Deep Uncertainty in Humanitarian Logistics:
Simulation and Analysis of the Interplay between Decisions and Uncertainty for Post-Disaster Facility Location Decisions

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DEEP UNCERTAINTY IN HUMANITARIAN LOGISTICS: SIMULATION AND ANALYSIS OF THE INTERPLAY BETWEEN DECISIONS AND UNCERTAINTY FOR POST-DISASTER FACILITY LOCATION DECISIONS

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EXECUTIVE SUMMARY

Research Background
Every year, many people suffer due to natural disasters. The frequency and impact of these natural disasters have increased, which underpins the importance of efficient and effective disaster response more than ever. One of the central aspects of effective disaster response is recognised to be humanitarian logistics.

Humanitarian response to disasters is challenging, because of the time pressure involved and the lack of reliable information. Therefore, decisions in disaster situations must be made while coping with collective stress and deep uncertainty. Important logistics decisions made under deep uncertainty, such as deciding on the locations of central logistics hubs, can reduce the uncertainty in the surrounding areas because they can enable better access to reliable information. This creates an interaction between decisions and uncertainty: decisions made under deep uncertainty cause a change of uncertainty for future decisions.

To address the interaction between decisions and uncertainty, this research aims to (1) find a way to make robust humanitarian facility location decisions over multiple periods to cope with time pressure and deep uncertainty, while considering multiple objectives, and (2) understand how different types of decisions affect the uncertainty space over time. To achieve these research objectives, this research introduces an approach for the simulation and analysis between decisions and uncertainty. This leads to the main research question of this study: *What are the analytical contributions of an approach that helps to simulate and analyse the interaction between decisions and uncertainty for post-disaster facility location decisions?*

To answer the main research question, firstly, the design of the approach for the simulation and analysis of the interaction between decisions and uncertainty is introduced, and secondly, this approach is applied to the post-disaster facility location problem as a proof of principle of the designed approach. Finally, the approach is evaluated based on the results from the application of the approach to the post-disaster facility location problem.

Approach for the simulation and analysis of the interaction between decisions and uncertainty

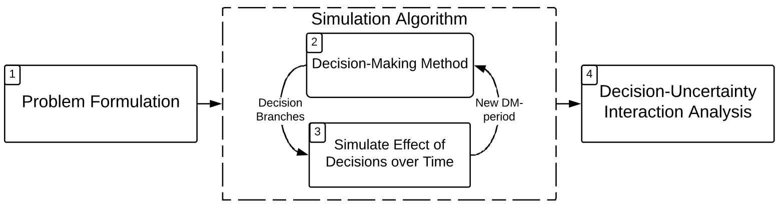

Figure 0.1: Conceptual Overview: Approach for Simulation and Analysis of the Interaction between Decisions and Uncertainty

The approach for simulation and analysis of the interaction between decisions and uncertainty consists of four parts, see Figure 0.1. The first part of the approach aims to create the problem formulation; the problem formulation involves (1) specifying how decisions can be made under uncertainty, (2) specifying how decisions influence the uncertainty space, and (3) gathering the required data for the simulation. The second part simulates which robust decisions can be made; an algorithm, based on the Many-Objective Robust Decision-Making (MORDM) framework, simulates robust decisions over multiple periods, while dealing with deep uncertainty and considering multiple objectives. The third part is simulated by the 'inter-period model'; this simulates the effects of the robust decisions on uncertainty over time and is specified in the problem formulation part. The combination of the second and the third part form the simulation algorithm for simulation of the interaction between decisions and uncertainty. The fourth part is the decision-uncertainty interaction analysis, which gives insight into the interaction between decisions and uncertainty with three different analyses: (1) analysis of objective trade-offs, (2) analysis of important scenarios, and (3) analysis of the effect of decisions on the reduction of uncertainty.

Proof of principle of the Approach: Post-Disaster Facility Location Decisions in the Aftermath of the 2015 Earthquake in Nepal

The designed approach is applied to the post-disaster facility location problem. A facility location model that fits the problem conceptualisation and can be integrated with the approach is developed. This model includes objectives that represent the efficiency, effectiveness and equity of humanitarian logistics. Then, a decision-making algorithm based on the MORDM framework is created, which uses enumerative optimisation and two different robustness metrics. These metrics are a signal-to-noise and a regret-based metric, which are selected for the re-evaluation of solutions under uncertainty to ensure robustness. For the simulation of the effect of decisions on uncertainty over time, an inter-period model is developed, where the reduction of uncertainty is dependent on the decisions. Finally, a stylised representation of the 2015 Nepal Earthquake is created for the post-disaster facility location problem to enable simulation.

Findings

The analysis shows that there are two types of facility location decisions; those that have low costs but limited effectiveness, or those that have high costs but are highly effective. Furthermore, it shows that there is not necessarily a trade-off between how well solutions score on effectiveness and equity. The scenario discovery analysis gives insight into the effect of uncertainty on facility location decisions. It shows that the most harmful scenarios are related to scarcity of transport vehicles, post-disaster fuel crises, a limited supply of relief goods and disaster victims that are highly dependent on aid. Specifically, the scenario discovery indicates the importance of reducing the uncertainty about remote valleys for more equitable humanitarian logistics.

The analysis of the effect of decisions on the reduction of uncertainty shows that prioritisation of effectiveness and equity have a positive relationship with the reduction of uncertainty, while the prioritisation of minimising costs has a negative relation with the reduction of uncertainty. Contemporary arguments for focussing on effectiveness and equity are based on ethical arguments, however, this novel insight introduces an additional argument to focus on these objectives. Furthermore, the analysis has indicated that the reduction of uncertainty leads to more optimal facility location decisions, which emphasises the importance of reducing the uncertainty.

Various recommendations for humanitarian logisticians are made based on the findings. Regarding the objective prioritisations, it is recommended that decision makers consider costs only as a constraint for making decisions because it is considered inhumane to not provide aid when the means are available. Decision makers should instead focus on making decisions that maximise effectiveness and equity while not compromising one of these two objectives. To shield against the most harmful scenarios, multiple suggestions are made to improve disaster preparedness. For improving disaster preparedness, the focus should be on ensuring reliable fuel reserves, providing public hazard education, and ensuring the availability of sufficient transport vehicles. Uncertainty about remote valleys is often reduced more slowly while this uncertainty can have a large impact on the equity of humanitarian logistics. Therefore, to better deal with the uncertainty inherent to post-disaster decision-making, it is important that information management focusses specifically on reducing the uncertainty of these remote valleys.

The evaluation of the designed approach indicates that the step-wise decision-making method based on the MORDM framework is very suitable for making decisions under deep uncertainty as it enables assimilation of new information over time. Furthermore, it shows that the decision-uncertainty interaction analysis offers new insight into the interaction between decisions and uncertainty. These insights have a mainly strategic and qualitative character.

Future research should focus on how this study on humanitarian logistics facility location decisions can be extended by adding complexity to the facility location model and including more empirical data for the simulation. Another interesting research direction is to look at how the approach can be improved or extended. This can be done by experimenting with the strength of the uncertainty reduction, experimenting with the number of periods simulated, using different optimisation algorithms, and looking at the variability of scenarios over time. Lastly, different problem domains can be explored for the application of the approach. An interesting, but similar, domain would be to look at slow-onset disasters where the disaster environment changes over time. More different, yet interesting application domains are related to commercial facility location decisions or investment decisions related to technology development.

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"The future depends on what we do in the present."

\- Mahatma Gandhi

Part I

Research Formulation

1 INTRODUCTION

Every year, many people suffer because of natural disasters, with an increase in frequency and impact due to factors such as climate change and urbanisation (Thomas & López, 2015). Some of these disasters bring grave consequences for society and individuals. The earthquake in Nepal 2015, with a magnitude of 7.8, instantly created a humanitarian crisis, affecting 8 million people and causing more than 9000 deaths (Centre for Research on the Epidemiology of Disasters, 2015). In 2017, a record of $27.3 billion was allocated to humanitarian response, although 41% of the UN-coordinated appeal fell short (Development Initiatives, 2018). These numbers indicate the importance of effective disaster response.

1.1 HUMANITARIAN LOGISTICS AND DEEP UNCERTAINTY

One of the central aspects of effective disaster response is recognised to be humanitarian logistics, which is a part of the field of logistics that focusses on problems related to disaster situations (Blecken, Hellingrath, Dangelmaier, & Schulz, 2009; Pettit, Beresford, Whiting, & Banomyong, 2011). Humanitarian logistics is characterised by a strong need for urgent action, decision makers being responsible for many lives, while decision makers of many different humanitarian organisations are involved. With more adequate humanitarian logistics, more lives can be saved, economic damage from disasters can be reduced, and societal impacts can be limited (Van Wassenhove, 2006).

When dealing with humanitarian crises, reliable information is often lacking and information management faces different challenges (Baharmand, Comes, & Lauras, 2017; Altay & Labonte, 2014). Decisions in disaster situations must be made urgently, while coping with collective stress and deep uncertainty (Barton, 1969; Rosenthal, t Hart, & Charles, 1989). Walker, Marchau, and Kwakkel (2013, p. 230) define deep uncertainty as the type of uncertainty where decision makers 'do not know' and 'cannot agree upon' which are the key factors, the information concerning those key factors, and the desirability of alternative outcomes and criteria. Logistics decisions made under deep uncertainty, such as deciding on the locations of central logistics hubs, can enable better access to information in the surrounding areas. This creates an interaction between decisions and uncertainty: Decisions made under uncertainty affect the uncertainty for future logistics decisions or decisions for disaster relief in general.

A possible way of dealing with deep uncertainty in humanitarian logistics is the Robust Decision-Making (RDM) approach, which is closely related to the Exploratory Modelling and Analysis (EMA) approach (Walker, Marchau, & Kwakkel, 2013, p. 239). The EMA approach stems from the idea that computational experiments can assist in reasoning about systems where there is significant uncertainty (Bankes, 1993). RDM focusses on finding strategies that perform well across a wide range of plausible scenarios, which can be preferred when systems are subject to deep uncertainty (Lempert, Groves, Popper, & Bankes, 2006; Rosenhead, Elton, & Gupta, 1972). These model-based decision-making approaches have primarily focussed on the long-term decision-making context. Examples such as scenario discovery (an EMA method used for scenario-based planning) or robust optimization (an RDM method), focus often on long-term policy problems with horizons of possibly multiple decennia (Halim, Kwakkel, & Tavasszy, 2016; Trindade, Reed, Herman, Zeff, & Characklis, 2017; Lempert, Popper, & Bankes, 2003). The use of these model-based approaches on urgent decision-making has remained largely unexplored, while they could prove helpful to assist in making humanitarian logistics decisions when limited or inadequate information is available.

Table 1.1: Preliminary Research Objective

The main focus of this thesis is to design an approach that can help to create a better understanding of the interaction between decisions and uncertainty for post-disaster facility location decisions. This focus is two-fold: It focusses on how decisions for humanitarian logistics can be taken while coping with the inherent deep uncertainties, and it focusses on how decisions influence the uncertainty in post-disaster environments.

The remainder of this introduction looks at the literature on humanitarian logistics decision-making and uncertainty, the decision-making environment, and existing model-based approaches for humanitarian logistics. This chapter concludes with a knowledge gap, identified based on the literature review.

1.2 BACKGROUND POST-DISASTER DOWNSTREAM HUMANITARIAN LOGISTICS

The literature on humanitarian logistics uses different typologies for different types of aid or disasters (Cozzolino, 2012). Disasters can be man-made or caused by nature, such as a nuclear accident or an earthquake, respectively. They can have a slow- or sudden-onset, such as a drought or a cyclone. Regardless of the type of the disaster, three main phases in disaster relief are preparation, immediate response, and reconstruction (Kovács & Spens, 2007). The relevance of uncertainty in sudden-onset natural disasters is evidently present for the immediate disaster response, which is where this thesis focusses on.

Natural disasters such as the 2015 Nepal earthquake create huge demands among the affected population. For the Nepal Earthquake, UN OCHA (2015) issued a flash appeal for a total of 415 million USD, to be able to bring life-saving assistance to the 8 million affected in Nepal for over the first three months after the disaster. A flash appeal is an analysis of the context and an initial plan to address acute humanitarian needs, issued within 5-7 days of the occurrence of major sudden-onset disasters. The relief material needed for major disasters consists of both food and non-food items (e.g., food and water, healthcare and shelter).

The supply chains for supplying relief goods to disaster victims have to deal with both upstream and downstream logistics. Upstream logistics refers to the logistics operations required for mobilisation, production, collection and transport of relief goods from all over the world to the international logistics hubs located in the affected area. Downstream logistics refers to the logistics operations required to distribute the relief goods from the entry points to the disaster victims. The entry points are the places where relief goods enter a country, such as airports, train stations, or seaports.

Challenges in upstream logistics are related to sourcing, prepositioning and transport. To deliver aid to the affected area as quickly as possible, relief items should be located as close as possible to disaster-prone areas (Balcik & Beamon, 2008). Challenges in downstream logistics are related to congestion at entry points, deciding on focus areas and transport obstacles. Capacity limitations of international logistics hubs (such as airports) or disrupted road infrastructures in disaster-affected regions can, for example, hinder the quick imports and transport of relief supplies (UNDP, 2017; Tuzun Aksu & Ozdamar, 2014).

Congestion on entry points, such as airports, emerges because they can often handle only a limited amount of cargo and have limited storage capacities (Moline, 2013). The inability to handle these relief supplies and transport them to the affected regions sometimes results in long delivery times of the most critical needs, or certain areas being completely deprived of humanitarian aid (Pattison, Burke, & Jones, 2015; HRRP, 2016). Hence, to relieve the burden on these entry points, it is important to transport the relief goods from the entry points to central distribution locations as quickly as possible.

1.3 CHALLENGES IN THE DECISION-MAKING ENVIRONMENT

The decision-making environment must be considered if a model-based approach aims at fully addressing deep uncertainty for post-disaster humanitarian logistics decisions. The chaotic settings and urgent needs result in a vastly different decision-making environment compared to long-term decision-making environments (Holguín-Veras, Jaller, Van Wassenhove, Pérez, & Wachtendorf, 2012). In this section, the most important challenges of this decision-making environment are discussed.

1.3.1 Post-Disaster Actor Environment

In the aftermath of a disaster, different organisations and actors need to work together to respond to the needs of the people in the affected area. The players involved in the decision-making process consist of numerous different organisations such as Non-Governmental Organisations (NGOs), military organisations, international organisations, the private sector, donors, the public sector, media, and individuals (Verity, n.d.; UN OCHA, 2013).

The plurality of decision makers results in diverging interests, objectives, and perspectives. Each of the humanitarian organisations has different mandates, goals, criteria, and ideas on how to achieve their goals. The goals of these players may often be conflicting (Stumpenhorst, Stumpenhorst, & Razum, 2011). For example, some humanitarian logistics organisations that provide relief supplies to the affected population might value common supply chain criteria, such as costs, delivery times, et cetera, while other humanitarian organisations might focus on coverage, equal distribution, and sustainability. When creating comprehensive solutions for disaster relief, it is essential to consider the variety of preferences of different organisations.

1.3.2 Coordination via the Cluster Approach

It is well understood that poor coordination in general has a negative effect on collective decision-making, especially in the chaotic decision-making environment inherent to disasters. Humanitarian coordination brings aid workers together and ensures aiming for shared objectives, so that humanitarian assistance is provided to the people who need it most (de Mul, 2002). As Boin, Kelle, and Clay Whybark (2010, p. 2) put it: "Coordination is the holy grail of disaster response". However, Tomasini and Van Wassenhove (2009a, p. 551) find that different actors often operate uncoordinatedly, not uncommonly with ambiguous objectives. When organisations focus on their own goals, without coordination, there is no holistic effort, making it harder to satisfy the needs of the affected people.

United Nations Office for the Coordination of Humanitarian Affairs (UN OCHA) is one of the organisations focusing on improving coordination and tries to align actors on long-term shared objectives rather than short-term opportunistic behaviour (Stumpenhorst et al., 2011). The Humanitarian cluster system aims to separate the responsibilities of organisations and to improve coordination within clusters. Organisations are grouped together into clusters, where each cluster is responsible for one the main sectors of disaster response, such as water, health, and logistics, and where each cluster has a cluster lead (Jensen, 2012; Jahre & Jensen, 2010). This thesis focusses on the transport of relief goods, where the Logistics Cluster has the role of cluster lead and hence is responsible for effective and efficient humanitarian logistics. A model-based approach to support the Logistics Cluster in collective decision-making should consider the ambiguity of organisations' objectives and support in reaching consensus.

1.3.3 Post-disaster information

The humanitarian coordination system relies on information sharing (Altay & Labonte, 2014). However, data reliability is problematic in the early phase of disaster response (Van de Walle & Comes, 2015). The importance of knowing the humanitarian needs makes uncertainty detrimental for coordination of disaster response. When gaps of the response are identified, the cluster will coordinate those gaps to be filled, while trying to avoid redundancies. Coordinated information management can be especially challenging because of the time pressure involved.

As mentioned in the introduction, decisions on the locations of central logistics hubs can affect the information that is available. One important information flow impediment is the inaccessibility of information, which can partly be resolved by gaining physical access to the area (Day, Junglas, & Silva, 2009). Placing a central logistics hub in an area is likely to lead to a reduction of uncertainty around its location. A central logistics hub requires field staff, communication infrastructure, material resources, et cetera and enables disaster relief activities. These activities, such as relief distribution, medical aid, et cetera, lead to more insight into the needs and the communication infrastructure helps to communicate this new information with the outside world.

1.3.4 Constraints of the Post-Disaster Humanitarian Logistics Decision-Making Environment

There are multiple constraints that have to be considered when making decisions for post-disaster humanitarian logistics operations (Holguín-Veras et al., 2012). An overview of the most important constraints is given in Table 1.2. These constraints create a vastly different decision-making environment for humanitarian logistics compared to commercial logistics.

Table 1.2: Post-Disaster Decision-Making Constraints

Constraint	Description
Budget constraint	Humanitarian organisations and their donors have limited budgets for addressing disaster-related problems. In order to choose their strategies, tactics and deploy their operations, these organisations have to select possible alternatives while staying within their budget.

Time constraint	Time is scarce in disaster relief, especially in the immediate disaster response phase. Decisions have to be made while coping with time pressure and collective stress, knowing that the delay of decisions can cost lives. For example: "If the delivery or [*sic*] water, food, blankets or shelter material are delayed this may result in additional deaths" (Cosgrave, 1996, p. 28).
Material and human resource constraint	The human and material resources needed for a disaster differ for each disaster type. After a disaster, the necessary type of material or expertise is often not available at location when needed. When it is available, the necessary quantities of people or material are often lacking where they are needed most (Young & Peterson, 2014).
Information and communication constraints	Information and communication constraints have been discussed in section 1.3.3. Even when information is available, the inability of communication for example due to the destruction of communication infrastructure can restrict access to this information (Ran, 2011).
Access or transport constraint	Distortion of road infrastructure leads to an access or transport constraint. For example, roads could be inaccessible because of major debris from hurricanes or bridges that provides main access to an area could be destroyed because of earthquakes (Pramudita, Taniguchi, & Qureshi, 2014).
Political constraint	Politicized environments can also put political constraints on humanitarian operations, especially when local governments are part of the conflict or when national governments have hidden agendas (Tomasini & Van Wassenhove, 2009b).

1.3.5 Incremental Decision-Making

To deal with these constraints in the complex and unpredictable nature of disasters, disaster responders should be flexible in their decisions (Mendonca, Beroggi, & Wallace, 2001). As post-disaster information is often dynamic with more and more reliable data being processed over time, decision makers should be able to change their strategy over time to adjust for information changes (Liu & Wang, 2018).

A sequential approach to decisions on logistics hub locations could lead to better outcomes by assimilating new information into each succeeding decision. Khalili, Babagolzadeh, Yazdani, Saberi, and Chang (2016) have focussed on such a multi-period approach where up-to-date information can be taken into account. They specifically propose the consideration of data uncertainty to be a possible venue for future research, which is the central focus of this thesis.

1.4 HUMANITARIAN LOGISTICS MODELS FOR DISASTER RESPONSE

There are different humanitarian logistics models in the response phase. The three main types are (last mile) vehicle routing (e.g. Ahmadi, Seifi, & Tootooni, 2015), location and allocation of distribution centres (e.g. Jabbarzadeh, Fahimnia, & Seuring, 2014), and mass evacuation (e.g. Bish, 2011). As mentioned earlier, this study focusses on the interaction between location decisions and uncertainty. Therefore, this literature review looks at facility location models with a special focus on the role of uncertainty.

1.4.1 Post-Disaster Facility Location Models

Table 1.3: Synthesis of Post-Disaster Facility Location Models

Article	Objectives					Model properties	
Authors year	Demand coverage	Fairness in distribution	Costs	Time	Other Objectives	Uncertainty	Multi-Period
Jabbarzadeh, Fahimnia, and Seuring (2014)			✓			Discrete scenarios	✓
Tricoire, Graf, and Gutjahr (2012)	✓		✓			Stochastic	
Rath, Gendreau, and Gutjahr (2016)	✓		✓			Discrete scenarios	
Tzeng, Cheng, and Huang (2007)		✓	✓	✓			✓
Nolz, Doerner, Gutjahr, and Hartl (2010)		✓		✓			
Vitoriano, Ortuño, Tirado, and Montero (2011)		✓	✓	✓	Priority, Security & Reliability		
Bozorgi-Amiri and Khorsi (2016)		✓	✓	✓		Stochastic	✓
Maharjan and Hanaoka (2018)	✓		✓				✓
Gutjahr and Dzubur (2016)	✓		✓				
Tavana, Abtahi, Di Caprio, Hashemi, and Yousefi-Zenouz (2017)			✓	✓			✓
Hong, Jeong, and Xie (2015)	✓		✓			Discrete scenarios	
Bozorgi-Amiri, Jabalameli, and Mirzapour Al-e-Hashem (2013)	✓		✓			Stochastic	
This Study	✓	✓	✓	✓		Deep Uncertainty	✓

In their literature review on (disaster unrelated) facility location models, Melo, Nickel, and Saldanha-da-Gama (2009) conclude that the lack of inclusion of (stochastic) uncertainty is a problem for facility location models. Seven years later, Habib, Lee, and Memon (2016) mention in their literature review on humanitarian logistics models that this has not been addressed in contemporary post-disaster facility location models. The assumption is often made to have complete information of the major relevant uncertainties.

Optimisation is frequently used to approach logistics problems, but to include the conflicting actor preferences inherent to the post-disaster environment, optimisation should be based on multiple criteria. Gutjahr and Nolz (2016) review the literature on multi-criteria optimisation in humanitarian aid and recommend future research to focus on the reliability criterion and more specifically on robust multi-objective optimisation models.

To see more specifically how deep uncertainty is taken into account in current humanitarian logistics models, a small literature review looks at how contemporary research on humanitarian post-disaster facility location models include aspects such as: multiple objectives, uncertainty, and multi-periodicity. The articles included in the literature review are selected from review papers and from an online search, see Appendix A for more details on the paper selection.

Many different objectives have been considered in the different facility location models. For example, Tzeng, Cheng, and Huang (2007) consider fairness in distribution, costs, and travel time. Most studies that focus on including many different objectives, do not include multi-periodicity and uncertainty (e.g. Vitoriano, Ortuño, Tirado, & Montero, 2011).

When uncertainty is considered, it does not focus on deep uncertainty. For example, Bozorgi-Amiri and Khorsi (2016) look at facility location in multiple periods and multiple objectives, but they only consider stochastic uncertainty. Similarly, the other articles that do consider uncertainty, merely consider stochastic uncertainty. Where stochastic uncertainty considers probabilities, deep uncertainty relates to the idea that we know nothing about these probabilities (Walker, Lempert, & Kwakkel, 2013). Omrani and Ghiasi (2017) consider data uncertainty. They present a (disaster unrelated) robust optimization approach for facility location where data uncertainty is considered, but they only take a single objective into account.

1.4.2 Synthesis of Humanitarian Logistics Models

The conclusion from the literature review is that contemporary research to facility location decisions has not considered the combination of deep uncertainty, multiple objectives, and multi-periodicity. Table 1.3 gives a synthesis of the reviewed literature. It also gives a preview of what this study focusses on. This study considers different objectives, multiple periods and deep uncertainty. More specifically, it looks at the interplay between decisions and uncertainty over time.

1.5 KNOWLEDGE GAP

The most important gap in the literature is that the presence of deep uncertainty is not well considered in humanitarian logistics modelling. The research that focusses on model-based decision-making for humanitarian logistics does consider different important aspects such as a variety of objectives, stochastic uncertainty, and multiple periods. However, the combination of all these different aspects has not yet been researched. Especially because the interplay between post-disaster facility location decisions and uncertainty is expected to play an important role in humanitarian logistics, this study aims to address this knowledge gap by designing an approach for the simulation and analysis of this interplay.

The design of this approach should acknowledge the duality of the interplay between decisions and uncertainty. Therefore, this study aims to (1) find a way to make robust humanitarian facility location decisions over multiple periods, to deal with time pressure and deep uncertainty, while considering multiple objectives, and (2) understand how different types of decisions affect the uncertainty space over time. This way, the approach should shed new light on the interaction between humanitarian facility location decisions and uncertainty.

Table 1.4: Scientific and Societal Relevance

Scientific contributions

- ✓ Provide an approach for the simulation and analysis of the interaction between decisions and uncertainty.
- ✓ Provide a method for making robust facility location decisions over multiple periods to cope with time pressure and deep uncertainty, while considering multiple objectives.
- ✓ Provide insight into the effect of decisions on the reduction of uncertainty for post-disaster facility location decisions.
- ✓ Provide insight into the effect of uncertainty on post-disaster facility location decisions.

2 RESEARCH GOAL AND METHOD

This chapter introduces the goal of this research and the methodology to attain the research goal. A preliminary research objective has been formulated in the introduction in Chapter 1 after which the knowledge gap is identified. This chapter indicates how this research fills this gap. First, the research goal is mentioned and based on these goals different research questions are formulated. The research methodology then describes how these questions are answered throughout this research.

2.1 RESEARCH GOAL AND RESEARCH QUESTIONS

The main research goal is to design an approach for the simulation and analysis of the interaction between decisions and uncertainty and use this approach to better understand this interplay for humanitarian logistics facility location decisions. A better understanding of the interplay between decisions and uncertainty can help decision makers to better cope with the uncertainty inherent to making post-disaster facility location decisions. The main research question that follows from the knowledge gap and this main research goal is:

What are the analytical contributions of an approach that enables simulation and analysis of the interaction between decisions and uncertainty for post-disaster facility location decisions?

Four guiding sub-questions are formulated to indicate the different components of which this research consists. A short elucidation of each question is given first, followed by the sub-question.

To find the analytical contributions of an approach, it is essential to have access to an approach for the simulation and analysis of the interplay between decisions and uncertainty. As this approach does not yet exist, the first part of this research focusses on designing the approach.

Sub RQ 1 *How can the interaction between decisions and uncertainty be simulated and analysed?*

To test and evaluate the designed approach, the approach is applied to the post-disaster facility location problem as a proof of principle. An important component of the designed approach is model-based simulation and analysis. The creation of a formal problem formulation helps to create a better understanding of the important factors of post-disaster facility location. It is important that the formal problem formulation captures the complexities of the post-disaster environment as described in the introduction and that it is compatible with the other components of the approach.

Sub RQ 2 *How can the post-disaster facility location problem be captured in a formal problem formulation that fits the designed approach?*

The purpose of the approach is to get a deeper understanding of the interaction between decisions and uncertainty. Important in this research is to analyse the results from the simulation of the interaction between decisions and uncertainty. This research focusses specifically on the analytical contributions because the gained insights are purely based on simulation and analysis and are not based on empirical data.

Sub RQ 3 *What are the analytical insights of the approach in the decision-uncertainty interaction for post-disaster humanitarian logistics facility location?*

The last part of this research focusses on evaluating how well the decision-making method performs while simulating and optimising decisions under uncertainty compared to a method that has perfect foresight.

Sub RQ 4 *How does the decision-making method perform compared to a method with perfect foresight?*

2.2 RESEARCH METHODOLOGY

On the highest abstraction level, the methodology of this research is based on a design cycle. The design cycle is a process where the approach is designed and evaluated iteratively so that the final design satisfies the objectives and requirements of the design (Simon, 1996; Hevner, 2007). The design cycle in this research focusses on the design and evaluation of an approach for simulation and analysis of the interaction between decisions and uncertainty. While the process of designing and evaluating this approach is iterative in nature, the design and the evaluation of the approach are presented linearly to prevent distractions from the storyline.

