSP. To begin with, multi-objective solution approaches such as lexicographic and weighted-sum methods were evaluated to determine the best method to apply for the analysis. The weighted-sum method outperforms the lexicographic method, returning the same solutions while requiring less processing time. As a result, the weighted-sum has been employed for the rest of the analysis.

The proposed stochastic problem is hard to solve as it is difficult to evaluate the expected cost of the second stage. It requires the solutions of a large number of second stage optimization problems as the number of possible scenarios is very large for the proposed problem. The scenario-based (deterministic equivalent) model of the stochastic problem has an exponential number of scenarios, which make it impractical to solve directly. Hence, a Sample Average Approximation Algorithm (SAA) is proposed to solve the problem. To estimate the performance of the SAA method, we first solve a small-scale case. The proposed SAA requires solving a considerable number of second-stage models so this method may not be appropriate for the larger instances.

A GRASP-based algorithm has been developed to be able to solve larger instances of the problem. To find evacuation allocations for the feasible solutions in the GRASP, we also propose a procedure combining a greedy approach for generating initial solutions and an iterative improvement algorithm for the local search.

5. Case Study with Istanbul Roadway networks

This chapter provides the case study implementation stages. Basically, the input data generations are explained such as defining network components, estimating resilience levels of links, generating alternative routes connecting demand-supplier nodes, and scenario generation.

Two case studies are applied using Istanbul roadway network datasets. Two data sets are used based on Istanbul Road network which are generated using two geographical information system (GIS) programs; ArcGIS and GoogleMaps. The city of Istanbul is located in a first-degree seismic zone and has experienced several earthquakes throughout its history. With around 15 million inhabitants, the city is spread 500 km^2 on either side of the Bosphorus strait.

The performance of the proposed methods is evaluated with the data of the expected earthquake scenarios of Istanbul. According to the research of JICA (Japan International Cooperation Agency), there are four possible earthquake scenarios for Istanbul which are Model A, B, C, and D, respectively. Model A is the most probable and Model C is the worst-case scenario [276]. Model C has a longer broken line, and accordingly, it leads to higher damage. Model B is similar to Model A, and Model D is similar to Model C. The JICA and IMM (Istanbul Metropolitan Municipality) reports provide the estimation of casualty numbers of each district for these two scenarios (Model A and C). We conduct two case studies of the Istanbul roadway network data (the simplified and detailed network) under the earthquake having a magnitude of 7.7, which is identified as the worst-case scenario (Model C) in the JICA report.

The first data set, which is named as the simplified network data of Istanbul roadway with 60 nodes and 83 links, is generated by Yucel et al. [246]. Figure 21 illustrates the simplified roadway network, which is mainly composed of two motorways, O1 and O2, which run along the east-west direction of the city. The secondary roads along the north-south direction, which are connected to motorways O1 and O2, expand the roadway network throughout the city.

Figure 21. The simplified roadway network representation of Istanbul [246]

The second data set is based on a more detailed Istanbul roadway network with 349 nodes and 1295 links generated using ArcGIS and Google Earth by Akbari and Salman [312]. Figure 22 displays the components of the detailed network and the active North Anatolian Fault line that is under the Marmara Sea that lies to the south of Istanbul. The links are categorized into groups with the risk separator due to their proximity to the epicentre of the earthquake according to the scenarios predicted in the JICA report.

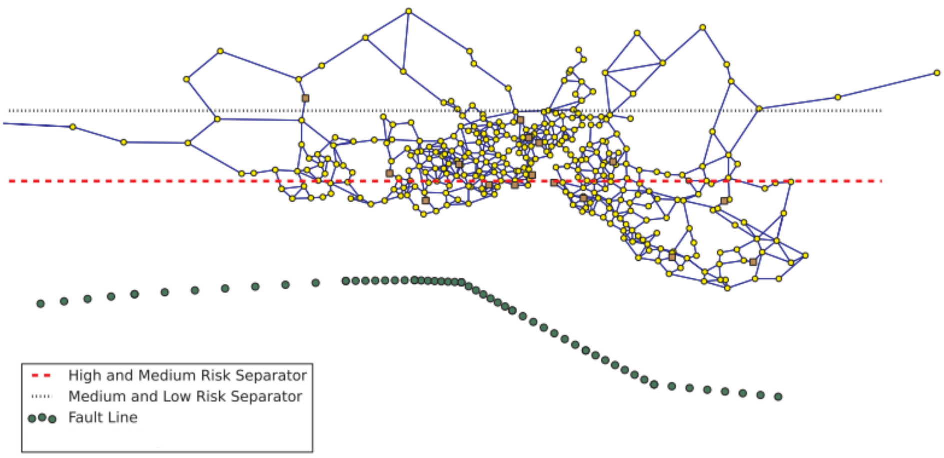

Figure 22. The detailed roadway network representation of Istanbul [312]

5.3. Defining Demand and Supplier Nodes

In the aftermath of an earthquake, extricating people and providing access to health care facilities are the top priorities followed by access to emergency operations infrastructures such as the emergency operations centres and supply distribution centres.

The simplified network consists of 60 nodes (26 demand nodes, 8 supplier nodes and 26 transhipment nodes) (see in Appendix D.1). For the simplified network, except for four districts, Beykoz, Sile, Çatalca, and Silivri, that have low populations and low earthquake risks according to JICA report, every other district is represented by a node. Some of the districts are identified as supplier locations including Bakırköy, Üsküdar, Sisli, Fatih, Kadıköy, Bahçelievler, Zeytinburnu, and Beyoglu, where the healthcare capacity is concentrated considering the number of hospitals and polyclinics as well as the number of beds in each district (see in Appendix D.2). The remaining districts, where the number of healthcare facilities is not sufficient to serve the casualties in the post-disaster stage, are identified as casualty demand locations. Therefore, these casualties would be transported to the identified supplier locations. The number of estimated casualties in each demand district is calculated by the casualty rates given in the JICA report, as listed in Appendix D.3.

For the detailed network, each district is represented by a different number of nodes based on the existing population densities of demand nodes (i.e., two nodes for Silivri, six nodes for Bahcelievler). Unlike the simplified network data, the supplier nodes represent the location of hospitals, depots, and airports rather than districts. The detailed network consists of 349 nodes (16 supply nodes, 154 demand nodes, and 170 transhipment nodes). Same as in the simplified network, the casualty demand is generated by using the casualty rates given in the JICA report and it is distributed equally for the demand nodes in each district (see in Appendix E.2).

5.2. Generation of Initial Resilience Levels

Roadway may become inoperable in the event of an earthquake. Earthquakes can cause cracks and deformations in roads obstructing the transportation. roadways are not equally vulnerable to an earthquake. Roads with a high regional seismic risk, for example, are more vulnerable to earthquake-related damage, whereas roads with a low regional seismic risk are more reliable. Furthermore, the structural qualities of bridges and viaducts define their earthquake risk, as well as the seismic vulnerability of the roads that carry these structures.

For a vulnerability assessment of the highway network, we need to estimate the reliability/resilience of individual links. To estimate the resilience levels, we use the survival probabilities calculated by Yucel et al. [246] for the simplified network. For the simplicity in scenario generation, we multiply the survival probabilities by 10 to compute the initial resilience levels so we assume that initial levels are in the range [1,10]. Accordingly, a link with a resilience level of 10 is the most resilient link, whereas a link with a resilience level of 1 is the riskiest and weakest.

In the following, we explain how survival probabilities are estimated and what components are considered (for additional details see [246]). The estimation of links' survival probabilities for the simplified network takes into account the seismic intensity and magnitude of the earthquake and the collapse of structures on the roadway. Survival probabilities, denoted by $prob_e$ for each link e, are computed using equation 5.3. Three components are considered in the estimation of the link survival probabilities: PGA_e is the peak ground acceleration level at link e depending on the magnitude, f_e is the seismic risk factor where link e is placed and epicentre of the earthquake, φ_e represents the earthquake vulnerability score based on the structures on link e.

$$prob_e = 1 - f_e PGA_e - \varphi_e \tag{5.1}$$

Yucel et al. [246] define the seismic intensity in terms of peak ground acceleration (PGA) level which measures how intensive the ground shakes in a given geographic area. Three risk levels are defined by PGA levels based on the consultation with an expert from the Turkish Federal Highway Administration (TFHA), where risk level 1 (corresponding to a 0.3–0.4 g PGA interval) shows the region with high seismic risk, risk level 2 (corresponding to a 0.2–0.3 g PGA interval) is the region with average seismic risk and risk level 3 (corresponding to a 0.1–0.2 g PGA interval) is the region with low seismic risk given in [276]. A link can be located in more than a single region, and it will be non-operational if one of its adjacent nodes fails. Therefore, the seismic risk level of a link is taken as the maximum seismic risk level of its adjacent nodes. The seismic risk factors of the links should lie between (0.95, 1], (0.9, 0.95], and (0.85, 0.9] for risk levels 1, 2, and 3, respectively, for an earthquake having a magnitude of 7.7, which is identified as the worst-case scenario in the JICA report. The seismic risk factor f_e of each link e is generated randomly in the interval specified for the corresponding risk level.

Yucel et al. [246] partition the links in each region according to the earthquake vulnerability of the vulnerable structures (bridges/viaducts) on them and estimate the earthquake vulnerability score of each link. To estimate vulnerability scores of bridges/viaducts, the preliminary earthquake risk assessment of bridges/viaducts are done by conducting with the scoring method of ATC 6-2 which is one of the widely used methods for the preliminary assessment and priority listing of structures. The network links, on which these structures are located, are identified using GoogleMaps and ArcGIS.

In this ATC 6-2, three factors, which are vulnerability, seismicity, and structural importance, are equally considered in estimation of vulnerability score of these structures. Vulnerability is related to structural parameters (bearing type, superstructure skew angle, minimum support length); seismicity represents the magnitude of the earthquake as well as the geology and geotechnical surroundings of the structure. Finally, the structure's importance is related to the daily average traffic, the physical size of the structure, the population surrounding the structure, its usage, and the structure's function in transit to key facilities such as hospitals and fire stations. Yucel et al. [246] exclude structural importance factor since they assume that all structures are equally important. For each bridge/viaduct, each factor is examined and assigned a score between 1 and 10. The scores are then multiplied by 3.33 (since they are equally essential) and summed to get the final score as seen in the equation 5.2.

$$5 * \left(\frac{Total\ score - 3.33 * (Structural\ importance)}{3.33}\right) \tag{5.2}$$

As a result, a bridge/viaduct with a total score of 100 is the riskiest structure, whereas a bridge/viaduct with a total score of 0 is risk-free. If a total score in the interval [70, 100] indicates that the structure is at high danger; a total score in the interval [55, 70] indicates that the structure is at medium risk; and a total score less than 55 indicates that the structure is at moderate risk. The earthquake vulnerability score (φ_e) will be 0.3, 0.2, an 0.1 correspond to the intervals [70, 100], [55, 70], and less than 55, respectively.

For the detailed network, we use the same procedure as applied for the simplified network to generate the initial resilience levels. The coordinates of detailed network links are available; therefore, we could identify the PGA and risk levels of the links. The bridges/viaducts and the coordinates of these structures are given in [313]. Arsik [313] estimate the vulnerability scores for each structure by using the same scoring method ATC 6-2. The vulnerability scores are taken from their research for the detailed network. We first identify network links on which these structures are located with GoogleMaps. Then, we estimate the resilience levels of detailed network links considering PGA levels, risk levels and vulnerability scores by using the formula given in 5.1.

5.3. Defining Routes

The selection of emergency routes is essential in pre-disaster planning activities. Finding the shortest route from each demand node to each supplier node is crucial in the planning stage. However, in the post-earthquake, the shortest route between demand and supplier nodes may not always be operational since the links on the shortest routes may be collapsed.

In the literature, there are various methods to generate a set of routes. The most-known one is the *k*-shortest route algorithm, which produces *k* shortest routes from one node to another node in a network [314]. An ordered list of k alternative routes connecting demand and supplier nodes are provided by k-shortest route algorithm. The drawback of this method is that it may generate similar routes with common links. If a common link of the two generated routes fails, then both routes fail. However, another route with a slightly higher distance may survive. Thus, it is more realistic to include a set of routes instead of only the shortest route into consideration. Yucel et al. [246] generate the routes (having no cycles) for the simplified network by using the *k*-shortest route algorithm and then eliminate the similar routes by the modified *p*-dispersion method [315]. In the *p*-dispersion method, the procedure selects a set of *p* routes out of a set of m candidate routes between demand and supplier nodes is selected with the objective of maximizing the minimum dissimilarity between any two selected routes. In the dissimilar route generation procedure, $dis_{r'r''}$ corresponds to the dissimilarity between route $r'$and r''. This dissimilarity is expressed in terms of the similarity index given below.

$$S(r', r'') = \frac{\frac{l(r' \cap r'')}{l(r')} + \frac{l(r' \cap r'')}{l(r'')}}{2} \tag{5.3}$$

where $l(r')$ is the length of route r' and $S(r',r'')$ is the similarity index between route $r'$and r''. Then, the dissimilarity is equal to:

$$dis_{r'r''} = 1 - S(r',r'') \tag{5.4}$$

The modified p-dispersion method finds the most dissimilar p routes by ensuring the shortest route is included. Therefore, Yucel et al. [246] generated a set of routes through the *p*-dispersion method that merges the set of k-shortest routes from a demand point to each supply point. They find 1132 alternative routes and we use these routes in the computational experiments.

For the detailed Istanbul roadway network, we generate the set of routes between demand and emergency facility locations. Overall, 10506 alternative routes, considering 1295 undirected links, are generated by using the k-shortest path algorithm. The routes have a considerable number of links: some of them have nearly 50 links whereas the average is 18 links. This case is different than the simplified network so the similarity of the routes may be high but that does not mean they need to be excluded. Therefore, for the detailed network, we include all these routes, but the proposed solution approaches use the shortest accessible ones for each demand-supplier pair.

5.4. Generation of Mitigation Projects

As mentioned previously in the Chapter 1, several mitigation strategies can be used, such as strengthening structures (bridges/viaducts) with cross braces and other reinforcements that can absorb some of the forces resulting from a seismic activity. These measures can be applied with the aim of improving the seismic resilience of susceptible links and, as a result, the post-earthquake survival status of roadways.

We assume that when a link is strengthened in the pre-disaster stage, its resilience level increases. In this study, resilience levels show the ability of a network/ roadway component to retain transportation functionality at varying levels. Yucel et al. [246] assume that strengthened links are much less likely to fail after an earthquake, therefore, the strengthened link survival probabilities are set to 98% in their analysis. Differently, we assume that a link will be mitigated to varied degrees but may still be inoperable after the earthquake due to the risk it carries. We include the projects with various levels of improvement on resilience levels because different mitigating options may be available for each link. Additionally, we consider the impacts of mitigation projects as being is dependent on the initial conditions of links. As stated in Section 5.2, resilience levels are identified considering where the links are located on and what structures exist on them. Therefore, if a link has a high risk level and a vulnerable component on it, in other words if a link has low resilience level compared to others, more emphasis on retrofitting projects is required for that link.

The cost of each project is determined based on the levels of improvement. We assume that there may be more than one project that can be implemented on a link $e \in E$ and the number of projects depends on its initial resilience level ρ_e. The links are divided into three groups according to their initial resilience level; link e in scenario s is in group 1 if $\rho_e \leq 3$, link e in scenario s is in group 2 if $3 < \rho_e \leq 6$, and lastly link e in scenario s is in group 3 if $6 < \rho_e \leq 10$. The links in group 1 have three project options having high, medium, and low impact levels. Similarly, if a link belongs to group 2, it has two projects and lastly, links in group 3, have just one project. After defining the impacts on resilience levels and the number of projects, cost values are generated based on degrees of improvement in resilience level and the initial resilience level. The pseudo-code showing the general concept of generating data relative to the mitigation projects is illustrated in Appendix F. For the coefficient for calculation of project cost is set to 25 for both network data sets.

5.5. Scenario Generation

In this section, we explain how to generate network scenarios for the representative data sets. For each scenario $s \in S$, there will be unique survivability threshold β_e^s value for each link e $\in E$. Therefore, each scenario would have different available routes in the network realizations for the initial state (without mitigation project application). For the computational experiments, we assume that the occurrence probabilities $prob_s$ are identical so we do not consider the probabilities in the case studies, and we calculate the objective functions as the average of all scenarios' objectives.

In our approach, we assume that if the link's resilience levels are lower than the survivability thresholds which are dependent on the scenario, the link fails and will not be operational. For both networks, the links are classified as high, medium, or low-risk due to their proximity to the epicentre of the earthquake and based on the presence of a vulnerable structure to the worst-case earthquake scenario described in the JICA report [276]. For the detailed network, as seen in Figure 22, low-risk links are those above the upper horizontal line, medium-risk links are those between the two horizontal lines, and high-risk links are those below the lower horizontal line. If nodes of a link are located in two different risk-level groups, it is placed that particular link in the riskier group. In order to eliminate less likely network scenarios, the risk levels of the links are taken into account in generating scenarios based the fact is the links with high-risk levels must be more resilient to survive.

Table 18. Risk levels and associated threshold values for the simplified network

Risk levels	Threshold values
Risk level 1 (high seismic risk)	7 or 6
Risk level 2 (average seismic risk)	6 or 5
Risk level 3 (low seismic risk)	5 or 4

Various earthquake-induced parameters as explained in Section 5.2 are considered while estimating the resilience levels. For this reason, we assume that links which have very high resilience levels (>7) will always be operational, even if they are classified as in high seismic risk level. Similarly, if a link has a very low resilience level (<4), it will be non-operational regardless of its risk level. On the basis of this assumption, we define two potential threshold values for each risk level (e.g., for risk level 1, the threshold can be either 6 or 7). Either one of these values can be selected as the survivability threshold for each link in a given scenario. As a result, there exist 2^{83} and 2^{1295} different scenarios for the simplified and detailed network, respectively.

Eliminating scenarios that are redundant in terms of survivability thresholds based on initial resilience levels would be beneficial for the computational time. As stated above, if the link e has a high initial resilience level, which is $\rho_e \geq 7$, that link will be operational for all scenarios. With the same reasoning, if the initial resilience levels are higher than maximum threshold values which are 6 for risk level 2 and 5 for risk level 3, these links will be operational for all scenarios. Links that match these criteria do not need to be considered when generating scenarios. After applying this reduction, we have 2^{21} (2,097,152) scenarios instead of 2^{83} for the defined initial resilience levels for the simplified network (see in Appendix A.3). The number of scenarios is till quite significant. We therefore implement the SAA algorithm described in Section 4.2.

5.6. Conclusion

This chapter explains the generation of the representative networks, selection of demand and supplier locations (nodes), link resilience levels, determination of mitigation projects, route generation, and scenario generation method for the case study. The input data generation is done for two different Istanbul roadway networks which is a simplified and detailed with 60 nodes, 83 links and 349 nodes, 1295 links, respectively. Specifically for estimating resilience levels, it was really challenging to conduct the previously introduced approach considering three different components (PGA_e is the peak ground acceleration level at link e, f_e is the seismic risk factor, φ_e represents the earthquake vulnerability score) for the detailed network. These three components are estimated based on the coordination information of the links and the vulnerable infrastructure's vulnerability scores. This was the first attempt to use such a large network NSPs in the OR literature. While the primary goal is to validate the developed solution methodologies for the next chapter, it would be possible to drive insights considering as many realistic parameters as feasible through this chapter.

To generate the alternative routes between demand-supplier nodes, the k-shortest route algorithm and p-dispersion algorithm are used. We include the projects with various levels of improvement on resilience levels because different mitigating options may be available for each link. The impacts of mitigation projects are considered as being is dependent on the initial conditions of links. Additionally, each scenario would have different available routes for the initial state. We assume that if the link's resilience levels are lower than the survivability thresholds which are dependent on the scenario, the link fails and will not be operational for the transportation. The threshold values are estimated considering the link risk levels as high, medium, or low-risk due to their proximity to the epicentre of the earthquake according and contains a vulnerable structure to the worst-case earthquake scenario described in the JICA report.

6. Results and Analysis

In this chapter, we first compare the two multi-objective approaches. We then apply the SAA procedure to the simplified network and use the proposed heuristic algorithm to solve the problem with the simplified netwrok. Finally, we utilize the heuristic algorithm to solve the problem with the detailed network to assess its efficiency on a larger instance. Figure 23 depicts the simplified network's demand and supply nodes. Some results in the following analysis are given using node numbers. We defined the budget levels by some preliminary analysis. Experiments have been performed for different budget levels for the simplified network, starting from 10% of the protection budget (the total cost of candidate projects) and increasing by 2.5% at each stage. Since the detailed network is significantly larger in terms of the number of links to be strengthned than the simplified network, we employ the budget levels starting from 2.5% and increasing by 2.5% at each step to draw more insights. These experiments continued until we reached the budget level at which all demand would be met to draw further insights for the simplified network.