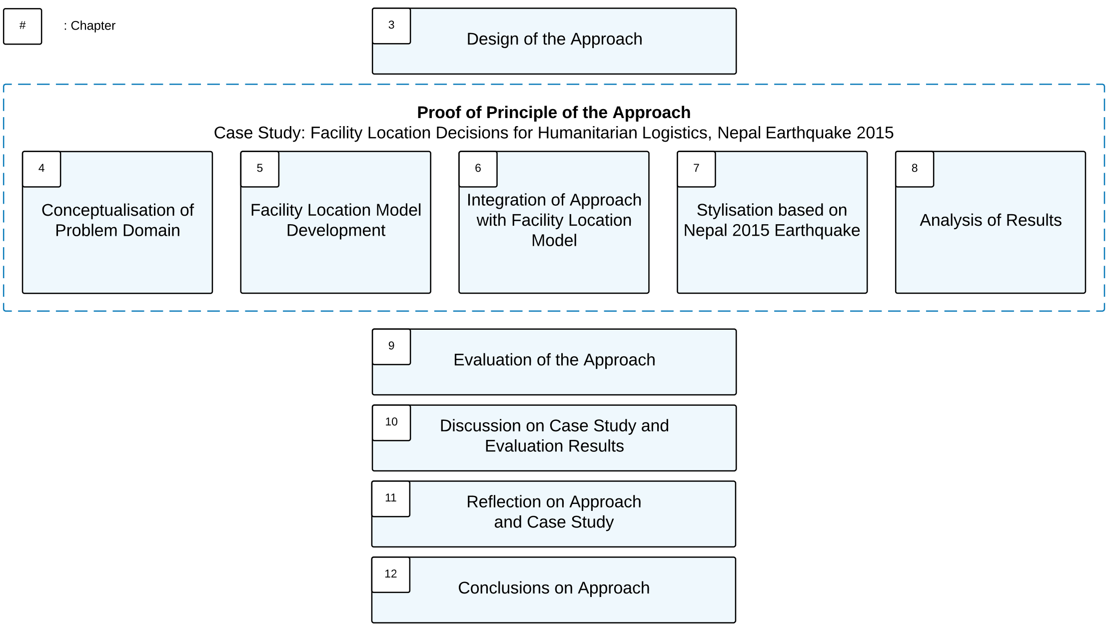


Figure 2.1: Research Outline

The complete outline for this research is shown in Figure 2.1. The outline consists of different parts. First, the decision-making approach for analysing the decision-uncertainty interaction is designed in Chapter 3. Second, a case study on facility location decisions for humanitarian logistics serves as a proof of principle of the approach in Chapters 4 to 8. The multiple steps of the proof of principle reflect the steps as described in the design of the approach. Third, the evaluation of the approach is presented in Chapter 9. Fourth, the results from the analysis and the evaluation are discussed in Chapter 10. Fifth, a reflection on the research, the approach, the assumptions and the findings are presented in Chapter 11. Finally, conclusions are drawn from the research and the research questions are specifically addressed in Chapter 12.

2.2.1 Proof of Principle of the Approach

As mentioned, the proof of principle follows five steps to showcase the designed approach. Without going too much into detail on the design of the approach, a short elucidation on the steps that constitute the proof of principle is given. The proof of principle is based on a case study on facility location decisions for humanitarian logistics after the 2015 earthquake in Nepal.

1. The first step is to give a conceptual description of the disaster characteristics and the important objectives for decision-making, in order to demarcate the problem domain.

2. The second step is to develop a facility location model that corresponds to the system conceptualisation. This facility location model is required to be compatible with the model-based approach.

3. The third step focusses on the integration of the facility location model with the designed approach.

4. To showcase the approach, the case study is based on stylised data to resemble the 2015 Nepal earthquake situation.

5. The simulation results are then analysed. The first analysis focusses on the objective trade-offs. The second analysis looks at which uncertainties are most relevant for decision-making. The third analysis aims to provide a better understanding of the effect of decisions on uncertainty by doing correlation and regression analysis of objective prioritisations and the reduction of uncertainty over time.

2.2.2 Evaluation of the Approach

To see how well the designed decision-making method of the approach performs for making decisions under uncertainty, Chapter 9 focusses on the evaluation of this decision-making method. The designed approach simulates different decisions while having to deal with uncertainty. The designed approach performs well when the simulated decisions solutions perform approximately as well as the solutions found by an optimisation method with perfect foresight. How well the approach approximates these optimal solutions is measured by comparing the Pareto fronts of the two solution sets and other metrics, which is explained in more detail in the corresponding analysis.

Part II

Design of the Approach

3 APPROACH FOR UNDERSTANDING THE INTERPLAY BETWEEN DECISIONS AND UNCERTAINTY

In this study, the focus is on the interaction between decisions and uncertainty for humanitarian logistics. An approach for analysing this interplay might also be relevant for other problem domains. Therefore, this approach is designed independently of humanitarian facility location decisions.

This chapter describes the design of this general approach for analysing the interaction between decisions and uncertainty. First, the problem characteristics for which the approach is designed and the design requirements are listed. Second, a conceptual overview of the designed approach is presented. Then, the four parts of the approach are separately elucidated. Finally, the flow of the approach is explained.

3.1 PROBLEM CHARACTERISTICS AND DESIGN REQUIREMENTS

To have a clear view for what type of problems the approach is designed, the specific problem characteristics are defined. These problem characteristics are translated into design requirements. This first section of this chapter lists these problem characteristics and requirements for a suitable approach.

Problem characteristics
These problem characteristics are abstracted from the post-disaster facility location problem. This way the designed approach is applicable to a category of problems with similar problem characteristics. The approach for the interaction between decisions and uncertainty is relevant for problems where:

- Sequential decisions have to be made.
- Decisions are subject to deep uncertainties.
- There are conflicting ideas on objective prioritisations.
- Models can be used to evaluate possible decisions.
- Decisions are subject to path-dependent relations. In other words, decisions affect the future decision space.
- Decisions are expected to affect the uncertainty space over time.

Approach requirements
The articulation of design requirements is important for the design of a complete and effective approach (Hevner, March, Park, & Ram, 2004). The approach is designed based on requirements

that are in line with the research goal and consider the problem characteristics. The approach should be able to:

- Help making robust decisions that account for deep uncertainty and lacking information.
- Evaluate decisions on multiple objectives while considering the conflicting objective prioritisations.
- Simulate the different robust decisions for multiple time-periods.
- Simulate the effect of decisions on the solution space in future periods to simulate path dependencies.
- Simulate the effect of decisions on the uncertainty space and available information at future periods.
- Keep track of all information for all decision sequences and all time-periods. Information that should be tracked for all sequences and periods includes the decisions made, the objective scores, and the uncertainty space. This information should be kept track of so that it can be used for analysis afterwards.
- Give insight into the objective trade-offs, the most important uncertainties, and the effect of decisions on uncertainty.

3.2 CONCEPTUAL OVERVIEW OF THE DESIGNED APPROACH

This section presents a conceptual overview of the designed approach. It will introduce the approach by briefly explaining each of the top-level parts of the approach. In the following sections, each of the parts will be elaborated separately in more detail.

The approach for simulation and analysis of the interplay between decisions and uncertainty consists of four parts. The first part of the approach is to create a problem formulation, the second part simulates which decisions can be made, the third part simulates the effects of these decisions on uncertainty over time, the final part is a decision-uncertainty interaction analysis which gives insight into the results of the simulation. The second and third part together simulate the interplay between decisions and uncertainty. See figure 3.1 for a conceptual overview of this approach.

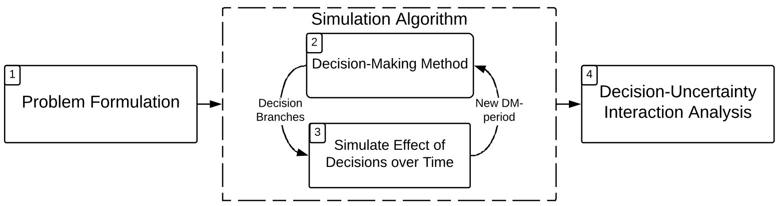


Figure 3.1: Conceptual Overview: Approach for Simulation and Analysis of the Interplay between Decisions and Uncertainty

The first part of the approach is the creation of a problem formulation. Rittel and Webber (1973) state that there is no definitive problem formulation of complex problems due to diverging perceptions of the problem. However, a well-defined problem formulation helps to structure a complex problem and makes it accessible to model-based approaches (Rosenhead, 1996). The plurality of problem perspectives is embraced by including multiple objective formulations.

The second part is a decision-making method, adapted from an existing a posteriori many-objective optimisation method that considers robustness. A posteriori many-objective optimisation methods give a set of possible solutions, that are non-dominated by the other solutions for different objective prioritisations (Pareto efficient) (Purshouse, Deb, Mansor, Mostaghim, & Wang, 2014). A solution is non-dominated when no other solution yields higher satisfaction on all objectives (Yu, 1974). To find the effects of the different objective prioritisations, the different solutions are simulated in the next decision-making period. This creates a tree-like structure, as is elucidated in section 3.2.1.

The third part simulates the effects of the decisions over time. It includes a calculation of how the decisions affect the decision space, uncertainty space or other external factors for future decision moments. This is calculated for each solution individually, for all solutions that are proposed by the decision-making method. This part simulates the time in between decision-making periods.

The fourth part is the decision-uncertainty interaction analysis. The decision-uncertainty interaction analysis helps to understand the interaction between decisions and uncertainty by doing three analyses. An objective trade-off analysis helps to understand the different objective prioritisations and their reciprocal relations. To understand the effect of lacking information and important uncertain factors, the analysis looks at what the most important scenarios are. The last analysis looks at the effect of the different objective prioritisations on uncertainty, to better understand how the uncertainty space is dependent on the different type of decisions.

Each of the four parts is individually explained in the following sections. But first, the tree-like structure that is created by the approach is explained. This helps to create a better conceptual understanding of the designed approach and the type of results that are produced by the simulation.

3.2.1 Tree of decision pathways

At each decision-making moment, different optional decisions are proposed by the decision-making method. To analyse the effect of choosing either of those proposed decisions, a separate branch is simulated in parallel for each decision. Branches connect to their originating and succeeding branches at the previous and next period, respectively. All simulated paths are referred to as "decision pathways".

The simulation of decision pathways is built on the idea that decision pathways are suitable when decision-making should be adaptive to cope with the highly uncertain environment and inter-temporal complexities (Wise et al., 2014). The inter-temporal complexity considered in this study is the interaction between decisions and uncertainty over time.

Decision pathways are possible sequences of decisions which the decision makers can choose over time. These possible decision pathways can be imagined as together constituting a decision tree, where each decision pathway is a branch in that tree. A conceptual illustration of a decision tree with decision pathways is shown in Figure 3.2. The blue and bold decision sequence represents a possible decision pathway.

The total number of combinations in a tree of decision pathways depends on the number of periods and the number of decisions at each period. It is straightforward that the size of the tree increases exponentially when the number of periods, or the number of decision for each period increases. Considering that for each node in the tree the decision-making method should be completed, this decision-making method should not be too computationally demanding, the number of periods should not be too large, and the number of solutions proposed per period should be limited. These considerations are taken into account for the selection of the decision-making method.

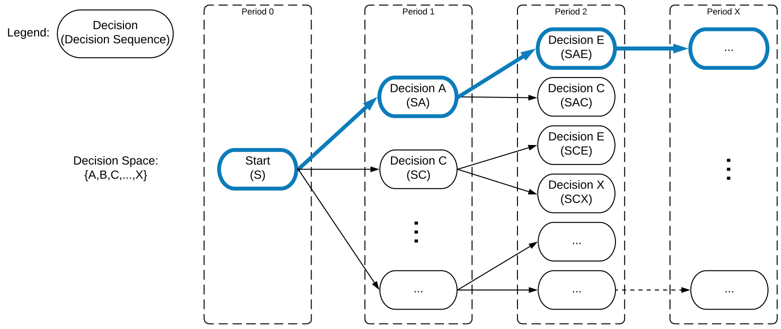


Figure 3.2: Decision Pathways

3.3 PART 1: PROBLEM FORMULATION

The first part of the approach focusses on creating an explicit problem formulation. Initially, a conceptualisation of the problem environment is created, which determines the aggregation level of the problem and what lies in- or outside the problem demarcation. The problem formulation is based on this conceptualisation of the system.

The XLRM framework is often used to help to create a structured problem formulation (Lempert et al., 2006; J. D. Herman, Zeff, Reed, & Characklis, 2014; Watson & Kasprzyk, 2017). Imposing the XLRM framework asks for an explicit separation of exogenous uncertainties ("X"), policy levers ("L"), relationships ("R") and performance metrics ("M") and helps to guide the process as an "intellectual bookkeeping mechanism" (Lempert et al., 2003). Combinations of levers can be used to create different possible alternatives. Combinations of exogenous uncertainties can be used to evaluate alternatives under different possible scenarios. The combination of performance metrics indicates how well an alternative performs given a scenario. The combination of relations determines how inputs (policy levers and exogenous uncertainties) translate into outputs (performance metrics). Based on the explicit problem formulation with the XLRM framework, a model can be implemented for further use in the decision-making method.

One element not present in the XLRM framework but a requirement for the design of the approach is the consideration of the robustness of a solution. To consider the robustness of alternatives, robustness metrics are defined. For the selection of adequate robustness metrics, it is necessary to consider the specific characteristics of the robust optimisation problem (Kwakkel, Eker, & Pruyt, 2016). Different robustness metrics indicate different aspects of what is called robustness. Therefore, it is preferred to use problem-specific metrics and to use multiple different robustness metrics. Mcphail et al. (2018) propose a framework that can be used for selecting proper robustness metrics based on problem characteristics.

How the effects of decisions on the uncertainty space are simulated, is formalised in the 'inter-period model'. The definition of this model is the third step in the problem formulation. The inter-period model defines how the decisions of the previous period bring about a change of the uncertainty space and the solution space.

The last important step of the problem formulation is to gather the necessary data for the simulation of the problem. It is important to have data for the possible solutions (decision space), certain variables and uncertain variables. Two types of uncertain variables are identified here: those uncertain variables that are expected to interact with the decisions, and those uncertain variables that are not expected to be dependent on decisions over time. For the uncertain variables that <u>are not</u> expected to be dependent on decisions, the uncertainty space is defined by estimating a lower boundary, an upper boundary, and a best-estimate. For the uncertain variables that <u>are</u> expected to be dependent on decisions, it is important to estimate their initial lower and upper boundaries, and a set of values that are regarded as the "ground truth". The ground truth is used to simulate the reduction of uncertainty over time towards these true values. These ground truth values are required for the decision-uncertainty interaction analysis, as explained later in this chapter.

3.4 PART 2: DECISION-MAKING METHOD

The second part is essentially a decision-making method with which robust solutions are selected to be simulated over time. Such a method should at least consider multiple objectives, robustness, and a plurality of objective prioritisations. Multi-objective optimisation methods with more than three objectives are called many-objective optimisation methods (Chand & Wagner, 2015). For multi- (and many) objective optimisation problems, objectives can be prioritised before, during, and after the multi-criteria optimisation, which corresponds to the a priori, interactive, and a posteriori approach (Marler & Arora, 2004; Purshouse et al., 2014).

Purshouse et al. (2014) define the different multi-criteria optimisation methods. 'A priori' prioritisation of objectives is more efficient in terms of computational costs, but requires explicit consensus on objectives between decision makers. 'Interactive prioritisation' requires the decision maker to be intensively involved during the optimisation process, which is not desirable in the case of analysing decisions. An 'a posteriori' decision-making approach can conduct multi-criteria optimisation without specific prioritisation of preferences up front, hence agreement between actors is no prerequisite (Purshouse et al., 2014). Since this is a requirement for the approach, an a posteriori many-objective optimisation algorithm considering robustness is desired for the design of this approach.

3.4.1 Selection of Decision-Making Method

There are different a posteriori many-objective optimisation methods that consider robustness. The Many-Objective Robust Decision-Making (MORDM) framework proposed by Kasprzyk, Nataraj, Reed, and Lempert (2013) includes a posteriori many-objective robust optimisation and is relatively computationally efficient compared to many-objective robust optimisation (MORO) methods. Where MORDM optimises for a reference scenario and then re-evaluates the optimal solutions under uncertainty for robustness testing, MORO integrates the robustness testing within the optimisation process. For each optimisation run, the uncertainty space is sampled, so that each solution is evaluated under uncertainty to calculate its robustness (Beyer & Sendhoff, 2007). Therefore, the optimisation process for MORO is more computationally expensive. Even though MORO expectedly results in more robust objectives, it requires more computation time than MORDM. As the designed approach benefits from a computationally efficient way of optimisation, the MORDM method is used.

3.4.2 MORDM Algorithm

Originally, the MORDM framework is not purely an algorithmic, but rather a collaborative decision-making framework (Kasprzyk et al., 2013). To use MORDM for multiple periods, each MORDM cycle is defined as an algorithm. This way, the MORDM algorithm can be used to simulate different decision pathways over multiple periods. In this section, the MORDM algorithm used for the designed approach is described.

The MORDM framework originally employs an interactive process with decision makers, where they select preferred solutions by using interactive visualisations. The interactivity of this format is not compatible with an algorithmic version of the MORDM framework, because the outcomes of such interaction are determined by non-deterministic factors such as diverging worldviews, preferences, and social interactions between decision makers. While this cannot be modelled or formalised, all possible outcomes are simulated by branching for each solution, as explained in Section 3.2.1. The algorithmic version of the MORDM framework used for the approach is conceptualised in Figure 3.3.

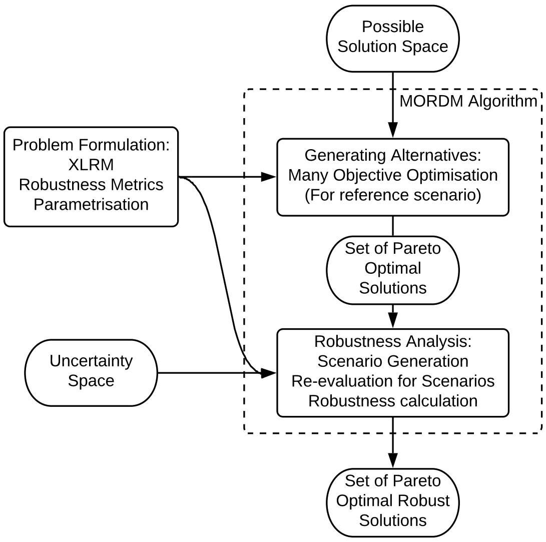


Figure 3.3: Many-Objective Robust Decision-Making Algorithm Design

The first step for the MORDM algorithm is to generate alternatives with the use of a Many-Objective Optimisation (MOO) method for a reference scenario. The reference scenario is the input parameter set, that is considered to be the current 'best estimate'. The specific optimisation algorithm to be used is dependent on the model and the possible solution space. Generally, multi-objective evolutionary algorithms (MOEAs) are used for many-objective optimisation, such as NSGA-II or BORG (Hadka & Reed, 2013; Deb, 2014). The many-objective optimisation with MOEAs results in a set of Pareto optimal solutions.

The next step is the robustness analysis. First, hundreds to thousands of scenarios are generated. This is done by sampling the uncertainty space with sampling techniques such as Monte Carlo sampling, Latin Hypercube sampling, et cetera. The set of Pareto Optimal solutions that resulted from the alternative generation step, are re-evaluated for each of the scenarios. The robustness metrics, as defined in the problem formulation, are calculated for each of the alternatives based on their performance for all scenarios. A non-dominated sort is then used to select those solutions that are Pareto efficient in terms of their robustness performance. This way, there is no a priori prioritisation on the different objectives and trade-off information of relevant (optimal) solutions is preserved.

Instead of communicating the outcomes with decision makers and interactively choosing alternatives based on decision makers' preferences as proposed by Kasprzyk et al. (2013), robust solutions should be selected for simulation over the next periods. Ideally, all Pareto optimal robust solutions are used for branching. However, when there are too many solutions in the remaining set, a subset of solutions should be selected for including in the succeeding periods. There are different options to select a set of robust solutions before forking for each robust solution. Straightforward solutions would be to increase the epsilon value for the non-dominated sorting algorithm, adding constraints on the objective scores for making a pre-selection of solutions, or choosing representative solutions from a clustered solution space (e.g. as proposed by Zio and Bazzo (2012)).

3.5 PART 3: DECISIONS AFFECTING UNCERTAINTY

The third part simulates the effect of decisions over time. After solutions are selected for branching, each solution is simulated as a decision in a different branch. Before the next decision-making period starts, different elements can change as a result of the chosen decisions. This is captured in the third element of the approach, as shown in figure 3.1, which simulates the inter-period changes.

The focus of the approach is on how the decisions influence the uncertainty space. However, decisions can also have a restraining effect on the available decision space for the next period. These effects are called path dependencies (Koch, Eisend, & Petermann, 2009; Nikolić, 2009). For example, certain decisions can be constrained because they require (e.g. financial) resources, which might have been already exploited during previous decision periods. Moreover, some decisions can only be taken once; when selecting decisions from a discrete and finite set of solutions, a solution cannot be chosen after having been selected during a previous period. In that case, decisions made in previous periods should be excluded in succeeding periods. These path dependent changes are responsible for the differences between different branches. This part focusses on simulating these path dependences as caused by the inter-period changes on both the uncertainty and solution space.

How the effects of decisions on the uncertainty space are simulated, is formalised in the 'inter-period model'. The definition of this model is part of the problem formulation. For each separate branch, this model is applied to that branch before the new decision-making method starts for the new period. This model is not comparable to the model as created for the MORDM algorithm, or such as the concept 'model' is usually interpreted. This inter-period model does not have an objective function, it merely sets up the relevant factors for the new period, based on the decisions as input.

3.6 PART 4: DECISION-UNCERTAINTY INTERACTION ANALYSIS

The fourth part of the designed approach is the decision-uncertainty interaction analysis. When the last decision period is simulated, the data generated by the simulation of the different decision pathways is analysed. To analyse the interplay between decisions and uncertainty, three main analyses are conducted.

Firstly, the analysis looks at the trade-offs between the different objectives. The performance of each of the decision pathways at the last period is used to analyse the trade-offs between objectives. To be able to compare the decision pathways, all decision pathway decisions are re-evaluated for the best-estimate reference scenario for all uncertain factors and the ground truth (as defined in the problem formulation) for all uncertainties that are expected to interact with the decisions. The trade-offs on the objectives for each decision pathway are analysed with a correlation analysis. To give insight into the multivariate relation between the decision pathways, a parallel coordinate plot is visualised. From the parallel coordinate plot, specific decision pathways with desired outcomes are selected and inspected to get insight into those decision pathways.

Secondly, the analysis looks at what uncertain factors have the most impact on the quality of the decisions. This can be done with a scenario discovery analysis. Scenario discovery is a model-based approach that helps to identify scenarios based on statistical or machine learning algorithms, instead of the more traditional way of identifying scenarios based on experts' perceptions (Bryant & Lempert, 2010; Kwakkel, Auping, & Pruyt, 2013). These scenarios can help to create a better understanding of how uncertainty can influence the quality of decisions.

Lastly, the analysis focusses on how different objective prioritisations relate to the reduction of uncertainty. It looks at whether different objective prioritisations have an effect on how much uncertainty is reduced, to better understand the effect of facility location decisions on uncertainty. This is done with a correlation and regression analysis. The performance of each of the decision pathways at the last period is checked for correlation and regression with the reduced uncertainty for each specific decision pathway.

3.7 FLOW THROUGH THE APPROACH

The previous sections have explained the designed approach. This section explains the flow through the approach to have a better idea of how the different parts are connected. Figure 3.4 presents the flowchart of the approach. Considerations on the choices for the flow through the approach are discussed in Appendix B.

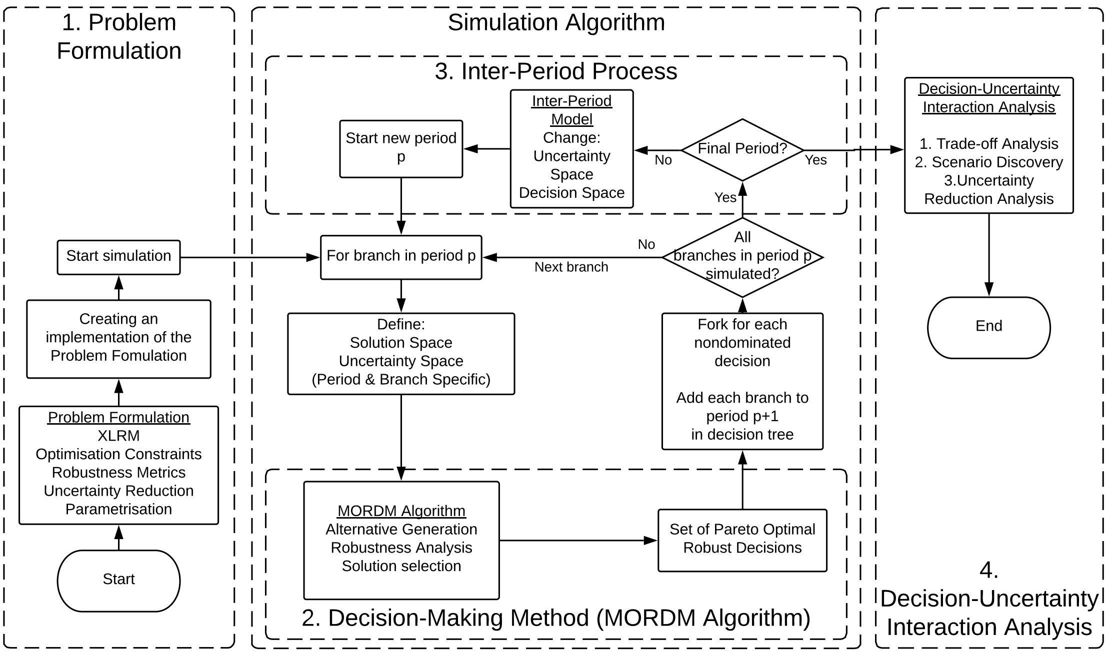


Figure 3.4: Flowchart of the Approach for Simulation and Analysis of the Interplay between Decisions and Uncertainty

Each of the four parts of the approach is also present in the flowchart, as is shown by Figure 3.4. However, the third part, the simulation of the effects of decisions over time, has a different name; it is called the 'inter-period process'. The problem formulation and the decision-uncertainty interaction analysis are phases that have to be performed by an analyst. The decision-making method and the inter-period process, however, are together an algorithmic process, which is set up by the analyst. The algorithm of these two parts is referred to as the simulation algorithm.

3.7.1 Elucidation of the Flow through the Approach.

To further clarify the approach, the flow through the approach is elucidated. The initial step is to create a problem formulation. The problem formulation is completed when it is implemented in a formal programming language. When the problem formulation is implemented, the simulation algorithm can be initiated. This starts at the initial period (period 0) and continues until the algorithm has finished simulating the last decision-making period.

The first step in the algorithm is to define the solution space and the uncertainty space for each branch (there is only a single branch at the initial period). The MORDM algorithm is simulated, which results in a set of Pareto optimal robust decisions. Each decision in the set is added as a new branch in the tree of decision pathways. When all branches in the current period are simulated, the algorithm continues to the inter-period process. For each of the branches in the new period of the tree of decision pathways, the uncertainty space and the decision space are changed based on the latest decision. A new period is initiated and this whole process is walked through again for each branch in the succeeding period.

After finishing the final period, the simulation algorithm ends and continues to the decision-uncertainty interaction analysis. The decision-uncertainty interaction analysis is conducted by an analyst who then interprets the results to better understand the interplay between decisions and uncertainty for the problem formulation.

The designed approach has been elaborately elucidated by first explaining each of the parts separately, followed by an explanation of the flow through the approach. The next chapters will focus on illustrating the designed approach with an application on the post-disaster facility location problem as a proof of principle of the approach.

Part III

Proof of Principle

4 THE POST-DISASTER FACILITY LOCATION PROBLEM

This and the following chapters focus on applying the approach for simulation and analysis of the interplay between decisions and uncertainty on the post-disaster facility location problem. This application serves as a proof of principle to illustrate the designed approach and create new insight into the interaction between post-disaster facility location decisions and uncertainty.

In Section 3.1, the problem characteristics for which the approach is designed are presented. Post-disaster facility location satisfies these given requirements. Multiple sequential decisions are made for the post-disaster facility location problem, while decisions are subject to deep uncertainty, and different actors have conflicting objectives. Decisions are path-dependent since they affect both the future possible decision space and the uncertainty space. It is possible to create a model that helps to evaluate possible decisions (see the literature review on facility location models in section 1.4. Moreover, it is unknown how decisions interact with the uncertainty space, but expectedly the uncertainty space can be influenced by facility location decisions. Because the post-disaster facility location problem satisfies all requirements of the approach, it is an appropriate case to use as a proof of principle for the approach.