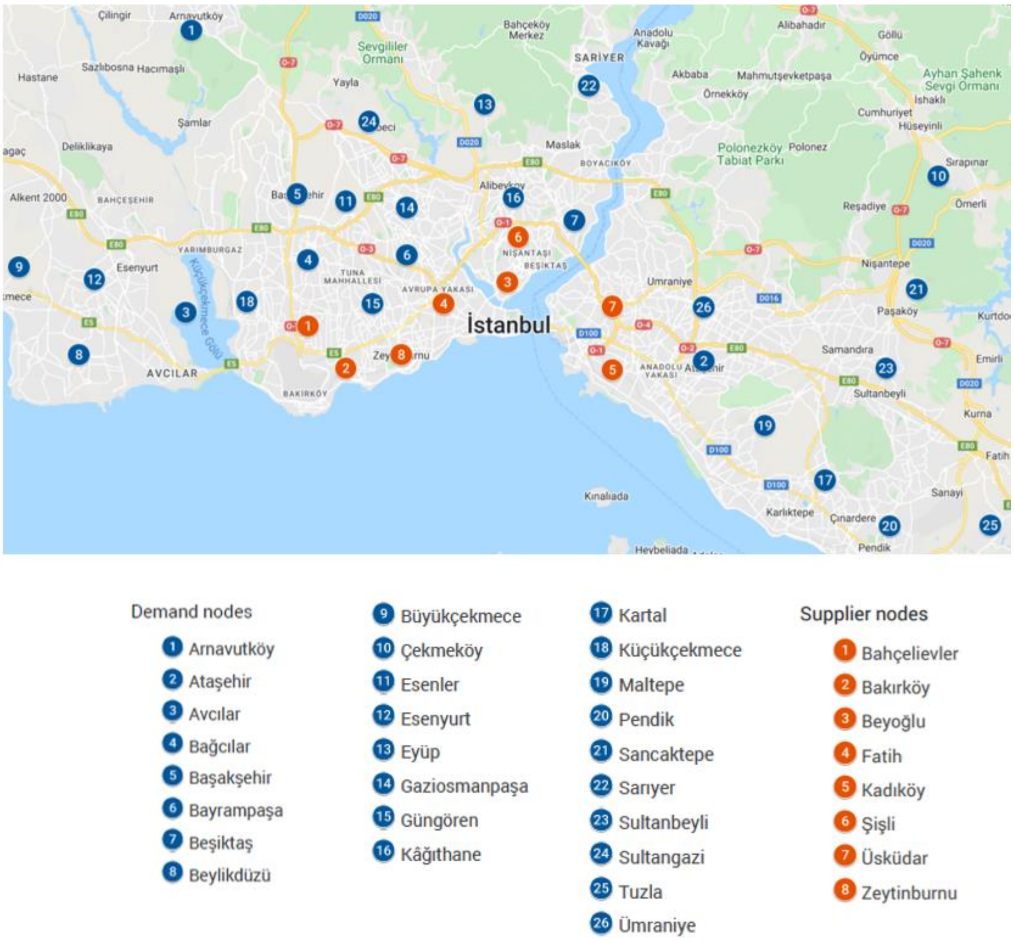

Figure 23. Demand and supplier nodes for the simplified network

The solution approaches were implemented using IBM ILOG OPL modelling language and solved with CPLEX OPL 20.1.0 solver and C++, on a computer with Intel Core 7, 2.80 GHz, 32 GB of RAM under a 64bit operating system.

6.1. Comparisons of the Multi-objective Approaches

The proposed model is implemented using two multi-objective approaches: the lexicographic and weight-sum based methods. We compare these two methods using the simplified Istanbul roadway network data with input parameters (including demand, capacity, initial resilience levels, project cost and impacts values) as detailed in Appendix D. 10 different scenarios for each replication are generated with the scenario generation method explained in Section 5.5. Each scenario $s \in S$ has its own set of survivability threshold β_e^s for each link e. We test the multi-objective approaches in terms of their impacts on primary and secondary objective values.

A new scenario set consisting of 10 different scenarios is created in each replication. We replicate 10 times with 10 scenarios for two budget levels including 15% and 20% and report the percentage of uncovered demand (*UD*%) (primary objective), average travel distance per evacuee (secondary objective) and solution time (CPU) in the Table 19 for both approaches. We calculate the average travel distance per evacuee as the total travel distance in evacuation operations divided by the total number of evacuated people using the following formula:

$$Avreage\ travel\ distance\ per\ evacuee = \frac{\sum_s^{|S|}\sum_i^{|I|}\sum_j^{|J|}\sum_r^{|R|} z_{ijr}^s l_r}{\sum_s^{|S|}\sum_i^{|I|}\sum_j^{|J|}\sum_r^{|R|} z_{ijr}^s}$$

The impact of the solution approaches on the mitigation decisions and objective function values is analysed. In both solution options, the chosen projects are identical and listed in Table 19. Both primary and secondary objective function values are equal in each replication for both methods. The lexicographic approach ensures to provide the optimal allocation decisions for both minimum total unmet demand and travel distance by solving two different mathematical models. The weighted-sum approach prioritizes minimizing total unmet demand while minimizing total travel distances as a secondary objective. As a result, the weighted-sum method achieves the same outcomes while taking less time to solve the model in each replication.

Table 19. Comparison of multi-objective solution approaches

Budget levels	Rep	Chosen Projects	UD% per scenario	Average travel distance (km)	CPU (secs) Weighted-sum method	CPU (secs) Lexicographic method
15%	1	16, 29, 33, 53, 64	2.85	27.85	130.37	193.42
	2	16, 30, 33, 53, 64,72	3.39	26.27	157.29	201.61
	3	16, 29, 33, 53, 64	2.21	28.64	138.17	207.49
	4	16, 29, 33, 53, 64	2.53	27.75	65.66	163.5
	5	16, 29, 33, 53, 64	3.51	27.90	136.37	205.17
	6	16, 29, 33, 53, 64	2.53	27.70	125.58	185.80
	7	1, 29, 30, 33, 53, 64	2.49	27.47	142.76	204.09
	8	1, 29, 30, 33, 53, 64	2.49	28.97	121.49	193.91
	9	16, 29, 33, 53, 64	2.86	27.55	112.37	182.41
	10	14, 16, 33, 53, 64,72	3.29	28.09	153.09	222.5
	Average		**2.82**	**27.82**	**128.32**	**195.99**
20%	1	1, 29, 30, 33, 53, 64,82	0.85	29.70	90.66	216.50
	2	16, 29, 33, 53, 64, 82	1.52	27.42	176.99	200.31
	3	16, 29, 33, 53, 64, 82	1.01	27.40	93.61	180.01
	4	16, 29, 33, 53, 64, 82	0.37	27.49	84.16	173.40
	5	16, 29, 33, 53, 64, 82	1.2	27.74	78.07	234.97
	6	16, 29, 33, 53, 64, 82	1.52	27.43	105.43	153.80
	7	16, 30, 33, 53, 64, 72, 82	0.93	26.76	79.17	180.90
	8	16, 29, 33, 53, 64, 82	0.37	28.21	91.79	164.31
	9	16, 29, 33, 53, 64, 82	0.97	28.09	84.42	157.52
	10	14, 16, 33, 53, 64, 72, 82	1.09	26.20	85.52	214.17
	Average		**0.98**	**27.644**	**96.982**	**187.58**

*Rep: Replication number

Since the project selections are identical, the available routes are the same in each scenario for each replication. On the other hand, evacuation allocations in the solutions of the methods are not the same for each scenario, indicating that alternative optimal solutions exist. We give an example including the results with same unmet demand and travel distance with slightly different allocations for both methods in Appendix G. Appendix G.1 and G.2 show the allocations in the 8th scenario of replication 10 provided by the lexicographic and weighted-sum methods. We observe that the evacuation demand for a few of demand points is allocated to different suppliers. For this particular scenario on replication 10, the allocations which are different are provided in Table 20 (the remaining allocations are the same in both methods). As seen in Table 20, while demand node 3 is allocated to supplier 8 only in the lexicographic method, two different supplier nodes (1 and 8) serve demand node 3 in the weighted-sum method. As another example, evacuees from demand node 18 are evacuated to supplier 1 in the lexicographic method's results whereas they are allocated to supplier 8 in the weighted-sum method's results. Despite these small difference in the allocations, the outcome, which is total unmet demand and travel time, remains the same so the average travel time per evacuee is the same in the optimal evacuation planning by both methods.

Table 20. Different allocations in both methods

Demand node	Supplier node	Route no	Evacuated people	Route length	Total travel distance
Lexicographic Method					
3	8	98	1988	34.87	69317.58
12	8	513	108	42.48	4588.164
12	1	532	93	53.49	4974.105
18	1	836	834	32.26	26902.34
		Total:	**3023**		**105782.2**
Weighted-Sum Method					
3	8	98	1262	34.87	44003.42
3	1	105	726	45.87	33301.62
12	1	532	201	53.49	10750.49
18	8	830	834	21.255	17726.67
		Total:	**3023**		**105782.2**

When it comes to strategic decisions, minor allocation disparities are irrelevant as long as the unmet demand and travel distance are the same. The weighted-sum approach is used in the following analyses because it finds optimal results in less time than the lexicographic method.

6.2. SAA Results

Recall from Section 4.2 that the SAA method requires the solution of N replications of the approximate the stochastic programming model, each involving S sampled scenarios. The objective function is subsequently evaluated using S' sampled scenarios for statistical validation of a proposed solution. This experimental work attempts to quantify the quality of the solution. Lower bound and upper bound of the solutions are estimated by the SAA procedure to evaluate the quality of the solutions. We implement the SAA procedure for the simplified network and report the results for various samples for a specific budget level which is %20. We begin with S=10 sample size and increase by 10 in each iteration until CPLEX

OPL is unable to solve the problem or the optimality gap is less than ε. We use $S^{'}$= 1000 scenarios to evaluate the expected objective function for a given solution. In each iteration, we generate new instances in the same manner as explained in Section 5.4.

We use 10 replications (N = 10) for every choice of sample size (S), and we define our stopping criteria as $\varepsilon = 0.1$ meaning that if the optimality gap is lower than ε then we terminate the algorithm. We start our algorithm with S=10, that is, we generate 10 scenarios and solve the corresponding SAA model optimally in each replication. Once all replications are done, we use the solution with the best objective value. We use the optimal values of the first-stage decision variables, y_p which represents the mitigation project selection decision, as in the best solution over all replications. In this step, $S^{'}$= 1000 independent second-stage problems are solved and the estimated upper bound is found. We continue to increase by 10 the sample size and apply the same procedure until the stopping criterion is satisfied.

Table 21 shows the deterministic equivalents of the SAA models corresponding to different values of S to emphasize the difficulty of solving the SAA model. With S=10, 20, 30, and 40, the SAA model can be solved, however CPLEX OPL gives a memory error once the sample size reaches 50. As a result, once the iteration, which has a sample size of 40, is completed, we terminate the SAA procedure even if the optimality gap is not lower than ε.

Table 21. Size of the deterministic equivalent of the SAA problem

Sample size	**Constraints**	**Variables**		**CPU interval (secs)**
		Binary	Integer	
S=10	22,153,094	2,355,505	2,355,650	[80,100]
S=20	44,306,104	4,710,895	4,711,300	[200,450]
S=30	66,459,114	7,066,285	7,066,950	[350, 700]
S=40	88,612,124	9,421,675	9,422,600	[800,2000]

Table 22 provides the objective function values of 10 replications obtained by the SAA algorithm for the given sample size values. The mitigation project selections are given in Table 23. The minimum objective function values determine the solution which is used to find the upper bound and the associated mitigation project selections are highlighted in Table 23.

Table 22. Objective function values for S=10, 20, 30, 40 scenarios and budget=20%

Sample size	Replications									
	n=1	n=2	n=3	n=4	n=5	n=6	n=7	n=8	n=9	n=10
S=10	**1379752**	2449453	1632637	1594897	1926133	2444926	1502049	1595108	1564921	1757252
S=20	1813809	**1350744**	1948732	1360372	2062018	3020437	1407805	3085745	1587484	1406822
S=30	2209234	**1332108**	1469101	2130820	1363521	1799932	1709411	2913213	2693094	1527489
S=40	1715671	2544958	1616044	2508412	1553979	**1395979**	2423177	1953245	2485795	2090078

Table 23. Mitigation project selections in the SAA algorithm for S=10, 20, 30, 40 scenarios and budget=20%

Replications	S=10	S=20	S=30	S=40
n=1	**1, 29, 30, 33, 53, 64,82**	14, 16, 33, 53, 64, 72, 82	16, 29, 33, 53, 64, 82	1, 29, 30, 33, 53, 64, 82
n=2	16, 29, 33, 53, 64, 82	**16, 29, 33, 53, 64, 82**	**16, 29, 33, 53, 64, 82**	1, 29, 30, 33, 53, 64, 82
n=3	16, 29, 33, 53, 64, 82	16, 29, 33, 53, 64, 82	16, 29, 33, 53, 64, 82	16, 29, 33, 53, 64, 82
n=4	16, 29, 33, 53, 64, 82	1, 29, 30, 33, 53, 64, 82	16, 29, 33, 53, 64, 82	16, 29, 33, 53, 64, 82
n=5	16, 29, 33, 53, 64, 82	14, 16, 33, 53, 64, 72, 82	16, 29, 33, 53, 64, 82	16, 29, 33, 53, 64, 82
n=6	16, 29, 33, 53, 64, 82	16, 29, 33, 53, 64, 82	16, 29, 33, 53, 64, 82	**16, 29, 33, 53, 64, 82**
n=7	16, 30, 33, 53, 64, 72, 82	16, 29, 33, 53, 64, 82	16, 29, 33, 53, 64, 82	1, 29, 30, 33, 53, 64, 82
n=8	16, 29, 33, 53, 64, 82	14, 16, 33, 53, 64, 72, 82	16, 29, 33, 53, 64, 82	16, 29, 33, 53, 64, 82
n=9	16, 29, 33, 53, 64, 82	16, 29, 33, 53, 64, 82	16, 29, 33, 53, 64, 82	16, 29, 33, 53, 64, 82
n=10	14, 16, 33, 53, 64, 72, 82	16, 29, 33, 53, 64, 82	1, 29, 30, 33, 53, 64, 82	16, 29, 33, 53, 64, 82

Table 24 shows the estimated gap between the upper and lower bounds for different number of sample size. We can see that as we increase the sample size, the estimated optimality gap between the upper bound and the lower bound decreases. As mentioned earlier, we terminate the SAA algorithm for S=40 scenarios as the SAA model with the bigger sample size (S=50) is not able to solve by CPLEX OPL. Even though the targeted optimal gap has not been reached, the best estimated gap value is less than 5% as seen in Table 24.

Table 24. Estimated gap for different choices of S and 20% budget level

Number of scenarios	Estimated lower bound	Estimated upper bound	Optimality gap (%)
S=10	1784713	3069128	41.8
S=20	1904397	2100275	9.3
S=30	1914792	2043220	6.28
S=40	2028734	2038586	4.83

Table 25 provides the unmet demand values for demand nodes over 40 scenarios in the best bound solution when we set the budget level equal to 20%. In this solution (*S*=40), there is unmet demand in only 18 out of 40 scenarios and evacuees at demand node 15 could not be transferred to a medical centre in 9 out of these 18 scenarios. In general, there are 3 demand nodes (8,9,15) where all evacuation demand cannot be met over the scenarios.

Table 25. Best upper bound solution for 40 scenarios

Scenario	**Demand node**	**Unmet demand**
1	15	573
2	15	573
6	15	573
11	15	573
12	8	399
16	9	25
17	8	25
20	15	573
21	9	25
22	9	399
22	15	573
23	15	573
27	9	25
28	9	25
31	15	573
35	9	25
36	15	573
40	9	25

The estimated optimality gap values are the smaller relative to the lower bound and upper bound values when the sample sizes are large enough, demonstrating that the SAA can identify satisfactory solutions for the simplified Istanbul network. The proposed SAA approach is not applicable for large instances (the detailed network) which we cannot solve optimally in CPLEX OPL even with modest sample size values.

6.3. Heuristic Algorithm Results

The GRASP algorithm is utilised for the simplified and detailed network. The GRASP algorithm's efficiency is validated by the optimal results obtained by CPLEX OPL for the simplified network. The algorithm is then used for the detailed network that CPLEX OPL is unable to solve. The analysis results and derived insights are presented in the following.

6.3.1. GRASP Parameter Setting

We perform the computational tests to determine the best values for all the parameters of the GRASP. For parameter setting, the simplified roadway network data is used with various budget levels. Each parameter set is tested with 5 different budget levels (15%, 17.5%, 20%, 22.5%, and 25%) and 40 different scenarios since the maximum sample size is 40 that we could acquire optimal results by CPLEX OPL. The levels for each parameter are listed in Table 26.

Table 26. Levels of parameters

Parameters	**Levels**
α (Coefficient to determine RCL)	0.1, 0.2, 0.3, 0.4, 0.5
$MaxIter$ (Maximum iterations for constructive phase)	10, 20, 30

15 different parameter combinations (α (5 levels) and $MaxIter$ (3 levels)) are tested for 5 different budget levels and 40 different scenarios. These levels are chosen according to the result of preliminary tests. Once α is higher than 0.5, the quality of results significantly decreases so the levels (0.1, 0.2, 0.3, 0.4, 0.5) are selected for the parameter calibration tests. Since a large number of neighbour solutions were produced for each initial solution, the optimal result could be achieved in a small number of iterations. The parameter levels are chosen to be able to provide optimal solutions while CPU remains reasonable after preliminary tests. Each combination is solved for three different scenario sets (each scenario set has 40 scenarios). Figure 24 illustrates the parameter combinations according to the average and maximum % gap

between the heuristic solution' and the optimal solution's primary objective function value for each budget level.

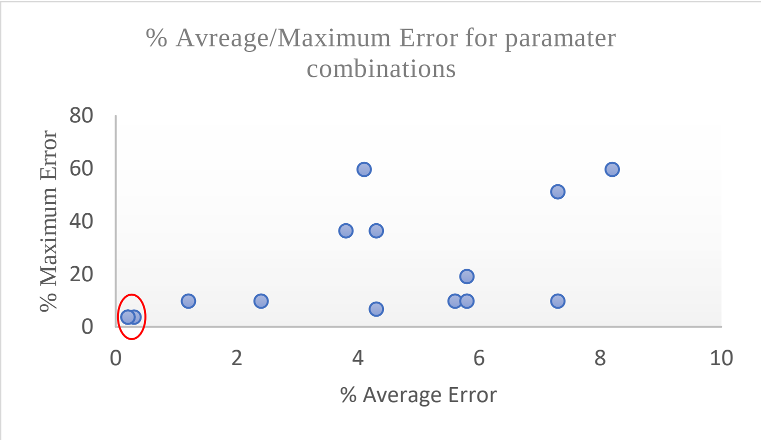

Figure 24. Error % of parameter combinations

The performance of each parameter combination is measured in terms of the average gap% from optimal results and the CPU time and we selected the best parameter combination that leads to minimum gap% and solution time from these combinations. The best parameter combinations for GRASP are α (0.4), $MaxIter$ (20) and α (0.4), $MaxIter$ (30). We selected the parameter combination (0.4, 20) that leads to an average error of 0.2% and a maximum error of 3.70% with less CPU. This combination finds the optimal solution (the mitigation project selections with the optimal unmet demand value) except one scenario with a budget level which means 1 out of 15 problems. Although it could not provide the optimal solution, it finds a good-quality solution which the gap in the primary objective is only 3.70%. Average CPU is 184 seconds. This combination is used for the rest of computation experiments.

6.3.2. Simplified Network Results

We first evaluate the performance of the proposed GRASP algorithm by comparing with the CPLEX OPL solutions. For various scenarios, we conducted experiments for varying budget levels on the simplified Istanbul roadway network.

We first conducted 10 experiments (replications) with 20 and 40 scenarios for a budget level of 20% to validate the GRASP procedure's performance using the optimal results provided by CPLEX OPL. Tables 27 and 28 show the projects that were chosen (mitigation decisions), the unmet demand ratio over all scenarios (*UD*%), the average travel distance per evacuee, and the solution time (CPU). Since the GRASP procedure finds the same mitigation decisions and unmet demand values as in optimal solutions, these are reported in one column only.

Table 27. Results for S=20 and B=20%

Budget levels %	Rep	Chosen Projects Optimal	*UD*%	Average travel distance (km) Optimal	Average travel distance (km) GRASP	CPU (secs) Optimal	CPU (secs) GRASP
20	1	14, 16, 33, 53, 64, 72, 82	1.24	26.06	28.69	388	62
	2	16, 29, 33, 53, 64, 82	0.84	28.05	30.42	287	61
	3	16, 29, 33, 53, 64, 82	1.21	27.6	29.77	298	139
	4	1, 29, 30, 33, 53, 64, 82	0.59	29.33	31.72	440	195
	5	14, 16, 33, 53, 64, 72, 82	1.28	26.36	29.66	247	132
	6	16, 29, 33, 53, 64, 82	2.13	28.23	30.54	233	176
	7	16, 29, 33, 53, 64, 82	0.87	28.09	30.17	201	140
	8	14, 16, 33, 53, 64, 72, 82	2.03	26.30	29.15	463	253
	9	16, 29, 33, 53, 64, 82	0.98	27.84	29.89	229	146
	10	16, 29, 33, 53, 64, 82	0.63	27.97	30.57	289	185
		Average	**1.18**	**27.58**	**30.05**	**307.5**	**148.9**

Table 28. Results for S=40 and B=20%

Budget levels %	Rep	Chosen Projects Optimal	*UD*%	Average travel distance (km) Optimal	Average travel distance (km) GRASP	CPU (secs) Optimal	CPU (secs) GRASP
20	1	1, 29, 30, 33, 53, 64, 82	1.07	28.01	30.55	1224	627
	2	1, 29, 30, 33, 53, 64, 82	1.58	28.10	30.53	878	585
		1, 14, 29, 33, 53, 64, 82		-	30.73		
	3	16, 29, 33, 53, 64, 82	1.00	27.95	29.77	922	280
	4	16, 29, 33, 53, 64, 82	1.56	27.76	30.13	627	368
	5	16, 29, 33, 53, 64, 82	0.97	27.84	30.10	1068	257
	6	16, 29, 33, 53, 64, 82	0.87	27.90	30.34	653	388
	7	1, 29, 30, 33, 53, 64, 82	1.51	28.16	30.54	798	329
	8	16, 29, 33, 53, 64, 82	1.21	27.55	30.13	1092	371
	9	16, 29, 33, 53, 64, 82	1.55	27.84	30.15	646	605
	10	16, 29, 33, 53, 64, 82	1.30	27.88	30.45	961	783
		Average	**1.26**	**27.90**	**30.29**	**886.9**	**459.3**

The GRASP algorithm performs very well in terms of primary objective and solution time (CPU). It yielded optimal results regarding the primary objective (unmet demand) much faster than CPLEX OPL for each replication. This is significant while solving problems with a large number of scenarios in GRASP. For each replication, the GRASP algorithm identifies the evacuation allocations that produce the same *UD*% with the optimal solutions. We compare the average travel distance per evacuee for each solution given by CPLEX OPL and the GRASP algorithm. For all replications, evacuation allocations are not identical so the average travel distance which is found by the GRASP algorithm is slightly more than the optimal solutions regardless of whether the chosen mitigation projects are the same.

Since this problem is handled at the strategic level, the most crucial decision is to determine which links to mitigate. In the case for S=40 (see Table 28), the average travel distance per evacuee resulting from GRASP's evacuation allocations is 2.4 km longer than the optimal results on average, but this discrepancy has no impact on choosing the best mitigation project sets. Since it is not an operational-level problem, the slight differences on the allocations do not matter regarding the strategic decisions as long as it finds the best strategic decisions. CPLEX OPL can easily identify optimal evacuation allocations for these selections as long as we find the best mitigation decisions.

There would be alternative protection planning decisions that provide the same *UD*% with the optimal solution. The GRASP algorithm reports all alternative solutions with the same *UD*%. For 40 sample size tests, two different project selections providing the same *UD*% are found in the second replication (see Table 28). {1, 28, 29, 33, 53, 64, 82} is the optimal solution whereas the other is an alternative solution {1, 14, 29, 33, 53, 64, 82}. Since the optimal project selection provides a better solution in terms of travel distance with a minor difference, the chosen solution is the same as in the optimal project selection in the GRASP algorithm as well. However, it demonstrates that other mitigation decisions would provide optimal solutions if minimising *UD*% would be considered as an only objective.

The GRASP algorithm performs very well for the problem with 40 sample size when B=20%. The algorithm’s performance is also tested with various budget levels (7 levels) and compared to the optimal results in terms of the ability of finding the optimal mitigation project selections, the associated objective function values, and CPUs for 40 sample size. Table 29 provides the *UD*% and average travel time per evacuee for both the GRASP algorithm and CPLEX OPL results. The GRASP algorithm finds the optimal mitigation decisions for every budget level. For each budget level, the GRASP algorithm allocates the evacuation demand resulted with the *UD*% with the optimal solutions. On the other hand, average travel distance per evacuee in the GRASP’s solutions is slightly more than the optimal results. Overall, the GRASP algorithm finds the optimal mitigation decisions with the allocations resulted with the same *UD*% in considerably less solution time.

Table 29. Comparison of GRASP and optimal results for various budget levels for S=40

Budget levels %	***UD*%**		**Average travel distance per evacuee**		**CPU (secs)**	
	CPLEX OPL	**GRASP**	**CPLEX OPL**	**GRASP**	**CPLEX OPL**	**GRASP**
10	8.1%	8.1%	27.85	30.19	713	152
12.5	5.4%	5.4%	27.3	29.77	1244	246
15	3.1%	3.1%	27.94	30.31	1286	202
17.5	2.2%	2.2%	26.78	29.87	1280	559
20	1%	1%	27.83	30.21	950	425
22.5	0.03%	0.03%	28.75	30.5	1248	315
25	-	-	25.41	29.31	1420	618

**UD*%: Uncovered demand percentage in all demand

We assess the GRASP algorithm's performance and confirm its efficiency on the problems with 20 and 40 sample sizes. As previously indicated, the maximum sample size for optimal results by CPLEX OPL is 40. Since the number of possible scenarios is rather large, we use the GRASP algorithm to solve problems that require a larger number of scenarios (1000 sample size). It is also explored how the sample size influences mitigation project selections at each budget level. Table 30 displays the selected projects as well as the objective function values for each budget level for 40 and 1000 sample sizes. The CPLEX OPL is unable to produce a solution for a sample size of 1000, so only the GRASP solutions are provided for that sample size. It can be seen that the ratio of covered demand increases when the budget level is raised. Except for one budget level which is *B*=10%, the mitigation decisions are the same across three other budget levels. This fact reveals the necessity of conducting experiments with the problems containing larger sample sizes.

Table 30. Results for S=40 and S=1000

S	Budget levels %	Chosen Projects	*UD%*	Average travel distance (km)		CPU (secs)	
		Optimal		Optimal	GRASP	Optimal	GRASP
40	10	16, 29, 53	1434 (8.1%)	27.85	30.19	713	152
	15	16, 29, 33, 53, 64	550 (3.1%)	27.94	30.31	1286	202
	20	16, 29, 33, 53, 64, 82	181 (1%)	27.83	30.21	950	425
	25	1, 16, 29, 30, 33, 48, 53, 72, 64, 82	-	25.41	29.31	1420	618
1000	10	14, 53, 64, 72	1503 (8.5%)	-	28.97	-	1923
	15	16, 29, 33, 53, 64	559 (3.2%)	-	30.32	-	5573
	20	16, 29, 33, 53, 64, 82	210 (1.2%)	-	30.23	-	9940
	25	1, 16, 29, 30, 33, 48, 53, 72, 64, 82	-	-	30.10	-	12946

**UD%*: Uncovered demand percentage in all demand

Table 31 shows the impacts of the budget levels on the *UD*%, minimum and maximum *UD*% over 1000 scenarios. In these scenarios, if no mitigation project is implemented, on average 20% of demand will not be evacuated. In fact, in some demand areas, this rate can reach 30%. With the lowest budget level which is B=10%, mitigation projects are implemented for 4 links, and as a result, this rate decreases to 8% on average. Additionally, it has been noticed that the *UD*% has gradually decreased in budget rises.

Table 31. Unmet demand values for various budget levels for S=1000

Budget level %	Average unmet demand per scenario (UD%)	Min unmet demand (UD%)	Max unmet demand (UD%)
0	3471 (19.7%)	2319 (13.1%)	5322 (30.1%)
10	1503 (8.5%)	796 (4.5%)	3226 (18.2%)
12.5	949 (5.4%)	796 (4.5%)	1525 (8.6%)
15	559 (3.2%)	392 (2.2%)	1525 (8.6%)
17.5	403 (2.3%)	392 (2.2%)	952 (5.4%)
20	210 (1.2%)	0	1525 (8.6%)
22.5	46 (0.26 %)	0	952 (5.4%)
25	0	0	0

*UD%: Uncovered demand percentage in all demand

Table 32 provides the details about the chosen projects, such as mitigated link, its initial resilience level, projects' impact, and seismic risk level depending on where that link is located, for various budget levels and a sample size equal to 1000.

Table 32. Mitigation decisions for various budget levels for S=1000

		Chosen Projects										
		1	14	16	29	30	33	48	53	64	72	82
Mitigated link		1	10	11	22	23	26	36	40	49	55	62
Seismic-risk level		High	High	High	High	High	Medium	Medium	Low	Medium	Medium	Low
Initial resilience level		6	6	6	6	6	4	4	3	4	4	3
Project impact		1	1	1	1	1	2	1	2	2	1	3
Ultimate resilience levels		7	7	7	7	7	6	5	5	6	5	6
Budget levels (%)	10		✓						✓	✓	✓	
	12.5			✓	✓				✓	✓		
	15			✓	✓		✓		✓	✓		
	17.5		✓	✓	✓		✓		✓	✓		
	20			✓	✓		✓		✓	✓		✓
	22.5		✓	✓	✓	✓	✓		✓	✓		✓
	25	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓

We explore how the mitigation decisions differ at various budget levels. For instance, while links 40 and 49 (project 53 and 64) are selected to mitigate for all budget levels, links 11, 22 and 26 are always mitigated if the budget is more than 12%. Link 62 is only chosen in higher budget levels *B*=20%, 22.5%, and 25%. Link 1 and 36 are only chosen to mitigate when *B*= 25%.

Looking at the ultimate resilience levels of the selected links, all mitigated links will be operational in every scenario (based on the survivability thresholds), with the exception of links 36 and 55. Since these links are located in a medium seismic risk region, their resilience level should be more than 5 or 6 to be operational according to the scenario. The ultimate resilience level of links 36 and 55 is 5. This means that whether this link is operational or not depends on the scenario.

Protecting a link may change the accessibility conditions on routes. Therefore, the entire evacuation plan should be modified to take into account the updated network condition. Table 33 provides the frequency of unmet demand for particular intervals over 1000 scenarios. These results are helpful to assess the benefits of increasing the available protection budget in terms of reducing the unmet demand. We present the graphs including the total unmet demand frequencies over 1000 scenarios for these budget levels in Appendix H.

Ideally, a decision should be made to meet all demands in all scenarios. This is achieved by increasing the budget level to 25%. With this upgrade to the protection plan, project 1 and 48, which were not previously included in the protection plan for other budget levels, are chosen.

Project 72 is also included in the protection plan; this project was only chosen for two budget levels which are *B*=10% and 25%.

Table 33. Results details various budget levels for S=1000

Budget levels %	Chosen Projects	UD% frequencies				Average travel distance (km)	CPU (secs)
		>0	>%3	>%6	>%10		
0	-	1000	1000	1000	1000	-	-
10	14, 53, 64, 72	1000	1000	434	319	28.97	1923
12.5	16, 29, 53, 64	1000	1000	264	-	29.78	8930
15	16, 29, 33, 53, 64	1000	277	15	-	30.32	5573
17.5	14, 16, 29, 33, 53, 64	1000	19	-	-	30.52	9582
20	16, 29, 33, 53, 64, 82	486	277	15	-	30.23	9940
22.5	14, 16, 29, 33, 53, 64, 82	304	19	-	-	30.41	11932
25	1, 16, 29, 30, 33, 48, 53, 64, 72, 82	-	-	-	-	30.10	12946

We choose one of best and worst-case among 1000 scenarios for each budget level to evaluate how the best and worst situation are for various budget levels. In the following, these best and worst cases are visualised on maps. Demand and supplier nodes are identified with blue and orange round shapes with node numbers, respectively. The isolated demand nodes where have no access to any supplier are highligted with red circles. The demand nodes where the demand is partially met but not totally are highligted with green circles. Allocations between a demand-supplier nodes are shown with blue straight lines.

Figure 25. A representative result of the worst case for budget=10 %, UD=18.2%

Once *B*=10%, we see that the unmet demand is above 10% in roughly 30% of the scenarios. One of the worst cases among 1000 scenarios in terms of the rate of unmet demand is presented in Figure 25. None of the victims in three demand nodes (3, 5, and 24) is evacuated and the demand in other three areas (4, 8, and 18) is not entirely met. While some suppliers (1 and 4) only serve to only one demand node, some suppliers serve with full capacity (3, 8, and 7).

Figure 26. A representative result of the best case for budget=10% and 12.5%, UD=4.5%

There are no scenarios with *UD*% above 10% when the budget level is 12.5%. The best case for both budget levels (*B*=10% and 12.5%) is the same and shown in Figure 26. There are two demand nodes (5 and 24) which are isolated. Figure 27 shows one of the worst-case scenarios when *B*=12.5%. Compared to the previous case, while there are 4 demand nodes which are not met the demand when *B*=12.5%, there are 6 demand nodes with unmet demand when *B*=10%. Basaksehir (demand node 5) and Sultangazi (demand node 24) remain as isolated. On the other hand, the evacuees in Avcilar (demand node 3) are transferred to two suppliers (Bakirkoy and Beyoglu) while no one could be evacuated from Avcilar when the budget level is 10%.

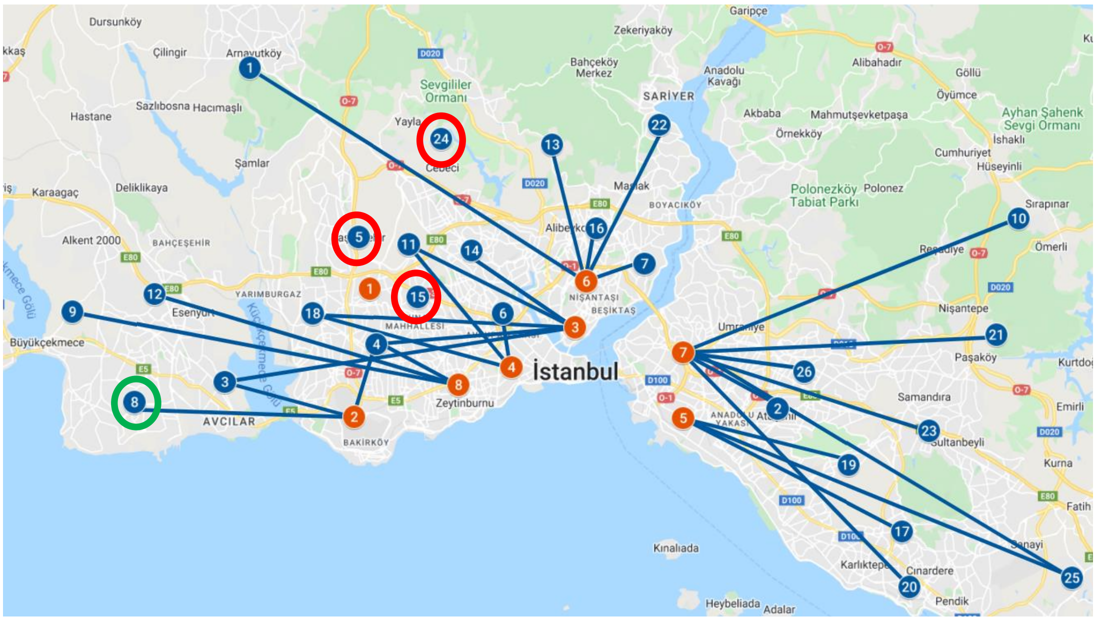

Figure 27. A representative result of worst-cases for budget=12.5%, UD=8.6%

Project 33 mitigating link 23 is added to the previously selected projects when the budget is increased from 12.5% to 15%. With this link being operational for each scenario, the number of scenarios with more than 6% *UD*% drops from 264 to only 15. The worst-case scenario for *B*=15% results in the same amount of unmet demand with the budget level being equal to 12.5%. However, the allocations are not identical, so while there are 3 demand nodes (8, 15, and 24) with unmet demand for *B*=15% (see Figure 28), there are four demand nodes (5, 8, 15, and 24) with unmet demand for *B*=12.5%. Once the budget level is increased, the allocations are updated regarding the accessibility between *i-j* (5-3) pairs and the people at Basaksehir (demand node 5) are transferred to Avcilar (supplier node 3). In the best case when *B*=15%, there is only one demand node (24, Sultangazi) which is isolated as seen in Figure 29.

Figure 28. A representative result of the worst-cases for budget=15%, UD=8.6%

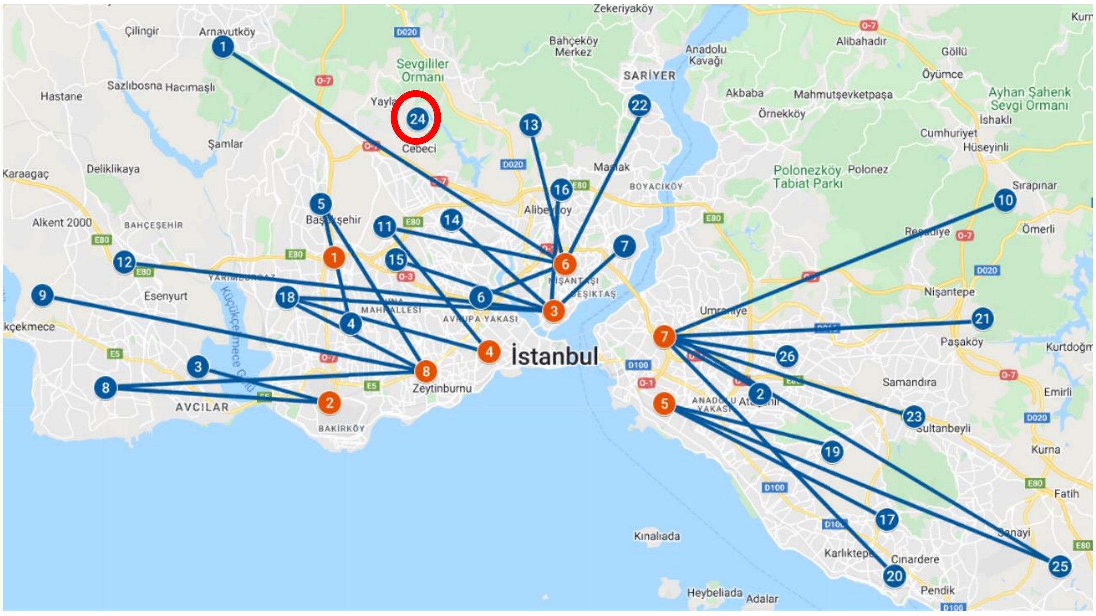

Figure 29. A representative result of the best-cases for budget=15%, UD=2.2%

The unmet demand ratio never exceeds 6% in any scenario when the budget is increased to 17.5%. When *B*=20%, the selected project 14 is removed, and project 82 is added in its place. All demand is met in more than 50% of the scenarios. The number of scenarios, where in the *UD*% is above 6%, has increased compared to the situation where the budget is 17.5%. However, since the algorithm focuses on minimising the total unmet demand over scenarios, we see that increasing the budget by 2.5% reduces the unmet demand by nearly half (see in Table 31). This increase in the budget level from 20% to 22.5% enables to mitigate two more links. Link 10 and 23 are operational in all scenarios. Eventually, all people in need can be evacuated in approximately 70% of the scenarios and the *UD*% is more than 3% in only 19 scenarios.

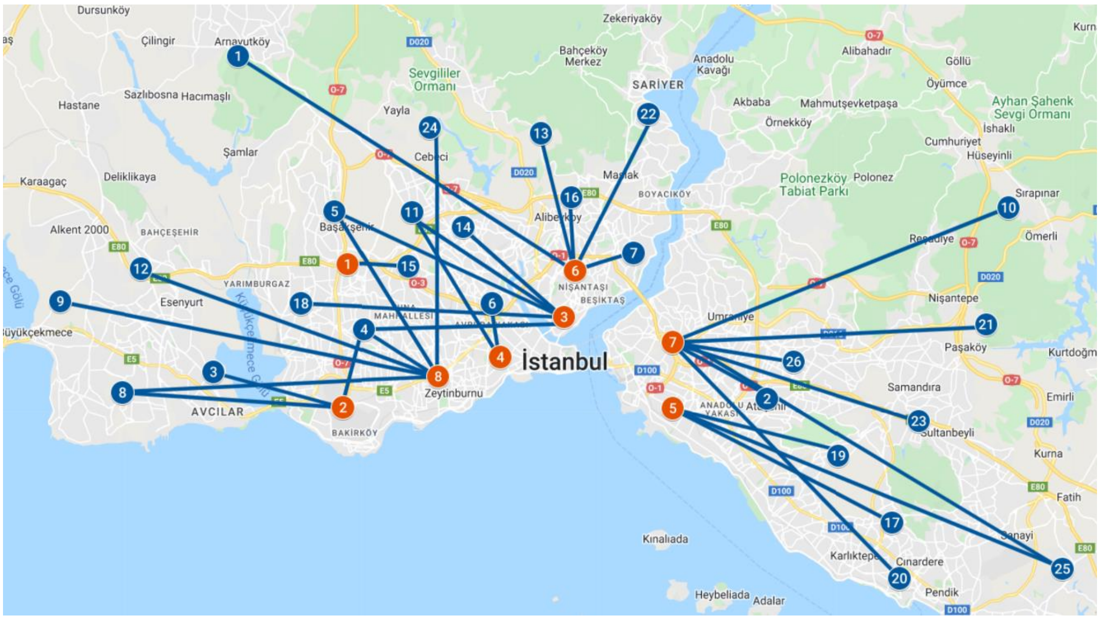

Figure 30. A representative result of the best-cases for budget=22.5 %, UD=0

Typically, the evaluation of a candidate solution requires considering all scenarios. We conducted the experiments for the previously utilised budget levels to evaluate the effect of sample size (*S*) on solution quality. We increase the sample size by 1000 in each iteration for the previously used budget levels. In Table 34, we report the chosen projects, the percentage of unmet demand (column *UD*%), and the elapsed CPU time (seconds) required to obtain the solution. It shows that there is no significant change in *UD*% as *S* varies. Additionally, the proposed algorithm chooses the same mitigation projects regardless of *S*. However, when the sample size is increased, the CPU time rises considerably.

Table 34. Sample size analysis

Sample size	Budget levels%	UD%	Chosen Projects	CPU (secs)
1000	10	8.5	14, 53, 64, 72	1923
	12.5	5.4	16, 29, 33, 53	8930
	15	3.2	16, 29, 33, 53, 64	5573
	17.5	2.3	14, 16, 29, 33, 53, 64	9582
	20	1.2	16, 29, 33, 53, 64, 82	9940
	22.5	0.26	14, 16, 29, 33, 53, 64, 82	11932
	25	-	1, 16, 29, 30, 33, 48, 53, 64, 72, 82	12946
2000	10	8.6	14, 53, 64, 72	4234
	12.5	5.4	16, 29, 53, 62	13880
	15	3.2	16, 29, 33, 53, 64	12763
	17.5	2.3	14, 16, 29, 33, 53, 64	25407
	20	1.2	16, 29, 33, 53, 64, 82	20307
	22.5	0.26	14, 16, 29, 33, 53, 64, 82	26759
	25	-	1, 16, 29, 30, 33, 48, 53, 64, 72, 82	28007
3000	10	8.5	14, 53, 64, 72	8332
	12.5	5.4	16, 29, 53, 62	20197
	15	3.2	16, 29, 33, 53, 64	19007
	17.5	2.3	14, 16, 29, 33, 53, 64	37785
	20	1.2	16, 29, 33, 53, 64, 82	32355
	22.5	0.22	14, 16, 29, 33, 53, 64, 82	37515
	25	-	1, 16, 29, 30, 33, 48, 53, 64, 72, 82	41717

*UD%: Uncovered demand percentage in all demand

In summary, the GRASP algorithm's efficiency is evaluated by comparing it to the ideal solutions for the problems with small sample sizes. The GRASP algorithm finds the optimal mitigation decisions with the optimal unmet demand values for each budget level. Afterwards, the impact of the sample size on the solution is investigated by increasing sample size to 1000, 2000, and 3000. The mitigation decisions with 1000, 2000, and 3000 sample sizes are identical for seven budget levels. As can be concluded from this, the solution reached for the problem involving 1000 scenarios for the simplified network is potentially the optimal for the problem involving all scenarios.