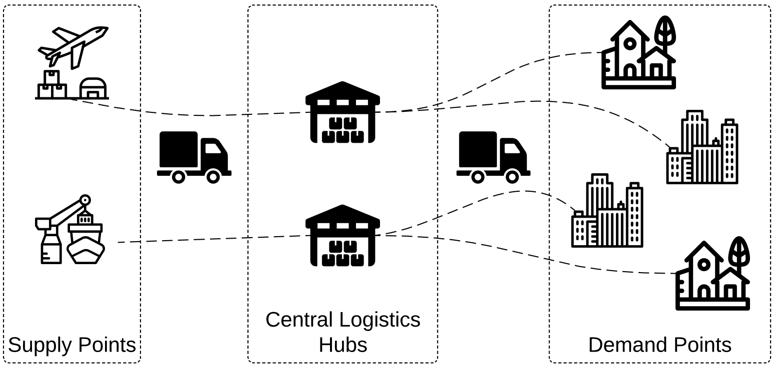
4.1 SYSTEM DESCRIPTION: A TWO-TIER HUMANITARIAN LOGISTICS SYSTEM

The considered problem is to decide on the locations of central logistics hubs immediately after a disaster has struck. Central logistics hubs are facilities which can function temporarily as logistics hubs, from where logistics is coordinated, and relief goods are distributed. These central logistics hubs are set up quickly in the aftermath of disasters to help supply relief goods to disaster victims.

The considered problem basically represents a two-tier facility location problem for humanitarian logistics. There are three important node types considered for the distribution of relief supplies over an affected area: points of relief supply, points of relief demand, and facility locations of central logistics hubs. A conceptual representation of the two-tier logistics system as considered for this case study is given in Figure 4.1.

Points of relief supply are nodes in an infrastructural network where relief supplies primarily enter the affected area to be further distributed to the disaster victims. Examples of supply points can include (international) airports, seaports, or train stations. Points of relief demand represent the aggregated demand of the affected population living in the city or area related to that demand point. The demand point is a central location in that city or area, from where people can pick up necessary relief items, or from where last mile distribution systems are deployed. These last mile distribution systems are not considered in this two-tier system. The central logistics hubs help to coordinate and distribute relief goods from points of relief supply to the affected areas. Relief supplies are transported from the points of relief supply to the central logistics hubs, from which they are transported to the points of relief demand.

Figure 4.1: Two-Tier Humanitarian Logistics System



Except for these three types of nodes, there are no other subcategories within the scope of this study. Last mile delivery (distribution from central points in affected cities and areas to the people's homes) is out of the scope for this research. Also, upstream logistics via which the points of relief supply are supplied with relief goods are out of the scope. The different types of nodes within the two-tier logistics system and possible instances are given in Table 4.1.

Table 4.1: Two-Tier Logistics Elements

Type	**Instances**
Supply Points	Airports and Seaports
Central Logistics Hubs	Unused industrial areas, empty schools, hospitals, et cetera
Demand Points	Central points in cities and areas with affected population

The relief supplies are transported from points of supply, via the central logistics hubs to areas of demand mostly by vehicles such as trucks or vans, and sometimes via air to areas that are hard to reach. For simplification, only a single type of road transport is considered. Roads are often inaccessible or disrupted in the aftermath of natural disasters, making some areas harder to reach and transport more expensive. In reality, when areas have limited access roads, they can in some case be completely disconnected from other regions (Pribadi, Puri, Hanafi, & Hadinata, 2018). For simplification, the accessibility of a city is assumed to be proportionate to the impact of the disaster of that region.

The demand for relief supplies in an area depends on multiple factors, among which the population and the impact of the disaster in that area. A city with more inhabitants has a higher demand for relief supplies than a city with a smaller population. A city more heavily impacted by a disaster has a higher demand for relief supplies than a similar city which is less affected by that disaster, and vice versa. For simplification, other area-specific factors that influence the relief demand are left out of scope, such as the build quality of the region's infrastructures or a region's level of preparedness for disastrous events.

As mentioned, both the accessibility of areas and the relief demand for each area are determined by how heavily they are affected by the disaster. The effect on these two factors is dependent on the type of disaster. This thesis focusses on sudden-onset natural disasters such as earthquakes, tsunamis or tropical storms. These sudden-onset natural disasters have in common that they often affect both the humanitarian needs of the affected population and the state of the road infrastructure. This is often in contrast with slow-onset natural disasters or man-made disasters such as droughts and refugee crises, respectively.

4.2 OBJECTIVES FOR POST-DISASTER FACILITY LOCATION

Section 1.3 briefly introduces the involved actors and coordination mechanisms. As described, the coordination of different sectors is organised by the cluster approach. Different clusters have different responsibilities, where the logistics cluster is responsible for the logistics sector and thus for the decisions on the locations of the central logistics hubs. The Logistics cluster exists from multiple groups and organisations and is part of a collective disaster response as coordinated by UN OCHA.

For humanitarian logistics, different criteria than in commercial logistics are generally considered (Çelik et al., 2012). The criteria for decision-making should reflect the criteria of the collective response. Of course, one important goal is to bring relief goods to as many victims in need as quickly as possible. However, as funding provided by donors is never unlimited, the costs of logistics operations should be kept low. Furthermore, the United Nations has pledged that "no one will be left behind" (United Nations, 2015), which should also be taken into account when making these facility location decisions.

To address the plurality of goals for humanitarian response, a set of objectives is needed that reflects the collective interest of the coordinated response. Generally, in the field of supply chain and logistics, performance is indicated by measuring efficiency and effectiveness, where effectiveness focusses on external performance, and efficiency focusses on internal performance (Borgström, 2005). In other words, effectiveness relates to the extent a purpose is achieved, and efficiency relates to the extent the use of resources is minimised to achieve it. Differently from commercial logistics, humanitarian logistics focusses on limiting human suffering instead of purely commercial objectives. Therefore, in humanitarian logistics, it is essential to consider human suffering while indicating performance. To minimise human suffering, it is not only important to consider the effectiveness of relieving disaster needs, but also to do so in a fair and impartial manner. Therefore, besides focussing on effectiveness and efficiency, a measurement of equity is included within the set of objectives to ensure fair and impartial distribution of relief supplies.

The literature review on post-disaster facility location models in section 1.4 shows that a variety of objectives is included in the different models. To include a comprehensive set of objectives, four objectives are selected that cover the effectiveness, efficiency, and equity of humanitarian logistics.

Effectiveness
An important goal is to help as many victims as well as possible, or to maximise the effectiveness of relief distribution. One way of maximising effectiveness is to ensure that as few victims as possible are deprived of relief material (Maharjan & Hanaoka, 2018). The objective in logistic terms is then to minimise the uncovered demand. Another way to define effectiveness is to look at the number of affected areas instead of the number of affected people. In each area affected by a disaster are victims that require some basic help to recover from that disaster. Regardless of the number of people within each area, all areas should be supplied with relief items (Tricoire, Graf, & Gutjahr, 2012; Hong, Jeong, & Xie, 2015). Based on this thought, the second objective for maximising effectiveness is to minimise uncovered demand points.

Efficiency
Another important goal is to have efficient humanitarian logistics. Considering that funds for disaster response are mostly restricted, efficient use of resources for humanitarian logistics is preferred. When the required financial resources for the transport of relief goods is limited, the remaining money can be used for either other logistics operations or can be allocated to other disaster response clusters. When a limited amount of money is allocated to the logistics cluster,

it is important to know what possible facility locations have higher costs than others. Knowing the costs related to facility location decisions can prevent that decisions are made that appear to be financially infeasible in retrospect. The most straightforward way to measure the efficiency of relief distribution is to calculate the total costs of transport. The costs of humanitarian facility location is included in almost every paper reviewed in the literature review, see the synthesis on the facility location models in section 1.4.2.

Equity
The United Nations' "no one is left behind"-policy emphasises the importance of equitable disaster response. An equity objective is included to focus on fair distribution of relief goods. An equitable distribution of relief supplies is one where the effects of a decision are fairly spread over different groups. Marsh and Schilling (1994) identify four dimensions for dividing groups: spatial, demographic, physical, and temporal. For this study, the focus is on a fair distribution over groups that are spatially divided. Regardless of where disaster victims live, they should all have access to relief goods to fulfil their needs. Victims have better access to disaster needs when they live geographically closer to the places where they can get the needed relief goods (Gutjahr & Dzubur, 2016). To ensure that every victim has equitable access to their needed goods, the maximum time that victims are located away from these goods should be minimised.

This chapter has given a description of the system that is considered as the post-disaster facility location problem. This system description helps to create a structured problem formulation. The next chapter will build on this problem description by defining the facility location model for humanitarian logistics.

5 FACILITY LOCATION MODEL FOR HUMANITARIAN LOGISTICS

This chapter defines the facility location model that is used to analyse the interaction between post-disaster facility location decisions and uncertainty. The facility location model is based on the conceptualisation of the humanitarian facility location problem as described in the previous chapter.

The model should be compatible with the designed approach, and more specifically with the simulation algorithm. The requirements for compatibility between the model and the approach are described in the first section of this chapter. The aim of the model is to comprehend the complexity of disaster characteristics. However, some simplifications and assumptions are made to represent the system by a model. These assumptions are presented and motivated in the second section of this chapter. The last section formulates the model with a description of the mathematical notation of the model.

5.1 MODEL REQUIREMENTS

In this section, the requirements for the model are listed and discussed. Elaborating on the requirements is necessary to design a model that fits within the methodological frameworks used in this thesis and correctly comprehends the system it represents.

1. The model should adhere to an XLRM structure. The XLRM structure is required for the model to integrate with the MORDM algorithm.
2. The model should be compatible with the MORDM algorithm. Using the XLRM framework is one way to facilitate integration, however, this requirement should also be taken into account while making other modelling decisions. The integration of the model and the MORDM algorithm is further discussed in Chapter 6.
3. The MORDM algorithm uses an a posteriori optimisation method. Therefore, the model should not prioritise objectives for the calculation of performance metrics.
4. The model should have very short computation times. The MORDM algorithm evaluates optimised alternatives for hundreds of scenarios for the robustness analysis. Also, the simulation algorithm requires to run the MORDM algorithm for each branch for each period. Considering that both the optimisation and the robustness analysis have to be run for each branch, the model has to be evaluated a tremendous number of times. Completing the multi-period simulation algorithm becomes intractable if a model is used with significantly long computation times. A trade-off for the complexity of the model has to be found, where the increase in runtime is minimised and the realistic value of the model is maximised. In other words, The complexity of the model should be as low as realistically possible.
5. The model should only include decision variables for the locations of central logistics hubs and no decision variables related to routing, allocation, inventory optimisation or other factors. The scope of this thesis is to look at the interaction between facility location decisions and uncertainty. Therefore, decisions related to other aspects are not considered

in this study. Besides, a model with fewer decision variables limits the time necessary for optimisation and is therefore preferred over a model that has multiple decision variables.

6. The model should be able to evaluate different central logistics hubs facility locations on performance metrics that reflect the diversity of objectives as described in section 4.2.
7. The model should at least represent the complexity of the problem as described in the system conceptualisation of post-disaster humanitarian logistics.

5.2 ASSUMPTIONS OF THE MODEL

A model is a simplification of a system. A set of assumptions is made for the definition of the facility location model, while considering their implications on both the complexity of the model and its resemblance to reality. These assumptions are listed in this section and the most important assumptions are motivated in the next.

1. The model considers the facility location problem as an uncapacitated problem. In other words, there are no restrictions on upstream supply to the supply points, on the supply from supply points to hubs, or from hubs to demand points. There are no restrictions on capacity of the logistics hubs either. When a receiving node is allocated to a supplying node, all demand is covered of the receiving node.
2. Each node in the model has a specific disruption that varies for each node based on how heavily that node is affected by the disaster.
3. The disruptions for each node determines both the reachability and the demand of that node.
4. The disruption for each node does not change over time. This means that the transportation times between nodes and the demand of each demand point remains stable over the multiple decision-making periods.
5. The transport times between different nodes are based on the combination of the normal fastest routing duration and the disruption of the destination node.
6. Demand is determined by the demand point's population and its disruption factor. Other factors that could have an impact on the demand for relief supplies have not been included in the model.
7. Supply points supply relief goods only to central logistics hubs. Only the central logistics hubs supply these relief goods to demand points. In other words, all transport of relief goods goes from supply points, via logistics hubs, to demand points.
8. Allocation: All demand points are allocated to the closest central logistics hub. An assumption made by most facility location models (Gutjahr & Dzubur, 2016).
9. Which logistics hub or supply point is closest, is determined based on the normal travel duration and not the disrupted travel duration, because the disrupted travel duration is uncertain.
10. When a demand point is further located than a specified maximum distance from the closest logistics hub, it is not allocated. Hence, its demand is not satisfied.
11. Demand points can only be allocated to a single central logistics hub. Central logistics hubs can only be allocated to a single supply point. However, multiple demand points can be allocated to a single central logistics hub and multiple hubs can be allocated to a single supply point.
12. Supply points are not allocated to other nodes since they are supplied by upstream logistics, which is out of scope.

13. A single vehicle type for road transport is considered for transport between supply points and logistics hubs and between logistics hubs and demand points. No other transport modes than road transport are considered.
14. The disruption of the travel duration is determined by the disruption factor of the relief receiving node. The central logistics hubs receive from the supply points and the demand points receive from the logistics hubs. The maximum disruption of the travel duration is double the normal duration.
15. Transport of relief goods from logistics hubs to demand points goes only directly between hub and demand point (back and forth), without including multiple demand points in one route. Optimised routing where multiple demand points are included in single routes is not considered.
16. The only costs that are considered for calculating the costs of facility location decisions are the transport costs. Costs associated with opening or operating a facility are not considered. The only decision variable in the model is the location of facilities, so no decision variables are included on the number of locations that are opened. Because the location of facilities has no effect on the opening and operations costs, these costs are not included.
17. Inventories and storage capacities of central logistics hubs are not considered.
18. A single homogeneous commodity is considered, representative for consumable food and non-food relief supplies.

5.2.1 Motivation of most important assumptions

Capacity of relief supply
Assumption 1 indicates that there are neither restrictions on the capacity of the central logistics hubs nor on the incoming (upstream) relief goods supplied by the supply points (i.e. Airports, Seaports, et cetera). This is assumed so that no decision variables have to be included on the allocation of supply. For example, for a capacitated model, it is required to determine how a limited supply of relief goods is distributed over two demand points that both lie within the maximum distance for which demand points are covered. A possible solution to this allocation problem is to model user equilibria as introduced by Gutjahr and Dzubur (2016). However, such a solution increases the complexity of the model significantly because extra decision variables are required. As mentioned in the requirements (section 5.1), it is desired to have the location of the central logistics hubs as the only decision variable. These assumptions characterise the model as an uncapacitated facility location model. However, some capacity constraints are considered: the maximum distance for which demand points can be covered is included as an uncertain variable. When there is only limited available supply of relief goods, the maximum distance for which demand points can be covered is smaller.

Allocation
Assumption 8 is related to the way demand points are allocated to central logistics hubs and how central logistics hubs are allocated to supply points. Multiple other options are considered for allocation of demand points to central logistics hubs:

1. Demand points are assigned to closest operational central logistics hubs (as assumed here).
2. Allocation of demand points to logistics hubs is optimised with the allocation of demand point to hub being a binary decision variable (0 or 1), such as in Maharjan and Hanaoka (2018).
3. Via a lower-level user-equilibrium, which takes both the distance as the expected supply into account, as proposed by Gutjahr and Dzubur (2016).

Option 2 and 3 both imply adding extra decision variables for optimising the allocation of demand points to hubs, which increases both complexity and runtime. Choosing the closest hub offers a simple solution for allocation without having to add extra decision variables. Therefore, the first option is chosen.

Assumption 9 mentions that the normal distance (before a disaster) is used to determine to which central logistics hub or supply point a demand point is allocated, instead of the actual distance after the disruption. This is based on the idea that the travel time after a disaster is uncertain at the moment of deciding on the allocation of demand points.

Transport
Assumption 15 relates to the simplification assumptions for vehicle routing. Optimised vehicle routing could lead to better performance of relief distribution, however, it would significantly increase the complexity of the model because additional decision variables would be required. The main argument is that the included decision variables should only be related to the locations of the central logistics hubs. Besides, in some disaster situations, optimised vehicle routing might not be possible for large-scale transport of relief goods. Transport vehicles might not have enough capacity to bring relief supplies to one demand point and then to the next in one route without returning to the distribution centre to fill the vehicle with new supplies.

5.3 MODEL FORMULATION

The facility location model for post-disaster logistics is formulated in this section. As prescribed by the designed approach, the formulation of the model adheres to the XLRM-structure. The order of the elements of the XLRM-structure is sometimes changed for a clearer presentation of each of these elements (Lempert et al., 2003). The first section gives the nomenclature of all indices and variables as used in the model. The notation includes the exogenous variables (X), the decision variables or 'levers' (L), the performance metrics (M), and the notation of endogenous variables as included in the relations between variables (R). The second section describes the performance metrics and finishes by giving the relations within the model.

Note that this facility location model is specifically meant to evaluate decisions for a single decision-making period. The multi-period decision-making is simulated by the multi-period simulation algorithm, which is further discussed in the next chapters.

5.3.1 Notation, parameters and decision variables

Notation of sets and indices:

I	Set of demand points, indexed by $i \epsilon I$, with $I = \{1, \ldots, i_{max}\}$
J	Set of potential central logistics hubs, indexed by $j \epsilon J$, with $J = \{1, \ldots, j_{max}\}$
K	Set of supply points, indexed by $k \epsilon K$, with $K = \{1, \ldots, k_{max}\}$
N	Set of nodes ($I \cup J \cup K$), indexed by $n \epsilon N$, with $N = \{1, \ldots, n_{max}\}$

Notation of exogenous variables:

NpA	Needs per affected. Units of relief supply needed for each disaster victim.
p_i	Population at demand point i.
UTC	Unit transport costs. The cost of transport per unit of relief supplies per hour.

$TD_{n1,n2}$ Travel duration between two nodes before disruption by the disaster (in hours).

DF_n Disruption factor for node n. A multiplication factor that determines the disruption of node n, with continuous range $[1, 2]$.

MCD Maximum covered distance: the maximum distance for which demand points are covered by central logistics hubs (in hours).

Notation of decision variables

X_j Binary decision variable. Indicating whether a central logistics hub is operational (1) or not operational (0). Vector X, indexed by j

Endogenous variables:

d_i Demand at demand point i

pd_j Projected demand at logistics hub j

$a_{n1,n2}$ Binary variable indicating direct allocation of nodes. 1 when node $n1$ is allocated to $n2$, 0 when node $n1$ is not allocated to $n2$.

$a_{i,j,k}$ Binary variable indicating indirect allocation of nodes. 1 when demand point i is allocated to supply point k via central logistics hub j, 0 if i is not allocated to k via j.

ATD Actual Travel Duration between n_1 and n_1.

$s_{n1,n2}$ Quantity of supply from node $n1$ to node $n2$

$TotTC$ Total Transport costs

$TotD$ Total demand of relief goods

$TotCD$ Total Covered Demand of relief goods

$TotUD$ Total Uncovered Demand of relief goods

UDP Number of Uncovered Demand Points

TT_i The travel time between a demand point and the closest operational logistics hub

$MaxTT$ Maximum Travel Time

Xnf_j Binary variable indicating whether central logistics hub j is operational but not functional

5.3.2 Performance metrics and relations

The objectives as discussed in section 4.2 are inspired by the objectives used by the reviewed articles from the literature review on post-disaster facility location models. Together, they form a comprehensive set of objectives for making post-disaster facility location decisions. Besides objectives, the model consists of a number of relations that calculate endogenous variables based on combinations of the exogenous and the decision variables. This section first presents the performance metrics by which the objectives are defined, and then the remaining relations that create the model.

Performance Metrics
The four objectives as described in section 4.2 are defined here as performance metrics. Two of the metrics focus on the effectiveness of humanitarian logistics, one on efficiency, and one on equity. No prioritisation of objectives is made on the performance metrics, as required for the a posteriori optimisation method.

The first objective function for effectiveness aims to minimise the total uncovered demand. The total uncovered demand is the total demand of all demand points minus the demand that is covered. The definition of this metric is similar to the implementation of Maharjan and Hanaoka (2018).

$$TotUD = TotD - TotCD \tag{5.1}$$

The second objective function for effectiveness aims to minimise the number of demand points that are uncovered. The number of uncovered demand points is the total number of demand points (cardinality of the set of demand points) minus the sum of all demand points that are allocated to central logistics hubs. The number of uncovered demand points cannot be negative since each demand point is only allocated to a single logistics hub. The definition of this metric is inspired by Nolz, Doerner, Gutjahr, and Hartl (2010).

$$UDP = |I| - \sum_j \sum_i a_{i,j} \tag{5.2}$$

The objective function for efficiency aims to minimise the costs of the transport of relief goods. The opening and operations costs of central logistics hubs are not considered as the number of locations opened during each period is no decision variable. Efficiency is often defined as being proportional to another metric. Here, however, efficiency is represented by only the cost function associated with the transport of relief goods. The total transport costs are calculated by the summation of the costs of all transport between supply points and logistics hubs, and between logistics hubs and demand points. This is similar to the calculation of costs by Rath, Gendreau, and Gutjahr (2016).

$$TotTC = \sum_k \sum_j ATD_{j,k} \cdot s_{k,j} \cdot UTC + \sum_j \sum_i ATD_{i,j} \cdot s_{j,i} \cdot UTC \tag{5.3}$$

The objective function for equity aims to minimise the maximum travel time. This equity metric measures the maximum time that needs to be travelled to bring relief goods to the furthest located disaster victims (Marsh & Schilling, 1994). This maximum travel time is equal to the longest travel time for any demand point to the closest logistics hub. The definition of this metric is inspired by Tzeng et al. (2007) and Marsh and Schilling (1994).

$$MaxTT = \max_{\forall i \in I}(TT_i, \dots) \tag{5.4}$$

Relations

The affected population is determined by the full population as represented by a demand point, multiplied with the disruption factor minus 1. The minus 1 is added because the disruption factor is a number between 1 and 2. The disruption factor minus 1 represents a ratio of the population that is affected.

$$Ap_i = p_i \cdot (DF_i - 1), \quad \forall i \tag{5.5}$$

The demand of a demand point is given by the affected population, multiplied by the units of relief supply needed for each disaster victim.

$$d_i = Ap_i \cdot NpA, \quad \forall i \tag{5.6}$$

Each demand point is allocated to the closest central logistics hub that is either made operational in the current or in an earlier period, if this hub lies within the maximum distance for which demand points are covered. If the closest operational hub is located further away than this maximum distance, the demand point is not allocated to any hub.

$$a_{i,j} = \begin{cases} 0, & \text{if } TD_{i,j} > MCD \\ 1, & \text{otherwise if } j = \arg\min_{\phi}\{TD_{i,\phi} \mid \phi \in J, X_{\phi} = 1\} \\ 0, & \text{otherwise} \end{cases}, \qquad \forall i \, \forall j \tag{5.7}$$

A demand point cannot be allocated to multiple logistics hubs. When two or more operational logistics hubs have the exact same travel duration to the demand point, the demand point is allocated to one of the two hubs without any preference for each of the hubs. This is captured in a constraint for the number of operational hubs to which a demand point is allocated. Each demand point can be allocated to zero or one operational logistics hub(s).

$$\sum_{j} a_{i,j} = [0 \mathinner{..} 1], \quad \forall i \tag{5.8}$$

Each operational hub is allocated to the closest supply point.

$$a_{j,k} = \begin{cases} 1, & \text{if } k = \arg\min_{\phi}\{TD_{j,\phi} \mid \phi \in K\} \\ 0, & \text{otherwise} \end{cases}, \qquad \forall j \, \forall k \tag{5.9}$$

An operational logistics hub cannot be allocated to multiple supply points. When two or more supply points have the exact same travel duration to the logistics hub, the hub is allocated to one of the two supply points without any preference for each of the supply points. This is captured in a constraint for the number of supply points to which a central logistics hub is allocated. Each hub can be allocated to zero or one supply point.

$$\sum_{k} a_{j,k} = [0 \mathinner{..} 1], \quad \forall j \tag{5.10}$$

Each demand point that is allocated to a logistics hub is indirectly allocated (via that hub) to a supply point.

$$a_{i,j,k} = \begin{cases} 1, & \text{if } a_{j,k} = 1, a_{i,j} = 1 \\ 0, & \text{otherwise} \end{cases}, \qquad \forall i \, \forall j \, \forall k \tag{5.11}$$

A logistics hub supplies relief goods to a demand point if that demand point is allocated to that hub. The supply from the logistics hub to the demand point is equal to the demand of that demand point.

$$s_{j,i} = d_i \cdot a_{i,j}, \quad \forall i \, \forall j \tag{5.12}$$

The projected demand at each central logistics hub is the accumulated demand of all demand points that are allocated to that hub.

$$pd_j = \sum_{i} s_{j,i}, \quad \forall j \tag{5.13}$$

A supply point supplies relief goods to a logistics hub if that demand point is allocated to that hub. The supply from the supply point to the hub is equal to the projected demand of that hub.

$$s_{k,j} = pd_j \cdot a_{j,k}, \quad \forall j \, \forall k \tag{5.14}$$

The actual travel duration after a disaster can be longer than normal due to infrastructural disruptions. The actual travel duration between demand points and logistics hubs is the disruption factor of the demand point multiplied with the normal duration.

$$ATD_{j,i} = ATD_{i,j} = TD_{j,i} \cdot DF_i, \quad \forall i \, \forall j \tag{5.15}$$

The actual travel duration between logistics hubs and supply points is the disruption factor of the logistics hub multiplied with the normal duration.

$$ATD_{k,j} = ATD_{j,k} = TD_{k,j} \cdot DF_j, \quad \forall j \, \forall k \tag{5.16}$$

The total demand is the sum of the demand of all demand points.

$$TotD = \sum_i d_i \tag{5.17}$$

The total covered demand is the sum of the demand of all demand points that are allocated to an operational central logistics hub. Another way to determine the total covered demand is to take the sum of the projected demand of all operational hubs.

$$\begin{aligned} TotCD &= \sum_j \sum_i a_{i,j} * d_i \\ &= \sum_k \sum_j a_{j,k} * pd_j \end{aligned} \tag{5.18}$$

The minimum travel time for each demand point to receive relief goods, is based on the actual travel duration between that demand point and the closest operational logistics hub. This travel time is calculated regardless of whether that demand point is allocated to that specific logistics hub.

$$TT_i = min(\{ATD_{i,j} | j \in J, \sum_k a_{j,k} = 1\}), \quad \forall i \tag{5.19}$$

It can happen that the decision variable indicates that central logistics hub j is operational, but no demand point is allocated to this hub. When this is the case, the projected demand of hub j is equal to zero and this hub is not functional. The binary variable 'operational but not functional' is 1 when the hub is operational, but does not have any projected demand, and is thus not functional.

$$XnF_j = \begin{cases} 0, & \text{if } X_j = 0 \\ 1, & \text{otherwise if } pd_j = 0 \\ 0, & \text{otherwise} \end{cases}, \quad \forall j \tag{5.20}$$

This facility location model as defined here is used for integration in the single- and multi-period simulation algorithm. The next chapter focusses on how these can be integrated. It describes the a posteriori optimisation method, the robustness analysis, and the simulation of decisions over multiple periods.

6 INTEGRATION OF MODEL WITH SIMULATION OF STEPWISE FACILITY LOCATION DECISIONS

This chapter describes the remaining components of the problem formulation part from the designed approach for the simulation and analysis of the interplay between post-disaster facility location decisions and uncertainty. The integration of the model with the simulation of stepwise facility location decisions enables the implementation of the simulation algorithm. The decision-making method for within each single period is described first and the simulation of multiple periods is defined next. The single- and multi-period decision-making algorithm is then implemented based on how the decision-making method is defined in this chapter.

6.1 SINGLE PERIOD DECISION-MAKING METHOD

The MORDM algorithm is used as a decision-making method at each period. Two important components of the MORDM algorithm are the many-objective optimisation and the robustness analysis. This section describes the optimisation method that is used and which constraints are included for the optimisation. Then it describes how the resulting solutions are re-evaluated under uncertainty and motivates the robustness metrics used for this re-evaluation.