6.3.3. Detailed Network Results

CPLEX OPL cannot solve the proposed model with the detailed network instance even for a single scenario. Here, the GRASP algorithm is applied to select which links in the detailed Istanbul roadway network should be mitigated considering how the demand is allocated in different scenarios. Due to the high solution times, we only employ five scenarios including one best-case, three medium-case, and one worst-case. The best-case scenario has the following minimum threshold levels for each link: 6 for high-risk level links, 5 for middle-risk level links, and 4 for low-risk level links. The medium-case scenarios are randomly generated as each scenario having one of two potential threshold values: 6 or 7 for high-risk level linkages, 6 or 5 for middle-risk level links, and 5 or 4 for low-risk level links. The highest threshold levels are chosen for each link in the worst-case scenario as 7 for high-risk level links, 6 for middle-risk level links, and 5 for low-risk level links. We defined the budget levels by some preliminary analysis. Experiments have been performed for different budget levels for the detailed network, starting from 2.5% of the protection budget (the total cost of candidate projects). We employ six budget levels starting from 2.5% and increasing by 2.5% at each step to draw more insights. These experiments continued until we reached the budget level at which all demand would be met to draw further insights. $B = 0$ corresponds to the current situation without any mitigation efforts.

There are 1295 network links on the detailed network and there is no need for mitigation projects for some links if a link's resilience level is high (>6) and/or in a low-seismic risk region. Therefore, for the detailed network, 364 projects are defined to strengthen the network links and accordingly improve the accessibility. The defined mitigation projects are provided in Appendix I.

In the computational experiments employing the simplified network, One-Step Local Search (LS) was used, and it has produced high-quality solutions. Multi-Step LS has not been evaluated for the experiments with the simplified network since the problem comprises a significant number of scenarios. In addition, One Step LS has found the optimal results for the problems involving a modest size of scenarios, for all budget levels. Since the number of scenarios in the analyses to be performed with the detailed network is not high, it has been decided to compare the two local search strategies on the solution quality. Table 35 reports the GRASP results with One-Step and Multi-Step LS methods for various budget levels. As observed in the *UD*% for each budget level, the GRASP algorithm with Multi-Step LS outperforms the version using the One-Step procedure. For the problem capturing these five scenarios, we start the computational experiments with B=2.5% and increase by 2.5% in each experiment. Once B=2.5%, 6 out of 10 projects are common in the results with both local search method. When B=15%, for both methods, 60 projects are chosen and 54 out of 60 projects are common. These differences in the mitigation decisions have impacts on the network accessibility and accordingly on the different allocations. Even though the UD% is only slightly different between the two LS methods, since each demand refers to the transfer of a person who needs medical care, these differences are undoubtedly significant. When the Multi-Step LS is implemented, the solution time is accordingly increased as expected but still reasonable for this problem.

Table 35. Comparison of local search methods for the detailed network

Budget levels %	Chosen Projects		Ratio of unmet demand (UD%)		CPU (secs)	
	One Step LS	Multi Step LS	One Step LS	Multi Step LS	One Step LS	Multi Step LS
2.5	**12, 41,** 43, 50, **119**, 124, 140, **145,** 156, 332	43, **46, 48**, 50, **62**, 124, 140, 156, **178**, 332	10.11	8.9	3797	7822
5	4, 7, **9**, 12, **41**, 43, 50, **53**, 62, 80, **119**, 124, 140, 145, 156, 178, 207, **286,** 332, **357**	**3**, 4, 7, 12, **28**, 43, **44, 46, 48**, 50, 62, 80, 124, 140, 145, 156, 178, 207, **223,** 332	7.78	6.1	5442	11811
7.5	**3**, 4, 7, **9**, 12, **18**, 28, 41, 43, 50, 53, 56, 62, 80, 108, 113, **119**, 124, 140, 145, 147, 156, 178, 207, 223, 239, 270, 332, **357**	4, 7, 12, 28, 41, 43, **44, 46, 48,** 50, 53, 56, 62, 80, 108**, 110**, 113, 124, 140, 145, 147, 156, 178, 207, 223, 239, 270, **302,** 332	5.6	4.3	7156	13655
10	4, 7, 12, **18**, 28, 41, 43, 44, 46, 48, 50, 53, 56, 57, 62, 77, 80, **85**, **96**, 104, 108, 110, 113, 124, 140, 145, 147, 156, 178, **207**, 223, 230, 239, 270, 275, 291, 302, **329**, 332, 357	**3**, 4, 7, **9**, 12, 28, **37,** 41, 43, 44, 46, 48, 50, 53, 56, 57, 62, 77, 80, 104, 108, 110, 113, 124, 140, **143**, 145, 147, 156, 178, **188**, 223, 230, 239, 270, 275, 291, 302, 332, 357	3.33	2.5	9391	15612
12.5	3, 4, 7, 9, 12, 28, 37, 41, 43, 44, 46, 48, 50, 53, 56, 57, **61**, 62, 71, 77, 80, 83, 104, 108, 110, 113, 120, 124, 140, 143, 145, 147, 156, 178, 188, 199, **203**, 212, 223, 230, 239, 256, 270, 275, 286, 291, 302, 329, 332, 357	3, 4, 7, 9, 12, **18**, 28, 37, 41, 43, 44, 46, 48, 50, 53, 56, 57, 62, 71, 77, 80, 83, 104, 108, 110, 113, **119**, 120, 124, 140, 143, 145, 147, 156, 178, 188, 199, 212, 223, 230, 239, 256, 270, 275, 286, 291, 302, 329, 332, 357	1.7	1.5	10057	16721
15	3, 4, 7, 9, 12, **18,** 28, 37, 41, 43, 44, 46, 48, 50, 53, 56, 57, **61**, 62, 71, 75, 77, 80, 83, **85**, 96, **104**, 108, 110, 113, 117, 119, 120, 121, 124, 140, 143, 145, 147, 156, 167, 178, 188, 199, 203, 212, 217, 223, 230, 239, 256, 270, 275, **286**, 291, 302, 329, 332, 354, **357**	3, 4, 7, 9, 12, 28, 37, **39**, 41, 43, 44, 46, 48, 50, 53, 56, 57, 62, **69,** 71, **73**, 75, 77, 80, 83, 96, **103**, 108, 110, 113, 117, 119, 120, 121, 124, 140, 143, 145, 147, 156, 167, 178, 188, 199, 203, **207**, 212, 217, 223, 230, **237,** 239, 256, 270, 275, 291, 302, 329, 332, 354	0.9	0.6	14042	19798

*Different projects in the results of both LS methods are highlighted in bold.

On the detailed Istanbul roadway network, we conduct experiments with varied budget levels for the mentioned five scenarios. In average, 20% of the total demand could not be evacuated in the initial state due to the accessibility difficulties according to the considered scenarios. Implementing 10 out of 364 projects with B=2.5% leads to a considerable improvement in UD% which drops from 20.1% to 8.9%. As expected, more links are mitigated as the budget increases, and the UD% eventually decreases as accessibility improves.

Table 36. UD% in the scenarios for various budget levels

Budget levels%	Worst	Middle 1	Middle 2	Middle 3	Best
0	27.7	17.1	16.1	17.9	-
2.5	19.5	6.9	6.9	11.1	-
5	15.7	3.1	5.6	6.3	-
7.5	10.9	2.2	4.5	4.1	-
10	6.1	1.7	1.3	3.1	-
12.5	4.7	0.4	0.9	1.6	-
15	0.3	-	-	-	-
15.25	-	-	-	-	-

We evaluate how the worst, middle, and best scenarios differ for various budget levels in terms of *UD*%. Since the survival states of links vary between the scenarios, the UD% for each scenario would be different. As in the proposed model, the chosen links are selected to minimize the average of total unmet demand in all scenarios. Table 36 provides the UD% in each scenario for the initial state and seven different budget levels. For the best scenario, there is no unmet demand in the initial state. We observe that while the unmet demand rate is 28% in the worst-case scenario, it is about 17% on average for the middle scenarios in the initial state. Even a small investment (*B=2.5%*) in strengthening links leads to significant improvement in evacuation allocation efficiency especially for the medium-case scenarios. When B=5%, the UD% reduced by half compared to the initial state in the worst-case scenario but still has a high value at around 15%. In the middle scenarios, the UD% decreased to 3% in the first scenario, and it was around 6% in the other medium-case scenarios. By raising B to 10%, the UD% decreased to 6% in the worst-case scenario. In other middle scenarios, the minimum and maximum UD% were 1.3% and 3.1%, respectively.

When B is increased to 15%, only one node's demand is not met in the worst-case scenario and the other demand is entirely met in the other scenarios. Instead of increasing the budget, we first determine the critical links which are not operational and connect this demand node and suppliers. There was only one link which is not operational and connects the associated demand node and suppliers. It has been seen that if only one additional project which is 18 is involved in the solution, all demand will be met for all scenarios. One-Step Local Search is applied by assigning this project as a single element in the *CL* and at the end, no better version of the solution is found. As a result, there was no other option but to increase the budget for this project to reach full coverage. Project 18 is implemented once B=15.25% so by upgrading the network accessibility all demand is met for all scenarios including the worst scenario with 61 out of 364 projects implementations (see last row of Table 36).

The solutions for some budget levels and scenarios are visualised on maps in the following. In these map representations, which include the worst-case and one of the three medium-case scenarios, each supplier node is represented by a different colour. The demand nodes allocated with these suppliers are likewise highlighted in the colour associated with that supplier. If a demand node is served by more than one supplier, that demand node is highlighted by the supplier colour where the majority of demand is transferred. If the demand at the demand nodes could not be met, these demand points are denoted by a different symbol in the maps (circle with a cross).

The disparity between scenarios is more obvious, especially when there is a limited budget for protection projects. Due to inaccessibility to the number of affected areas, there are more isolated demand nodes in the worst-case scenarios. For instance, when B=2.5%, 30 out of 154 affected areas are isolated and no one can be evacuated from these areas in the worst-case scenario as seen in Figure 31. In the medium-case scenario given in Figure 31, 19 affected areas are isolated, which is still quite high. While no one can be transferred to suppliers 1 and 2 from any demand node in the worst-case scenario, evacuation activities are carried out to Sabiha Gokcen Airport (supplier 1) from 2 demand nodes and to Ataturk Airport (supplier 2) from 6 demand nodes, respectively in the given medium case scenario.

When the budget level is increased to 5%, 25 out of 154 affected areas are isolated and no one can be evacuated from these areas in the worst-case scenario. Additionally, there was no evacuation from any region to supplier 1 in the worst-case scenario, as with the previous budget level. However, since the roads connecting supplier 2 and affected areas were strengthened by the projects, evacuation activities are carried out to supplier 2 from 6 affected areas even in the worst-case scenario.

When B=7.5%, 19 out of 154 affected areas are isolated and no one could be evacuated from these areas in the worst-case scenario. In one of the medium-case scenarios, 7 affected areas are isolated. When the budget is increased to 7.5%, 3 in the worst-case scenario, and 7, 6, and 6 affected areas in the middle case scenarios are allocated by supplier 1, that had not been evacuated from any region with the previous budget levels.

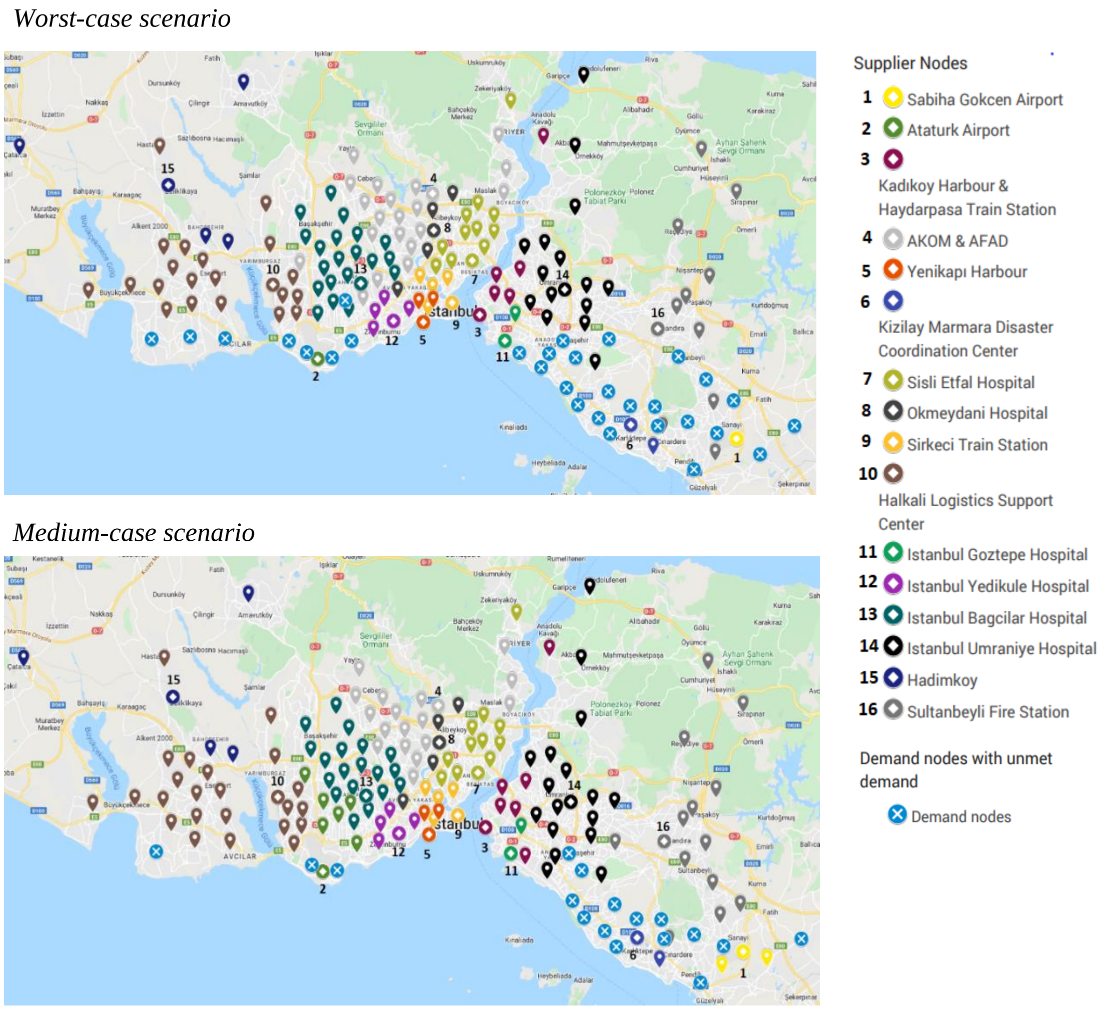

Figure 31. Worst- and medium-case scenario for B=2.5%

Figure 32 represents the worst- and a medium-case scenario solutions for B=10%. With 10% budget level, the demand of 11 out of 154 demand regions could not be met in the worst-case scenario. Looking at the medium case scenarios, we see that the evacuation demand for 2, 4, and 5 (given in Figure 32) affected areas could not be met. By increasing the budget by an additional 2.5%, the number of affected areas whose demand could not be met decreased to 5 in the worst-case scenario (B=12.5%). While all demand is met in one of the medium-case scenarios, demand for 1 and 2 demand areas cannot be met in the other medium-case scenarios.

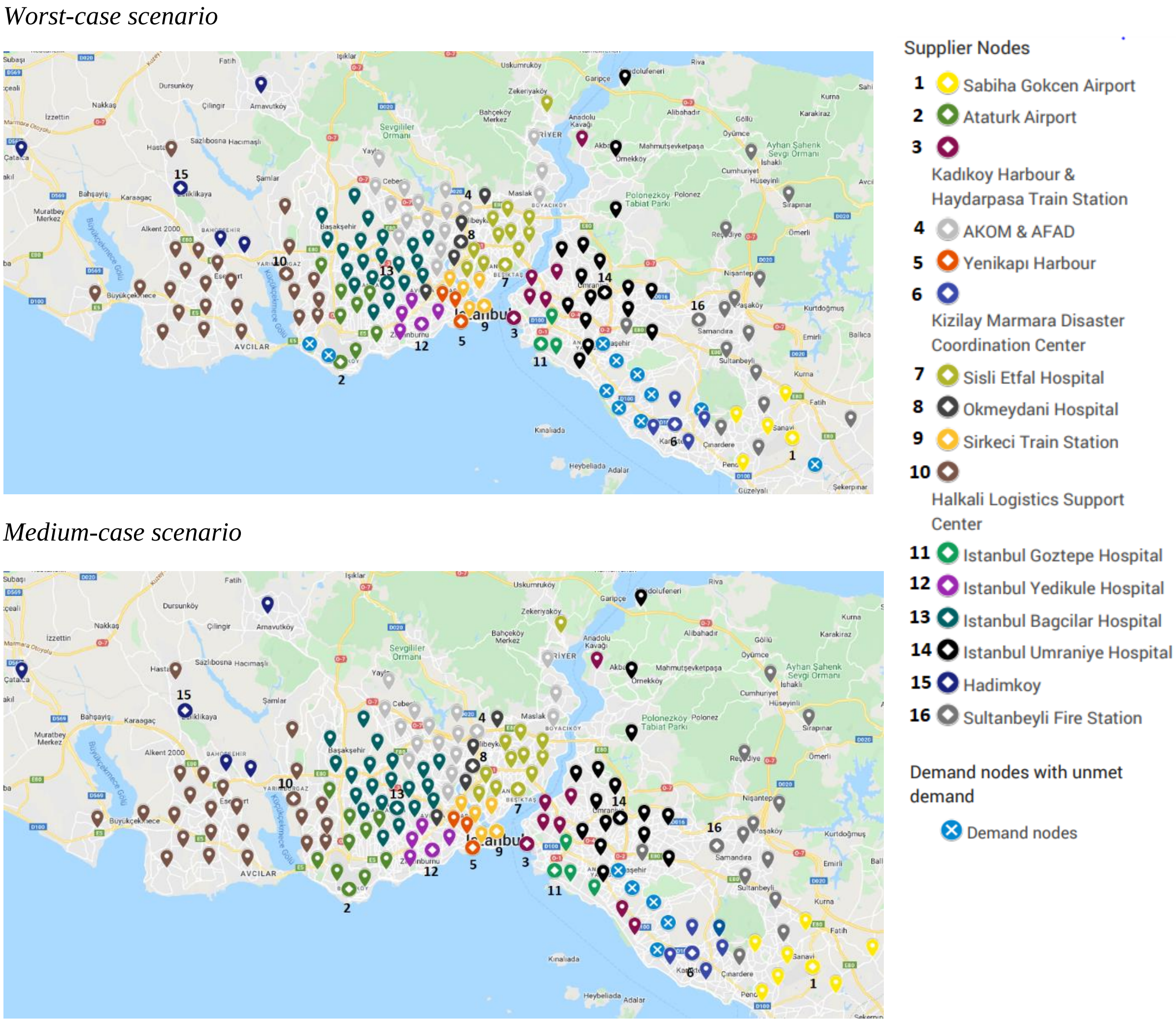

Figure 32. Worst- and medium-case scenario for B=10%

Worst-case scenario

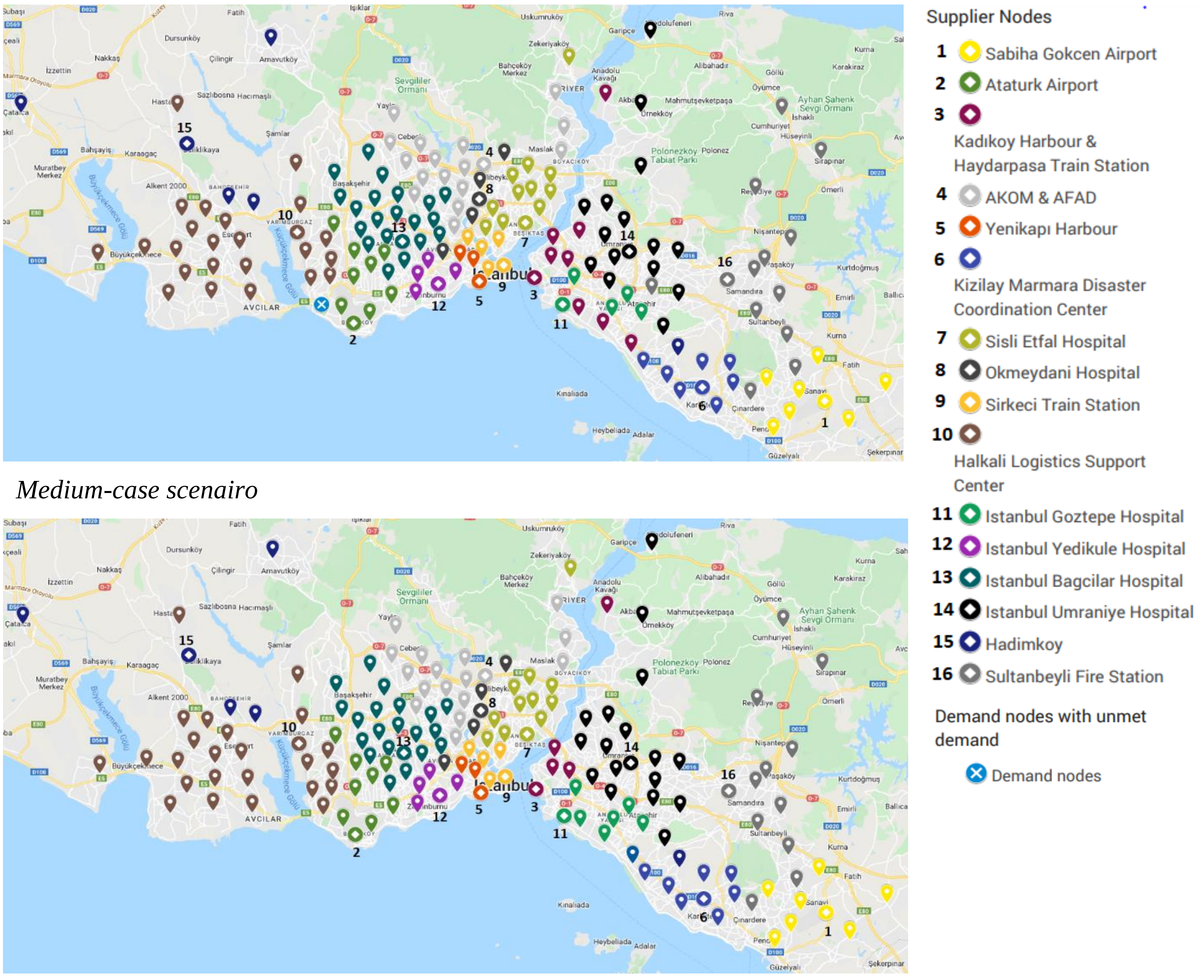

Figure 33. Worst- and medium-case scenario for B=15%

Finally, Figure 33 presents the worst- and a medium-case scenario solutions for *B*=15%. Some allocations differ between scenarios. For example, in the worst-case scenario, only the injured people in 4 demand nodes were evacuated to Istanbul Goztepe Hospital (supplier 11), while in the other 3 middle scenarios, 7, 6 and 7 were evacuated, respectively. On the other hand, disaster areas transferred to Istanbul Bagcilar Hospital (supplier 13) are the same in all scenarios, as accessibility is generally good. Since one of the critical links (roads) is non-operational, there is a demand node that has no access to any supplier in the worst-case scenario, even though it is extremely close to a supplier as shown on the solution in Figure 33. Eventually, this affected area has no connection to the identified suppliers, so no one is evacuated from that area in the worst-case scenario.

We observe that the affected areas where evacuation demand is not met are concentrated in specific regions. As illustrated in Figure 22 (see Chapter 5 and Appendix J), these regions are located in the high-risk areas and the effect of this fact is clearly noticeable in the findings. Evacuation from the earthquake-affected areas in these regions could not be carried out without necessary protection projects due to road inaccessibility.

6.4. Conclusion

In this chapter, we first compare the multi-objective approaches. The weighted-sum method finds the same results as the lexicographic method while taking less time to solve the model. Since the solution is theoretically always Pareto optimal with the lexicographic method, it has been decided to utilize the weighted-sum method in the following analyses.

Secondly, we apply the SAA method to reduce the scenario set to a manageable size. When sample numbers are large enough, the estimated optimality gap values are nearly 5%, suggesting that the SAA can find good solutions for the simplified Istanbul network. The SAA approach is inapplicable for large instances (the Istanbul detailed network), which we cannot solve optimally in CPLEX OPL even with small sample size values since we need to solve the model optimally with a suitable sample size.

Thirdly, the optimal results obtained by CPLEX OPL for the simplified network verify the efficiency of the GRASP algorithm for modest scenario sizes. The GRASP algorithm finds the optimal mitigation decisions with the optimal unmet demand values for each budget level for S=40. The effect of sample size on the solution is next studied by increasing the sample size to 1000, 2000, and 3000. For seven budget levels, the mitigation decisions with 1000, 2000, and 3000 sample sizes are equal. As a result, the solution found for the problem involving 1000 scenarios for the simplified network is potentially the optimal mitigation selections for the problem involving all scenarios.

Fourthly, the GRASP algorithm is applied to select which links in the detailed Istanbul roadway network should be mitigated considering how the demand is allocated in different scenarios. Due to the high solution times, we only employ five scenarios including one best-case, three medium-case, and one worst-case for the detailed network. We compare the situations for various budget levels through the results and map representations. The affected areas where evacuation demand is not met are concentrated in the regions which have high seismic intensity in the anticipated earthquake scenario (Model C in JICA report, see Appendix J). The findings show that, especially in low-budget protection planning cases, evacuation operations from these areas mostly could not be carried out due to road inaccessibility.

Different findings have been obtained in the computational experiments performed using two different networks belonging to the same geographical region. For example, in the simplified network results, there was no unmet demand arising from any accessibility issues even with the low budget levels, on the Anatolian side which has high-seismic regions. On the other hand, in the detailed network results, the affected areas with unmet demand were mostly on the Anatolian side, at almost all budget levels.

7. Conclusions

This chapter is split into two sub sections. Section 7.1 provides an overview of the entire thesis and highlights key findings. Section 7.2 discusses some of the limitations to this research and the future research recommendations.

7.1. Research Summary

At the start of this thesis, the conducted review stands apart from past and recent DOM review papers, given that we review studies dealing with earthquake-oriented problem definitions or those involving the use of earthquake disaster case studies. Throughout, we have precisely categorized studies based on the disaster stage(s) being dealt with, methodology(ies) applied, and specific planning/operational problem type. We also provide details about the extent of stakeholder involvement (see Appendix B) and information relating to case studies (i.e., type of infrastructure network examined, if any, and whether real or randomly generated data were used) (see Appendix C). The main conclusions were that most studies have concentrated on a particular stage of an EOM disaster, with preparedness and response problems receiving by far the most attention. Recent research has begun to investigate the merging of two or more disaster stages. In terms of modelling and solution methodology, mathematical programming and heuristics are by far the most widely used for most problem types, though there are exceptions. Finally, most studies have little or no stakeholder involvement.

To fill some of the highlighted research gaps in the first part of the dissertation, a Capacitated Network Strengthening Problem (CNSP) was formulated as a two-stage stochastic programming model in Chapter 3. This model offers several advances over existing works. The proposed model was the first attempt to address the protection and evacuation planning in an integrated manner by maximising the efficiency in post-earthquake evacuation operations (minimising the unmet demand and travel time simultaneously). We define resilience levels to estimate survival states of links, and we assume that the protection operations can improve the resilience levels of network links; however, they cannot guarantee that there will be no damage at all. Hence, we assume that estimated post-earthquake survival states of network links depend on the resilience level for a particular earthquake scenario. We believe that this approach is more realistic in terms of estimating survival states and assessment of protection strategies. In addition, the model considers the capacitated ERCs which has not been addressed in the literature before. If there is a backlog in the ERCs serving in certain locations, an already difficult situation may devolve into chaos so no one will be able to receive medical care. As a result, the capacity constraint is critical in this case.

In order to solve the CNSP, due to the model's multi-objective structure, multi-objective solution approaches such as lexicographic and weighted-sum methods were evaluated to determine the best method to apply for the analysis. The proposed stochastic problem is hard to solve as it is difficult to evaluate the expected cost of the second stage and it requires the solutions of a large number of second stage optimization problems as the number of possible scenarios is very large for the proposed problem. The scenario-based (deterministic equivalent) model of the stochastic problem has an exponential number of scenarios, which make it impractical to solve directly. Hence, a sample average approximation algorithm (SAA) is proposed to solve the problem. To estimate the performance of the SAA method, we first solve a small-scale case. The proposed SAA requires solving a considerable number of second-stage models so this method was not appropriate for the larger instances. Therefore, a GRASP-based algorithm has been developed to be able to solve larger instances of the problem. The GRASP algorithm uses a procedure combining a greedy approach for generating initial solutions and iterative improvement algorithm for local search to find evacuation allocations for the feasible solutions.

Two case studies are conducted using Istanbul roadway network datasets (the simplified and detailed network) under the earthquake having a magnitude of 7.7, which is identified as the worst-case scenario in the JICA report. Experimental results using the simplified network data have proven that the weighted-sum method outperforms the lexicographic method while requiring less processing time, so the weighted-sum has been employed for the rest of the analysis. In the experiments for the application of the SAA, when sample numbers are sufficient, the estimated optimality gap values are nearly 5%, suggesting that the SAA can find good solutions for the simplified Istanbul network. The GRASP-based heuristic algorithm was able to find the optimal mitigation decision obtained by CPLEX OPL for the simplified network for modest scenario sizes (S=40). The effect of sample size on the solution is next analysed by increasing the sample size to 1000, 2000, and 3000. The mitigation decisions with 1000, 2000, and 3000 sample sizes were equal at varied budget levels. As a result, the solution developed for the problem involving 1000 scenarios for the simplified network could be considered the best mitigation decisions for the problem including all scenarios. Lastly, the heuristic algorithm is applied to select the links to strengthened in the detailed Istanbul roadway network. Due to the high solution times, we have employed only five scenarios including one best-case, three medium-case, and one worst-case scenario for the detailed network. According to the results, the affected areas where evacuation demand is not met are concentrated in the regions which have high seismic intensity in the anticipated earthquake scenario (Model C in JICA report, see Appendix J). The findings show that, especially in low-budget protection planning cases, evacuation operations from these areas mostly could not be carried out due to road inaccessibility in the detailed network. Different findings have been obtained in the computational experiments performed using two different networks belonging to the same geographical region. This fact reveals that more reliable findings can be obtained since the detailed network covers other roads besides highway roads. For instance, in the simplified network results, there was no unmet demand arising from any accessibility issues even with the low budget levels, on the Anatolian side which has high-seismic regions. On the other hand, the affected areas with unmet demand were mostly on the Anatolian side, at almost all budget levels in the detailed network results. As a nutshell, the level of detail with which the used network is handled, as well as the supplier and demand locations identified, have a considerable impact on the solution.

7.2. Future Research Directions

Based on our extensive analysis of the conducted review in Chapter 2, we have identified the current gaps in the field and outlined a roadmap for future research to enhance the real-world applicability of OR methods applied to EOM in particular and potentially to DOM more generally. Some of these reaffirm findings and recommendations derived in previous surveys on OR applied to DOM, like the need for (i) more integrated planning that involves decision making across multiple disaster stages, such as infrastructure protection planning (mitigation) combined with relief distribution or evacuation (response) or shelter site location and RDC pre-positioning and inventory management (preparedness) combined with evacuation and relief distribution (response); (ii) more emphasis on and enabling of stakeholder and multi-agency coordination; (iii) integration of OR methods with information systems that provide real- and near real-time data, including the use of data provided by UAVs and social media; (iv) defining clear and realistic model inputs/assumptions; and (v) greater use of interdisciplinary and multi-methodology approaches, including behavioural OR to more accurately represent human behavioural responses. Other recommendation we provide, however, are new or much less emphasized in previous reviews. For example, we observe that in many studies, problem specifications are framed in terms of generic disasters as opposed to being specifically focused on earthquakes. This has resulted in a general failure to address the importance of cascading effects and secondary disasters caused by aftershocks. We also highlight the frequent lack of stakeholder involvement in problem identification and methodological approach, leading to less realistic problem definitions and uptake by practitioners. We argue that stakeholder involvement from the beginning and the use of Soft OR for problem structuring and conceptual modelling would help ensure that any Hard OR methods being developed are well-grounded within a stakeholder perspective. Finally, we observe that case studies could be improved by better data generation and earthquake scenario development, for example defining data inputs appropriate to the spatial scale being analysed and more precisely assigning probabilities to earthquake scenarios.

From a modelling prespective, this dissertation has a Capacitated Network Strengthening Problem but the proposed model is still far from being comprehensive and could be extended in a number of ways. For example, while the CNSP only deals with mitigation decisions for strengtehing road networks, it is assumed that the facilities, which serve the affected population, do not suffer capacity loss due to damage that may occur in the aftermath of an earthquake. In summary, protection strategies on the suppliers could be included to the problem context and formulation as an extension of this research that would mitigate the possible damage which would prevent them from working at full capacity. These projects would have impacts on the service capacity; hence, the service capacity would be changed according to the mitigation decisions. Another possible extension for future research can be the split of protection budget for these mitigation activities for transportation links and critical facilities.

In the proposed problem definition, we exclude the possibility of road blockage due to the collapse of roadside buildings. On the other hand, earthquake-caused road damage can be classified as direct or indirect. The term "direct damage" refers to road system damage caused by seismic activity, whereas "indirect damage" refers to road system impediments generated by other effects on the road system [316]. Therefore, even if the road is not damaged, it may be blocked due to debris of collapsed buildings. Consequently, more research including various protection techniques including both reinforcing the vulnerable components of the roadways (e.g., bridges/viaducts) and incorporating roadside structures (e.g., buildings) is required.

In this study, we estimate the resilience levels of links considering the seismic intensity of the earthquake and the collapse of structures on the roadway. Specifically for estimating resilience levels, it was challenging to carry out the previously described strategy while considering the distinct components (PGA_e is the peak ground acceleration level at link e, f_e is the seismic risk factor, φ_e represents the earthquake vulnerability score) for the detailed network. These three components are estimated based on the coordination information of the links and the vulnerable infrastructure's vulnerability scores estimated by [313]. Future research may consider involving various seismology techniques which may be particularly beneficial in assessing damage levels in this case as in [176,254].

The proposed CNSP does not consider the potential of subsequent aftershock damage and in spite of their importance, only a small handful of papers we reviewed explicitly consider cascading or secondary effects or subsequent disasters caused by aftershocks. Liberatore et al. [82] for example develop a multi-level optimization model for deciding which hospitals to reinforce given the presence of propagating damage across a network. Work by Ozbay et al. [176] on shelter site location, Zhang et al. [185]on evacuation planning, and Yan et al. [230] on road infrastructure restoration is notable for incorporating uncertain damage from aftershocks to improve the robustness of proposed solutions. Clearly, there is need for future EOM research to treat and analyse earthquakes more holistically, both in the mitigation and preparedness stages by hedging against cascading and secondary effects and in the response and recovery stages by recognizing the importance of aftershocks and the need for adaptive planning.

Different integrated models combining different DOM stages should be addressed to fill the gap in the literature. For instance, it is critical to reach the affected areas for providing search and rescue operations and the second stage of the problem could have included decisions to get rescue workers to the site. Future models could consider that the number of rescue workers would be dependent on the estimated demand and the locations of these workers could be defined as another type of supplier which is different than the critical facilities in the current model. As stated in Chapter 2, tasks related with recovery and mitigation overlap in certain ways. A better understanding of the relationships between protection methods and damage states that result in lower recovery costs is an important research issue that deserves more attention in OR literature. Recovery operations, on the other hand, can function as a catalyst for mitigation. Despite the strong linkages between mitigation and recovery, we discovered only one study addressing this combination of DOM phases, by Cho and Park [248]. There is clear need to investigate the trade-offs between investing in infrastructure protection and the related economic and social costs of disruption and recovery. Furthermore, integrating three DOM stages, namely mitigation, response, and recovery, would provide a broader and more insightful decision-making viewpoint for determining protection planning strategies while taking into account the impact on post-disaster operations. Specifically, future research may incorporate the facility and infrastructure restoration decisions into the proposed two-stage stochastic programming model in this dissertation.

From a methodological perspective, some modifications could be performed to increase the performance of the GRASP on large data sets. Particularly for the detailed network, the number of links in each route may be very high so mitigating one of them would not affect accessibility since a route may have several non-operational links. Therefore, the devised method to estimate contribution of a project to accessibility in the constructive phase of the GRASP remains limited here. Estimating benefit of projects by grouping can be considered for non-operational links on the same route. Furthermore, alternative local search method could be assessed to avoid local optima in the neighbourhood exploration.

Computational experiments have been performed on a limited number of scenarios, particularly for the detailed network. To perform more analysis, the proposed algorithm should be faster and more efficient. Instead of determining evacuation allocations for each neighbour solution produced in the local search, a mechanism similar to the one we devised in the constructive phase of the GRASP can be used to anticipate whether or not the solution will improve the current existing solution. As a result, there would be no need to find evacuation allocations for neighbour solutions which are certain to have no positive effect on the solution, so the procedure would be computationally improved.

It is obvious that the scenario definition in this research limits the comprehensiveness of the findings and insights. Various network scenarios that could occur in the anticipated earthquake scenario have been investigated. The reason for considering only an earthquake scenario was that the information regarding the seismic intensity of regions depending on where fault line would break was provided in the report. Therefore, it was possible to obtain these parameters to be used to estimate resilience levels. To avoid these limitations, future research may consider involving different scenarios prepared by experts into their case studies, rather than using scenarios provided in existing reports or articles. In addition, the scenario generation approach would exclude possible network realizations for the sake of fast computation. As mentioned in Section 2.3.3.1, greater attention should be paid to properly assigning probabilities to each scenario when multiple scenarios are included since scenarios are not infrequently given equal chance of occurrence. Clearly, more scientific approaches are needed, perhaps involving interdisciplinary methods in scenario generation, and also for estimating the scenario occurrence probabilities. Neural network approaches (i.e., Bayesian networks) could be used to estimate the more likely scenarios according to the ground-motion predictions so the occurrence probability can be assigned to each scenario based on the neural network applications.

Different findings have been obtained in the analyses using two different network datasets for the same geographical region. It has been concluded that the results obtained using the detailed network are more realiable and informative for real life decision making. This finding has confirmed the requirement of using real network data of sufficient detail, as highlighted in Chapter 2. Future research should consider defining the demand and supply nodes, links, and critical facilities ideally based on information provided by local authorities, to give a more realistic picture.

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Appendicies

Appendix A. Details of mathematical programming and heuristic approaches for relief distribution problems.

	Decision(s)				
Reference	Logistics activities	Goods	Mode of transport	**Objective(s)**	**Case Study**
Najafi et al. [161]	RDC-AA	Multi	Multi	Minimize unserved injured people, unmet demand, and number of vehicles required	-
Mohammadi et al. [162]	ES-RDC-AA	Single	Multi	Minimize set-up and transport costs of relief, transport cost of injured, variability in transport cost (both) and transport time (both)	2017 Iran-Iraq earthquake
Khalilpourazari et al. [163]	LCC-CW-RDC-AA	Single	Multi	Minimize set-up, procurement, transport and holding costs and transport time of blood and transport cost and time of injured	2017 Iran-Iraq earthquake
Mansoori et al. [164]	RDC-AA	Multi	Multi	Minimize unmet demand for relief and number of people not evacuated to shelters or hospitals	Tehran, Iran
Fereiduni et al. [165]	ES-RDC-AA	Multi	Single	Minimize transport, operation, holding and evacuation costs	Tehran, Iran
Liu & Guo [177]	ES-RDC-AA	Multi	Multi	Maximize min. fill rate, fill rate difference and set-up, procurement and transport costs	2008 Wenchuan earthquake
Sabouhi et al. [178]	RDC-AA	Single	Single	Minimize transport time of relief and evacuees to shelters	Tehran, Iran
Liu et al. [178]	RDC-AA	Multi	Multi	Minimize total weighted unmet demand	2008 Wenchuan earthquake
Baharmand et al.[190]	CW-RDC-AA	Multi	Multi	Minimize operating, staff and transport costs, response time and unmet demand	2015 Nepal earthquake
Safaei et al. [189]	ES-CW-RDC-AA	Multi	Single	Minimize set-up, procurement, holding and transport costs, unmet demand and supply risk	Mazandaran, Iran
Khare et al. [214]	RDC-AA	Multi	Multi	Minimize transport cost and unmet demand	2015 Nepal earthquake
Hosseini-Motlagh et al. [187]	CW-RDC-AA	Multi	Single	Minimize procurement, holding and wastage costs of blood, set-up cost of emergency shelters and expected unmet demand for blood	Kermanshah, Iran
Gao [188]	RDC-RDC	Multi	Multi	Minimize supply shortages and transport time	2008 Sichuan earthquake
Fazli-Khalaf et al. [181]	LCC-CW-RDC-AA	Single	Multi	Minimize set-up, blood collection/testing and fixed/variable transport costs and transport time and maximize reliability of testing	2003 Bam earthquake
Vitoriano et al. [182]	RDC-AA	Single	Multi	Minimize transport cost, max. response time, unmet demand and max. unmet demand and maximize route link reliability & security	2010 Haiti earthquake
Camacho-Vallejo et al. [183]	ES-RDC-AA	Multi	Multi	Minimize response time and transport cost	2010 Chile earthquake
Cao et al. [184]	RDC-AA	Multi	Multi	Minimize set-up and processing costs, task completion time and carbon emissions	-
Zhang et al. [185]	RDC-AA	Multi	Multi	Minimize expected response time, transport cost and unmet demand	2008 Wenchuan earthquake
Ferrer et al. [186]	RDC-AA	Single	Multi	Minimize transport cost, max. response time, unmet demand and max. unmet demand and maximize route link reliability & security	2010 Haiti earthquake

Hu et al. [212]	RDC-AA	Multi	Single	Maximize overall utility of relief and min. utility satisfaction rate	2008 Wenchuan earthquake
Balcik [192]	RDC-AA	Single	Single	Maximize min. coverage ratio	2011 Van earthquakes
Cao et al. [193]	CW-RDC-AA	Multi	Single	Maximize min. satisfaction at each response substage and minimize max. deviation in satisfaction at each substage and across substages	2008 Wenchuan earthquake
Lin et al. [189]	RDC-AA	Multi	Single	Minimize unmet demand, response time, transport cost and maximize equity	1994 Northridge earthquake
Wang & Sun [195]	RDC-AA	Multi	Single	Minimize fixed/variable transport costs and unmet demand	2013 Ya'an earthquake
Lei et al. [196]	RDC-AA	Single	Single	Minimize tardiness of medical operations	2011 Tōhoku earthquake
Nedjati et al. [197]	RDC-AA	Single	Single	Minimize unmet demand and response time	-
Vahdani et al. [198]	CW-RDC-AA	Multi	Multi	Minimize set-up, holding, unused inventory and transport costs, vehicle travel time and route reliability	-
Xiong et al. [199]	CW-RDC-AA	Single	Multi	Minimize response time and max. response time	-
Rezaei et al. [200]	RDC-AA	Single	Multi	Minimize unmet demand and variability in unmet demand	Yazd City, Iran
Nolz et al. [201]	RDC-AA	Single	Single	Minimize victim travel distance, unmet demand, transport cost and max. response time	Manabí, Ecuador
Zahedi et al. [202]	RDC-AA	Multi	Multi	Minimize procurement and transport costs and unmet demand	2017 Iran-Iraq earthquake
Bruni et al. [203]	RDC-AA	Single	Single	Minimize waiting time and variability in waiting time	2010 Haiti earthquake
Hu et al. [213]	ES-RDC-AA	Multi	Multi	Minimize vehicle rental, transport and handling costs and unmet demand	2013 Ya'an earthquake
Kirac & Bennett [204]	RDC-AA	Single	Single	Maximize accurate satisfied demand	2010 Haiti earthquake
Chang et al. [205]	RDC-AA	Single	Multi	Minimize unmet demand, response time and transport cost	1999 Chi-Chi earthquake
Zheng et al. [206]	RDC-AA	Multi	Multi	Minimize response time and unmet demand	2013 Dingxi earthquake
Ferrer et al. [207]	RDC-AA	Single	Multi	Minimize fixed/variable transport costs, response time and unmet demand and maximize equity and route link reliability & security	2010 Haiti earthquake
Penna et al. [208]	RDC-AA	Single	Multi	Minimize transport cost	2010 Haiti earthquake
Liu et al. [209]	RDC-AA	Multi	Multi	Maximize expected fill rate and minimize set-up, procurement and transport costs	2008 Wenchuan earthquake
Ma et al. [210]	RDC-AA	Multi	Single	Minimize unmet demand for blood products	2008 Wenchuan earthquake
Wang et al. [211]	RDC-AA	Multi	Multi	Minimize set-up and transport costs and max. response time and maximize min. route reliability	2008 Wenchuan earthquake

Appendix B: List of studies which are either focus on earthquakes in their problem description or have partial or significant stakeholder involvement.