6.1.1 Many-Objective Optimisation

There are different methods for a posteriori many-objective optimisation. Evolutionary algorithms are often used for optimisation of complex models, because they are often suitable for problems with challenging properties, such as non-linearity, discreteness and problem formulations with many (four or more) objectives (Reed, Hadka, Herman, Kasprzyk, & Kollat, 2013). The model, as described in section 5, is a non-linear and 'non-smooth' programming model for which Multi-Objective Evolutionary Algorithms (MOEAs) are ideally suited (Kwakkel, Haasnoot, & Walker, 2015). However, one of the limitations of MOEAs is the speed of finding 'optima'. Another general optimisation approach is enumerative optimisation. With enumerative optimisation, all possible solutions over a finite predefined search space are evaluated (Coello, Lamont, & Van Veldhuizen, 2007). This becomes infeasible when search space becomes large. For a model with relatively few options in the full solution set, it is faster to use an enumerative optimisation approach.

For this post-disaster facility location problem, there are relatively few possible solutions in the full solution set. In the facility location model, there is a decision variable for each central logistics hub, which indicates whether that hub is operational or non-operational. Each period, a single logistics hub is made operational. Hence, the decision variables of the model are a discrete space of x binary decisions, resulting in a vector of x possible options, where x is the number of optional central logistics hubs. An enumerative optimisation approach would require x model evaluations. As this is much faster than applying a MOEAs for optimisation, the enumerative optimisation approach is used.

The input parameters for the optimisation of central logistics hub locations are based on best-estimate values for all uncertain variables. The set of results, given by the enumerative optimisation, contains for each possible location a score on each objective. All locations that are non-dominated by the other locations are selected to form a Pareto-optimal solution set or the Pareto front. All solutions in the Pareto front set have scores that are not exceeded with respect to all objectives by any other solution (Reed et al., 2013, p. 439). All solutions that lie within the Pareto-optimal solution set are analysed for their robustness.

OPTIMISATION CONSTRAINTS. Optimisation constraints can be added for pruning the set of feasible solutions in the Pareto front. A single optimisation constraint is used to limit the solutions proposed by the optimisation method. Solutions, where one of the central logistics hubs does not provide relief goods to any demand point, are excluded from the solution set. These solutions are excluded because there is no point in having non-functional central logistics hubs. As defined in section 5.3, variable Xnf_j indicates for each central logistics hub if it is operational but not functional (with value 1). If any of the logistics hubs is operational but not functional, the solution is excluded from the solution set. Mathematically, a solution is excluded if: $\{1\} \subseteq \{XnF_j | j \in J\}$.

6.1.2 Evaluation on robustness

In this section, the robustness analysis is described. The robustness analysis consists of a re-evaluation of solutions under deep uncertainty and the calculation of robustness scores on different robustness metrics.

Re-evaluation under deep uncertainty

The model, as described in Chapter 5, has a set of exogenous variables. Some of these variables have known values (e.g. population), while others have uncertain values (e.g. needs per affected). All variables subject to uncertainty are used to create multiple scenarios. The specific variables and the used data are described in more detail in the next chapter (7).

For each of the uncertain variables, a range of possible values is defined. Then, Latin hypercube sampling is used to generate a predefined number of scenarios. Latin hypercube sampling combines some desirable features from random sampling and stratified sampling, which produces more stable analysis outcomes than random sampling (Helton & Davis, 2003, p. 32). Each of the solutions in the Pareto-optimal front is then re-evaluated for each of the generated scenarios. Each solution's robustness is then calculated with the use of robustness metrics.

Robustness Metrics

To compare the different alternatives on their robustness, some robustness metrics are defined. Kwakkel, Eker, and Pruyt (2016, p. 223) make a distinction between three families of robustness metrics: statistical, regret, and satisficing metrics. Statistical robustness metrics look at the distribution of the performance of each solution for possible scenarios. A solution is more robust when the distribution of its performance is more inclined towards the desired outcome. Regret-based metrics look at the difference in performance of a solution compared to the best performing solution for the same scenario (Savage, 1972). A solution is more robust when it is has low regret for all possible scenarios. Satisficing robustness metrics are robustness metrics that indicate the range of scenarios that have acceptable performance relative to a minimum threshold performance (Mcphail et al., 2018, p. 170; Simon, 1956). A solution is more robust when it satisfies the minimum threshold performance for a higher number of scenarios.

Uncertainty has also been considered in some of the reviewed articles in section 1.4. Bozorgi-Amiri, Jabalameli, and Mirzapour Al-e-Hashem (2013) and Jabbarzadeh et al. (2014) consider robustness based on linear stochastic programming, which is unfit for the minimisation of variance (Beyer & Sendhoff, 2007). Both these articles penalise solutions that fail to meet desired performance or that are unsolvable for different scenarios. An analyst is responsible for the threshold definition of satisfactory performance. This is in essence similar to satisficing robustness metrics as described above. Rath et al. (2016) consider a discrete set of stochastic scenarios by comparing the average performance on a single objective (minimising costs). This means they are essentially using statistical robustness metrics to choose solutions. Bozorgi-Amiri and Khorsi (2016) consider uncertainty in four discrete scenarios without consideration of robustness, which they propose for future research.

As mentioned in the description of the framework in Section 3.3, it is advised to use multiple robustness metrics (Kwakkel, Eker, & Pruyt, 2016). Nevertheless, "the choice of robustness metrics is not straightforward" (J. D. Herman, Reed, Zeff, & Characklis, 2015, p. 4). Ideally, to embrace decision makers' preferences comprehensively, a robustness metric from each of the three categories is selected. However, satisficing robustness metrics require an indication of the minimum satisficing performance of an alternative. To not influence the outcomes of the analysis by including subjective values of satisficing performance, no satisficing metric is included in the calculation of robustness values. One robustness metric from each of the other two categories will be selected for the evaluation of robustness.

From the statistical robustness metrics, a metric is chosen that indicates whether a robust solution has a good average performance with limited dispersion around it, which is a kind of signal-to-noise ratio, as introduced by Kwakkel, Eker, and Pruyt (2016, p. 224). Since for all objectives used in the facility location model minimisation is assumed, this signal-to-noise metric is only mathematically defined for minimisation problems. The signal to noise metric for alternative a is the mean of the performance of a multiplied by the standard deviation of the performance of a. This robustness metric is calculated for each alternative:

$$SNR_a = (\mu_a + 1) \cdot (\sigma_a + 1), \quad \forall a \tag{6.1}$$

The $+1$ is added to prevent cases where the μ_a or σ_a is close to zero (Kwakkel, Eker, & Pruyt, 2016).

The second family of metrics are regret-based metrics. From the regret-based robustness metrics, a metric is chosen that indicates the difference between the performance of an alternative and the best-performing alternative, given a specific scenario (Giuliani & Castelletti, 2016, p. 412). The regret criterion used to measure the regret for the different alternatives, is based on the minimax regret criterion (Savage, 1972). For minimisation on all objectives, the maximum regret metric is defined as follows: given that a is the set of all alternatives and s is the set of all scenarios, the regret for alternative a_i for scenario s_x is:

$$r_x(a_i) = \max_a(f(a, s_x)) - f(a_i, s_x), \quad \forall x, \forall i \tag{6.2}$$

The maximum regret for alternative a_i is the maximum difference of a_i with the best performing alternative for each possible scenario s_x.

$$r(a_i) = \max_{x \in s}(r_x(a_i)), \quad \forall i \tag{6.3}$$

The scores on the robustness metrics are calculated based on the outcomes of the re-evaluation of the Pareto-optimal solutions under deep uncertainty. For the humanitarian logistics facility location problem, the model contains four different objectives. Both the maximum regret and the signal-to-noise criterion are calculated for all four objectives. This results in eight different robustness indicators that can be used to determine the robustness of the possible solutions.

Non-dominated sorting of robust solutions
The MORDM algorithm finishes by returning a set of robust solutions. This set is obtained by doing a non-dominated sort. To not lose trade-off information between objectives, non-dominated sorting on all eight indicators (2 robustness metrics times four performance metrics) is used to select solutions. The optional logistics hubs locations form a discrete nominal decision space, which makes clustering to reduce the number of solutions in the set infeasible. All solutions in the remaining set of Pareto efficient robust solutions are returned by the MORDM algorithm.

6.2 SIMULATION OF MULTI-PERIOD DECISION-MAKING

Decisions at each decision-making period are made by the single period decision-making method, which is the MORDM algorithm. Over multiple decision-making periods, the uncertainties change based on the taken decisions. This section describes first how the uncertainty changes and then how the process of making multiple decisions over multiple periods is defined in the simulation algorithm.

6.2.1 Changing uncertainty over time

This section presents the 'inter-period model' which determines how the dynamic uncertainties change over time, based on time and distance. The variables that are subject to dynamic uncertainty are the disruption factors of the demand points and the facility locations. These factors are dependent on the decisions on which central logistics hubs should be made operational. Each of the dynamic uncertain variables has four values: the true value, the best estimate, an upper limit, and a lower limit. The upper and lower limit together define the uncertainty range for that variable.

To formalise the uncertainty reduction model, the different variables are notated as: **Indices**

N	Set of nodes (nodes can be demand points or central logistics hubs), indexed by $n \ \epsilon \ N$, with $n = \{0, \dots, n_{max}\}$
P	Set of periods, indexed by $p \ \epsilon \ P$, with $p = \{0, \dots, p_{max}\}$

Variables

$URF_{n,p}$	Uncertainty Reduction Factor for node n at period p
d_n	Distance to closest operational logistics hub for each node n
$BE_{n,p}$	Best Estimate value for the disruption factor of node n at period p
TV_n	True Value for the disruption factor of node n at period p
$UL_{n,p}$	Upper Limit for the disruption factor of node n at period p
$LL_{n,p}$	Lower Limit for the disruption factor of node n at period p

The uncertainty reduction factor is a function of distance and time. The uncertainty dynamics is caused by two drivers: the locations of central logistics hubs and time. When a logistics hub is closer to a demand point, more uncertainty is reduced for that demand point. But, even when no hubs are located close to demand points, new information about these places becomes available over time. The uncertainty is reduced more when a node is located closer to other operational logistics hubs. The uncertainty is reduced more when there is more time in between two decision-making periods. The uncertainty reduction factor has a continuous range between 0 and 1. An uncertainty reduction factor of 0 means that the uncertainty is not reduced, while an uncertainty reduction factor of 1 means that the uncertainty is reduced completely.

$$URF_{n,p} = f(d,t), \quad \forall n \, \forall p, \quad 0 < URF < 1 \tag{6.4}$$

The assumption is made that the uncertainty cannot increase over time (i.e. no negative reduction).

$$f(d,t) \geq 0 \tag{6.5}$$

Each period is assumed to have an equal length, so the time variable becomes a constant instead. The function for the uncertainty reduction factor then only depends on the distance of a demand point to the operational facility locations.

$$URF_{n,p} = f(d), \quad \forall n \, \forall p, \quad 0 < URF < 1 \tag{6.6}$$

When the the distance increases, the uncertainty reduction factor decreases:

$$f'(d) \leq 0 \tag{6.7}$$

The parametrisation of function f, which indicates how strongly information is reduced, is discussed in the next chapter. The uncertainty reduction factor can then be used to determine the new best estimate value, the upper limit, and the lower limit of the uncertainty space. The new best estimate value is calculated by reducing the difference between the old best estimate value and the true value with the uncertainty reduction factor. This implies that the best estimate value always moves towards the true value.

$$BE_{n,p+1} = TV_n + (TV_n - BE_{n,p}) * (1 - URF_{n,p}), \quad \forall n \, \forall p \tag{6.8}$$

Also the new upper and lower limit are calculated based on the uncertainty reduction factor. The new upper and lower limit is the new best estimate value plus or minus the old distance (respectively) reduced by the uncertainty reduction factor. Both the upper and the lower limit remain centred around the best estimate value.

$$LL_{n,p+1} = BE_{n,p+1} - 0.5 * (UL_{n,p} - LL_{n,p}) * (1 - URF_{n,p}), \quad \forall n \, \forall p \tag{6.9}$$

$$UL_{n,p+1} = BE_{n,p+1} + 0.5 * (UL_{n,p} - LL_{n,p}) * (1 - URF_n, p), \quad \forall n \, \forall p \tag{6.10}$$

While the best estimate value, the upper limit, and the lower limit are dynamic over time, the real value remains constant.

6.2.2 Multi-period simulation algorithm for facility location decisions

This chapter has described how decisions are proposed for each period and how these decisions influence the uncertainty space over time. This section describes how the algorithm that simulates multiple periods of decision-making and decisions affecting uncertainty works for central logistics hubs location decisions. By doing so, it gives insight into the assumptions that have been made for the simulation of multi-period decision-making.

At the initial decision-making period, the supply point(s) are the only operational node(s) in the disaster area. No central logistics hub is operational yet. Each period, the single-period decision-making method proposes different robust optimal solutions, which are all simulated in different branches. For each branch in each period, only a single central logistics hub is made operational. Decisions made in previous periods cannot be reversed in the following decision-making periods. The allocation of demand points to central logistics hubs can change over time when a new logistics hub becomes available that is closer to that demand point. When the algorithm has finished the last decision-making period, the algorithm is terminated. The next step in the approach is then the decision-uncertainty interaction analysis where the results generated by the algorithm are analysed.

In between each decision-making period, the uncertainty changes based on the central logistics hub location decisions. The uncertainty for the disruption factors of central logistics hubs and demand points is reduced each period, based on how close their locations are to the operational logistics hubs. The disruption factors themselves do not change, only the uncertainty about their true values. It is assumed that in case of an uncertainty reduction, the best estimate value of each disruption factor moves towards the real values. The upper and lower limits of the uncertainty are always centred around this best estimate value. When the uncertainty reduces, the bandwidth between the upper and the lower limit is reduced with the uncertainty reduction factor. Because each branch of the tree has a different sequence of decisions, the reference scenario (collection of all best-estimates for all disruption factors) is specific for each branch.

6.2.3 Implementation & Verification

For details on the implementation of the single-period and the multi-period decision-making algorithm, such as the enumerative optimisation, the non-dominated sorting algorithm, scenario generation, re-evaluation under uncertainty, the robustness metrics and the robustness calculation, or the implementation of the uncertainty reduction algorithm, the reader is referred to the GitHub page related to this research: Github.com/TRomijn/Thesis. On this GitHub page, the Python implementation of the models and algorithms can be found. In Appendix C the different software packages used are mentioned. Appendix D discusses the verification and the validation.

The next chapter focusses on the parametrisation of this case study on central hub location decisions for humanitarian logistics. The Nepal Earthquake in 2015 is used to set up the case study with data so that the algorithm can be used for the simulation of central logistics hub location decisions. The generated results are used for the last phase of the approach: the decision-uncertainty interaction analysis.

7 POST-DISASTER FACILITY LOCATION DECISIONS FOR THE 2015 NEPAL EARTHQUAKE

The post-disaster facility location problem is introduced in the previous chapters as a case study to showcase the designed approach. In this chapter, the case study will be specified for the 2015 Nepal Earthquake.

As illustrated in the introduction in Chapter 1, the impacts of the 2015 Nepal earthquake were disastrous. The disaster situation is fit for the case study on post-disaster facility location decisions, because of different characteristics. The earthquake is a sudden-onset disaster, which disrupted much of the road infrastructure in Nepal in April 2015 (World Food Programme, 2015a). A large part of the country had been affected by the earthquake, both in urban and (remote) rural areas (Pattison et al., 2015). Quickly after the disaster, logistics operations needed to be set up to distribute aid to the affected areas, while dealing with the uncertainty inherent to sudden-onset disasters.

The case study on post-disaster facility location decisions for the 2015 Nepal earthquake serves as a proof of principle of the designed approach. This implies that it is not the goal to replicate the Nepal 2015 earthquake and its impacts. The use of Nepal for this case study relies on stylisation of the available data. This study describes three categories of data used for the study: certain data, static uncertain data, and dynamic uncertain data. The certain data includes locations of cities, populations, and the number of periods that are simulated. The static uncertain data includes uncertain factors that remain uncertain over time, such as the transport costs. The dynamic uncertain data describes the factors of which uncertainty is reduced over time based on facility location decisions.

7.1 CERTAIN DATA

The first category of data required for the facility location model is the static certain variables. These are variables that have definite parameter values that are known and are (assumed to be) not subject to any uncertainty. This includes the number of periods simulated, the population of the demand points, and the locations of the demand points, central logistics hubs, and the supply points. After the choices on these variables have been motivated, a graphical representation of all included nodes in Nepal is given in Figure 7.1. An overview of the used data and reference to the data sources is given in Appendix E.

Number of Periods
The number of periods determines the number of central logistics hubs that are made operational and the amount of uncertainty that is reduced. As the computation time of the approach grows exponentially (see Section 3.2.1), the number of periods to simulate should not be too large. A number of four periods is chosen, which simulates four facility location decisions, one location for each period. The number of four periods is expected to be enough to analyse the effects of decisions on uncertainty, but not too large to have unmanageable computation times. Each period spans one week and each period has the same length. The length of periods is also related

to the degree of uncertainty reduction, as more information becomes available for each period when a period covers a longer time-period. No variable period duration is considered, something that is proposed for future research.

Demand Points
To represent the places where disaster victims live, both larger cities and remote valleys are included in the set of demand points. In Nepal, there are some larger cities, such as Pokhara or Nepal's capital Kathmandu. However, besides the larger cities, a part of the Nepalese population lives in less populated and remote valleys of the Himalayas. Therefore, it is important to also consider these less populated and more remote areas for disaster relief. Moreover, by including remote valleys, the analysis could give insight into the importance of uncertainty on these less populated places. Both larger cities and remote valleys are included in the set of demand points.

In total, a number of 35 demand points are included for in the model. Of these 35 demand points, 30 are larger cities and 5 are remote valleys. From a database containing information on all cities in Nepal with a population of at least 1000 people, the 30 cities with the largest population are selected as larger cities and the 5 smallest cities in the dataset are selected to represent the remote valleys. The assumption is made that official population estimates are correct and not subject to uncertainty.

Supply points
To represent the places where upstream relief supply provided by other countries enters the affected country, international transport hubs are used as supply points. International transport hubs can be international airports, ports connected to international waterways or international railway stations.

In Nepal, the availability of these international transport hubs is fairly limited. Tribhuvan International Airport in Kathmandu is Nepal's only international airport for now. After the 2015 earthquake, there are plans in development by the Nepalese authorities to strengthen the disaster preparedness of the Nepalgunj airport, so that in the future it can better be used for relief supply and possibly as an incoming node for upstream supply (UNDP, 2017). Nepal is a landlocked country and has no waterway transport which can be used to import relief supplies. Nepal does have an old railway connection with India and a planned new railway connection with China, however, the current railway infrastructure is not sufficient to transport relief supplies from outside the country (Pokharel & Acharya, 2015). Therefore, the only transport hub to represent supply points in Nepal is the Tribhuvan International Airport in Kathmandu. During the disaster response in 2015, there were some other entry points over land from India, however, these were controlled by Indian authorities (Logistics Cluster, 2015). Since these entry points were not centrally coordinated by the logistics cluster, they are not considered for this study.

Optional Central Logistics Hubs
For the selection of optional central logistics hubs, it is important to look at some of the requirements of these hubs. Some general requirements for these hubs are that they should be well-connected to the country's road-infrastructure, have enough space to accommodate large amounts of relief supplies and in- and outgoing trucks, and satisfy basic goods storage requirements such as rain protection. For the case, it is also important that the facilities are similarly distributed as the country's population. Hospitals are chosen because they are often relatively well-connected to the country's infrastructure and because they are presumably similarly distributed over the country as the population. Other types of facilities, such as schools, could have been chosen equally well. A pragmatic way of selecting a number of optional central logistics hubs in Nepal is used. From all hospitals in Nepal, 20 different hospitals are randomly selected to represent optional facilities to function as central logistics hubs.

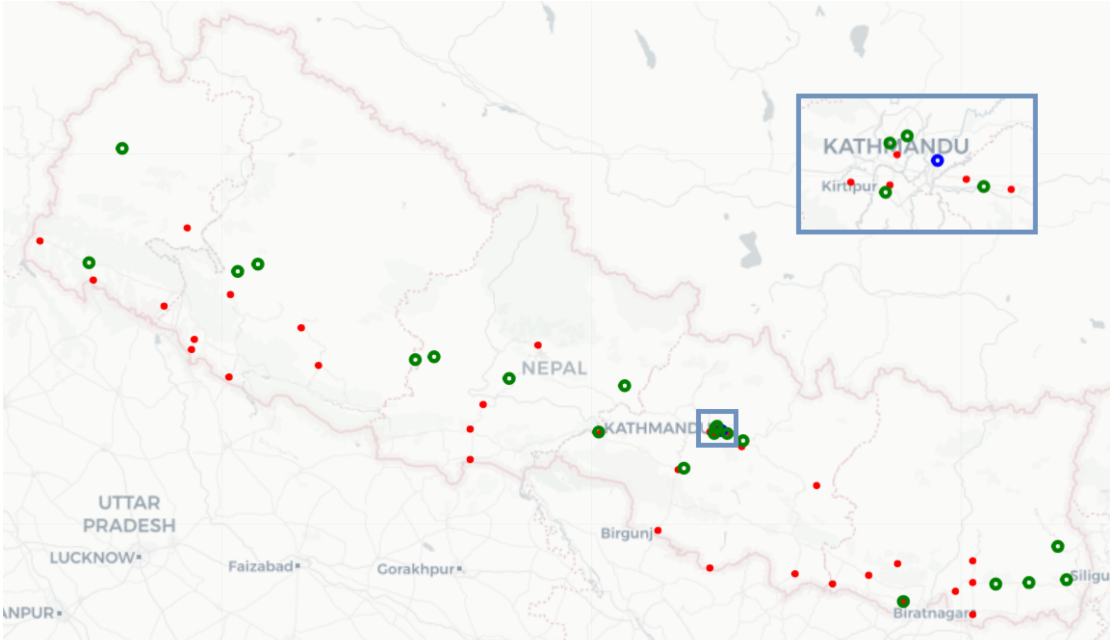


Figure 7.1: Nepal Data Instantiation
Green Circles: Demand points
Red Dots: Optional Central Logistics Hubs
Blue Circles: Supply Points

Road infrastructure
Route durations between the different nodes represent the road infrastructure. As mentioned in section 5.2, only road transport is considered in the facility location model. Therefore, it is possible to use the route durations provided by route planners. Route durations are obtained by finding the fastest routes between the coordinates of the supply points, demand points and optional facility locations. OpenStreetMap data can be used and is used for the collection of routing data (Luxen & Vetter, 2011).

7.2 STATIC UNCERTAIN DATA

The second category of required data for the facility location model is the static uncertain parameters. These are variables that have indefinite parameter values and are subject to uncertainty. For these values, it is required to find lower and upper limits that define valid ranges for these variables. These ranges represent the uncertainty of the variables, which can be any value within these ranges. Each variable also has a best estimate value, which is included in the reference scenario used for the optimisation.

An estimation and calculation of parameter values and uncertainty ranges of the transport costs, the maximum covered distance, and how much relief supplies are needed per victim, are presented in Appendix E.

Transport Costs
The type of transport is not a decision variable in this study, so the costs of truck transport are used for estimation of the transport cost, as this is the most usual way of transport. The transport costs in Nepal after the earthquake are largely uncertain due to the unknown fuel prices, vehicle scarcity, and road conditions. Severe fuel scarcity after the Nepal earthquake

has caused a major increase in fuel prices. Also, the road conditions are reflected by the total transport costs via the disruption factor that affects the actual route duration.

Maximum covered Distance
Reflects the capacity of available transport vehicles such as trucks and capacity of supply from upstream logistics. For example, when there are too few trucks or too little relief goods available, the demand points that can be covered by a facility location is also limited. In that case, the demand points that are located closest to the facility locations are supplied with relief material by the central logistics hubs.

Needed Relief Supplies
Wisetjindawat, Ito, Fujita, and Eizo (2014) distinguish four different phases after the disaster: 1) Emergency relief, 2) Relief efforts for victims living at shelters, 3) Relief efforts for victims moved to temporary houses, and 4) Relief efforts for victims resuming normal lives. Wisetjindawat et al. (2014) find that for each phase different type of relief goods are needed and the needs of victims increase over time after the disaster. In the first phase of disaster relief, the most basic survival needs need to be distributed such as water, food, medicines et cetera. During the second, third and fourth phase, these basic survival needs are still needed, but the variety of goods increases over time as victims move from shelters to temporary houses and then back to normal life. This underpins the importance of choosing the right facility locations, as the facilities are still used during the later phases of disaster relief. In this study, the focus is on this first phase, emergency response, where the priority lies with setting up central logistics hubs as quickly as possible and while information is largely uncertain.

Duran, Ergun, Keskinocak, and Swann (2013) make the distinction between consumable and non-consumable goods. Consumable goods need to be continuously supplied to the affected areas, such as food and medical supplies. Non-consumable goods need only be supplied once and can then be used during the entire disaster operations, such as tents and cellular phones. Consumable products include both food and non-food products. These products are mostly required in the whole affected area after natural disasters, depending on how severely regions are affected. Also because the relief items change over time, this study considers a single homogeneous relief good that represents consumable food and non-food items that are continuously supplied to the disaster area.

7.3 DYNAMIC UNCERTAINTY: DISRUPTION FACTORS

The third category of required data for the facility location model is the dynamic uncertain parameters. These are variables that have indefinite parameter values and are subject to uncertainty, which changes dynamically over time. For these parameters, there are initial lower and upper limits that define the possible ranges of the uncertainties, but these limits can change over time based on the decisions that are made.

7.3.1 Initial Uncertainty

For all supply points, optional facility locations and demand point, there is a factor that indicates how strongly that place is affected by the disaster. These "disruption factors", relate to the humanitarian needs of and the route duration towards those areas. Right after the disaster, these factors are completely unknown. However, over time, more information helps to make better estimations of these disruption factors. All disruption factors for each node should have an initial lower and upper limit and a best estimate value.

The disruption factors of demand points and optional facility locations are related to how hard that specific certain area is hit. The assumption is made that initially, there is no information on the impact distribution of a disaster. Therefore, the disruption factors initially have maximal lower and upper limits of the possible uncertainty range. The best estimate values of each of the disruption values are the midpoint of the lower and upper limits of the uncertainty range.

7.3.2 Ground Truth

The true values of the disruption factors need to be determined to reduce the uncertainty towards the ground truth and is needed for the decision-uncertainty interaction analysis. Detailed and extensive information is available on how hard different areas in Nepal are struck by the earthquake. For simplification, however, the ground truth is determined with a radial function based on the epicentre of the 2015 earthquake.

The ground truth of the disruption values is calculated with a radial function based on the great circle distance between the coordinates of the node representing the area and the earthquake's epicentre. The values of the disruption factors for each area are between 1 and 2. 1 means not affected at all. 2 means everyone is affected and route durations increase by a factor 2. The closest node receives the maximum disruption value of 1.9 and the furthest node gets the minimum disruption value of 1.1. The disruption factors do therefore not resemble the same values as the 2015 earthquake, but as a proof of principle, the difference is not directly relevant. The formulas used to determine the ground truth disruption values and the resulting values are presented in Appendix E.

7.4 UNCERTAINTY REDUCTION

A central postulate in this thesis is that uncertainty reduces over time and proportionately to the remoteness of places. As elucidated in section 6.2.1, there is a dual explanation for the uncertainty reduction. New information about disaster-struck areas spreads to the neighbouring areas. Logisticians gain more new information about places that are easily reachable for disaster relief activities and less about more remote places. However, also regardless of the proximity of a place, new information about disaster-struck areas becomes available over time. The function used for determining the uncertainty reduction considers both these mechanisms.

A graphical representation of the function used for determining the uncertainty reduction is plotted in Figure 7.2. The horizontal axis shows the distance of an area to operational central logistics hubs. The vertical axis shows the reducing effect of location decisions on uncertainty per period. Each period, the disruption factor of each area is reduced by the uncertainty reduction factor based on the travel time from the operational central logistics hubs.

The maximum uncertainty reduction is 80%. This implies that if a demand point is located at the same location as the central logistics hub, relief workers can estimate very well how strongly that demand point has been affected; 80% of the uncertainty is then reduced between decision-making periods. However, most demand points have a larger distance to the closest facility location. The uncertainty reducing effect caused by time is 10%. Regardless of the distance to the closest facility location, the uncertainty reduces with a minimum of 10%, as shown in Figure 7.2. The function is arbitrarily chosen as there is no empirical research available on the strength of this uncertainty reducing effect.

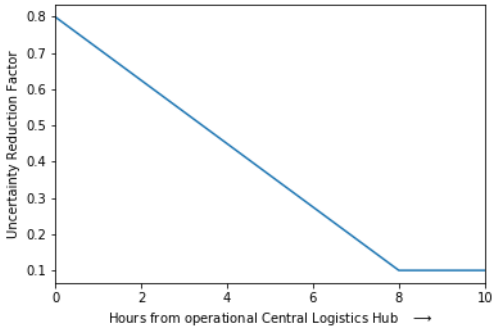


Figure 7.2: Uncertainty Reduction Factor as a function of travel time

The inter-period model defines how the uncertainty ranges change based on the uncertainty reduction factor. This inter-period model has been defined in section 6.2.1. Basically, the distance between the ground truth and the best estimate reduces with the uncertainty reduction factor. The interval of the lower and upper limit also reduces with this factor, while the limits remain centred around the best estimate.