Study	Focus on Earthquakes	Stakeholder Involvement		
		No involvement	Partial involvement	Significant involvement
Mitigation Stage				
Bagheri et al. [45]	✓	✓		
Sun & Chen [46]	✓	✓		
Li et al. [47]	✓	✓		
Feng et al. [48]	✓	✓		
Sun et al. [49]	✓	✓		
Chang et al. [50]	✓		✓	
Gertsbakh & Shpungin [51]	✓	✓		
Jin & Wang [52]	✓	✓		
Dadfar et al. [54]	✓	✓		
King et al. [55]	✓		✓	
Nabian & Meidani [56]	✓	✓		
Sinaga et al. [57]	✓	✓		
Akin et al. [58]	✓	✓		
Cankaya et al. [59]	✓		✓	
Moradi et al. [60]	✓		✓	
Kumlu & Tudes [61]	✓		✓	
Yariyan et al. [62]	✓			✓
Ahmad et al. [63]	✓	✓		
Akpabot et al. [64]	✓	✓		
Carreño et al. [65]	✓		✓	
Tayfur & Bektas [66]	✓	✓		
Piscini et al. [67]	✓	✓		
Alizadeh et al. [68]	✓			✓
Janalipour & Taleai [69]	✓	✓		
Mangalathu et al. [70]	✓	✓		
Sadrykia et al. [71]	✓			✓
Ranjbar & Nekooie [72]	✓			✓
Aghamohammadi et al. [73]	✓	✓		
Gul & Guneri [74]	✓		✓	
Ikram & Qamar [75]	✓	✓		
Asim et al. [76]	✓	✓		
Zolfaghari & Peyghaleh [80]	✓	✓		
Aydin [82]	✓		✓	
Chu & Chen [83]	✓		✓	
Döyen & Aras [84]	✓	✓		
Edrissi et al. [85]	✓	✓		
Preparedness Stage				
Görmez et al. [88]	✓			✓
Khojasteh & Macit [90]	✓	✓		
Paul & Wang [91]	✓	✓		
Boostani et al. [93]	✓		✓	
Rezaei et al. [95]	✓		✓	
Chen & Wang [95]	✓	✓		
Salehi et al. [96]	✓		✓	
Cavdur et al. [97]	✓		✓	
Noyan et al. [99]	✓	✓		
Charles & Lauras [100]			✓	
Bozorgi-Amiri et al. [101]			✓	
Mahootchi & Golmohammadi [102]	✓		✓	

Lejeune [103]				✓			
Salman & Yucel [105]				✓			
Molladavoodi et al. [106]	✓			✓			
Haghi et al. [107]	✓		✓				
Ghasemi et al. [108]	✓	✓					
Saeidian et al. [110]	✓				✓		
Verma and Gaukler [111]	✓		✓				
Xing [112]	✓					✓	
Paul & MacDonald [113]	✓		✓				
Javadian et al. [114]				✓			
Mohammadi et al. [115]	✓					✓	
Tofighi et al. [116]	✓		✓				
Bell et al. [117]	✓		✓				
Acar et al. [118]	✓		✓				
Battarra et al. [120]	✓					✓	
Yang et al. [121]	✓			✓			
Das & Hanoka [122]	✓		✓				
Xu et al. [123]				✓			
Cimellaro et al. [124]	✓					✓	
Gul et al. [125]	✓			✓			
Shavarani et al. [127]	✓		✓				
Bayram et al. [129]				✓			
Bayram & Yaman [130]				✓			
Trivedi & Singh [131]	✓					✓	
Zhao et al. [134]	✓			✓			
Hu et al. [135]	✓	✓					
Xu et al. [136]	✓				✓		
Preece et al. [137]	✓						✓
Rafiei et al. [138]	✓		✓				
Srivichai et al. [139]	✓		✓				
Kuyuk et al. [140]	✓		✓				
Mase et al. [141]	✓		✓				
Li et al. [142]	✓		✓				
Mousavi et al. [143]	✓		✓				
Chin et al. [144]	✓				✓		
Lee at al. [145]	✓		✓				
Oliveira et al. [146]	✓				✓		
Wang et al. [147]	✓		✓				
Mulia et al. [148]	✓				✓		
Oth et al. [149]	✓		✓				
Response Stage							
Bai et al. [152]	✓	✓					
Kim et al. [153]	✓	✓					
Schweier & Markus [154]	✓					✓	
Chu & Zhong [156]	✓		✓				
Ahmadi et al. [157]	✓		✓				
Chaudhuri & Bose [158]	✓			✓			
Najafi et al. [161]	✓		✓				
Mohammadi et al. [162]	✓		✓				
Khalilpourazari et al. [163]	✓			✓			
Mansoori et al. [164]	✓			✓			
Mills et al. [166]				✓			
Caunhye & Xie [167]	✓					✓	
Oksuz & Satoglu [168]				✓			
Kilci et al. [169]	✓			✓			

Pérez-Galarce et al. [170]	✓		✓			
Forcael et al. [171]	✓		✓			
Chen et al. [172]	✓		✓			
Liu [174]	✓		✓			
Ozbay et al. [176]	✓		✓			
Liu & Guo [177]	✓		✓			
Liu et al. [179]	✓					✓
Liu et al. [180]	✓			✓		
Baharmand et al. [190]	✓					✓
Fazli Khalaf et al. [181]	✓			✓		
Camacho -Vallejo et al. [183]				✓		
Zhang et al. [185]				✓		
Ferrer et al. [186]				✓		
Lin et al. [194]				✓		
Nedjati et al. [197]	✓			✓		
Vahdani et al. [198]	✓		✓			
Xiong et al. [199]	✓		✓			
Rezaei et al. [200]	✓		✓			
Zahedi et al. [202]	✓		✓			
Penna et al. [208]	✓			✓		
Liu et al. [209]	✓					✓
Wang et al. [211]	✓		✓			
Xu et al. [213]	✓		✓			
Sheu [216]	✓					✓
Yagci et al. [217]	✓		✓			
Recovery Stage						
Kasaei & Salman [218]	✓	✓				
Hu & Sheu [220]	✓			✓		
Onan et al. [221]				✓		
Hwang et al. [224]				✓		
González et al. [225]	✓		✓			
Caunhye et al. [226]	✓		✓			
Nozhati et al. [228]	✓		✓			
Yan et al. [229]	✓		✓			
Yan et al. [230]				✓		
Yan et al. [231]				✓		
Longman & Miles [235]				✓		
Luna et al. [236]	✓			✓		
Gosavi et al. [237]	✓			✓		
Integrated Stages						
Yucel et al. [246]					✓	
Edrissi et al. [249]	✓		✓			
Salman & Gul [238]					✓	
Mohamadi & Yaghoubi [242]	✓				✓	
Ni et al. [250]	✓		✓			
Mete & Zabinsky [239]	✓				✓	
Ahmadi et al. [240]	✓		✓			
Golabi et al. [241]					✓	
Sahebjamnia et al. [244]					✓	
Xu et al. [255]	✓				✓	
Yan & Shih [256]	✓		✓			
Sakuraba et al. [257]	✓		✓			
Li & Teo [258]	✓		✓			

Appendix C. Details of applied case studies involving the use of infrastructure network data.

Study	**Earthquake Scenario**	**Infrastructure Type**		
		Transportation	Electricity	Water
Mitigation Stage				
Bagheri et al. [45]	W/ERS			Real
Li et al. [47]	Random		Real	
Günneç & Salman [49]	W/ERS	Real		
Jin & Wang [52]	W/ERS			Real
Mohaymany et al. [54]	Random	Random		
Dadfar et al. [55]	W/ERS			Real
King et al. [56]	W/ERS			Real
Nabian & Meidani [57]	W/ERS	Real		
Peeta et al. [79]	W/ERS	Real		
Lu et al. [80]	Random	Random		
Liberatore et al. [82]	W/ERS	Real		
Aydin [83]	W/ERS	Real		
Chu & Chen [84]	W/ERS	Real		
Döyen & Aras [85]	Random	Random		
Edrissi et al. [86]	W/ERS	Random		
Preparedness Stage				
Görmez et al. [88]	W/ERS	Real		
Zokaee et al. [89]	Random	Real		
Khojasteh & Macit [90]	W/ERS	Real		
Paul & Wang [91]	W/ERS	Real		
Rahafrooz & Alinaghian [92]	Random	Random		
Boostani et al. [93]	Random	Real		
Rezai et al. [94]	W/ERS	Real		
Chen & Wang [95]	Random	Real		
Salehi et al. [96]	W/ERS	Real		
Cavdur et al. [97]	W/ERS	Real		
Yahyaei & Bozorgi-Amiri [98]	W/ERS	Real		
Noyan et al. [99]	W/ERS	Real		
Bozorgi-Amiri et al. [101]	W/ERS	Real		
Mahootchi & Golmohammadi [102]	W/ERS	Real		
Renkli & Duran [104]	W/ERS	Real		
Salman & Yucel [105]	W/ERS	Real		
Molladavoodi et al. [106]	W/ERS	Real		
Ghasemi et al. [108]	W/ERS	Real		
Lu [109]	Random	Random		
Saeidian et al. [110]	W/ERS	Real		
Verma & Gaukler [111]	Random	Real		
Paul & MacDonald [113]	W/ERS	Real		
Mohammadi et al. [115]	W/ERS	Real		
Tofighi et al. [116]	W/ERS	Real		
Bell et al. [118]	Random	Real		
Acar et al. [119]	W/ERS	Real		
Yang et al. [122]	W/ERS	Real		
Xu et al. [124]	W/ERS	Real		
Shavarani et al. [127]	W/ERS	Real		
Coutinho-Rodrigues et al. [128]	Random	Real		
Bayram et al. [129]	W/ERS	Real		
Bayram & Yaman [130]	W/ERS	Real		
Trivedi & Singh [131]	W/ERS	Real		
Kınay et al. [132]	W/ERS	Real		
Xu et al. [136]	W/ERS	Real		
Response Stage				
Ahmadi et al. [157]	W/ERS	Real		
Najafi et al. [161]	Random	Random		

Mohammadi et al. [162]	W/ERS	Real		
Khalilpourazari et al. [163]	W/ERS	Real		
Mansoori et al. [164]	Random	Real		
Caunhye & Nie [167]	W/ERS	Real		
Oksuz & Satoglu [168]	W/ERS	Real		
Kilci et al. [169]	Random	Real		
Pérez-Galarce et al. [170]	Random	Real		
Forcael et al. [171]	Random	Real		
Liu [179]	W/ERS	Real		
Liu & Guo [177]	Random	Real		
Sabouhi et al. [178]	Random	Real		
Liu et al. [180]	W/ERS	Real		
Baharmand et al. [191]	W/ERS	Real		
Safaei et al. [189]	W/ERS	Real		
Khare et al. [214]	W/ERS	Real		
Hosseini-Motlagh et al. [187]	W/ERS	Real		
Gao [188]	Random	Real		
Baharmand et al. [190]	W/ERS	Real		
Fazli Khalaf et al. [181]	Random	Real		
Vitoriano et al.[182]	W/ERS	Real		
Camacho -Vallejo et al. [183]	W/ERS	Real		
Cao et al. [184]	W/ERS	Real		
Zhang et al. [185]	Random	Real		
Ferrer et al. [186]	W/ERS	Real		
Hu et al. [212]	W/ERS	Real		
Balcik [192]	W/ERS	Real		
Cao et al. [193]	W/ERS	Real		
Lin et al. [194]	W/ERS	Real		
Wang & Sun [195]	W/ERS	Real		
Lei et al. [196]	W/ERS	Real		
Nedjati et al. [197]	Random	Random		
Vahdani et al. [198]	Random	Random		
Xiong et al. [199]	Random	Real		
Rezaei et al. [200]	W/ERS	Real		
Zahedi et al. [202]	W/ERS	Real		
Bruni et al. [203]	W/ERS	Real		
Hu et al. [213]	W/ERS	Real		
Chang et al [205]	W/ERS	Real		
Zheng et al. [206]	W/ERS	Real		
Penna et al. [208]	W/ERS	Real		
Liu et al. [209]	Random	Real		
Wang et al. [211]	W/ERS	Real		
Xu et al. [215]	Random	Real		
Yagci et al. [217]	W/ERS	Real		
Recovery Stage				
Kasaei & Salman [218]	W/ERS	Real		
Tüzün Aksu & Özdamar [219]	Random	Real		
Hu & Sheu [220]	W/ERS	Real		
Özdamar et al. [221]	Random	Real		
Ajam et al. [223]	W/ERS	Real		
González et al. [225]	W/ERS		Real	Real
Caunhye et al. [226]	Random	Real		
Smith et al. [227]	Random		Real	Real
Nozhati et al. [228]	W/ERS		Real	
Yan et al. [229]	Random	Real		
Yan et al. [230]	Random	Real		
Yan et al. [231]	Random	Real		
Rey & Bar-Gera [233]	Random	Real		

Luna et al. [236]	W/ERS			Real
Gosavi et al. [237]	Random	Real		
Integrated Stages				
Hu et al. [245]	W/ERS	Real		
Yucel et al. [246]	W/ERS	Real		
Edrissi et al. [249]	Random	Random		
Salman & Gul [238]	W/ERS	Real		
Mohamadi & Yaghoubi [242]	W/ERS	Real		
Ni et al. [250]	W/ERS	Real		
Mete & Zabinsky [239]	W/ERS	Real		
Bozorgi et al. [251]	W/ERS	Real		
Ahmadi et al. [240]	Random	Real		
Golabi et al. [241]	W/ERS	Real		
Sahebjamnia et al. [244]	Random	Real		
Fereiduni et al. [243]	Random	Real		
Çelik et al. [253]	W/ERS	Real		
Liberatore et al. [254]	W/ERS	Real		
Xu & Song [254]	Random	Real		
Yan & Shih [256]	Random	Real		
Sakuraba et al. [257]	W/ERS	Real		
Li & Teo [258]	Random	Real		

Appendix D. Details of the simplified Istanbul highway network data

Appendix D.1. The details of the simplified Istanbul highway network nodes

Node No	District Name	Node Type	Node No	District Name	Node Type
1	Arnavutkoy	Demand	31	Tuzla	Demand
2	Atasehir	Demand	32	Umraniye	Demand
3	Avcilar	Demand	33	Uskudar	Supplier
4	Bagcilar	Demand	34	Zeytinburnu	Supplier
5	Bahcelievler	Supplier	35	J1	Transhipment
6	Bakirkoy	Supplier	36	J2	Transhipment
7	Basaksehir	Demand	37	J3	Transhipment
8	Bayrampasa	Demand	38	J4	Transhipment
9	Besiktas	Demand	39	J5	Transhipment
10	Beylikduzu	Demand	40	J6	Transhipment
11	Beyoglu	Supplier	41	J7	Transhipment
12	Buyukcekmece	Demand	42	J8	Transhipment
13	Cekmekoy	Demand	43	J9	Transhipment
14	Esenler	Demand	44	J10	Transhipment
15	Esenyurt	Demand	45	J11	Transhipment
16	Eyup	Demand	46	J12	Transhipment
17	Fatih	Supplier	47	J13	Transhipment
18	Gaziosmanpasa	Demand	48	J14	Transhipment
19	Gungoren	Demand	49	J15	Transhipment
20	Kadikoy	Supplier	50	J16	Transhipment
21	Kagithane	Demand	51	J17	Transhipment
22	Kartal	Demand	52	J18	Transhipment
23	Kucukcekmece	Demand	53	J19	Transhipment
24	Maltepe	Demand	54	J20	Transhipment
25	Pendik	Demand	55	J21	Transhipment
26	Sancaktepe	Demand	56	J22	Transhipment
27	Sariyer	Demand	57	J23	Transhipment
28	Sisli	Supplier	58	J24	Transhipment
29	Sultanbeyli	Demand	59	J25	Transhipment
30	Sultangazi	Demand	60	J26	Transhipment

Appendix D.2. The number of hospitals, policlinics, and beds on the supplier points

District	Number of Hospitals	Number of policlinics	Number of beds
Sisli	21	0	1,597
Kadikoy	20	42	1,127
Uskudar	17	16	2,036
Fatih	16	16	1,081
Bahcelievler	12	0	1,126
Gaziosmanpasa	11	0	491
Bakirkoy	10	10	4,229
Beyoglu	8	15	861
Gungoren	6	1	207
Bayrampasa	6	12	259
Kartal	6	9	918
Zeytinburnu	6	10	1,325
Maltepe	5	2	85
Pendik	5	11	244
Avcilar	5	6	323
Eyup	4	10	75
Umraniye	4	24	87
Buyukcekmece	4	0	134
Besiktas	4	0	173
Bagcilar	4	23	177
Kucukcekmece	4	23	177
Esenler	3	11	147
Silivri	3	0	147
Kagithane	3	0	285
Beykoz	3	6	300
Sariyer	3	15	510
Catalca	1	0	50
Tuzla	0	0	0

Appendix D.3. Number of casualties (demand values) at demand nodes

Node No	District name	Population	Casualty rate	Demand
1	Arnavutkoy	197,271	1.3	2565
2	Atasehir	290,818	1.1	3199
3	Avcilar	490,630	2.7	13247
4	Bagcilar	741,909	1.1	8161
7	Basaksehir	206,846	1.3	2689
8	Bayrampasa	294,292	2.4	7063
9	Besiktas	365,083	1.2	4381
10	Beylikduzu	222,357	2.8	6226
12	Buyukcekmece	183,208	4.8	8794
13	Cekmekoy	141,400	0.5	707
14	Esenler	541,250	1.2	6495
15	Esenyurt	102,692	1.3	1335
16	Eyup	302,214	1.4	4231
18	Gaziosmanpasa	434,167	0.6	2605
19	Gungoren	212,016	1.8	3816
21	Kagithane	395,000	0.8	3160
22	Kartal	429,615	1.3	5585
23	Kucukcekmece	647,077	1.3	8412
24	Maltepe	438,727	1.1	4826
25	Pendik	516,667	1.2	6200
26	Sancaktepe	148,200	0.5	741
27	Sariyer	222,333	0.3	667
29	Sultanbeyli	256,545	1.1	2822
30	Sultangazi	434,500	0.6	2607
31	Tuzla	143,185	2.7	3866
32	Umraniye	664,800	0.5	3324

Appendix D.4. The simplified Istanbul highway network links and resilience levels

Link No	Node 1	Node 2	Resilience level	Link No	Node 1	Node 2	Resilience level
1	Bagcilar	Bahcelievler	6	48	Umraniye	J13	6
2	Bahcelievler	Bakirkoy	6	49	Atasehir	J14	4
3	Arnavutkoy	Besiktas	6	50	Sultanbeyli	J15	6
4	Avcilar	Beylikduzu	6	51	Sultanbeyli	J16	7
5	Beylikduzu	Buyukcekmece	7	52	Tuzla	J17	6
6	Avcilar	Esenyurt	6	53	J15	J17	6
7	Beylikduzu	Esenyurt	7	54	Bayrampasa	J18	7
8	Beyoglu	Fatih	7	55	J2	J18	4
9	Bayrampasa	Gaziosmanpasa	8	56	J3	J18	6
10	Bahelievler	Gungoren	6	57	Kagithane	J19	8
11	Avcilar	Kucukcekmece	6	58	Sisli	J19	9
12	Bahcelievler	Kucukcekmece	6	59	J8	J19	5
13	Bakirkoy	Kucukcekmece	7	60	J10	J19	5
14	Kartal	Maltepe	8	61	Gaziosmanpasa	J20	9
15	Cekmekoy	Sancaktepe	7	62	Sultangazi	J20	3
16	Pendik	Sancaktepe	7	63	J7	J20	9
17	Eyup	Sariyer	9	64	J12	J20	5
18	Sariyer	Sisli	8	65	Uskudar	J22	7
19	Kartal	Tuzla	9	66	J5	J22	2
20	Umraniye	Uskudar	7	67	J14	J22	2
21	Bakirkoy	Zeytinburnu	7	68	J21	J22	2
22	Fatih	Zeytinburnu	6	69	Kadikoy	J23	7
23	Gungoren	Zeytinburnu	6	70	Maltepe	J23	7
24	Esenyurt	J1	7	71	J14	J23	2
25	Bagcilar	J2	8	72	J21	J23	7
26	Basaksehir	J2	4	73	J10	J24	5
27	J1	J2	7	74	J13	J24	6
28	Esenler	J3	6	75	Cekmekoy	J25	9
29	Beyoglu	J4	8	76	J13	J25	7
30	Besiktas	J5	9	77	J14	J25	6
31	J4	J6	5	78	Kartal	J26	7
32	Eyup	J7	8	79	J14	J26	8

33	Eyup	J8	8
34	Kagithane	J8	8
35	J4	J8	2
36	J7	J8	4
37	Beyoglu	J9	7
38	Kagithane	J9	9
39	J4	J9	7
40	J5	J9	3
41	Sariyer	J10	8
42	Sisli	J10	9
43	Bayrampasa	J11	7
44	Fatih	J11	7
45	J6	J11	7
46	Gaziosmanpasa	J12	8
47	J3	J12	9

80	J16	J26	7
81	J15	Pendik	6
82	J2	Kucukcekmece	7
83	J1	Buyukcekmece	7

Appendix E. Details of the detailed Istanbul highway network data

Appendix E.1. The details of the detailed Istanbul highway network nodes

Node No	longitude	latitude	Node Type	Node Population	Node Description
1	28.73042435	41.19620204	Demand	176735	Arnavutköy
2	28.63054586	41.14141311	Demand	38796	Arnavutköy
3	28.87289137	41.05710333	Demand	133870	Esenler
4	28.88459599	41.07372069	Demand	106173	Esenler
5	28.86264679	41.06676192	Demand	46162	Esenler
6	28.87943377	41.03963888	Demand	175416	Esenler
7	28.70861753	40.98484372	Demand	130317	Avcılar
8	28.70401148	41.00636023	Demand	109955	Avcılar
9	28.69708323	41.02810681	Demand	126244	Avcılar
10	28.71233866	41.05985982	Demand	40724	Avcılar
11	28.82603922	41.03735406	Demand	157973	Bağcılar
12	28.82603954	41.05264153	Demand	22568	Bağcılar
13	28.83580208	41.04582377	Demand	75225	Bağcılar
14	28.84796939	41.05375763	Demand	97793	Bağcılar
15	28.8451874	41.04076859	Demand	112838	Bağcılar
16	28.81348406	41.04698208	Demand	15045	Bağcılar
17	28.859753	41.04722211	Demand	90270	Bağcılar
18	28.85512843	41.03059192	Demand	180540	Bağcılar
19	28.83491034	41.02442695	Demand	90440	Bahçelievler
20	28.85183218	41.01750725	Demand	114557	Bahçelievler
21	28.82006505	41.01946826	Demand	18088	Bahçelievler
22	28.83741704	41.00765634	Demand	174850	Bahçelievler
23	28.8559592	41.00175034	Demand	162791	Bahçelievler
24	28.8251008	41.00566389	Demand	42205	Bahçelievler
25	28.80585378	40.97318872	Demand	121536	Bakırköy
26	28.83624196	40.96830188	Demand	99438	Bakırköy
27	28.68513192	41.06502291	Demand	126558	Başakşehir
28	28.75720258	41.09220291	Demand	96584	Başakşehir
29	28.79873407	41.08463038	Demand	109906	Başakşehir
30	28.90006955	41.05866595	Demand	113264	Bayrampaşa
31	28.90510223	41.04469265	Demand	80903	Bayrampaşa
32	28.91108905	41.03275937	Demand	75510	Bayrampaşa
33	29.02976715	41.06532485	Demand	136196	Beşiktaş
34	29.00186332	41.04659138	Demand	50374	Beşiktaş
35	28.63843293	41.00101466	Demand	78323	Beylikdüzü
36	28.66662757	40.98674024	Demand	80770	Beylikdüzü
37	28.62109631	40.98478412	Demand	85666	Beylikdüzü
38	28.9782243	41.03132716	Demand	68661	Beyoğlu
39	28.97092004	41.03843174	Demand	73566	Beyoğlu
40	28.96034503	41.04480166	Demand	102992	Beyoğlu
41	28.59557811	41.02245914	Demand	116050	Büyükçekmece

42	28.54518899	41.01751035	Demand	94950	Büyükçekmece
43	28.64605836	41.03749455	Demand	93710	Esenyurt
44	28.63484966	41.05568196	Demand	18742	Esenyurt
45	28.65874431	41.04280286	Demand	112452	Esenyurt
46	28.64305615	41.02238292	Demand	43731	Esenyurt
47	28.66991183	41.01737263	Demand	118699	Esenyurt
48	28.67405508	41.03713901	Demand	149936	Esenyurt
49	28.66369049	41.0293318	Demand	87463	Esenyurt
50	28.88643779	41.17832406	Demand	32538	Eyüp
51	28.93046985	41.0853483	Demand	126536	Eyüp
52	28.92917685	41.04173268	Demand	108459	Eyüp
53	28.94185957	41.06842433	Demand	93998	Eyüp
54	28.95653995	41.02118119	Demand	72397	Fatih
55	28.94172333	41.03035461	Demand	89432	Fatih
56	28.93317057	41.00811554	Demand	106466	Fatih
57	28.97605815	41.01031066	Demand	38328	Fatih
58	28.93717219	41.01883599	Demand	63880	Fatih
59	28.95444754	41.00883623	Demand	55362	Fatih
60	28.89334416	41.07943246	Demand	69301	Gaziosmanpaşa
61	28.89676465	41.07020413	Demand	118801	Gaziosmanpaşa
62	28.90764902	41.06982293	Demand	99001	Gaziosmanpaşa
63	28.91108073	41.06216769	Demand	123752	Gaziosmanpaşa
64	28.92594578	41.06227216	Demand	84151	Gaziosmanpaşa
65	28.87325763	41.02849141	Demand	98193	Güngören
66	28.866769	41.01482044	Demand	162633	Güngören
67	28.89538519	41.01452443	Demand	46028	Güngören
68	28.97096437	41.07527873	Demand	51451	Kağıthane
69	28.96617373	41.06499884	Demand	72888	Kağıthane
70	28.98314047	41.06965141	Demand	85751	Kağıthane
71	29.00153848	41.07176933	Demand	94326	Kağıthane
72	28.98352296	41.07908757	Demand	124339	Kağıthane
73	28.78337722	40.9883292	Demand	122115	Küçükçekmece
74	28.77309225	40.9967847	Demand	144318	Küçükçekmece
75	28.78758746	40.99895656	Demand	103612	Küçükçekmece
76	28.88815564	41.00020561	Demand	52616	Zeytinburnu
77	28.86883001	40.98321148	Demand	114002	Zeytinburnu
78	28.90791009	40.99098747	Demand	125695	Zeytinburnu
79	29.06071521	41.03644303	Demand	69503	Üsküdar
80	29.03020209	40.99377863	Demand	64156	Üsküdar
81	29.03234273	41.02733708	Demand	112274	Üsküdar
82	29.06618407	41.0554634	Demand	101581	Üsküdar
83	29.0730137	41.00715359	Demand	96234	Üsküdar
84	29.04870212	41.01273062	Demand	90888	Üsküdar
85	29.14030059	41.02213784	Demand	66012	Ümraniye
86	29.14078282	41.00437961	Demand	125424	Ümraniye
87	29.08813362	41.03212085	Demand	118822	Ümraniye

88	29.10921735	41.04497616	Demand	72614	Ümraniye
89	29.09836535	41.01427364	Demand	138626	Ümraniye
90	29.16644141	41.01990935	Demand	85816	Ümraniye
91	29.09031753	41.05922923	Demand	52810	Ümraniye
92	29.38893927	40.90998593	Demand	89787	Tuzla
93	29.34917977	40.87943965	Demand	119020	Tuzla
94	29.58599384	41.14994887	Demand	31718	Şile
95	29.2836127	40.94998394	Demand	133019	Sultanbeyli
96	29.27527302	40.98363154	Demand	95898	Sultanbeyli
97	29.25062535	40.96957542	Demand	80430	Sultanbeyli
98	29.28744503	41.03014115	Demand	30441	Sancaktepe
99	29.19728141	40.98311049	Demand	73057	Sancaktepe
100	29.24816921	41.0042591	Demand	200908	Sancaktepe
101	29.32830178	40.99810388	Demand	12928	Pendik
102	29.35650745	40.96552346	Demand	6464	Pendik
103	29.3673244	41.00672667	Demand	12928	Pendik
104	29.31644034	40.93182374	Demand	103420	Pendik
105	29.26148689	40.91377175	Demand	168058	Pendik
106	29.29663446	40.90348506	Demand	116348	Pendik
107	29.26940684	40.87798321	Demand	226231	Pendik
108	29.11655259	40.94261058	Demand	113054	Maltepe
109	29.13029346	40.92814183	Demand	108344	Maltepe
110	29.15103377	40.95646852	Demand	51816	Maltepe
111	29.16659698	40.93946629	Demand	103633	Maltepe
112	29.15485616	40.91678687	Demand	94212	Maltepe
113	29.16839266	40.90295223	Demand	98364	Kartal
114	29.19120712	40.91497504	Demand	93893	Kartal
115	29.22197756	40.92669991	Demand	71538	Kartal
116	29.22586153	40.9098041	Demand	89422	Kartal
117	29.20219354	40.89363259	Demand	93893	Kartal
118	29.05662154	40.98762141	Demand	81007	Kadıköy
119	29.07884182	40.98531006	Demand	86070	Kadıköy
120	29.06012014	40.97261238	Demand	116447	Kadıköy
121	29.09562214	40.97218045	Demand	101259	Kadıköy
122	29.0864512	40.96012657	Demand	121510	Kadıköy
123	29.24983204	41.07273951	Demand	126560	Çekmeköy
124	29.3197628	41.10280059	Demand	80916	Çekmeköy
125	29.12713782	41.08985751	Demand	71936	Beykoz
126	29.23522431	41.20963657	Demand	42170	Beykoz
127	29.27789616	41.13886859	Demand	39689	Beykoz
128	29.13710526	41.20231189	Demand	27286	Beykoz
129	29.08920778	41.1500362	Demand	66975	Beykoz
130	29.16743469	40.98436521	Demand	77135	Ataşehir
131	29.13835242	40.98996323	Demand	81195	Ataşehir
132	29.11261211	40.98297312	Demand	113673	Ataşehir
133	29.12738627	40.96868098	Demand	133971	Ataşehir

134	28.79726149	41.00828429	Demand	92512	Küçükçekmece
135	28.78015237	41.01173332	Demand	103613	Küçükçekmece
136	28.79530576	41.02148389	Demand	85111	Küçükçekmece
137	28.7981652	41.04150869	Demand	62908	Küçükçekmece
138	28.76221	41.05762829	Demand	25903	Küçükçekmece
139	29.04173129	41.10154661	Demand	77188	Sarıyer
140	29.04473844	41.12188149	Demand	107391	Sarıyer
141	29.03536466	41.15070353	Demand	60408	Sarıyer
142	29.04961802	41.18015731	Demand	90611	Sarıyer
143	28.18843901	41.08350015	Demand	93554	Silivri
144	28.29242169	41.07889299	Demand	62369	Silivri
145	28.90627316	41.09506625	Demand	101038	Sultangazi
146	28.87570985	41.0935349	Demand	116194	Sultangazi
147	28.89050465	41.10705753	Demand	55571	Sultangazi
148	28.86820147	41.10233677	Demand	136401	Sultangazi
149	28.85876244	41.11259976	Demand	95986	Sultangazi
150	28.99758336	41.09851741	Demand	49396	Şişli
151	28.99867531	41.08314949	Demand	82326	Şişli
152	28.99906704	41.05901646	Demand	76838	Şişli
153	28.9784608	41.05365516	Demand	65861	Şişli
154	29.05708267	41.1672824	Junction	0	
155	29.02798208	41.1398396	Junction	0	
156	29.05392874	41.13828533	Junction	0	
157	29.00433828	41.10042955	Junction	0	
158	29.0253937	41.09351274	Junction	0	
159	29.03994222	41.09079268	Junction	0	
160	29.00931019	41.08289898	Junction	0	
161	28.95510194	41.09874306	Junction	0	
162	29.01339849	41.06554889	Junction	0	
163	29.0209029	41.05645701	Junction	0	
164	29.00909552	41.05348655	Junction	0	
165	28.97826473	41.06703576	Junction	0	
166	28.96036531	41.0556959	Junction	0	
167	28.96866581	41.05210999	Junction	0	
168	29.00681051	41.04158279	Junction	0	
169	28.98497152	41.03686436	Junction	0	
170	28.96788873	41.0252104	Junction	0	
171	28.97507697	41.02319596	Junction	0	
172	28.94495786	41.04750064	Junction	0	
173	29.02696166	41.07631071	Junction	0	
174	28.9067811	41.08998289	Junction	0	
175	28.87313911	41.07963139	Junction	0	
176	28.84755884	41.11079473	Junction	0	
177	28.95309002	41.06373677	Junction	0	
178	28.93691054	41.03824551	Junction	0	
179	28.95941183	41.02084123	Junction	0	

180	28.97030094	41.01654537	Junction	0
181	28.97360016	41.00213294	Junction	0
182	28.92385351	41.02815745	Junction	0
183	28.90485918	41.01222302	Junction	0
184	28.92354425	40.99024487	Junction	0
185	28.92308762	41.0194537	Junction	0
186	28.88479934	41.0010907	Junction	0
187	28.87823241	41.0156036	Junction	0
188	28.88465879	41.04462418	Junction	0
189	28.84308184	41.06028541	Junction	0
190	28.81152003	41.06035485	Junction	0
191	28.7436946	41.06179247	Junction	0
192	28.6825963	41.05463823	Junction	0
193	28.63496338	41.08755979	Junction	0
194	28.68707047	41.02988029	Junction	0
195	28.67793615	41.00501038	Junction	0
196	28.75915927	40.98198017	Junction	0
197	28.62849671	41.0206834	Junction	0
198	28.64882439	40.98551598	Junction	0
199	28.56328458	41.01814586	Junction	0
200	28.8187737	40.99280259	Junction	0
201	28.82173758	40.98340903	Junction	0
202	28.79285058	40.98927432	Junction	0
203	28.81089676	41.02725242	Junction	0
204	28.85084449	40.99207377	Junction	0
205	28.84753146	41.02437237	Junction	0
206	28.84909352	41.04317171	Junction	0
207	28.79337733	41.05045506	Junction	0
208	28.80788435	41.04594018	Junction	0
209	28.72243053	40.98570594	Junction	0
210	28.67896698	40.99140816	Junction	0
211	29.04444326	41.03478087	Junction	0
212	29.04866719	41.02244419	Junction	0
213	29.02563868	41.00587174	Junction	0
214	29.056573	40.99909041	Junction	0
215	29.07298524	40.99249636	Junction	0
216	29.09485452	40.98134355	Junction	0
217	29.11640171	40.99588553	Junction	0
218	29.12064216	41.03033854	Junction	0
219	29.07479443	41.0207589	Junction	0
220	29.08327539	41.09213092	Junction	0
221	29.09098426	41.08892738	Junction	0
222	29.09623743	41.09457606	Junction	0
223	29.17536506	41.16296051	Junction	0
224	29.13113337	41.12246348	Junction	0
225	29.08538865	41.06046324	Junction	0

226	29.10517686	41.02920761	Junction	0	
227	29.08580706	41.02862468	Junction	0	
228	29.06201756	41.00844334	Junction	0	
229	29.06681976	40.979141	Junction	0	
230	29.10478802	40.96436745	Junction	0	
231	29.12044625	40.95089679	Junction	0	
232	29.1294812	40.94310465	Junction	0	
233	29.13864766	40.93570154	Junction	0	
234	29.14573773	40.93051374	Junction	0	
235	29.15243242	40.92482699	Junction	0	
236	29.17240433	40.91884027	Junction	0	
237	29.18951943	40.91326785	Junction	0	
238	29.21162466	40.90630164	Junction	0	
239	29.23838884	40.88842307	Junction	0	
240	29.2618025	40.87806784	Junction	0	
241	29.27223556	40.86704734	Junction	0	
242	29.31358452	40.87943936	Junction	0	
243	29.32436223	40.9144191	Junction	0	
244	29.21525898	40.94565349	Junction	0	
245	29.25770927	40.97173118	Junction	0	
246	29.20628789	40.98217114	Junction	0	
247	29.15509471	40.99440844	Junction	0	
248	29.12609385	40.97906539	Junction	0	
249	29.29698968	40.9535236	Junction	0	
250	29.27386006	41.04195237	Junction	0	
251	28.46253713	41.14156296	Demand	65811	Çatalca
252	29.27117278	41.16096834	Junction	0	
253	29.43750596	41.11785114	Junction	0	
254	29.34420706	41.00525515	Junction	0	
255	29.34596736	40.92941147	Junction	0	
256	29.36733201	40.90051099	Junction	0	
257	29.28636213	40.91782227	Junction	0	
258	29.2601609	40.89868519	Junction	0	
259	29.23732878	40.87593714	Junction	0	
260	29.18483954	40.88594994	Junction	0	
261	29.13904099	40.90697563	Junction	0	
262	29.11708537	40.93279446	Junction	0	
263	29.09706586	40.95180171	Junction	0	
264	29.05511418	40.96779109	Junction	0	
265	29.04111255	40.9765492	Junction	0	
266	29.03759025	40.98906177	Junction	0	
267	29.05531074	41.04931327	Junction	0	
268	29.03780368	41.04227388	Junction	0	
269	29.03054842	41.04920997	Junction	0	
270	29.06686031	41.09165497	Junction	0	
271	29.05559749	41.09118951	Junction	0	

272	29.20458518	41.01574622	Junction	0
273	29.18251773	41.01626781	Junction	0
274	29.21422997	41.00822202	Junction	0
275	29.22880971	40.9904646	Junction	0
276	29.24088399	41.00813435	Junction	0
277	29.23500863	41.02701144	Junction	0
278	29.27363964	41.01196042	Junction	0
279	29.18095154	40.95943716	Junction	0
280	29.15402458	40.9747435	Junction	0
281	29.12188195	41.01124194	Junction	0
282	29.09758722	41.00692358	Junction	0
283	29.08946326	40.99754646	Junction	0
284	29.08702574	41.01512654	Junction	0
285	29.07643195	41.04564889	Junction	0
286	29.09514218	41.04411692	Junction	0
287	29.12110642	41.05012037	Junction	0
288	29.10674256	41.06961446	Junction	0
289	29.06799661	41.08166752	Junction	0
290	29.08039987	41.08107439	Junction	0
291	29.03745778	41.15376391	Junction	0
292	29.05407539	41.11357072	Junction	0
293	29.07096085	41.12532507	Junction	0
294	29.0489618	41.096738	Junction	0
295	29.04328822	41.07507143	Junction	0
296	29.03984027	41.06246559	Junction	0
297	28.85237848	40.97616021	Junction	0
298	28.76919478	41.03386077	Junction	0
299	28.77014531	41.06223745	Junction	0
300	28.77135887	41.08197859	Junction	0
301	28.94428905	41.12971796	Junction	0
302	28.89264686	41.1620525	Junction	0
303	28.91639744	41.0820999	Junction	0
304	28.9355018	41.0803198	Junction	0
305	28.92670867	41.07141046	Junction	0
306	28.91895403	41.05018711	Junction	0
307	28.90066018	41.02070725	Junction	0
308	28.89605517	41.0341562	Junction	0
309	28.86733075	41.03473037	Junction	0
310	28.90472456	40.99794159	Junction	0
311	28.88469371	40.97811542	Junction	0
312	28.81751504	40.96421523	Junction	0
313	28.73854354	40.97744761	Junction	0
314	28.60492697	40.99753978	Junction	0
315	28.65976161	41.00848898	Junction	0
316	28.71092874	41.01898287	Junction	0
317	28.36859865	41.05877091	Junction	0

318	28.46459904	41.05779801	Junction	0	
319	28.50882499	41.08922102	Junction	0	
320	28.66496632	41.15931435	Junction	0	
321	28.51323317	41.17851045	Junction	0	
322	28.79518234	41.23094152	Junction	0	
323	28.7870273	41.15181787	Junction	0	
324	29.31092385	40.9014117	Supply		Sabiha Gokcen Airport
325	28.82058332	40.9820251	Supply		Ataturk Airport
326	29.01268828	41.00551556	Supply		Kadıkoy Harbour & Haydarpasa Train Station
327	28.96252402	41.08799177	Supply		AKOM & AFAD
328	28.95406457	41.00237773	Supply		Yenikapı Harbour
329	29.18949605	40.90773898	Supply		Kizilay Marmara Disaster Coordination Center
330	28.99040444	41.05788316	Supply		Sisli Etfal Hospital
331	28.97493187	41.06459566	Supply		Okmeydani Hospital
332	28.97989873	41.01571168	Supply		Sirkeci Train Station
333	28.76664543	41.01785044	Supply		Halkali Logistics Support Center
334	29.05686753	40.98504032	Supply		Istanbul Goztepe Hospital
335	28.91526139	41.00266826	Supply		Istanbul Yedikule Hospital
336	28.870421	41.029948	Supply		Istanbul Bagcilar Hospital
337	29.10089175	41.03331937	Supply		Istanbul Umraniye Hospital
338	28.64073723	41.11654366	Supply		Hadimkoy
339	29.26757049	40.98162785	Supply		Sultanbeyli Fire Station
340	29.01561291	41.02582821	Junction	0	
341	28.95202047	41.08518516	Junction	0	
342	28.80453945	41.00062336	Junction	0	
343	28.92793296	41.0001139	Junction	0	
344	29.05469652	41.08130964	Junction	0	
345	29.02445596	41.06055885	Junction	0	
346	29.06991018	40.96605119	Junction	0	
347	29.11183247	40.958546	Junction	0	
348	29.05376173	41.0354348	Junction	0	
349	29.01526765	41.09680771	Junction	0	