This chapter concludes the problem formulation and the set-up of the multi-period simulation algorithm. The simulation algorithm is used to simulate the decision-making method and the inter-period process for each period. The next chapter includes the decision-uncertainty interaction analysis, which is the last part of the designed approach for the simulation and analysis of the interaction between decisions and uncertainty. The decision-uncertainty interaction analysis uses the results from the simulation of the simulation algorithm.

8 RESULTS: DECISION-UNCERTAINTY INTERACTION ANALYSIS FOR POST-DISASTER FACILITY LOCATION DECISIONS

The last part of the designed approach is the decision-uncertainty interaction analysis. Before the chapter starts with the analysis of this interaction, the outcomes of the simulation algorithm are described. Then, the analysis looks at (1) the trade-offs between objective prioritisations, (2) the scenario discovery to find the most important uncertainties, and (3) the relation between objective prioritisations and uncertainty reduction.

8.1 DESCRIPTION OF THE RESULTS

The duration of the simulation of all decision-making periods was 2 hours, 45 minutes and 14 seconds. This simulation is performed on a laptop with Intel Core i5 CPU, 2.3 GHz and 8 GB of RAM.

The complete simulation of the interplay between decisions and uncertainty has resulted in a vast amount of possible branches of decision sequences that decision makers could take. Period 0 is the initial decision-making moment, where the decision maker had 6 choices. For each of these choices, a separate branch is forked and simulated as if that choice has been implemented in period 1. In period 1 the decision-making process has to be simulated for each of the 6 different branches. This process has continued until four subsequent decisions have been made (simulated) for each possible branch. Where period 1 has 6 branches, period 2 has 38, period 3 has 231 and period 4 has 1152 branches. For each period but the last (period four), the decision-making process has been simulated by running the algorithmic version of MORDM. In total, the MORDM algorithm has been run 276 times. Considering that each MORDM cycle evaluates on average almost 6 solutions per cycle ($6^4 = 1296 > 1152$) and 500 scenarios for each solution, the model has been run approximately 800.000 times. This illustrates the computational intensity of the simulation of the interplay between decisions and uncertainty.

8.2 TRADE-OFFS OF OBJECTIVE PRIORITISATIONS

This analysis looks at the trade-offs between the objective prioritisations for humanitarian logistics facility location decisions. Each of the branches in the tree of decision pathways consists of four decisions on the locations of humanitarian logistics hubs. The first part of this trade-off analysis looks at the correlation between the four objective scores for each of the decision pathways. The second part looks at the multivariate relations between the objective scores and zooms in on some of the interesting solutions.

8.2.1 Correlation between Objective scores

The correlation analysis looks at the bivariate relations between each of the objective scores of each of the solutions in the tree of decision pathways. To compare each of the solutions, all decision pathways are re-evaluated for the ground truth values of the disruption values and the reference scenario for the remaining uncertain variables. The resulting set contains the objective scores for each of the objectives for each of the decision pathways.

The first hypothesis for this analysis is that the total transport costs have a negative relationship with the other three objectives: total uncovered demand, the number of uncovered demand points, and the maximum travel time. These three objectives are indicators of effective and equitable disaster logistics. The increase in effectiveness and equity is expectedly associated with an increase in costs. The second hypothesis for this analysis is that the objectives of minimising uncovered demand and the number of uncovered demand points have a positive relation. The rationale for this second hypothesis is that covering an additional demand point likely results in additional covered demand. The third hypothesis is that the maximum travel time has a positive relationship with the number of uncovered demand points and the total uncovered demand. When more demand points are covered, the travel times of these demand points decreases, which leads to a decrease in maximum travel time when the furthest location is covered.

The scores on the different objectives are visually presented in Figure 8.1. The graphs on the upper-right side are scatter graphs for the different objective combinations. The graphs on the lower-left side are bivariate Kernel Density Estimation (KDE) graphs for the different objective combinations. These bivariate KDE graphs are symmetrical on the left diagonal with the scatter graphs in the upper-right side (note that the axes are mirrored). The graphs on the left diagonal are univariate KDE graphs for the different objective scores, as presented on the x-axis. These graphs give an idea of the relations amongst the different objective scores of the different facility location combinations.

The scatter and distribution plots provide visual insight into the relations between the different objectives. To test the relations statistically, a correlation matrix is presented in Table 8.1. The values as presented in the table are Pearson correlation coefficients. Where the correlation coefficients are presented, the P-value is smaller than 0.05 and thus significant.

The scatter and KDE plots in Figure 8.1 show that the objective scores for the number of uncovered demand points and the maximum travel time are more or less normally distributed. The objective scores for the total transport costs and the total uncovered demand, however, have both two peaks. In the scatter plot for these two objectives, two 'islands' of observations can be distinguished. The graphs suggest two types of solutions: high costs with low total uncovered demand, and low costs with high total uncovered demand.

Table 8.1: Correlation Table

N = 1152	Total Costs	# Uncovered Demand Points	Total Uncovered Demand	Max. Travel Time
Total Costs	X	-0.804957	-0.800322	-0.202847
# Uncovered Demand Points	-0.804957	X	0.882739	0.149474
Total Uncovered Demand	-0.800322	0.882739	X	Not Significant
Max. Travel Time	-0.202847	0.149474	Not Significant	X

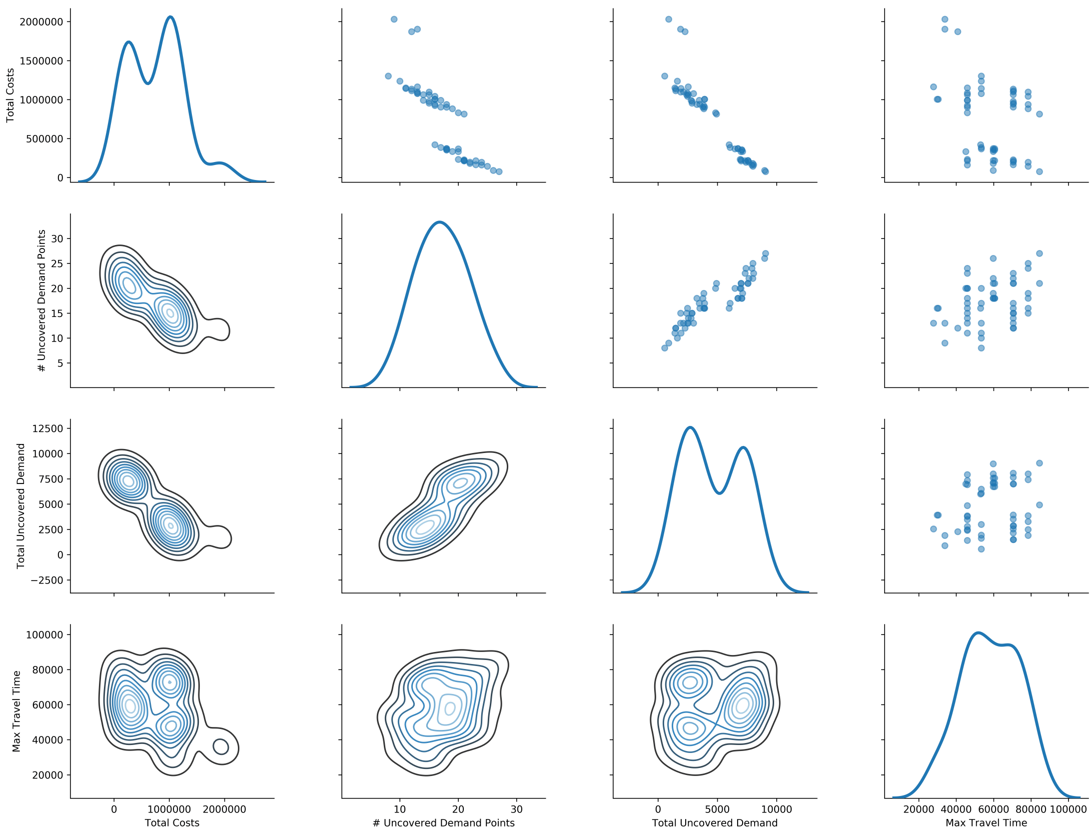


Figure 8.1: Scatter and KDE plots for all objectives

Evans (1996) classifies the correlation coefficients into correlation strengths. The correlation results in Table 8.1 show that three variable relations are very strongly correlated: (1) the number of uncovered demand points has a negative relationship with total costs, (2) the number of uncovered demand points has a positive relationship with total uncovered demand, and (3) the total costs has a negative relationship with total uncovered demand. One variable relationship is weakly correlated: the maximum travel time has a negative relationship with total costs. One variable relationship is very weakly correlated: the maximum travel time has a positive relationship with the number of uncovered demand points. No significant correlation is found between the maximum travel time and total uncovered demand.

The first hypothesis can be confirmed: total transport costs have indeed a negative relationship with the other three objectives: total uncovered demand, the number of uncovered demand points, and the maximum travel time. However, the correlation between total costs and the maximum travel time is only weak. A possible explanation could be that the scores on maximum travel time change only in discrete steps, for which the score is only reduced when the furthest located demand point is covered. In some cases, when the furthest located demand point is covered this could result in more costs, but in many cases, the costs are very dependent on other factors, without influencing the maximum travel time. Different scores on total costs can be associated with the same value for the maximum travel time.

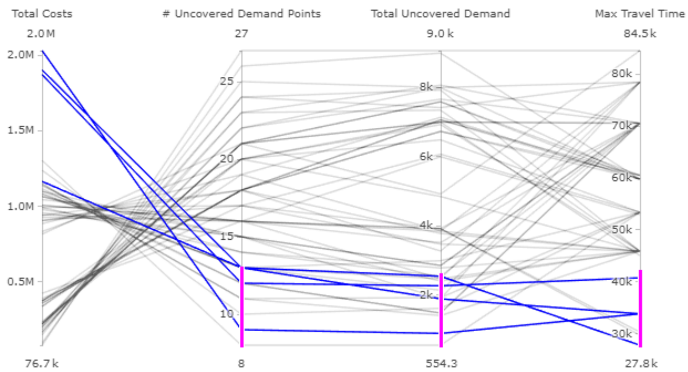
The objectives of minimising uncovered demand and the number of uncovered demand points have a positive relation. This was also hypothesised at the beginning of this analysis, so this second hypothesis can also be confirmed. The very strong positive correlation indicates that these two objectives can be regarded as two different formulations of effectiveness. Therefore, these two objectives both represent the effectiveness criterion.

The third hypothesis can only partly be confirmed. The maximum travel time does have a (very weak) positive relationship with the number of uncovered demand points, however, the maximum travel time does not have a significant relationship with the total uncovered demand. A possible explanation for this could be that the demand points with the longest travel times do not have more demand compared to other demand points. When the furthest located demand points are covered, this could be at the expense of other demand points. Therefore, a decrease in maximum travel time does not relate to a decrease in uncovered demand.

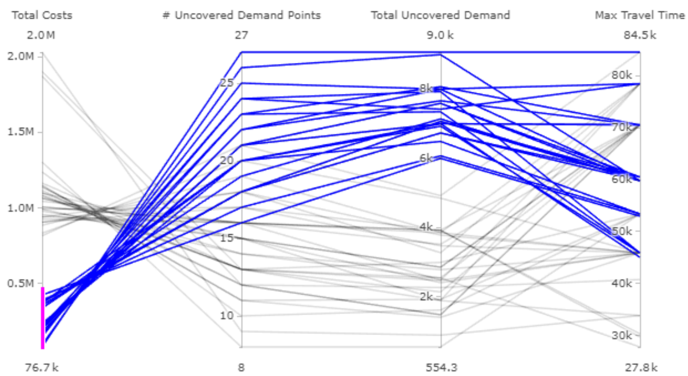
8.2.2 Combining objective prioritisations

The previous section gives insight into the trade-offs between objectives with bivariate analysis. In this section, the multivariate relations between the objectives is analysed by showing the objective scores of the different solutions in parallel coordinate plots and by selecting specific solutions to show the corresponding facility location decisions as made in that decision pathway.

Where the classic scatter diagram is a fundamental tool in displaying patterns in datasets with two or three dimensions, the parallel coordinate plot enables visualisation of multivariate data with many dimensions (Wegman, 1990). A parallel coordinate plot displays data on different parallel axes. Each axis represents one dimension for one of the objectives in the dataset. For each data point in a dataset, the values for the different variables are projected on the different parallel axes. Then, for each data point, the values on the different axes are connected by a line. Each line in the parallel coordinate plot thus represents a single data point in the dataset.



(a) Decision pathways selected with high costs, low number of uncovered demand points, low total uncoverd demand, low maximum travel time

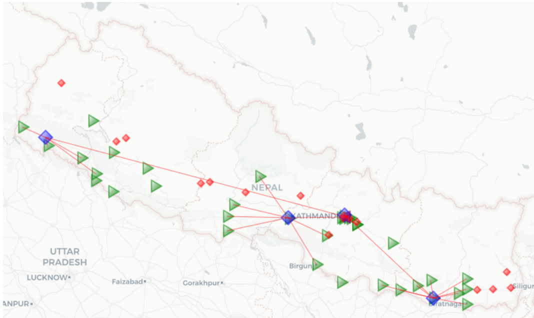


(b) Decision pathways selected with low cost

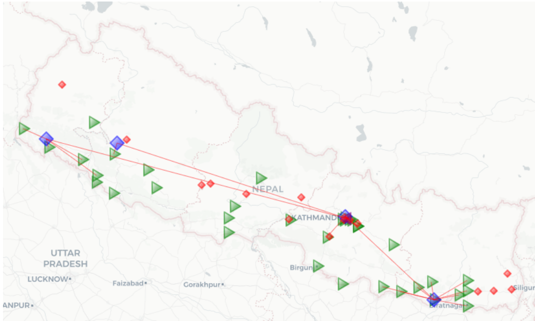
Figure 8.2: Parallel Coordinate Plot with solutions selected

Figure 8.2 shows two parallel coordinate plots, where each line represents the scores of one decision pathway on each of the objectives. In the first, Figure 8.2a, the different solutions that score well on minimising the number of uncovered demand points, the total uncovered demand, and the maximum travel time are selected. In the second, Figure 8.2b, the different decision pathways that score well on minimising the total costs are selected.

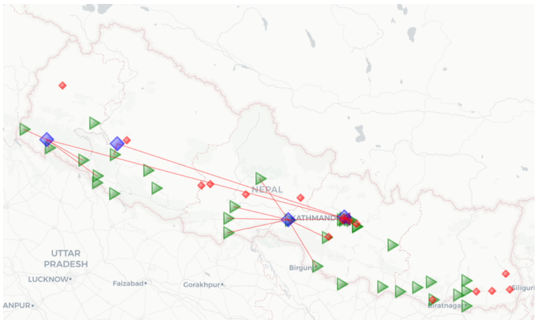
Each decision pathway corresponds to a combination of four different facility locations. From each of both selections as shown in Figure 8.2a and 8.2b, two decision pathways are selected for visualisation. From the selection in Figure 8.2a, the decision pathway with the least number of uncovered demand points, and the decision pathway with the lowest maximum travel time are selected. From the selection in Figure 8.2b, the decision pathway with the lowest total costs, and the decision pathway with the lowest number of uncovered demand points are selected. The four selected solutions and their corresponding facility locations are shown in Figure 8.3.



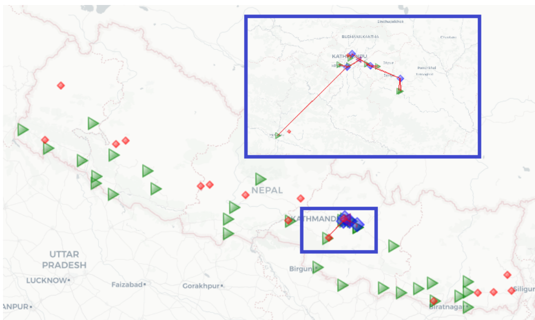
(a) Lowest # Uncovered Demand Points & Total Uncovered Demand



(b) Lowest Maximum Travel Time



(c) Low Total Costs, with relatively low # Uncovered Demand Points



(d) Lowest Total Costs

Figure 8.3: Nepal Maps with Facility Locations, Demand Points and Supply Points
Green Triangles: Demand points
Red Diamonds: Non-Operational Central Logistics Hubs
Blue Diamonds: Operational Central Logistics Hubs
Purple Triangle: Supply Point

The maps as depicted in Figure 8.3 show the different facility locations for each decision pathway. Each decision pathway picked out from the selection in the parallel coordinate plots is shown in a separate map. Each map contains different elements. The green triangles represent the demand points (i.e. the cities and remote valleys) in Nepal. The purple triangle represents the supply point in Nepal, Kathmandu Airport. The blue squares are operational facility locations and the red squares are non-operational facility locations. The red lines that connect some of the green triangles with the blue squares indicate the allocation of demand points to facility locations. When a demand point lies within the maximum covered distance of the closest facility location, it is allocated to that facility location. These maps give insight into the locations of the facilities that are decided to be operational for the different decision pathways.

The decision pathways with lower total costs have more facilities with concentrated locations around Kathmandu (Figure 8.3c & 8.3d), while the decision pathways with a low number of uncovered demand points, low total uncovered demand, and short maximum travel time have facilities with locations that are much more spread out over the country (Figure 8.3a & 8.3b. A possible explanation could be that when central logistics hubs are more concentrated around the supply point, less demand can be covered and fewer relief goods are transported. This corresponds to the observation that the decision pathways associated with low total costs have many areas in Nepal that are uncovered.

8.2.3 Frequently Chosen Facility Locations and Decision Sequences

Each of the maps in Figure 8.3 shows the four central logistics hubs that score best on the four selected objective prioritisations. However, there are multiple decision sequences that can to each of these maps. Therefore, for each of the four selected objective prioritisations that are highlighted in Figure 8.3 the decision-making sequences are analysed. Also, the frequency of how often each central logistics hub is selected for these four different prioritisations is looked at. Appendix F describes the used methodology and presents the results. Here, the most important outcomes are presented.

The results show that there is an overlap between the facility location decisions that are made for different objective prioritisations. One of the possible facility locations is chosen for each of the four selected objective prioritisations (CLH3). Another facility is chosen for three of the four objective prioritisations (CLH7). Three facilities are chosen for two objective prioritisations (CLH11, CLH12 & CLH19). This indicates that some of the possible facility locations can be a good choice regardless of the objective prioritisation.

The analysis of the decision sequences shows in which sequence the facility locations are most often chosen for each of the objective prioritisations. It shows that the facility location which is chosen for each of the four objective prioritisations (CLH3), is also chosen most often at the first decision-making period for three of the four objective prioritisations. For the other objective prioritisation this location is chosen at the second decision-making period. This suggests that it is a good idea to choose CLH3 regardless of the objective prioritisation. The analysis looks closer at the location of CLH3 and it appears that this facility location is located closest to the supply point (Tribhuvan International airport) of all facility locations and is located in Kathmandu, the largest demand point.

8.3 IMPORTANT SCENARIOS FOR FACILITY LOCATION DECISIONS

Often, scenarios are associated with different possible futures. For this analysis, scenarios refer to the different possible truths in an environment where the truth is uncertain because of incomplete information. In other words, instead of referring to different possibilities of 'how it will be', it refers to different possibilities of 'how it is'.

Scenario discovery is a model-based approach that helps identify scenarios based on statistical or machine learning algorithms, instead of the more traditional way of identifying scenarios based on experts' perceptions (Bryant & Lempert, 2010; Kwakkel et al., 2013). These statistical or machine learning algorithms are used to identify combinations of uncertain variables that result in cases of interest (Halim et al., 2016). The cases of interest for this analysis are the worst performing scenarios. Identification of the uncertain variables that cause these worst performing scenarios can help decision makers direct their efforts on gathering the most valuable information. The algorithm that is used for this analysis is the Patient Rule Induction Method (PRIM) (Friedman & Fisher, 1999), which helps to find the subregions for the input space that results in the worst-case outcomes. The version of PRIM as used for this scenario discovery analysis is an improved version of the original method as proposed by Friedman and Fisher (1999), which can handle heterogeneous uncertainties and multinomial classified outcomes, as proposed by Kwakkel and Jaxa-Rozen (2016).

8.3.1 Methodology for scenario discovery.

The scenario discovery analysis is conducted on each of the objectives, which gives more nuanced analytical insight than when the different objectives are aggregated (Shortridge & Guikema, 2016). Each decision pathway shares the same uncertainty ranges for the static uncertainties, but the ranges for the disruption factors are specific to each decision pathway because they are dependent on the sequence of facility location decisions. Scenario discovery is an analytical process and too time-consuming to do for multiple branches. Therefore, the analysis is conducted for a single branch of the tree of decision pathways. The first branch of the last period is used for the scenario discovery.

To select the cases of interest for each objective, the 80th percentile of the objective score is selected. Because minimisation on each of the objectives is preferred, the 80th percentile contains all solutions that are among the 20% worst cases. The PRIM algorithm is instantiated with the binary classification of the cases of interest as the dependent variable, and both the different uncertainties as explanatory variables. The uncertainties include the disruption factors of both the facility locations and the demand points and includes the static uncertain variables. The minimum coverage threshold is set to 0.8.

To find the first box, the trade-off for the peeling trajectory is plotted. Multiple possible points for the first box are inspected and compared, after which one point is selected where both the coverage and the density are relatively high and all restricted dimensions have quasi-p-values that are larger than 0.05. Sometimes, PRIM selects policies (facility locations) as restricted dimensions, which are excluded from the scenario discovery because these are no uncertainties. The same procedure is used to check for additional boxes. The properties of the boxes, such as the different restricted dimensions, the coverage and the density, are presented and interpreted as scenarios in this analysis. The peeling trajectories for each of the boxes are shown in Appendix G.

8.3.2 Scenarios Discovery for Total Transport Costs

The PRIM algorithm is run to find the scenarios that lead to the highest total transport costs. The first box that is selected from the peeling trajectory, has a coverage of 0.978, a density of 0.507, and has 3 restricted dimensions. A high coverage and a medium density mean that this box bound by these three dimensions contains a large proportion of the cases of interest, but that there are also cases inside the box that are not one of these 20% worst cases. This box has been selected, as further peeling would result in non-significant quasi-p-values for additional uncertain factors. The PRIM algorithm cannot find any additional boxes, as the second box does not meet the threshold criteria. The first box is shown in figure 8.4.

The scenario that results in the cases with the 20% highest total transport costs is dependent on three dimensions: the costs of transport for a single unit of relief goods, the demand for each

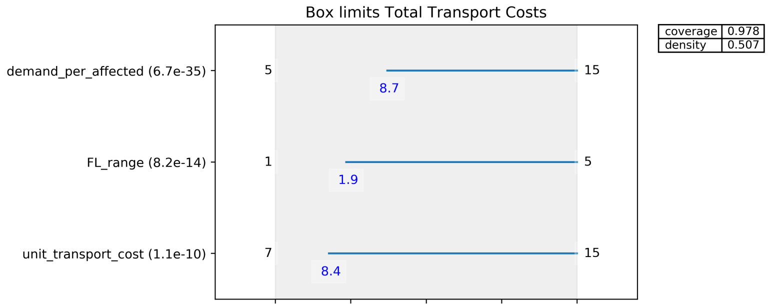


Figure 8.4: Box limits for the first box for Total Transport Costs

affected person, and the maximum distance for which demand points can be covered. The total transport costs are the highest for the scenario where these three variables are relatively high at the same time.

These three dimensions are directly related to the quantity of relief goods that have to be distributed or the costs for the transport of each unit of relief goods. When facility locations can cover demand points within a larger perimeter, more transport is required to distribute relief supplies to those demand points. When the demand per affected increases, the supplied relief material increases (assumed there is sufficient supply). The transport costs for a single unit of relief goods are the marginal costs. For all these three factors counts that when they increase, an increase in the total transport costs is a direct result, which offers a logical explanation why these variables are found to be impactful.

8.3.3 Scenarios Discovery for Number of Uncovered Demand Points

The PRIM algorithm is run to find the scenarios that lead to the highest number of uncovered demand points. The first box that is selected from the peeling trajectory, has a coverage of 1, a density of 0.624, and has a single restricted dimension. A coverage of 1 and a medium density means that this box bound by this single dimension contains all of the cases of interest, but that there are also cases inside the box that are not one of these 20% worst cases. This box has been selected, as further peeling would result in restricting a dimension that is not related to uncertainty, but to specific facility locations. The PRIM algorithm cannot find any additional boxes, as the second box does not meet the threshold criteria. The first box is shown in figure 8.5.

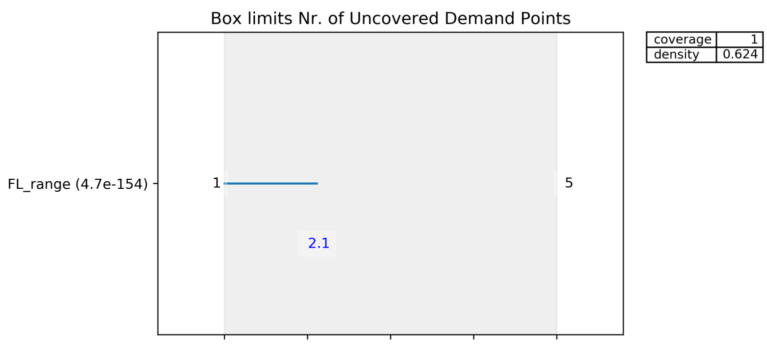


Figure 8.5: Box limits for the first box for Number of Uncovered Demand Points

The scenario that results in the cases with the 20% highest number of uncovered demand points is dependent on a single dimension: the maximum distance for which demand points can be covered. The number of uncovered demand points is the highest for the scenario where the maximum distance for which demand points can be covered is very small.

If only demand points that are close to facility locations can be covered with relief supplies, more demand points remain uncovered. When this distance is very low, it results in the most negatively impacting scenario on the number of uncovered demand point, offering a logical explanation why the maximum covered distance is found to be impactful.

8.3.4 Scenarios Discovery for Total Uncovered Demand

The PRIM algorithm is run to find the scenarios that lead to the highest total uncovered demand. The first box that is selected from the peeling trajectory, has a coverage of 0.936, a density of 0.637, and has 2 restricted dimensions. A high coverage and a medium density mean that this box bound by these two dimensions contains a large proportion of the cases of interest, but that there are also cases inside the box that are not one of these 20% worst cases. This box has been selected, as further peeling would result in an increasing number of restricted dimensions with non-significant quasi-p-values. The PRIM algorithm cannot find any additional boxes, as the second box does not meet the threshold criteria. The first box is shown in figure 8.6.

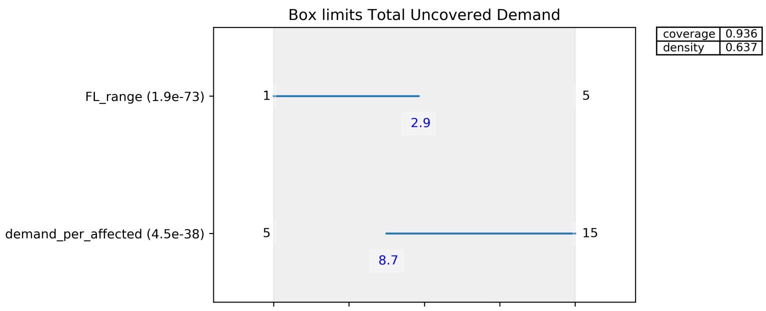


Figure 8.6: Box limits for the first box for Total Uncovered Demand

The scenario that results in the cases with the 20% highest total uncovered demand is dependent on two dimensions: the demand for each affected person and the maximum distance for which demand points can be covered. The total uncovered demand is the highest for the scenario where the distance for which demand can be covered is small and where the demand for each affected person is not small.

If only demand points that are close to facility locations can be covered with relief supplies, more demand points remain uncovered. When fewer demand points are covered, more people remain in the need for relief supplies. If at the same time the demand per affected is higher, the total demand increases, resulting in more uncovered demand. The combination of these individual relations results in the most negatively impacting scenario on total uncovered demand.

8.3.5 Scenarios Discovery for Maximum Travel Time

The PRIM algorithm is run to find the scenarios that lead to the longest maximum travel time. The first box that is selected from the peeling trajectory, has a coverage of 1, a density of 1, and has 2 restricted dimensions. A coverage and density that are both equal to one, means that this box bound by these two dimensions contains all cases of interest without cases inside the box that are not one of these 20% worst cases. This box has been selected, as it is the last point in the peeling trajectory. The PRIM algorithm cannot find any additional boxes, as the second box does not meet the threshold criteria, which is because the first box already found a perfect box for all cases of interest. This first box is shown in figure 8.7.

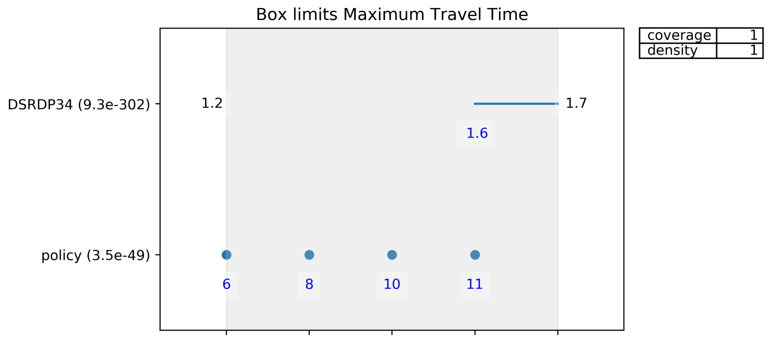


Figure 8.7: Box limits for the first box for Maximum Travel Time

A very different type of scenario is the result of the scenario discovery analysis for the maximum travel time. The scenario that results in the cases with the 20% highest maximum travel time is dependent on three specific policies and on the disruption factor of a single demand point. Here, the specific policies (facility locations) are included because it helps to understand why the disruption factor of a specific demand point comes out as the most harmful factor. The numbers of these policies refer to the numbers of the facility locations as given in Appendix E. The maximum travel time is the highest where the disruption factor of a specific demand point is high and when one of these three specific policies is chosen.

A logical explanation for this disruption factor to be so impactful could be that the related demand point is the demand point with the maximum travel time. The demand point related to this disruption factor is indeed one of the most remotely located places and is also one of the five added remote valleys, see Appendix E. An explanation for these three policies to be so impactful could be that this specific demand point has the largest maximum travel time, regardless of whether one of these facility locations are active. Other facility locations would be closer to this demand point and thus reduce the maximum travel time. The locations of the facility locations related to the policies are indeed located on the other side of Nepal, see Appendix E.

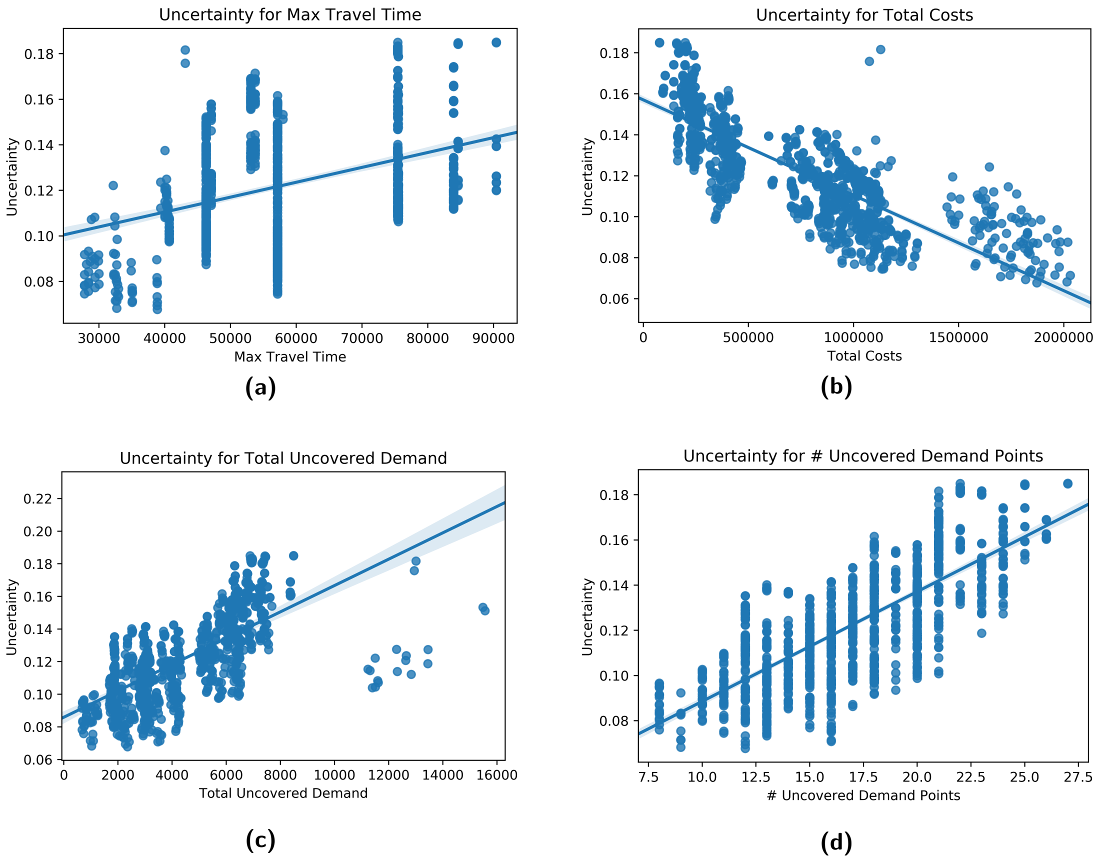
8.4 EFFECT OF FACILITY LOCATION DECISIONS ON UNCERTAINTY

This analysis focusses on how different objective prioritisations relate to the reduction of uncertainty. Each period, decisions are made with specific objective prioritisations. The hypothesis is that the branches where has been focussed on coverage-related objectives are associated with smaller uncertainty ranges. This is expected because combinations of facility locations that score well on coverage are expected to be closer to more demand points, which would lead to a faster reduction of uncertainty. To check this hypothesis, a regression analysis is conducted, which can give insight into the relationship between objective prioritisations and remaining uncertainty space. The added value of using a regression analysis compared to a correlation analysis is that it can give additional insight into the linearity of the relationship.

The dependent variable for the regression analysis is the uncertainty range. The four explanatory variables are the scores on each of the objectives during the last period. To measure the uncertainty range at each different branch (the dependent variable), a metric to measure uncertainty is used that represents the size of the total uncertainty space at that specific branch. The total uncertainty space of interest for each branch is the combination of uncertainty ranges for all disruption factors of the demand points and facility locations. The metric used to indicate the size of this uncertainty space is the mean of all disruption factor uncertainty ranges for a specific branch and is referred to as the "mean uncertainty bandwidth".

The mean uncertainty bandwidth for each of the disruption factors is 1 at the initial period, which means that for each demand point it is unknown whether 100% or 0% of the population has been affected by the disaster. This uncertainty bandwidth is reduced over time, as defined in the inter-period model (see section 6.2.1). An uncertainty bandwidth of 0.30 at the last period, means that the distance between the lower and the upper limit of the uncertainty range includes 30% of the uncertainty relative to the initial period. In this example, 70% of the uncertainty has been reduced.

First, a simple linear regression model is estimated for each objective, to see whether the relationship of each objective with the uncertainty range is significant and linear or non-linear. Then, a multiple regression model is estimated, to see whether the relations are also significant when combined, or whether variability in the uncertainty reduction is explained by the other variables.



(a) (b) (c) (d)

Figure 8.8: Simple Regression Plots for all Four Objectives

8.4.1 Simple Linear Regression

The results of the simple linear regression for each of the objectives are shown in Figure 8.8. Based on visual observation of the regression plots, it looks like all objectives prioritisations are correlated with the remaining uncertainty in the last period. The numerical results of the simple regression analysis are given in Table 8.2.

Table 8.2: Simple Regression Analysis Results

N = 1152	Total Costs	Nr. of Uncovered Demand Points	Total Uncovered Demand	Max. Travel Time
Slope	-4.66E-8	0.00486	8.08E-06	6.54E-7
Intercept	0.157	0.0400	0.0859	0.0843
R-squared	0.648	0.578	0.472	0.139
p_value	1.11e-262	1.24E-217	1.41.E-161	3.47E-39
std_err	1.01E-9	1.22E-4	2.52E-7	4.80E-8

Table 8.2 shows that all regression lines are significant; all p-values are lower than 0.05. To check whether the results of the simple regression analysis are linear, a residual plot has been created for each explanatory variable. From observation of the residual plots for each objective, it seems that none of the variables is non-linearly related to the dependent variable. The residual plots are presented in Appendix H.

The slope of three out of four objectives is positive, namely for maximum travel time, total uncovered demand, and number of uncovered demand points. Total costs, however, are negatively correlated with the average remaining uncertainty. The R-squared (the square of the Pearson correlation coefficient) is the highest for the relationship between uncertainty and the total costs. This indicates that the transport costs have the strongest correlation with the average uncertainty reduction for a specific decision pathway. The slope for each objective in the simple regression analysis is not directly relevant, because the regression line is estimated on data generated with the simulation algorithm and not on empirical data, and therefore dependent on the accuracy of input parameters.

The positive correlation of average remaining uncertainty at a decision pathway with the maximum travel time, the total uncovered demand and the number of uncovered demand points and the negative correlation with total transport costs is more or less in accordance with the hypothesis as stated at the beginning of this analysis: decision pathways that have focussed on objectives related to coverage are associated with smaller uncertainty ranges. However, the maximum travel time and the total costs were not expected to correlate with the remaining uncertainty space. A multiple regression analysis points out whether these correlations can be explained by variability of the other explanatory variables.

8.4.2 Multiple Regression

The regression model used for the multiple regression is an Ordinary Least Squares (OLS) regression. The model includes a constant and all explanatory variables as linear regressors. The linear function used to fit the linear regression model is:

$$\begin{aligned} Uncertainty =& \beta_0 + \beta_1 \cdot TotalCosts + \beta_2 \cdot Nr.ofUncoveredDemandPoints + \\ & \beta_3 \cdot TotalUncoveredDemand + \beta_4 \cdot Max.TravelTime \end{aligned} \tag{8.1}$$

The results from the multiple regression model are presented in Table 8.3. From the results of the multiple regression analysis, it appears that all explanatory variables have a significant relationship with the average remaining uncertainty. This shows that each of the objective prioritisations has an independent effect on the variability of the uncertainty reduction.

Table 8.3: Multiple Regression Analysis Results

R-squared = 0.781 N = 1152			
	Coefficient	std err	P-value
Constant	0.0742	0.0038	0.000
Total Costs	-2.58E-08	1.34E-09	0.000
Nr. of Uncovered Demand Points	0.0014	0.0002	0.000
Total Uncovered Demand	2.30E-06	3.74E-07	0.000
Max. Travel Time	5.69E-07	2.59E-08	0.000

8.4.3 Effect of Uncertainty Reduction on Optimisation Results

The reduction of uncertainty in the disaster environment is important for both humanitarian logisticians and other relief workers. To check whether the reduction of uncertainty indeed leads to improved facility location decisions, Appendix I looks at the relation between the reduction of uncertainty and the optimality of the decision-making method outcomes. It does so by correlating the size of the uncertainty space with the optimality of the final-period decision-making method outcomes of each decision pathway. Appendix I elaborates on the used methodology and the numeric results. Here, the most important outcomes are presented.

The optimality of the final-period decision-making method is measured with the S-metric or the hypervolume. This hypervolume metric indicates the volume that is covered by the objective scores for all solutions in the Pareto set, with respect to the reference point (Brands, 2015, p. 71). Figure 8.9 illustrates the hypervolume in a 2-dimensional space (representing 2 objectives) for four solutions. Pareto fronts with a larger hypervolume are more optimal than Pareto fronts with smaller hypervolumes.

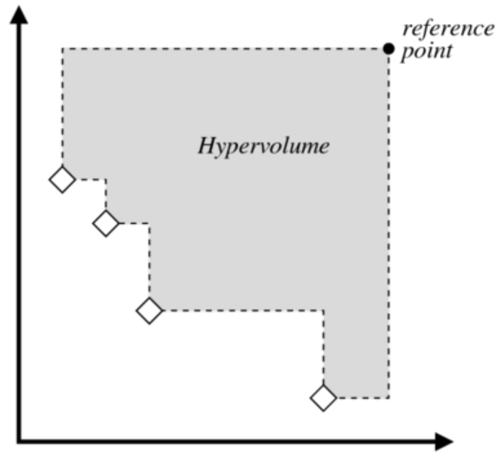


Figure 8.9: Hypervolume in a 2-Dimensional space (for minimisation on both dimensions), Modified from (Fonseca et al., 2006)

Initially, no correlation is found between the reduction of uncertainty and the optimality decision-making method outcomes. However, a higher cardinality of a Pareto set leads to an easier attainment of higher hypervolumes (Brands, 2015). To correct for this, the hypervolume of each Pareto set is divided by its cardinality. Then, when the hypervolumes are corrected for the cardinality, a significant relation is found between the reduction of uncertainty and the relative hypervolume size. The regression analysis shows that there is a moderately strong correlation between the uncertainty reduction and the optimality of the optimisation outcomes. Specifically, it shows that when the uncertainty reduces, the relative hypervolume size increases. In other words, the optimisation of the branches with a smaller uncertainty space produces more optimal results than the optimisation of branches with a larger uncertainty space. This emphasises the importance of the reduction of uncertainty for making post-disaster facility location decisions.

Part IV

Evaluation & Discussion

9 MEASURING PERFORMANCE OF THE MULTI-PERIOD DECISION-MAKING METHOD UNDER UNCERTAINTY

The central approach in this thesis has been designed for simulation and analysis of the interaction between decisions and uncertainty. This approach existed partly of a decision-making method that enabled to make robust decisions for multiple objectives while dealing with incomplete information and uncertainty. This Many-Objective Robust Decision-Making method has been used in a step-wise manner to enable the assimilation of new information and reduced uncertainty. To evaluate this step-wise decision-making method, this chapter analyses how well this method performs compared to an approach with perfect foresight. The analysis focusses on comparing different characteristics of the Pareto front and the distribution of the objective scores of the solutions.

9.1 OPTIMISATION UNDER UNCERTAINTY VERSUS OPTIMISATION WITH PERFECT FORESIGHT

The simulation algorithm has simulated the decision-making method and the reduction of uncertainty over time. The solutions that are given by this algorithm are compared to solutions that have been optimised with 'perfect foresight'. The optimisation with perfect foresight uses the ground truth values for the dynamic uncertain variables and the reference scenario for the static uncertain variables. Enumerative many-objective optimisation is used to evaluate all possible solutions. This optimisation with perfect foresight gives a set of solutions that covers the full Pareto front for the ground truth.

For a fair comparison of the results for the optimisation under uncertainty and the optimisation with perfect foresight, the solutions obtained with the simulation algorithm are re-evaluated for the ground truth values of the disruption factors and the reference scenario for the static uncertain variables. Each of the solution sets is evaluated for the same input values and can be compared on characteristics of their respective Pareto fronts and the distribution of the objective scores of the solutions.

9.2 PARETO FRONT COMPARISON

This section focusses on how well the solutions of the optimisation under uncertainty approximate the Pareto front of the optimisation with perfect foresight. The solution set for the optimisation under uncertainty includes many more solutions than the Pareto front of the optimisation for perfect foresight. Therefore, new metrics are introduced to be able to analyse the difference between the two solution sets.

The first metric that is used is the hypervolume metric, which is introduced in section 8.4.3. Pareto fronts with a larger hypervolume are more optimal than Pareto fronts with smaller hypervolumes. Each Pareto front includes a set of solutions, with for each solution the scores on the four objectives.

Before computing the hypervolume of each Pareto front, unity-based normalisation is used to normalise the scores on each objective between 0 and 1 over all sets of objective scores (i.e. over all Pareto fronts). Then the hypervolumes are computed by using a reference point that equals 1 for all objectives, as the reference point represents the upper boundaries for the objective scores (Brands, 2015).

The solution set from the optimisation under uncertainty also obtains solutions that are not in the Pareto front for the ground truth. Therefore, it is insightful to also check how the worst possible solutions as given by the optimisation under uncertainty perform compared to the optimal solutions. To do so, the hypervolume of the worst-case solutions are computed in addition to the hypervolume of the Pareto set. The worst-case solutions are referred to as the "inverse Pareto set" or the "inverse Pareto front". In Figure 9.1 the inverse Pareto front is marked by the red points and the normal Pareto front is marked by the green points. The inverse Pareto front is obtained by doing non-dominated sorting where the optimisation direction is switched (maximisation instead of minimisation). The hypervolume of the inverse Pareto set is marked by the dark blue shaded surface and the hypervolume of the (normal) Pareto set is marked by the combination of the light blue and the dark blue shaded surface. The hypervolume of the inverse Pareto set gives insight into how well the designed approach performs minimally.

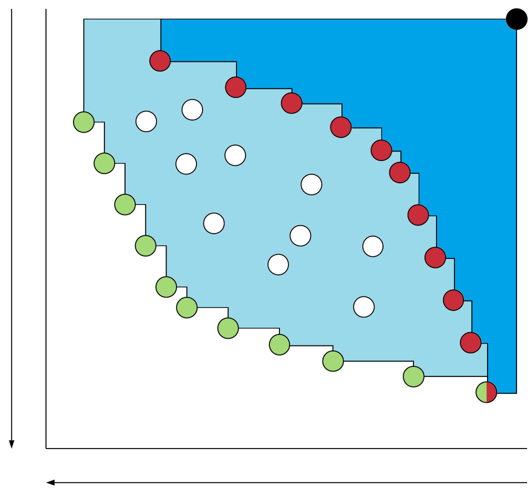


Figure 9.1: Illustration of a Pareto front and an inverse Pareto front

To compare the Pareto fronts on hypervolumes, the scores on each objective should be normalised. Unity-based normalisation is used to normalise the scores on each objective between 0 and 1, for the minimum and maximum values of the combined sets. The reference point for the hypervolume computation is set on the maximum scores for each objective. Since all objective scores have been normalised, the reference point is a vector of ones, where the length equals the number of objectives (i.e. [1,1,1,1]).

The hypervolumes for both Pareto frontiers are presented in Table 9.1. The difference between the hypervolumes of the Pareto fronts is 9.85e-06, which is practically zero. The difference between the hypervolumes of the Pareto front for optimisation with perfect foresight and the hypervolume of the inverse Pareto front for optimisation under uncertainty is 0.265. For insight into how the Pareto front is composed, it is possible to look at the ratio of solutions that create the Pareto front. The Pareto front with solutions optimised with perfect foresight contains 55

Table 9.1: Hypervolume Comparison

Pareto Set	Hypervolume	N Solutions	Difference with perfect foresight
Pareto front for optimisation with perfect foresight	0.521	55	-
Pareto front for optimisation under uncertainty	0.521	54	9.85e-06
Inverse Pareto front for optimisation under uncertainty	0.256	44	0.265

solutions. The Pareto front with solutions created by the Multi-Period Optimisation for Dynamic Uncertainty contains 68 unique solutions.

Coverage & Density

The hypervolumes give insight into how well the best or the worst solutions from the optimisation under uncertainty compare to the optimal solutions as optimised for perfect foresight. This does, however, give no insight into how frequent the different decision pathways end up at these solutions. Therefore, two additional metrics are introduced: coverage and density.

Each solution as proposed by the optimisation under uncertainty represents one branch in the tree of decision pathways. To understand how frequent the different decision pathways end up at the best, the worst, or intermediate solution, the density of these subsets of solutions in the full set of solutions is calculated. The density of a subset indicates which fraction from the full set consists of that subset ($|x|$ denotes the cardinality of x):

$$Density = \frac{|subset|}{|full\, set|} \tag{9.1}$$

Furthermore, because the options in the decision space are discrete, solutions that are proposed by the optimisation under uncertainty can also appear in the "true Pareto front" as optimised with perfect foresight. To indicate the number of solutions that appear within the true Pareto front, the coverage is calculated:

$$Coverage = \frac{|subset|}{|true\, Pareto\, front|} \tag{9.2}$$

Table 9.2: Coverage and Density of subsets for optimisation under uncertainty

Subset	Density of subset	Coverage of True PF
Pareto Front	53.3%	98.2%
Inverse Pareto Front	20.2%	27.3%
Intermediate Solutions	38.4%	0%

The coverage and the density are calculated for three subsets of the solutions as found by the optimisation under uncertainty: the Pareto front, the inverse Pareto front and all remaining 'intermediate' solutions. The results are presented in Table 9.2. The percentages of the density of the three sets of solutions are together larger than 100%. This is because there is an overlap of 11.9% between the solutions of the Pareto front and the inverse Pareto front: $Pareto\, front \cap inverse\, Pareto\, front = 11.9\%$. Figure 9.1 illustrates how this is possible: The point in the right-bottom of the graph is in both the Pareto front and in the inverse Pareto front.

9.3 COMPARISON OF THE DISTRIBUTIONS FOR THE OBJECTIVE SCORES

To further look at the differences between the solutions proposed by the multi-period approach under uncertainty and by the optimisation process with perfect foresight, the distribution of the solutions over the different variables are analysed. To show the distribution, Kernel Density Estimation (KDE) is used to plot the distribution of all solutions for each objective. A Gaussian function with relatively small kernel size is used, to not over smooth the density distribution. To give extra insight into the distribution of the objective scores, a 'rug plot' is added to each KDE-plot, which shows small marks for the exact x-values.

Minimisation of each objective is preferred, so the solutions with values on the left side of the X-axis are preferred over solutions with values on the right side of the Y-axis. Optimisation with perfectly accurate input parameters axiomatically provides a better estimation of the optimal solutions than optimisation with uncertainty. Therefore, the hypothesis is that the distribution of the solutions optimised with perfect foresight is more left-centred than the solutions as optimised with the multi-period decision-making method under uncertainty.

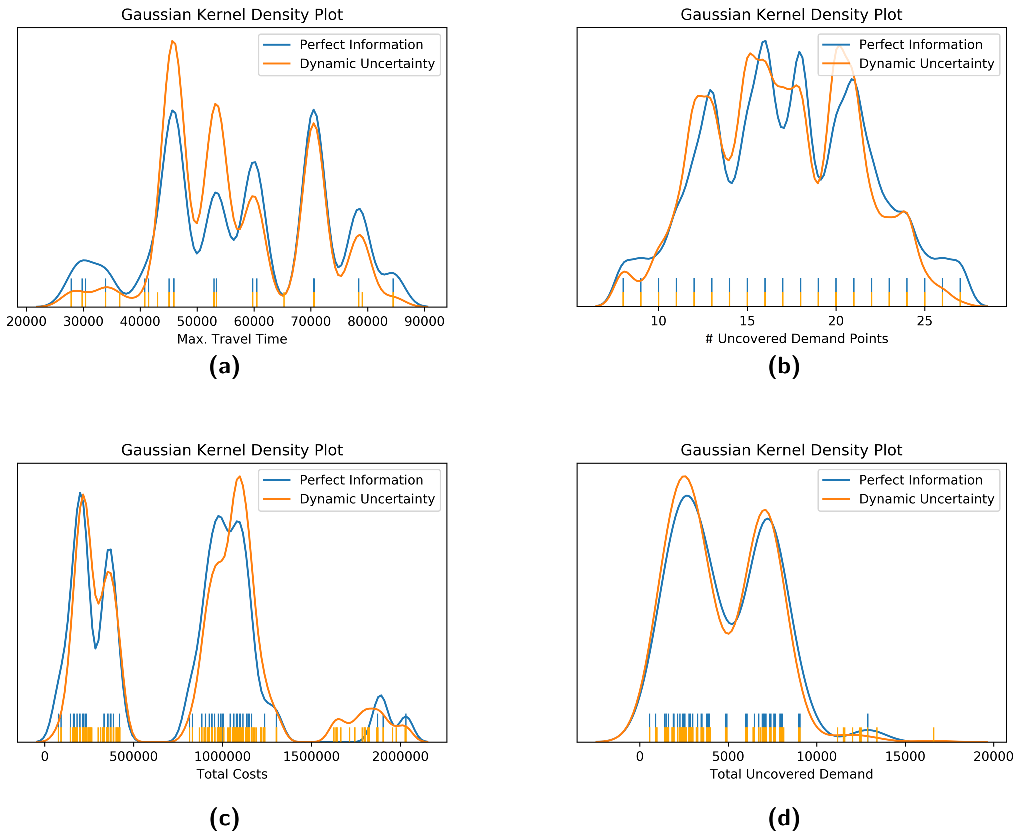


Figure 9.2: Kernel Density Plots for all Four Objectives

The distribution curves for each objective are given in Figures 9.2. In each sub figure, the blue curve represents the distribution of the solutions given by the optimisation process with perfect foresight. The orange curve represents the distribution of the solutions given by the multi-period simulation algorithm. The marks at the bottom of the figures indicate the scores on each objective for all points in the solution set. The height of these marks is irrelevant, but is different for the blue and orange marks, in order to be able to distinguish their positions.

It should be noted that the number of points in the solution set is much larger for the solutions as optimised with dynamic uncertainty than the solution set as optimised with perfect foresight. The set for perfect foresight contains 55 observations. The set for dynamic uncertainty contains 1152 observations.

What stands out from the distribution curves in Figure 9.2, is that all distribution curves are similar. Differences in distribution curves are based on small details. The distribution curves for the maximum travel time and the number of uncovered demand points in Figures 9.2a and 9.2b share a common characteristic: their first peaks (closest to the origin) are somewhat larger for the solutions for perfect foresight than for dynamic uncertainty, even though the difference is small. The same counts for their last two peaks. For both of these objectives, the differences in height between the peaks for perfect foresight seem smaller than the differences in height of the peaks for dynamic uncertainty. This could indicate a slightly more even distribution of solutions for perfect foresight compared to dynamic uncertainty.

The distribution curves for total costs in Figure 9.2c are again similar to each other. There is a small difference between the two peaks of the second bell curve, where the peak of the solutions for dynamic uncertainty is slightly larger for higher costs and the peak of the solutions for perfect foresight is slightly larger for lower costs. The third bell curve (the smallest of the three) is shifted more to the right for the solutions for perfect foresight compared to the solutions for dynamic uncertainty.

The distribution curves for total uncovered demand in Figure 9.2d are almost identical. A small difference is observed from the first peak, where the solutions for dynamic uncertainty is slightly larger. The difference, however, is minimal.

A general conclusion drawn from the analysis is that the distributions of the different solution sets are similar. The hypothesis that the distributions for the solution set optimised with perfect foresight would be more located on the left side of the X-axis is not confirmed based on these results.

10 DISCUSSION ON RESULTS

In this chapter, the results as presented in Chapter 8 and 9 are discussed in the context of decision-making in humanitarian logistics. Furthermore, it discusses the designed approach for simulation and analysis of the interaction between decisions and uncertainty, based on an evaluation of the decision-making method and an evaluation of the decision-uncertainty interaction analysis.

10.1 DISCUSSION ON OBJECTIVE TRADE-OFFS

The most distinct result from the objective trade-off analysis in section 8.2 is the negative relation between total costs and the other objectives. The analysis shows that there are basically two types of facility location decisions: (1) those that are low cost but have limited effectiveness, and (2) those that have high costs but are highly effective. Furthermore, minimisation of costs is (less strongly, but still significantly) related to a decrease in equity. This indicates that focussing on minimising costs limits the effectiveness and the equitability of post-disaster humanitarian logistics. That does not imply that decision makers should not focus on minimisation of costs. As humanitarian logistics are largely dependent on sponsors, minimisation of costs remains to play an important role. However, as the 'rule of rescue' states: one has the ethical obligation to provide aid when the means are available (Pinkerton, Johnson-Masotti, Derse, & Layde, 2002; McKie & Richardson, 2003). Therefore, the prioritisation of costs should be subordinate to prioritising effectiveness and equity of humanitarian relief aid. This is in accordance with the findings of Cookson, McCabe, and Tsuchiya (2008), who conclude that to be considered a humane society, a departure should be made from cost efficiency. In humanitarian logistics modelling, the consideration of costs would be more appropriately included as a constraint, rather than be included in the objective function. This way, for a given budget, the effectiveness and equity can be optimised as much as possible.

The relation between the effectiveness and equity criterion is less strong. The analysis shows that it is possible to find solutions that score well on both the effectiveness and the equity objectives, but also solutions that score well on effectiveness but poorly on equity, and vice versa. This indicates that it is possible to find solutions that perform well on both equity and effectiveness. Gralla, Goentzel, and Fine (2014) show that decision makers value effectiveness more than the equity objective. As the analysis shows that it is unnecessary to compromise equity at the cost of effectiveness, the challenging task on which decision makers should focus is to find those specific solutions that do not compromise either effectiveness or equity.

As effectiveness and equity are generally prioritised over costs (Gralla et al., 2014), this sends a clear message to donors of humanitarian aid: for effective and equitable disaster relief, sufficient funding is required. Low-cost solutions that perform relatively well on effectiveness and equity are scarce or non-existent depending on what is perceived as acceptable. The responsibility for coordinators of humanitarian logistics is to find the most effective and equitable solutions for within the constraints of a given budget. The bottleneck of effective and equitable logistics is the funding supplied by the donors of humanitarian aid.