Appendix E.2. The casualty rates and demand values for demand nodes of the detailed network

Node Type	Node Population	Node Description	Casualty Rate	Population	Demand
Demand	176735	Arnavutköy	1.3	141244	1837
Demand	38796	Arnavutköy	1.3	141244	1837
Demand	133870	Esenler	1.2	112586	1352
Demand	106173	Esenler	1.2	112586	1352
Demand	46162	Esenler	1.2	112586	1352
Demand	175416	Esenler	1.2	112586	1352
Demand	130317	Avcılar	2.7	112220.5	3030
Demand	109955	Avcılar	2.7	112220.5	3030
Demand	126244	Avcılar	2.7	112220.5	3030
Demand	40724	Avcılar	2.7	112220.5	3030
Demand	157973	Bağcılar	1.1	93140.625	1025
Demand	22568	Bağcılar	1.1	93140.625	1025
Demand	75225	Bağcılar	1.1	93140.625	1025
Demand	97793	Bağcılar	1.1	93140.625	1025
Demand	112838	Bağcılar	1.1	93140.625	1025
Demand	15045	Bağcılar	1.1	93140.625	1025
Demand	90270	Bağcılar	1.1	93140.625	1025
Demand	180540	Bağcılar	1.1	93140.625	1025
Demand	126558	Başakşehir	1.3	153419.667	1995
Demand	96584	Başakşehir	1.3	153419.667	1995
Demand	109906	Başakşehir	1.3	153419.667	1995
Demand	113264	Bayrampaşa	2.4	91578.3333	2198
Demand	80903	Bayrampaşa	2.4	91578.3333	2198
Demand	75510	Bayrampaşa	2.4	91578.3333	2198
Demand	136196	Beşiktaş	1.2	91324.5	1096
Demand	50374	Beşiktaş	1.2	91324.5	1096
Demand	78323	Beylikdüzü	2.8	117470.667	3290
Demand	80770	Beylikdüzü	2.8	117470.667	3290
Demand	85666	Beylikdüzü	2.8	117470.667	3290
Demand	116050	Büyükçekmece	4.8	127051.5	6099
Demand	94950	Büyükçekmece	4.8	127051.5	6099
Demand	93710	Esenyurt	1.3	136368.429	1773
Demand	18742	Esenyurt	1.3	136368.429	1773
Demand	112452	Esenyurt	1.3	136368.429	1773

Demand	43731	Esenyurt	1.3	136368.429	1773
Demand	118699	Esenyurt	1.3	136368.429	1773
Demand	149936	Esenyurt	1.3	136368.429	1773
Demand	87463	Esenyurt	1.3	136368.429	1773
Demand	32538	Eyüp	1.4	100128.25	1402
Demand	126536	Eyüp	1.4	100128.25	1402
Demand	108459	Eyüp	1.4	100128.25	1402
Demand	93998	Eyüp	1.4	100128.25	1402
Demand	72397	Fatih	1.4	7384.83333	104
Demand	89432	Fatih	1.4	7384.83333	104
Demand	106466	Fatih	1.4	7384.83333	104
Demand	38328	Fatih	1.4	7384.83333	104
Demand	63880	Fatih	1.4	7384.83333	104
Demand	55362	Fatih	1.4	7384.83333	104
Demand	69301	Gaziosmanpaşa	0.6	98392.4	591
Demand	118801	Gaziosmanpaşa	0.6	98392.4	591
Demand	99001	Gaziosmanpaşa	0.6	98392.4	591
Demand	123752	Gaziosmanpaşa	0.6	98392.4	591
Demand	84151	Gaziosmanpaşa	0.6	98392.4	591
Demand	98193	Güngören	1.8	96480.3333	1737
Demand	162633	Güngören	1.8	96480.3333	1737
Demand	46028	Güngören	1.8	96480.3333	1737
Demand	51451	Kağıthane	0.8	89605	717
Demand	72888	Kağıthane	0.8	89605	717
Demand	85751	Kağıthane	0.8	89605	717
Demand	94326	Kağıthane	0.8	89605	717
Demand	124339	Kağıthane	0.8	89605	717
Demand	122115	Küçükçekmece	1.3	99102.625	1289
Demand	144318	Küçükçekmece	1.3	99102.625	1289
Demand	103612	Küçükçekmece	1.3	99102.625	1289
Demand	66012	Ümraniye	0.5	10146.8571	51
Demand	125424	Ümraniye	0.5	10146.8571	51
Demand	118822	Ümraniye	0.5	10146.8571	51
Demand	72614	Ümraniye	0.5	10146.8571	51
Demand	138626	Ümraniye	0.5	10146.8571	51
Demand	85816	Ümraniye	0.5	10146.8571	51
Demand	52810	Ümraniye	0.5	10146.8571	51
Demand	89787	Tuzla	2.7	1337	37
Demand	119020	Tuzla	2.7	1337	37
Demand	133019	Sultanbeyli	0.5	112007	561
Demand	95898	Sultanbeyli	0.5	112007	561
Demand	80430	Sultanbeyli	0.5	112007	561
Demand	30441	Sancaktepe	0.5	145577.667	728
Demand	73057	Sancaktepe	0.5	145577.667	728
Demand	200908	Sancaktepe	0.5	145577.667	728
Demand	12928	Pendik	1.2	101699.143	1221

Demand	6464	Pendik	1.2	101699.143	1221
Demand	12928	Pendik	1.2	101699.143	1221
Demand	103420	Pendik	1.2	101699.143	1221
Demand	168058	Pendik	1.2	101699.143	1221
Demand	116348	Pendik	1.2	101699.143	1221
Demand	226231	Pendik	1.2	101699.143	1221
Demand	113054	Maltepe	1.1	102663.2	1130
Demand	108344	Maltepe	1.1	102663.2	1130
Demand	51816	Maltepe	1.1	102663.2	1130
Demand	103633	Maltepe	1.1	102663.2	1130
Demand	94212	Maltepe	1.1	102663.2	1130
Demand	98364	Kartal	1.3	94.1352	2
Demand	93893	Kartal	1.3	94.1352	2
Demand	71538	Kartal	1.3	94.1352	2
Demand	89422	Kartal	1.3	94.1352	2
Demand	93893	Kartal	1.3	94.1352	2
Demand	126560	Çekmeköy	0.5	132254	662
Demand	80916	Çekmeköy	0.5	132254	662
Demand	77135	Ataşehir	1.1	106273.5	1170
Demand	81195	Ataşehir	1.1	106273.5	1170
Demand	113673	Ataşehir	1.1	106273.5	1170
Demand	133971	Ataşehir	1.1	106273.5	1170
Demand	92512	Küçükçekmece	1.3	99102.625	1289
Demand	103613	Küçükçekmece	1.3	99102.625	1289
Demand	85111	Küçükçekmece	1.3	99102.625	1289
Demand	62908	Küçükçekmece	1.3	99102.625	1289
Demand	25903	Küçükçekmece	1.3	99102.625	1289
Demand	77188	Sarıyer	0.3	86803.5	261
Demand	107391	Sarıyer	0.3	86803.5	261
Demand	60408	Sarıyer	0.3	86803.5	261
Demand	90611	Sarıyer	0.3	86803.5	261
Demand	101038	Sultangazi	0.6	106913	642
Demand	116194	Sultangazi	0.6	106913	642
Demand	55571	Sultangazi	0.6	106913	642
Demand	136401	Sultangazi	0.6	106913	642
Demand	95986	Sultangazi	0.6	106913	642

Appendix F. Algorithm for calculating the impact and cost of mitigation projects

Algorithm for calculating the impact and cost of mitigation projects

Inputs: ρ_e: initial resilience level, C: coefficient for calculation of project cost

Outputs: δ_{pe}: improvement on resilience level of link e when project p is implemented

c_p: cost of project p

For e=1 to E

For s=1 to S

If $\rho_e \leq 3$, **then**

Step 1: Generate random number φ between 1 and (10 -ρ_e)

Step 2: Generate three (low, medium, high impact) projects for link e in scenario s:

Project 1 (low): generate random number σ_1 between 1 and (1- φ)/3 and update $\delta_{pe} = \sigma_1$

Project 2 (medium): generate random number σ_2 between (1- φ)/3 and 2(1- φ)/3 and update $\delta_{pe} = \sigma_2$

Project 3 (high): generate random number σ_3 between 2(1- φ)/3 and (1- φ) and update $\delta_{pe} = \sigma_3$

Step 3 : Calculate the cost of for all generated projects; $c_p = \delta_{pe} * C$

Else If $\rho_e \leq 6$, **then**

Step 1: Generate random number φ between 1 and (10 -ρ_e)

Step 2: Generate two projects for link e in scenario s:

Project 1: generate random number σ_1 between 1 and (1- φ)/2 and update $\delta_{pe} = \sigma_1$

Project 2: generate random number σ_2 between (1- φ)/2 and (1- φ) and update $\delta_{pe}^{s} = \sigma_2$

Step 3 : Calculate the cost of for all generated projects; $c_p = \delta_{pe} * C$

Appendix G. Multi-objective approaches results (same unmet demand and travel distance with different allocations)

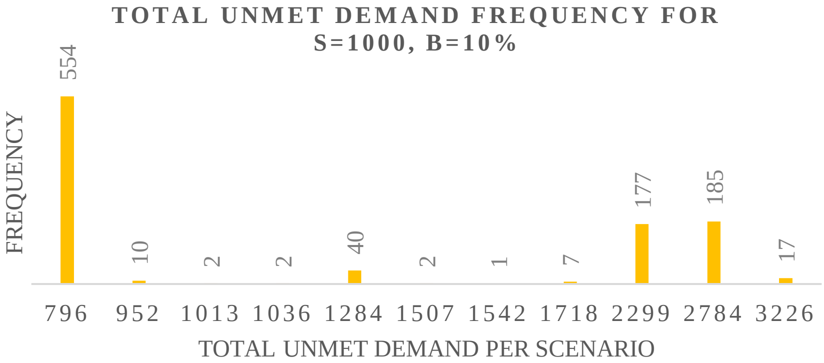
Appendix G.1. Lexicographic method's results for replication 8 for b=400

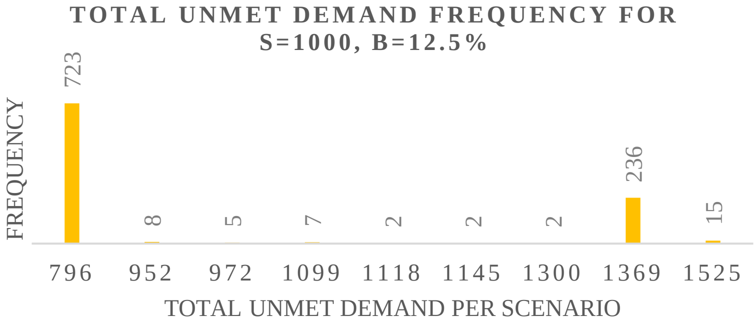
Demand node	Supplier node	Route no	Evacuated people	Route length	Total travel distance
1	3	2	385	19.58	7537.145
2	7	54	480	15.97	7667.04
3	**8**	**98**	**1988**	**34.87**	**69317.58**
4	2	129	1225	22.79	27916.53
5	8	191	404	38.76	15658.23
6	4	226	1060	7.18	7609.74
7	3	306	658	17.66	11621.6
8	2	359	347	40.54	14068.42
10	7	413	107	19.30	2065.207
11	6	442	975	26.98	26305.5
12	**8**	**513**	**108**	**42.48**	**4588.164**
12	**1**	**532**	**93**	**53.49**	**4974.105**
13	6	544	635	22.30	14162.41
14	4	608	391	12.93	5054.457
15	1	688	573	6.32	3620.214
16	3	736	474	11.15	5283.678
17	5	807	838	25.73	21565.09
18	2	825	428	8.79	3759.98
18	**1**	**836**	**834**	**32.26**	**26902.34**
19	5	877	724	12.67	9174.528
20	7	906	930	40.20	37383.21
21	7	918	112	31.27	3502.576
22	6	932	101	15.98	1613.778
23	7	980	424	27.97	11860.55
24	6	995	392	19.78	7753.368
25	5	1074	438	46.58	20400.29
25	7	1079	142	54.52	7741.13
26	7	1084	499	5.57	2780.927
		Total:	15765		381887.8
			Average travel distance per evacuee:		24.22377

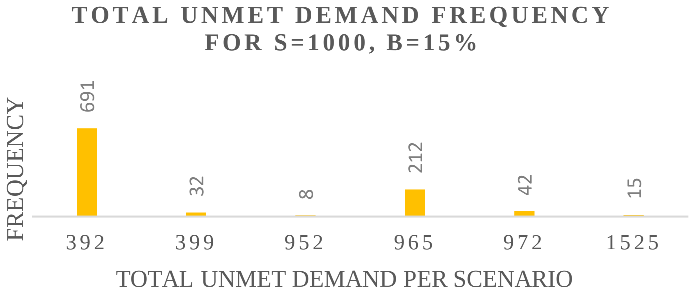
Appendix G.2. Weighted-sum method's results for replication 8 for b=400

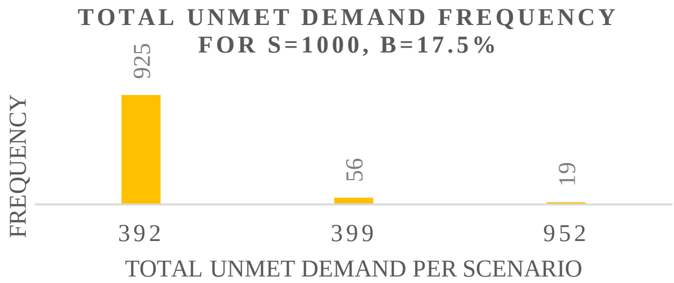
Demand node	Supplier node	Route no	Evacuated people	Route length	Total travel distance
1	3	2	385	19.58	7537.145
2	7	54	480	15.97	7667.04
3	**8**	**98**	**1262**	**34.87**	**44003.42**
3	**1**	**105**	**726**	**45.87**	**33301.62**
4	2	129	1225	22.79	27916.53
5	8	191	404	38.76	15658.23
6	4	226	1060	7.18	7609.74
7	3	306	658	17.66	11621.6
8	2	359	347	40.54	14068.42
10	7	413	107	19.30	2065.207
11	6	442	975	26.98	26305.5
12	**1**	**532**	**201**	**53.49**	**10750.49**
13	6	544	635	22.30	14162.41
14	4	608	391	12.93	5054.457
15	1	688	573	6.32	3620.214
16	3	736	474	11.15	5283.678
17	5	807	838	25.73	21565.09
18	2	825	428	8.79	3759.98
18	**8**	**830**	**834**	**21.255**	**17726.67**
19	5	877	724	12.67	9174.528
20	7	906	930	40.20	37383.21
21	7	918	112	31.27	3502.576
22	6	932	101	15.98	1613.778
23	7	980	424	27.97	11860.55
24	6	995	392	19.78	7753.368
25	5	1074	438	46.58	20400.29
25	7	1079	142	54.52	7741.13
26	7	1084	499	5.57	2780.927
		Total:	15765		381887.8
			Average travel distance per evacuee:		24.22377

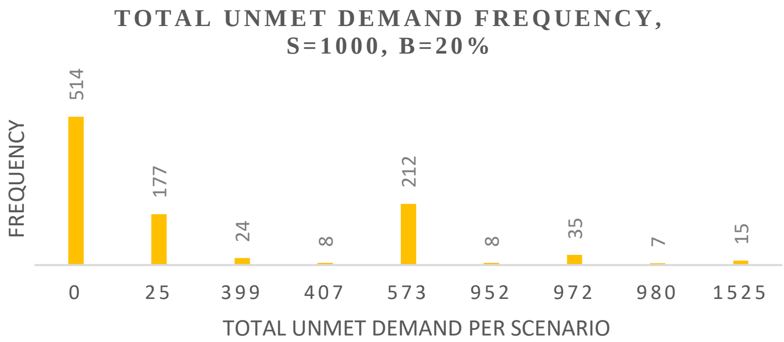
Appendix H. Total unmet frequencies for S=1000 and B= 10%, 12.5%, 15%, 17.5%, 20%, 22.5%, 25% (Total demand per scenario=17672)



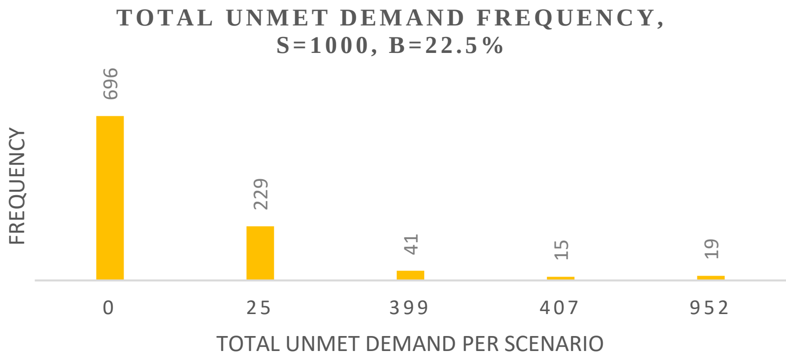





TOTAL UNMET DEMAND FREQUENCY FOR S=1000, B=17.5%
FREQUENCY
925
56
19
392
399
952
TOTAL UNMET DEMAND PER SCENARIO


TOTAL UNMET DEMAND FREQUENCY, S=1000, B=20%
FREQUENCY
514
177
24
8
212
8
35
7
15
0
25
399
407
573
952
972
980
1525
TOTAL UNMET DEMAND PER SCENARIO

…


TOTAL UNMET DEMAND FREQUENCY, S=1000, B=22.5%
FREQUENCY
696
229
41
15
19
0
25
399
407
952
TOTAL UNMET DEMAND PER SCENARIO

Appendix I. Mitigation Projects for Detailed network

Project No	Strengthen Link	Project No	Strengthen Link	Project No	Strengthen Link	Project No	Strengthen Link	Project No	Strengthen Link
1	13	41	392	81	442	121	498	161	818
2	15	42	394	82	443	122	499	162	820
3	22	43	395	83	444	123	500	163	821
4	23	44	396	84	445	124	530	164	822
5	116	45	398	85	446	125	534	165	824
6	117	46	401	86	447	126	574	166	825
7	118	47	402	87	448	127	576	167	826
8	119	48	403	88	449	128	584	168	827
9	120	49	408	89	450	129	588	169	828
10	157	50	409	90	451	130	599	170	829
11	158	51	412	91	452	131	599	171	830
12	159	52	413	92	453	132	600	172	831
13	160	53	414	93	454	133	604	173	834
14	296	54	415	94	455	134	607	174	835
15	302	55	416	95	456	135	608	175	836
16	306	56	417	96	457	136	609	176	844
17	312	57	418	97	458	137	652	177	848
18	313	58	419	98	459	138	690	178	863
19	320	59	420	99	460	139	693	179	866
20	321	60	421	100	461	140	716	180	873
21	322	61	422	101	462	141	738	181	874
22	323	62	423	102	463	142	739	182	875
23	324	63	424	103	464	143	740	183	876
24	326	64	425	104	465	144	745	184	877
25	327	65	426	105	466	145	746	185	878
26	328	66	427	106	467	146	750	186	879
27	336	67	428	107	468	147	753	187	880
28	337	68	429	108	469	148	755	188	881
29	338	69	430	109	470	149	756	189	882
30	339	70	431	110	471	150	757	190	883
31	341	71	432	111	472	151	759	191	884
32	348	72	433	112	473	152	761	192	885
33	350	73	434	113	489	153	770	193	886
34	353	74	435	114	490	154	771	194	887
35	374	75	436	115	491	155	772	195	888
36	376	76	437	116	493	156	793	196	889
37	388	77	438	117	494	157	794	197	890
38	389	78	439	118	495	158	797	198	891
39	390	79	440	119	496	159	803	199	892
40	391	80	441	120	497	160	817	200	893

Project No	Strengthen Link	Project No	Strengthen Link	Project No	Strengthen Link	Project No	Strengthen Link	Project No	Strengthen Link
201	894	241	934	281	987	321	1111	361	1287
202	895	242	935	282	988	322	1112	362	1288
203	896	243	936	283	989	323	1113	363	1289
204	897	244	937	284	990	324	1114	364	1294
205	898	245	938	285	991	325	1167		
206	899	246	939	286	992	326	1172		
207	900	247	940	287	993	327	1174		
208	901	248	941	288	994	328	1175		
209	902	249	942	289	995	329	1176		
210	903	250	943	290	996	330	1177		
211	904	251	944	291	997	331	1178		
212	905	252	946	292	998	332	1179		
213	906	253	947	293	999	333	1180		
214	907	254	948	294	1000	334	1181		
215	908	255	949	295	1001	335	1205		
216	909	256	950	296	1002	336	1206		
217	910	257	951	297	1003	337	1207		
218	911	258	952	298	1004	338	1208		
219	912	259	953	299	1005	339	1217		
220	913	260	954	300	1006	340	1218		
221	914	261	955	301	1007	341	1219		
222	915	262	956	302	1008	342	1226		
223	916	263	957	303	1009	343	1227		
224	917	264	969	304	1010	344	1236		
225	918	265	970	305	1011	345	1237		
226	919	266	971	306	1012	346	1238		
227	920	267	972	307	1013	347	1239		
228	921	268	974	308	1015	348	1240		
229	922	269	975	309	1023	349	1241		
230	923	270	976	310	1023	350	1256		
231	924	271	977	311	1048	351	1257		
232	925	272	978	312	1049	352	1260		
233	926	273	979	313	1050	353	1261		
234	927	274	980	314	1051	354	1280		
235	928	275	981	315	1052	355	1281		
236	929	276	982	316	1066	356	1282		
237	930	277	983	317	1083	357	1283		
238	931	278	984	318	1085	358	1284		
239	932	279	985	319	1086	359	1285		
240	933	280	986	320	1088	360	1286		

Appendix J. Seismic Intensity Map for Worst-case (Model C) in JICA report