10.1.1 Decision Sequences

The analysis of the frequency of facility location decisions and decision sequences gives additional insight into which specific facilities locations could be chosen by decision makers. One facility location is chosen for all objective prioritisations, and most often also at the first decision-making period. This shows that even if decision makers value different objective prioritisations, some facility locations can be found that support each of the different objectives. An obvious strategy is to start by choosing this location. This specific location is located closest to both the supply point (Kathmandu Airport) and Nepal's biggest city; its capital Kathmandu. If the assumption is made that a country's largest populated city is mostly located close to an international airport, the strategy would be to initially place a central logistics hub close to both the airport and the largest populated city. While it seems plausible to use this as a decision-making heuristic, no conclusive answer can be given on whether this is generalisable for other disaster situations.

10.2 DISCUSSION ON IMPACTFUL SCENARIOS

In the results chapter, the different scenarios have been presented as combinations of uncertain factors. In Table 10.1, a synthesis of the most harmful scenarios for each objective is given. The table shows that some uncertainties are involved in multiple harmful scenarios for different objectives. This section discusses how each of these uncertain factors might be influenced, to understand how this analysis can be used to shield against harmful scenarios or restrict their impact.

Table 10.1: Synthesis most harmful scenarios

Objectives	Harmful Scenarios			
	Unit Transport Cost	Demand per Affected Person	Maximum Distance Covered	Disruption Factor Specific Demand Point
Total Transport Costs	High	High	High	
# Uncovered Demand Points			Small	
Total Uncovered Demand		High	Small	
Max. Travel Time				High Disruption of Remote Valley with Small Population

High unit transport costs have a harmful effect on the efficiency of humanitarian logistics in terms of transport costs. Hence, the unit transport costs should be kept low. The unit transport costs are dependent on different factors, which consist for the largest part of the capacity of trucks and fuel costs, as elucidated in Appendix E. Fuel shortages are more likely to emerge during disasters due to the increased need of fuel for emergency power generation and transport of relief goods, possible bottlenecks of international provisions, and destruction of fuel storages (Kai, Ukai, Ohta, & Pretto, 1994; McEntire, 2014). It is important to prevent a fuel crisis in order to maintain reasonable fuel prices. In the preparation phase, countries could therefore focus on creating sufficient fuel reserves and reliable storages. In the response phase, it is important to ensure a resilient and affordable fuel supply into the country.

The high demand per affected person has an impact on both the total transport costs (efficiency) and the total uncovered demand (effectiveness). Hence, the demand per affected person should be kept low. The demand per affected person is dependent on different factors such as the type and impact of a disaster, how well an area is prepared for such a disaster, et cetera. While the type and impact of a disaster are external factors, the disaster preparation receives already focus in humanitarian aid literature. Public hazard education helps to increase disaster preparedness and reduces the needs for affected people (Muttarak & Pothisiri, 2013). To reduce the vulnerability of people to natural hazards, disaster preparedness activities can focus on making people more independent, such as public hazard education.

The maximum distance that is covered by facility locations has a conflicting relationship between effectiveness and efficiency. Contrasting scenarios for the maximum covered demand are harmful to keeping costs low and effectiveness high. On basis of the rule of rescue, as explained in section 10.1, decision makers should try to keep cover a large distance to increase the effectiveness. The maximum distance that can be covered is dependent on factors such as available transport resources and available relief supply. This has received early attention in humanitarian logistics. Prepositioning of relief goods and disaster preparedness of countries are known to help with ensuring the availability of relief supply and transport vehicles (Balcik & Beamon, 2008).

The most harmful scenario for the maximum travel time, as found in the scenario discovery analysis, is the specific disruption factor of a specific demand point. This specific demand point is the area with the longest travel time to have access to relief goods. Interestingly, this demand point is a remote valley with a small population. This stresses the importance of valuing equity in the objective trade-offs. When not enough emphasis is put on the equity objective, especially the remote valleys are disadvantaged in terms of the time they should wait for relief goods. This is in accordance with the findings of Chandes and Paché (2010), who observed that while some remote areas have no or only partial support, central areas are sometimes oversupplied. This result from the scenario discovery analysis also stresses that information about those remote valleys is especially important for knowing which areas have to wait for relief support the longest and how long this wait actually is. Without this information, decision makers could assume everyone receives relief aid within 'acceptable' time, while this is not necessarily the case. The equity objective is very sensitive to uncertainty on the remote valleys with smaller populations.

10.3 DISCUSSION ON THE EFFECT OF DECISIONS ON UNCERTAINTY REDUCTION

The simulation of decision pathways has offered new insights into the interaction between facility location decisions and uncertainty. The analysis in section 8.4 has focussed on the effects of different objective prioritisations of decisions on the reduction of uncertainty.

Prioritisation of each objective is correlated with the reduction of uncertainty over time. Prioritising the effectiveness or the equity objectives appears to have a significant positive relationship with the reduction of uncertainty. Prioritisation of minimisation of costs appears to have a negative relationship with the reduction of uncertainty.

An explanation for the positive relation of uncertainty reduction with prioritisation of effectiveness and equity could be that focussing on these objectives leads to more dispersed central logistics hub locations. When these facility locations are more dispersed, it is easier to help people in need over the whole country and in addition reduce the uncertainty for those and the surrounding areas.

An explanation for the negative relation of uncertainty reduction with the prioritisation of minimising total transport costs (efficiency) could be that facility locations that are concentrated around the supply point are associated with very limited transport costs. When decision makers focus too much on minimisation of transport costs, this would negatively affect the demand points that receive relief supplies because further located areas cannot be covered. Of these further located uncovered demand points, no uncertainty can be reduced due to their distance to the operational facility locations.

Contemporary arguments for focussing on effectiveness and equity in humanitarian logistics are predominantly based on an ethical argument, such as argued by Holguín-Veras, Pérez, Jaller, Van Wassenhove, and Aros-Vera (2013). This is embodied in the vision of the United Nations who pledged that *'no one is left behind'* (United Nations, 2015). This study supports this view and argumentation, as discussed in section 10.1. However, next to the ethical argument of focussing on bringing relief aid to as many people, at as many places, as fast as possible, this research offers another argument why it is especially important to focus on these objectives. To help people in need as well as possible, it is necessary to know which people at which locations are hit hardest and what conditions are faced when trying to reach them. By having facility locations with more coverage, shorter waiting times, and more places addressed, not only the help is more effectively and equitably distributed, also the uncertainty is more reduced. This helps to make better decisions subsequently. Not only can reduced uncertainty help making better decisions on facility locations; this same information can in those disaster situations be used to make better decisions in other aspects of disaster response.

To conclude, next to the ethical argument of focussing on effectiveness and equity, this insight offers an additional argument to prioritise effectiveness and equity for humanitarian logistics facility location decisions. Focussing on equity and effectiveness leads to more uncertainty reduction which enables better decisions for disaster response.

10.3.1 Less uncertainty, better disaster response

The presence of uncertainty is known to make humanitarian response more complex and prone to risk (Van Wassenhove, 2006). Therefore, a reduction of uncertainty in post-disaster environments can support all humanitarian aid workers in their activities (and not only logisticians). The quantitative analysis shows that the amount of uncertainty plays an important role in the decision-making on facility locations. More specifically, it shows that reducing uncertainty can lead to more optimal facility location decisions. This emphasises the importance of reducing uncertainty while making facility location decisions.

10.4 DISCUSSION ON THE DESIGNED APPROACH

10.4.1 Evaluation of the decision-making method under uncertainty

Chapter 9 has analysed how well the decision-making method based on the Many-Objective Robust Decision-Making (MORDM) framework performs. The analysis compared how well this multi-period decision-making method performs compared to an optimisation method with perfect foresight. This section discusses the results that stem from this analysis.

The optimal solutions proposed by the decision-making method under uncertainty are divided into three subsets after being re-evaluated for the ground truth: the Pareto front, the inverse Pareto front, and the remaining intermediate solutions. Interestingly, the difference of the hypervolume of the Pareto front with the hypervolume as obtained by the optimisation method for perfect foresight is negligible. This remarkable result indicates that the step-wise MORDM method performs very well while dealing with uncertainty. However, the step-wise MORDM method also proposed solutions that are not optimal when re-evaluated for the ground truth.

The hypervolume of the inverse Pareto front is a little less than half the hypervolume as obtained by the optimisation method for perfect foresight. The substantial bandwidth between the best possible solutions and the worst possible solutions as proposed by the step-wise MORDM method indicates that there are still suboptimal solutions in the solution set.

The density and the coverage of the different subsets (Pareto front, inverse Pareto front, and remaining intermediate solutions) over the complete set of solutions give a better understanding of the proportions of solutions and how they are divided over these subsets. The results show that more than half of the solutions as proposed by the step-wise MORDM method under uncertainty is Pareto efficient. This indicates that it is more likely that decision makers who use the step-wise MORDM method end up at Pareto efficient solutions than at suboptimal solutions. To understand how much worse-off these dominated solutions are compared to the Pareto efficient solutions, the analysis has looked at the distribution of the scores on the objectives.

The distribution of the scores on objectives is very similar. There are only some minor differences between the distribution of the scores on objectives for the solution set as optimised under uncertainty and the solution set for optimisation with perfect foresight. This is noteworthy because the considerable size of the bandwidth between the hypervolumes of the Pareto front and the inverse Pareto front would indicate that sub-optimal solutions have much lower objective scores. A possible explanation would be that the sub-optimal solutions do not score much worse than the optimal solutions for each individual objective, but rather on the combination of objectives.

Two explanations for the suboptimal solutions are worth mentioning. The first is that decisions made in the earliest decision-making periods are made for a much larger uncertainty space than in later periods. This could very well result in some sub-optimal decisions at early stages. Due to path dependencies, the final solutions that originate from these initial 'missteps', are then also suboptimal as a result. The other explanation is that some decision pathways do not reduce the uncertainty as much as the other decision pathways. This could result in making suboptimal decisions in later decision-making stages. Hence, it would be especially important to focus on the reduction of uncertainty in the earlier stages of the disaster response.

In general, the conclusion is that the step-wise decision-making method based on the MORDM framework is a very suitable method to deal with the uncertainty inherent to humanitarian logistics facility location. The assimilation of uncertainty reduction over time is expected to play a considerable role and should be considered while making humanitarian logistics facility location decisions.

10.4.2 Evaluation of the decision-uncertainty interaction analysis

The decision-uncertainty interaction analysis part of the approach for simulation and analysis for the interaction of decisions and uncertainty has focussed on three key subjects: the trade-offs between objectives, the effect of uncertainties on decision-making, and the effect of decisions on the reduction of uncertainty.

The analysis of the trade-offs between the objectives provides a deeper understanding of not only the effects of prioritising different objectives, but also the relations between the different objectives. This is in line with earlier research on many-objective optimisation, see Deb (2010) or more specifically Matrosov et al. (2015).

The insight from the scenario discovery analysis has been used to identify important factors that can have a large impact on the success of humanitarian logistics facility location decisions. The finding that scenario discovery can help with identifying vulnerabilities and enabling policy refinement is in line with the current literature, see Kwakkel, Walker, and Haasnoot (2016). The practical insights provided by this analysis can be used to improve the disaster preparedness of countries. This way it uses these insights to shield against vulnerabilities before the disaster strikes.

The last part of the decision-uncertainty interaction analysis focussed on the effect of different objective prioritisations on the reduction of uncertainty. The ability to simulate and analyse the effect of objective prioritisations on the reduction of uncertainty is the biggest innovation of this research as no other approach is found to be existent to do so. In the case of humanitarian logistics facility location decisions, it resulted in a novel perspective on why decision makers should prioritise specific objectives. More specifically, next to the ethical argument of prioritising the equity and effectiveness objectives, it shows that focussing on equity and especially effectiveness also helps to reduce uncertainty in disaster areas. This is especially very relevant in situations, such as during disasters, where the interaction between decisions and uncertainty plays an important role.

11 REFLECTION

"Essentially, all models are wrong, but some are usefull"

Box and Draper (1987)

This research introduces a novel approach for the simulation and analysis of the interplay between decisions and uncertainty. For the design of the approach, and for its application on humanitarian facility location decisions for the 2015 Nepal earthquake, many choices and assumptions are made. This chapter reflects on the most important assumptions, the limitations, and the generalisability of this research.

11.1 REFLECTION ON DESIGNED APPROACH

11.1.1 Reflection on Assumptions

The most central and important assumptions that have been made while designing the approach are related to the modelling of the dynamic uncertainty space. The fundamental proposition of this research is that it is possible to capture uncertainty dynamics in a model. The uncertainty dynamics are modelled based on two important simplifications of reality. The first simplification is the assumption that the uncertainty space can only become smaller over time. The second simplification is the assumption that the uncertainty and the estimations always converge toward the ground truth. In practice, it could be possible that uncertainty increases over time and estimations become less accurate, for example, due to an overload of unstructured and biased information coming from social media. Hence, for good and robust decisions, it is of central importance to make accurate estimations of the uncertainty space. It underpins the necessity of focussing on information management in post-disaster situations to create better situational awareness. Whether it is correct to assume that uncertainty reduces over time and that decision makers are able to estimate the uncertainty with relative accuracy is something that should be pointed out by empirical research.

11.1.2 Limitations

The most important limitation of the approach is the relatively high computational intensity. The algorithm that simulates the different branches of decision pathways requires a very large number of model evaluations. At each period, for each step, an optimisation algorithm and re-evaluation of the resulting solutions under uncertainty are required. For this research, the model and the optimisation process used are relatively light, allowing for very rapid simulation for each decision-making period. Especially with more computationally demanding modelling approaches, such as agent-based modelling or large discrete event simulations, the simulation time can become extraordinarily long. With the current computation power, the designed approach for simulation and analysis of the interaction between decisions and uncertainty should only be used for models that are computationally not too demanding. A solution for using heavier models with this approach can be to use a computer cluster for parallel computation.

As indicated in the design of the approach, the number of new solutions found for each branch has a big impact on the number of branches that should be simulated each period. To keep the number of new branches for each period low, methods such as clustering or pruning the solutions are proposed. However, in the case study, it was not necessary to use these methods to reduce the number of new branches for each period. Future research should point out how suitable these methods are and what the effects are on the ability of the decision-making method to approximate the true Pareto front as optimised with perfect foresight.

An obstacle for using the approach is the implementation complexity of the simulation algorithm. The difficulty and time consumption of the implementation of the algorithm can be a barrier to the use of the approach. The implementation of the algorithm in this research is not ready to use for application to other problems or models. An open source library of the required tools could help to enable easy access to implementation and use of the approach.

The evaluation of the decision-making method based on the computation of different metrics cannot be compared to other optimisation methods. The numeric values for the different metrics do give insight into how well the stepwise multi-period MORDM method approximates optimal solutions. However, no benchmarks are available that indicate whether the multi-period MORDM method outperforms other decision-making methods. For the method to be compared with other methods, a comparative study based on a benchmark case can be conducted.

11.2 REFLECTION ON CASE STUDY

To showcase the designed approach, it has been applied to post-disaster facility location problem for the 2015 earthquake in Nepal as a proof of principle. The application of the approach on this problem relies on different simplifications of the post-disaster environment and stylisations of the disaster data available for the 2015 earthquake in Nepal. This section reflects on the limitations of the case study as a proof of principle for the approach.

11.2.1 Facility Location Model

The humanitarian logistics facility location model as defined for the case study is an important part of the case study but has not been the primary focus of this research. Other variants of humanitarian logistics facility location model could as well be used for integration with the framework. Therefore, this thesis does not put forward the model itself as necessarily being an improvement on other models on complexity and comprehending reality. It is part of the proof of principle to show how different important elements can be used in a model-based decision-making method (such as uncertainty, multiple objectives without prioritisation, multi-periodicity and robustness).

Compared to other models, such as mentioned in section 1.4.2, the simplification level of the facility location model is relatively high. For example, the objectives as defined for the used model represent efficiency, effectiveness, and equity. However, different, or more complex, objective formulations can be used to grasp different aspects of these concepts (e.g. minimising deprivation costs as effectiveness metric (Holguín-Veras et al., 2016)). It is clear that there is room for improvement of this facility location model so to better capture the complexity of the post-disaster environment. The current model has, however, proved to be useful for getting insight into the strategic objective prioritisations. Possible improvements are further discussed in section 12.4 on future research.

11.2.2 Simplification of Uncertainties

The most central uncertainties in this research are the dynamic uncertain factors, of which the uncertainty reduces over time. Only a single uncertain factor has been included in the simulation and analysis, namely the disruption of affected nodes. Two important assumptions are made for these dynamic uncertain factors which could limit the validity of the research outcomes. The first assumption is that the disruption factors represent both the needs and the reachability of the related nodes. The rationale behind this assumption is that when a node is more heavily affected by an earthquake, there are higher needs and road infrastructure is more heavily disrupted. In reality, however, this might not always be the case. The second assumption is that the process of uncertainty reduction might be overly simplified. For example, differences in dissemination speeds are not included, while the population density might affect information dissemination (Zhang, Huang, Su, Zhao, & Zhang, 2014). These two limitations can be addressed in future research.

11.2.3 Stylisations of 2015 Nepal earthquake situation

The case study is based on the 2015 earthquake in Nepal. The stylisation of the earthquake in Nepal enabled parametrisation of the simulation. However, due to the stylisation, the simulation does not realistically reflect the situation in Nepal after the 2015 earthquake. A relatively small number of cities, remote valleys, and hospitals has been used to represent the different demand points, and potential central logistic hub locations. Also, the scale of the disaster is different; the 2015 earthquake impacted about half of the country (mostly Kathmandu region), while for this study the whole country is simulated to be affected.

Especially the number of potential locations can have an effect on the ability of the approach to estimate the Pareto front of optimal solutions. With a larger number of potential central logistics hub locations, the optimisation under uncertainty would expectedly approximate optimisation with perfect foresight worse, leading to a larger difference in hypervolumes. However, a larger number of potential central logistics hub locations would also have resulted in a longer simulation time.

The discrepancy in the scale of the disaster diminishes the ability to validate the optimal locations of facility locations. Because a larger area of the country is simulated to be affected, the different cities and remote valleys have different needs than was the case in reality. Therefore, the optimal locations of central logistics hubs in this study do not match actual decisions on facility locations.

11.2.4 Parametric assumptions

There are two other important parametric assumptions that could be of influence on the results of the analyses. These two assumptions are related to how strongly the uncertainty reduces over time and how long this process continues.

The strength of the uncertainty reduction has been motivated in section 7.4. A stronger reduction of uncertainty could result in a stronger connection between the objective prioritisations and the reduction of uncertainty because the effects of location decisions on the reduction of uncertainty are more profoundly present. A large reduction of uncertainty could also result in a better approximation of the real Pareto front because the optimisation algorithm under uncertainty optimises with values that are more similar to the ground truth. While the strength of uncertainty reduction is important for the outcomes, this study has not experimented with different rates of uncertainty reduction. A very interesting aspect to look at is how strong the reduction of uncertainty should be for this approach to be useful.

How long the reduction of uncertainty continues in the simulation depends on the number of periods that is simulated. When more periods are simulated, more uncertainty is reduced eventually. When fewer periods are simulated, much less uncertainty is reduced eventually. If too few periods are simulated, it could be that there is not yet a significant effect of the objective prioritisations of objectives on the uncertainty of uncertainty. However, when too many periods are simulated, it could be that the effect is less visible, because for each prioritisation of objectives the uncertainty has completely been reduced. Ultimately, the number of periods for which uncertainty is reduced should reflect how long the uncertainty reduces in reality. While it might be hard to measure this empirically, future research can look at how the interaction between decisions and uncertainty depends on the number of decision-making periods simulated.

11.2.5 Reflection on generalisability

The generalisability of this case study for humanitarian logistics facility location partly depends on how well some important variables are parametrised. Since this parametrisation is not based on empirical data, it could very well be that the parameters do not reflect reality. For this reason, the numerical simulation and analysis results have not been used for quantitative insight, but rather for qualitative insight.

Some characteristics of this case study do not reflect important properties of other disaster types that are relevant for humanitarian logistics facility location problems. This research looked only at a post-disaster situation with a single impact. Often, disasters have more than a single impact moment; earthquakes can have aftershocks and landslides can occur after hurricanes have made landfall. Such 'multi-impact disasters' are related to different properties that have not been considered. For multi-impact disaster situations, the ground truth could change over time; cities that had been moderately hit by a hurricane, can be hit by landslides later on and thus increasing their need for help. Due to these events, the ground truth changes, but also the uncertainty can increase. These dynamics as caused by multi-impact disasters have not been considered in this research. Therefore, the results of this case study can not directly be generalised for disasters with these different properties. However, the approach might be equally suitable or interesting for different disaster types, on which future research can focus.

The purpose of the case study on humanitarian logistics facility location was to serve as a proof of principle for the designed approach for simulation and analysis of the interaction between decisions and uncertainty. Due to the stylisation and other limitations as discussed in this chapter, the results of the case study are less generalisable for humanitarian logistics facility location.

11.2.6 Reflection on analyses

Scenario Discovery Analysis
The analysis for the scenario discovery is based on a single branch of the tree of decision pathways. The results of the scenario discovery analysis can differ between different decision pathways due to the different uncertainty spaces and the different decisions taken at the previous period(s) for each decision pathway. As scenario discovery is an analytical and not a purely algorithmic process, doing scenario discovery for multiple branches is highly labour-intensive. A possible way to deal with this is to find a way to do the scenario discovery on the ensemble of branches in a single analysis while accounting for the different path dependent properties of each branch.

Furthermore, the scenario discovery results can differ for the different time periods. This research has not looked at whether the most harmful scenarios differ between earlier decisions or later decisions in the decision sequence. An analysis that can compare the scenario discovery results over different time periods can give answers to questions such as: "What scenarios are most important in the immediate response?" or "Which scenarios become more important over time".

For this case study on humanitarian logistics facility location decisions, especially the most harmful scenario on the maximum travel time are expected to be different over time and for different decision pathways. The scenarios for the maximum travel time point at uncertainties for specific demand points and facility locations. These are the dynamic uncertainties, which are specific for each decision pathway. The scenario discovery analyses for the other objectives point at the static uncertainties as being involved in the most harmful scenarios. These results are likely to be less dependent on which branch is selected for analysis because the static uncertainties are the same for each decision pathway. Future research could give more insight into the dynamics of scenarios over time and for different possible decision pathways.

Effect uncertainty on decision optimality
Although the analysis presented in section 8.4.3 indicates that the reduction of uncertainty leads to better facility location decisions, it has not given meaningful into how much it improves decisions. Further research is required to see the effect of the reduction of uncertainty. This can be done by comparing the a simulation with the reduction of uncertainty and without the reduction of uncertainty. The two Pareto fronts of the simulation results can then be compared by using the metrics introduced in section 9.2.

12 CONCLUSIONS & RECOMMENDATIONS

This research started by emphasising the importance of humanitarian logistics and looking at the challenges it faces. Then, the literature review on the post-disaster decision-making environment and on the humanitarian logistics model-based disaster response approaches sheds light on the knowledge gap this research aims to address: this research aimed to (1) find a way to make robust humanitarian facility location decisions over multiple periods, while dealing with deep uncertainty, and considering multiple objectives, and (2) understand how different types of decisions affect the uncertainty space over time. Together this should help to obtain a better understanding of the interaction between humanitarian facility location decisions and uncertainty.

An approach for the simulation and analysis of the interaction between decisions and uncertainty has been designed. This approach is illustrated with a proof of principle by applying the approach on a case study on humanitarian logistics facility location decisions for the 2015 Nepal earthquake. The results of the simulation and analysis of the interaction between decisions and uncertainty have been discussed and reflected on. To conclude this research, this chapter addresses the research questions formulated at the beginning of this research. Furthermore, this chapter gives recommendations for humanitarian logistics practitioners, concludes on the scientific contributions, and makes suggestions for future research.

12.1 REVISITING THE RESEARCH QUESTIONS

This section will give an answer to the research questions. First, the sub questions are addressed and ultimately the main question is answered.

Sub RQ 1 *How can the interaction between decisions and uncertainty be simulated and analysed?*

The designed approach for the simulation and analysis of the interaction between decisions and uncertainty consists of 4 parts: the problem formulation, the decision-making method, the simulation of the effects of decisions over time, and the decision-uncertainty interaction analysis. The second and third part together form a model-based simulation algorithm, which simulates the interaction of (robust) decisions and uncertainty over time. A conceptual overview of the approach is shown in Figure 12.1.

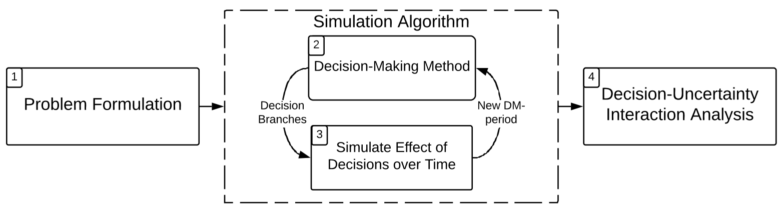


Figure 12.1: Conceptual Overview: Approach for Simulation and Analysis of the Interplay between Decisions and Uncertainty

The problem formulation part consists of four steps. First, an explicit structured problem formulation is created based on the XLRM framework, based on which a model can be implemented for further use in the decision-making method. Second, robustness metrics should be selected based on the problem characteristics. Third, the inter-period model is defined. This inter-period model defines how decisions affect the uncertainty space in the next decision-making period. Fourth, the data for the simulation algorithm should be gathered, consisting of the solution space, certain data, and the uncertainty space. This uncertainty space can include static uncertainty and dynamic uncertainty. Static uncertainties remain constant over time, while the dynamic uncertainties change based on the decisions that have been made. For the dynamic uncertainties also the ground truth should be defined to enable the simulation of the reduction of uncertainty towards these true values.

The decision-making method is the first of the two parts of the simulation algorithm. This decision-making method is an algorithm based on the MORDM framework, which includes an a posteriori many-objective optimisation method and a robustness analysis method which re-evaluates all solutions under deep uncertainty. Based on each solution's robustness scores, the Pareto efficient robust solutions are proposed as optimal decisions.

The effects of decisions on the uncertainty space are simulated based on the 'inter-period model'. This inter-period model is the second part of the simulation algorithm for simulating the interaction between decisions and uncertainty. By simulating each proposed solution for the next period, a tree of possible decision pathways emerges. Each branch of the tree consists of a sequence of decisions and has a specific uncertainty space based on the decision sequence.

The last part of the designed approach is the decision-uncertainty interaction analysis. This part compares the branches of the tree of possible decision pathways to get insight into what decisions are related to a stronger reduction of uncertainty. The decision-uncertainty interaction analysis consists of multiple analyses to understand the objective trade-offs, the influence of uncertainty on facility location decisions, and the effect of decisions on the reduction of uncertainty.

Sub RQ 2 *How can the post-disaster facility location problem be captured in a formal problem formulation that fits the designed approach?*

The formal problem formulation that fits the designed approach is based on a conceptualisation of the post-disaster humanitarian logistics facility location problem. The formal problem formulation is composed of a facility location model, two robustness metrics, and an inter-period model which enables the simulation of the effects of decisions on the reduction of uncertainty.

The facility location model is a two-tier facility location model. It includes three different types of nodes for supply points, central logistics hubs and demand points. The supply points are the entry points of relief goods into the country. Demand points represent the aggregated demand of the affected population living in a city or area. The central logistics hubs help to coordinate and distribute relief goods from points of relief supply to the demand points. There is a number of optional facility locations for placing these central logistics hubs. The decision variables are related to which facility locations are chosen to operate as central logistics hubs.

The facility location model includes four objectives related to the efficiency, effectiveness and equity of humanitarian logistics. These four objective functions focus on minimising the total transport costs of relief supply (efficiency), the uncovered demand (effectiveness), the number of uncovered demand points (effectiveness), and the maximum travel time to reach the furthest located disaster victims (equity).

The dynamic uncertain factors that interact with facility location decisions are related to how heavily demand points are affected by the disaster. This is captured in a disruption factor for each node in the system. The disruption factor of demand points is determined by the needs of its population and how well it can be reached from other nodes, while the disruption factor of central logistics hubs is determined only by how well it can be reached.

Two different robustness metrics are selected to be used to evaluate how well different solutions perform under a variety of scenarios. A variant of a signal-to-noise ratio is chosen to indicate whether a robust solution has a good average performance with limited dispersion around it. A maximum regret-based metric is chosen to indicate the maximum regret of choosing a solution compared to the best performing solution for a variety of scenarios. Both robustness metrics are to be minimised.

The dynamic uncertainty reduces based on the decisions on central logistics hubs locations and on time. This dynamic uncertainty is defined as a lower and upper bound and a best estimate centred in between these bounds. Each dynamic uncertainty variable has a true value towards which the lower and upper bounds converge towards based on the decisions made over time. The static uncertainties have a lower and upper bound and a best estimate value that represents the reference scenario which is used for optimisation.

Sub RQ 3 *What are the analytical insights of the approach in the decision-uncertainty interaction for post-disaster humanitarian logistics facility location?*

The analysis of trade-offs between different objectives gives insight into the relations between the objectives. It shows that there are basically two types of facility location decisions; those that have low costs but limited effectiveness, or those that have high costs but are highly effective. Highly effective and highly equitable humanitarian logistics have more dispersed facility locations, while low-cost humanitarian logistics have more concentrated facility locations. The minimisation of costs can be considered as an inhumane choice since it is at the expense of the effectiveness. Furthermore, the analysis shows that it is possible to find solutions that score well on both effectiveness and equity and therefore it is unnecessary to compromise either effectiveness or equity.

The scenario discovery analysis gives insight into the effect of uncertainty on facility location decisions. The most harmful scenario for keeping the costs low is when transport vehicles or fuel are unavailable or scarce. The most harmful scenario for having effective humanitarian logistics is when the needs per disaster victim are very high or when central logistics hubs can only supply relief goods to closely located demand points due to a limited supply of relief foods. The most important uncertainty for equitable humanitarian logistics appears to be related to the specific disruption factors of the furthest located remote valleys. This indicates the importance of reducing the uncertainty of the disruption of the most remote valleys for equitable humanitarian logistics.

The prioritisation of different objectives is related to how fast the uncertainty is reduced over time. Prioritisation of minimising costs has a negative relation with the reduction of uncertainty, while prioritisation of effectiveness and equity has a positive relationship with the reduction of uncertainty. Highly effective and equitable humanitarian logistics have more dispersed facility locations, which leads to a larger reach and more uncertainty reduction but is also associated with higher costs. Contemporary arguments for focussing on effectiveness and equity in humanitarian logistics are predominantly based on ethical arguments. However, these insights show another reason to focus on these objectives: focussing on effectiveness and equity for humanitarian logistics facility location helps to reduce of uncertainty in post-disaster environments. Furthermore, the analysis has indicated that the reduction of uncertainty leads to more optimal facility location decisions, which emphasises the importance of reducing the uncertainty.

Sub RQ 4 *How does the decision-making method perform compared to a method with perfect foresight?*

The step-wise decision-making method is compared to an optimisation method with perfect foresight to get better insight into how well the step-wise MORDM algorithm performs for making decisions under uncertainty.

The step-wise MORDM method appears very suitable to deal with incomplete information. The comparison of hypervolumes of the decision-making method under uncertainty and the optimisation with perfect foresight shows that the difference between the optimal solutions as proposed by either of these optimisation methods is negligible. This indicates that the step-wise approach finds the same optimal solutions under uncertainty as an optimisation approach with perfect foresight. However, there is a substantial bandwidth in the performance of the best and the worst solutions as proposed by the decision-making method under uncertainty.

Each solution proposed by the decision-making algorithm represents a possible decision pathway. The analysis shows that it is more likely that decision makers that use the step-wise MORDM method end up at Pareto efficient solutions than at sub-optimal solutions. Based on the comparison of the distributions of the objective scores, the sub-optimal solutions appear to no be much worse-off than optimal solutions because the distributions are very similar. This indicates that the step-wise decision-making method based on the MORDM framework is very suitable to make decisions under deep uncertainty, as it enables assimilation of new information over time.

Answer to Main Research Question
Together, the answers to the sub research questions give individually already a relatively complete answer to the main research question. The main research question that is addressed in this research is:

What are the analytical contributions of an approach that enables simulation and analysis of the interaction between decisions and uncertainty for post-disaster facility location decisions?

The decision-uncertainty interaction analysis gives insight into the interaction between decisions and uncertainty by looking at three different aspects: (1) the trade-offs between objectives, (2) the effect of uncertainty on facility location decisions and (3) the effect of decisions on uncertainty.

The analysis of the trade-offs between the different objectives has given a deeper understanding of the relation between the different objectives. The scenario discovery analysis helps to understand the effect of uncertainty on facility location decisions by identifying the most harmful scenarios. These insights can help to improve disaster preparedness by shielding against identified vulnerabilities. Furthermore, the simulation of the various decision sequences allows for analysis of the effect of different decision sequences on the reduction of uncertainty, and show that this reduction has an impact. Hence, the analysis of the effect of objective prioritisations on uncertainty offers novel insight into the interaction between decisions and uncertainty.

The insights from the approach are mainly strategic of character. Also, because of the lack of empirical data on important variables such as the strength of the uncertainty reduction, the results from the quantitative analysis mainly offers qualitative insights. The qualitative insights are used to give recommendations on humanitarian logistics facility location decisions, as synthesised in section 12.2. These recommendations are most relevant to decision makers and logisticians such as coordinating humanitarian organisations (e.g. UN OCHA and the Logistics Cluster).

12.2 RECOMMENDATIONS FOR HUMANITARIAN LOGISTICIANS

Based on the analysis of the simulation results and the discussion on these results, new insights have been developed for humanitarian logistics facility location decision-making. These new insights are synthesised here in this chapter to present the results of this research accessibly to humanitarian logistics practitioners. Three different categories of recommendations are given. The first category focusses on the recommendations for objective prioritisation in humanitarian logistics facility location decision-making. The second category focusses on how the disaster preparedness can be improved based on the conclusions of this research. The third category focusses on how decision makers can better deal with uncertainty.

12.2.1 Effectiveness, Equity and Efficiency

The discussion on the prioritisation of different objectives has received quite some attention in this research. This has resulted in four important recommendations.

1. To improve the efficiency of humanitarian logistics, the costs should only be considered as a constraint for decision-making. There are two important reasons for this recommendation: (1) The minimisation of costs leads to solutions that have sub-optimal effectiveness and equity, and (2) it is considered inhumane to not provide aid when the means are available.

2. The focus on coverage as a primary objective in post-disaster relief distribution has come from an ethical standpoint, that 'no one should be left behind'. This study, however, has pointed out another argument for focussing on coverage. Prioritising effectiveness and equity objectives helps to reduce the uncertainty in post-disaster environments.

3. This study has indicated that it is possible to make facility location decisions that perform well on both effectiveness and equity. The challenging task for logisticians is to find those solutions that do not compromise either effectiveness or equity.

4. Furthermore, logistics coordinators and also humanitarian aid coordinators such as UN OCHA should communicate a clear message to donors of humanitarian aid: effective and equitable logistics is dependent on financial support. Limitations on budgets directly impede the effectiveness and equitability of humanitarian logistics.

12.2.2 Improving Disaster Preparedness

Some of the most harmful scenarios for efficient, effective, and equitable disaster response can be prevented by focussing on disaster preparedness. To shield against exorbitant fuel prices during the disaster response, fuel crises must be prevented. In the preparation phase, it is important to focus on creating sufficient fuel reserves and reliable fuel storages. In the response phase, it is important to focus on having resilient and affordable fuel supply into the country.

Disaster preparedness activities that focus on making people more independent can help to reduce the vulnerability of people to natural hazards. The needs for affected people can, for example, be reduced by investing in public hazard education.

To be able to cover the needs of the disaster victims, availability of relief supply and transport equipment that is suitable for disaster response should be ensured. Prepositioning of relief goods has focussed on facilitating quick supply of relief goods. Disaster-prone countries should focus on improving their ability to distribute relief goods when a disaster strikes by having sufficient transport vehicles available.

12.2.3 Decision-making and uncertainty

The results of this study indicate that remote valleys could be disadvantaged compared to more populated areas if not enough focus is put on the equity objective or on the reduction of uncertainty. The equity objective for humanitarian logistics is very sensitive to uncertainty about the disruption of remote valleys with smaller populations. Without reliable information about remote valleys, decision makers could assume everyone receives relief aid within 'acceptable' time, while this is not necessarily the case. Therefore, information management should especially focus on reducing the uncertainty for these remote valleys.

When a step-wise decision-making method such as proposed in this research is used, it is important to have the most up-to-date and reliable information just before a new facility location decision is made. Acknowledging that reliable and accurate information is often lacking, information managers should focus on not only communicating on the best estimates but also on the lower and upper bounds to acknowledge and specify the uncertainty space.

12.3 SCIENTIFIC CONTRIBUTIONS

This thesis has created deeper insight into the interaction between decisions and uncertainty for humanitarian logistics facility location decisions. The scientific contributions that follow from this research are:

- **Provide a method for making robust facility location decisions over multiple periods, while dealing with time pressure and deep uncertainty, and considering multiple objectives.**
  The literature review on model-based approaches for humanitarian logistics facility location decision-making shows that many of these approaches consider either one or a combination of important aspects such as uncertainty, multiple periods, or multiple objectives. The stepwise decision-making method based on the MORDM framework of Kasprzyk et al. (2013) enables decision makers to make robust decisions with a posteriori prioritisation on many objectives and allows for assimilation of new information over time. The proof of principle of humanitarian logistics facility location decision-making is an illustration of the provided method.

- **Provide an approach for the simulation and analysis of the interaction between decisions and uncertainty.**
  The combination of the decision-making method and the algorithm for simulating the gradual reduction of uncertainty over time allows for the design of an approach that can simulate and analyse the interaction between decisions and uncertainty. By simulating all possible decisions resulting from the decision-making method and their effects on uncertainty, analysis can give insight into the effects of different types of decisions. The designed approach is illustrated based on a proof of principle of humanitarian logistics facility location decision-making.

- **Provide insight into the role of deep uncertainties in making post-disaster facility location decisions.** The trade-off and the scenario discovery analysis give a better understanding of the relations between different perspectives on objective prioritisations, and how the uncertainties can negatively affect the attainment of these objectives.

- **Provide insight into the effect of different objective prioritisations on the reduction of uncertainty for post-disaster facility location decisions.**
The designed approach enables the analysis of the effect of post-disaster facility location decisions on the reduction of uncertainty. This analysis shows that more effective and equitable humanitarian facility location decisions are related to a faster reduction of uncertainty.

- **Indicate quantitatively that the reduction of uncertainty leads to more optimal facility location decisions.**
The designed approach enables the analysis of the influence of the size of the uncertainty space on the optimality of proposed solutions by a decision-making method. It shows that, when facility location decisions are made based on a decision-making method such as the MORDM-based method, a reduction of uncertainty leads to more optimal humanitarian facility location decisions.

12.4 FUTURE RESEARCH DIRECTIONS

Throughout this research report, possible research directions have been proposed for future research. In this section, the most important directions for future research are proposed. These directions are split into three different categories. The first category of future research directions is related to how this case study on humanitarian logistics facility location decisions can be extended:

- The facility location model developed for the case on humanitarian logistics facility location is a relatively simple model. Some existing facility location models for post-disaster facility location problems also consider last-mile distribution, choice of vehicles, allocation decisions, or additional constraints. Interesting future research directions are related to how more detailed models for humanitarian logistics can be integrated with the approach for simulation and analysis of the interaction between decisions and analysis and whether this results in additional insights.

- This research has applied different stylisations to be able to illustrate a proof of principle of the approach. A more detailed case study which includes more data on demand points, supply points and optional facility locations might give additional insights.

- The current stepwise decision-making method as proposed in this research facilitates making decisions under deep uncertainty and assimilate new information when it becomes available over time. While the current research is mainly theoretical, a decision support system based on the decision-making method can help decision makers make better decisions in practice. Future research could then especially focus on the practical issues related to the use of such a model-based approach for post-disaster situations.

The second category of future research directions is related to how the designed approach can be improved, or how the analysis can be extended.

- In this research, only a single strength of the reduction of uncertainty has been used for the simulation. To understand whether the results of this research are also valid for different rates of uncertainty reduction, it is possible to do experiments on this rate of uncertainty reduction. This gives insight into what threshold is needed for the interplay between decisions and uncertainty to start playing a significant role and a stepwise decision-making method to become fruitful.

- Similarly, future research can also focus on experimenting with the number of decision-making methods.

- The proof of principle in this research uses enumerative optimisation. With a low number of binary decision variables, this is a computationally efficient choice, but multiple continuous decision variables are included, this becomes infeasible. Future research could focus on how well the approach performs while using Multi-Objective Evolutionary Algorithms (MOEAs) in combination with solution selection techniques as clustering.

- The scenario discovery analysis is only conducted for a single decision sequence. Possibly, the results of the scenario discovery analysis differ for the different decision sequences or for different periods. The design of an algorithmic version of scenario discovery could look at whether most important scenarios change over time and whether the most important scenarios are dependent on the decision sequence.

- As a last suggestion, future research could look at how this designed approach relates to research on adaptive policy pathways. Possibly, the designed approach can prove helpful in the design of these adaptive policy pathways.

The third category of future research directions is related to other applications of the designed approach:

- A similar problem within humanitarian logistics, but with different characteristics that could be interesting for future research, is making (either medical or logistics) facility location decisions for slow-onset disasters such as a virus epidemic (e.g. Ebola outbreak). The biggest difference with the stylised case study on a sudden-onset disaster as studied in this research is that a slow-onset disaster has a constantly changing environment. This means that not only the uncertainty space changes over time but also the ground truth of some important variables can change over time. The application of the designed approach to such a problem could lead to very interesting future research.

- Where the applicability of the designed approach is clear for the case of humanitarian logistics facility location decisions, it is hypothesised that there are also different problem domains where the decisions that are made affect the uncertainty space. Future research should explore the applicability of the approach for these other problem domains. One similar problem domain, but with different characteristics, are commercial facility location decisions. A very different example to which the approach can be applied is making decisions on investments in innovation.

  - Facility location decisions can have an effect on the uncertainty space. Whether these facility location decisions are local, regional or national, deciding on placing a facility could lead to more and more accurate information about that region. A company that wants to enter the market in a new country can face many uncertain factors such as a different business environment, culture, demand for the company's product, regulations, et cetera. The choice for a facility location in a specific country can then lead to the reduction of uncertainty of one or more of these factors in these countries.

  - Investment decisions related to technology development can also lead to a reduction of uncertainty. When investments are made in a certain technology, more information becomes known about the possibilities and the costs related to that technology. The approach can for such a problem domain be used to simulate and analyse the effect of investment decisions on the reduction of uncertainty.

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Part V

Appendices

A LITERATURE SEARCH HUMANITARIAN FACILITY LOCATION MODELS

This appendix gives insight into how the different papers included in the literature review are selected. The literature review looks at facility location models for the disaster response phase of humanitarian logistics. Next to facility location models, als covering tour problem models are included, because covering tour problems are essentially facility location problems where all demand points should be covered (Gendreau, Laporte, & Semet, 1997).

Two ways of searching for relevant literature to include in the review are used. Some articles are selected from an existing literature review on humanitarian logistics models and some articles are found by a literature search using the Scopus Database.

The literature review by Habib et al. (2016) briefly discusses properties such as uncertainty, multiple objectives and multiple periods. However, the literature review does not provide enough insight into these properties to draw conclusions on how they are considered. Therefore, some articles mentioned to deal with uncertainty, multiple objectives and multiple periods are selected for further review.

To get insight into the latest developments of humanitarian logistics modelling, an additional search for new literature is performed with Scopus. Different keywords and keyword combinations are used to search for literature. Table A.1 shows three different sets of keywords that have been used. Combinations of keywords from each of these three sets are used to search for articles.

Table A.1: Keywords for Literature Search

Set 1	**Set 2**	**Set 3**
"humanitarian logistics", "disaster response", "disaster relief", "post-disaster", "post disaster"	"facility location", “model”, “optimisation”	"uncertainty", "stochastic", "robustness", "robust", "multi-period", "multi period", "multi-objective", "multiobjective", "objective" "multi-criteria", "criteria"

The search results contain many different relevant and irrelevant papers. From each of the articles, the titles and abstracts are scanned to get an idea of their relevance. Articles are then selected based on the following criteria:

- Article reports on a facility location model
- The facility location model focusses on humanitarian logistics for the disaster response phase.
- The facility location model considers multiple objectives, uncertainty, or multiple periods.

B IMPLEMENTATION OF THE APPROACH

B.1 FLOW THROUGH THE APPROACH: BREADTH FIRST OR DEPTH FIRST

For simulation of the decision pathways tree, there are two possibilities: breadth-first or depth-first. See figure B.1 for a comparison between breadth-first and depth-first. Breadth-first follows the first in first out principle. It creates a queue of solutions, which is not very memory-intensive. Depth-first follows the last in last out principle. It creates a large stack of processes and uses backtracking to find the task at hand. This is relatively memory-intensive, especially when doing it is implemented recursively in Python.

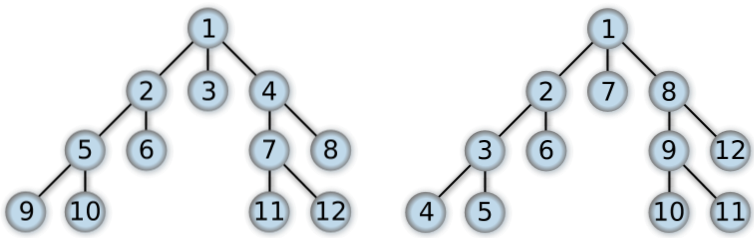


Figure B.1: Breadth-First vs Depth-First algorithm

From the flow chart diagram in figure 3.4, one can observe that the framework as formalised here, uses the breadth-first order of simulation. The reason is rather technical than conceptual; breadth first is less reliant on computer memory for the programming language used for implementation of the framework for the case (i.e. Python) and will therefore be faster and more efficient. It is desired to keep the computational load of the iterative cycle as small as possible. The framework can already be very demanding computationally, so it is better to choose the option that has the least impact on computational power or memory.

C SOFTWARE IMPLEMENTATION

The facility location model, the MORDM algorithm, the inter-period model and the multi-period simulation algorithm have been implemented in Python. The complete implementation can be found at Github.com/TRomijn/Thesis. Most of the code is either documented or self-explaining. An overview of the software packages that have been used for the implementation is given in Table C.1. Information on the package versions is essential for replicability of this research.

Table C.1: Software Packages used for the implementation in Python

Package	Version	Description of use	Scientific Reference
Python	3.6.4	General programming language used for implementation	
ema_workbench	1.1.3	Package used for the re-evaluation of optimal solutions under uncertainty (robustness analysis)	Kwakkel (2017)
folium	0.5.0	Visualisation of the data instantiation for Nepal	
geopandas	0.3.0		
geopy	1.13.0	Calculation of great circle distance	
json	2.0.9		
Pareto.py	1.1.1-3	Nondominated sorting for multi-objective problems	Woodruff and Herman (2013)
numpy	1.14.2	Scientific programming package for multi-dimensional array operations	
osmnx	0.8.1	Sample data for hospitals (or other places of interest) in any given country	Boeing (2017)
python-osrm	0.11.1	A Python wrapper around the OSRM API (Open Source Routing Machine), which uses OpenStreetMap data for determining shortest routes. Used for determining normal travel times between different nodes in the facility location model	
pandas	0.23.0	Package for handling data structures	
pygmo	2.6	Calculation of hypervolumes	
re	2.2.1	Packaged used for implementing a natural sorting algorithm	
requests	2.18.4	Used for downloading country and city specific data such as population and coordinates	
matplotlib	2.2.2	Package used for creating visualisations	
seaborn	0.8.1	Package used for creating visualisations	
statsmodels	0.8.0	Package for estimation of different statistical models, used for linear regression	
SciPy	1.0.0	Scientific computing package used for Linear regression	

D VERIFICATION AND VALIDATION

An ill implementation of the simulation algorithm could lead to invalid results of the analysis. Therefore, it is important to verify the implementation of the proof of principle to showcase the approach. This appendix elucidates the implementation and verification process to give insight into the steps taken to ensure a correct implementation of the proof of principle. Furthermore, it gives insight into the validity of the simulation. Where the verification considers how well a computerised model represents a conceptualisation, the validation considers how well a computerised model represents reality. (Schlesinger et al., 1979)

There are two different methods with which the implementation is verified: functional and structural testing. Structural (or white box) testing looks at whether components are correctly implemented, while functional (or black box) testing looks at whether components show the expected function (Hevner et al., 2004; Juristo & Vegas, 2003). The following two sections describe the structural and functional testing and the third section discusses the validity of the simulation algorithm.

D.1 STRUCTURAL TESTING

Throughout the implementation process of the different parts of the approach, each of the written functions have been tested by using structural testing. This has been an important part of the implementation process.

These white box testing procedures ensure that the programmer knows exactly what each line of code does and that it does what it is supposed to do. This includes an extensive code walk-through each time when a function is written, and checking whether potential errors are prevented. The full Python code can be found on Github.com/TRomijn/Thesis

D.2 FUNCTIONAL TESTING

After the implementation of each of the components, these components are verified with functional testing. This section reports on the extensive functional testing steps taken to test the implementation of the simulation. This ensures that the simulation is correctly implemented and the results are reliable.

The functional testing steps are categorised for the humanitarian facility location model, the inter-period model for simulating the effect of decisions on uncertainty, the algorithmic MORDM decision-making method, and the simulation of the different branches of in the tree of decision pathways. This gives insight into the verification of each of these steps.

Table D.1: Verification steps for the implementation the simulation algorithm

Verification Step	Verification status
Verification Facility Location Model: Each of these tests is performed by doing a test run of the model. The results as given by the model are each time compared with a manual computation for each of the relevant node types. Besides, by graphically representing the model outcomes each time (i.e. showing a map), problems can more easily be detected.	
Correct calculation of Demand for each demand point	Confirmed
Correct calculation of disrupted travel durations	Confirmed
Correct allocation of demand points to closest facility locations	Confirmed
Correct allocation of facility locations to closest supply points	Confirmed
Correct calculation of total transport costs	Confirmed
Correct calculation of uncovered demand	Confirmed
Correct calculation of number of uncovered demand points	Confirmed
Correct calculation of the maximum travel time	Confirmed
Verification Data Instantiation: These tests are performed for each of the three node types (demand point, facility location, and supply point). The cross-checking of data between different data sources ensures correct use of data.	
Cross-check whether the retrieved data on coordinates and population corresponds to information from other online sources	Confirmed
Cross-check routing durations retrieved with OSRM API with Google Maps routing.	Confirmed
Check whether the function for computing the (hypothetical) ground truth values functions correctly	Confirmed
Verification MORDM Algorithm: The MORDM methodology consists of multiple steps. Initially, the MORDM is implemented such as the normal methodology prescribes. During the next step, each of separte parts of the MORDM algorithm have been linked together, so that no manual tasks have to be done to do the MORDM analysis. Afterwards, the (computational) results of the original MORDM methodology are compared to the results of the MORDM algorithm.	
Check whether the nondominated sorting algorithm functions correctly.	Confirmed
Check whether the enumerative many-objective optimisation algorithm links the right facility locations to their corresponding outcomes.	Confirmed
Validate whether it is possible that the optimised solutions are indeed non-dominated based on visualisation of the solutions on a map.	Confirmed
Check whether the facility location model is correctly integrated with the EMA Workbench.	Confirmed
Check whether the robustness metrics are calculated correctly.	Confirmed
For the algorithmic version of the MORDM framework, check whether the algorithm produces the same results as the MORDM framework where all steps are individually verified.	Confirmed
Verification of the Multi-Period simulation algorithm: The multi-period simulation model is initially run with a smaller number of scenarios for each MORDM cycle and less periods. This way the simulation algorithm is faster completed and enabled easier verification of the algorithm. Each of the intermediate optimisation and robustness testing results are saved so that it is possible to backtrack the processes. Also, this way the proposed solutions are saved in multiple ways and formats, so that the intermediate results and the final results can be cross-checked for verification.	

Check whether each decision pathway is correctly labelled.	Confirmed
Check whether each succeeding solution is added to the correct decision pathway.	Confirmed
Check whether the solutions in the tree of decision pathways correspond to the nondominated solutions from the single period MORDM algorithm.	Confirmed
Each decision pathway has a label, an EMA model instance, variable uncertain data and chosen facility locations. check whether each of these properties are correctly linked to their belonging decision pathway.	Confirmed
Verification Inter-Period Model: The inter-period model simualtes the change of uncertainty and is included in the multi period simulation algorithm. The multi-period simulation algorithm is tested first, so that the effect of the inter-period model is isolated for the testing. This way, problems related to the inter-period model can more easily be identified.	
Check whether the uncertainty of all nodes in the system reduces over time.	Confirmed
For a specific node in the system, check whether the uncertainty limits reduces with the correct percentage based on both distance and time. Also check whether the best-estimate moves towards the ground truth values with the correct percentage.	Confirmed

D.3 VALIDITY

The validity of the simulation depends on the conformity of the computerised model to reality. The approach introduced in this research is applied to the post-disaster facility location problem for the 2015 Nepal Earthquake as a proof of principle. Therefore, both the validity of the simulation to the situation in Nepal after the earthquake and of the humanitarian facility location problem are relevant.

Because of the applied stylisations, the stylised case study does not realistically reflect the post-disaster situation of Nepal. Therefore, the validity of the simulation to Nepal Earthquake is questionable at the least. These stylisations enable the simulation of the proof of concept but also limit the validity to the disaster situation in Nepal.

The simulation algorithm of this research has not been validated with expert validation. Therefore, a very important next step is to validate the results and the simulation with experts. These experts can indicate the validity and suggest improvements on the model and approach.

The simulation algorithm shows outcomes that seem to reflect reality. For example, the locations of the central logistics hubs are located on logical places. The results show no selected locations which are nonsensical. Also, each of the results as presented in Chapter 8 is reasonably arguable and deemed valid based on face validation of the researcher. However, because this is not an objective validity test, more elaborate validation methods are required to be conclusive regarding the validity of the simulation algorithm and the produced results.

E DATA GATHERING AND PREPARATION

E.1 PYTHON DATA PREPARATION

The data preparation is done with Python. The used packages are mentioned in Appendix C. The data preparation process is documented in the jupyter notebooks which can be found on Github.com/TRomijn/Thesis. The data processing process can be done for countries automatically, with up to a total of 100 nodes in a country.

E.2 STATIC CERTAIN DATA

The data for the different demand points is given in Table E.1. The 30 largest cities of Nepal are included as demand points. Furthermore, the last five demand points are the remote valleys that have been added. No population information was available on these areas, and therefore they have been assigned a population of 1000 inhabitants. The data on the population and coordinates of these cities and remote valleys is retrieved from Geonames.org.

Table E.1: Demand Point Data

ID	Name	Population	Latitude	Longitude
DP0	Kathmandu	1442271	27.70169	85.3206
DP1	Pokhara	200000	28.26689	83.96851
DP2	Pātan	183310	27.67657	85.31417
DP3	Biratnagar	182324	26.45505	87.27007
DP4	Birgañj	133238	27.01709	84.8808
DP5	Dharān	108600	26.81436	87.27972
DP6	Bharatpur	107157	27.6768	84.43589
DP7	Janakpur	93767	26.7288	85.92628
DP8	Dhangadhi	92294	28.70137	80.58975
DP9	Butwāl	91733	27.70055	83.44836
DP10	Mahendranagar	88381	28.96399	80.17715
DP11	Hetauda	84775	27.42839	85.03219
DP12	Madhyapur Thimi	83036	27.68056	85.3875
DP13	Triyuga	71405	26.7919	86.699
DP14	Inaruwa	70093	26.60675	87.1478
DP15	Nepalgunj	64400	28.05	81.61667
DP16	Siddharthanagar	63367	27.5	83.45
DP17	Gulariyā	53107	28.2058	81.34532
DP18	Titahari	47984	26.66371	87.27403
DP19	Panauti	46595	27.58466	85.52122
DP20	Tikāpur	44758	28.52823	81.11798
DP21	Kirtipur	44632	27.67872	85.2775

DP22	Tulsīpur	39058	28.13099	82.29726
DP23	Rājbirāj	33061	26.53968	86.74796
DP24	Lahān	31495	26.72022	86.48258
DP25	Birendranagar	31381	28.60194	81.63389
DP26	Panauti	27602	27.58453	85.51484
DP27	Gaur	27325	26.76448	85.27841
DP28	Siraha	24657	26.65422	86.20795
DP29	Tānsen	23693	27.86731	83.5467
DP30	Bardiyā	1000	28.30058	81.3536
DP31	Rāmechhāp	1000	27.3256	86.08768
DP32	Salyān	1000	28.37858	82.1703
DP33	Bhaktapur	1000	27.67298	85.43005
DP34	Achhām	1000	29.05	81.3

A list of all hospitals in Nepal is retrieved from OpenStreetMap data (OpenStreetMap contributors, 2018). A sample of hospitals represent the optional central logistics hubs. With the OSMnx package (Boeing, 2017) all hospitals in Nepal are retrieved from which a sample is taken to select 20 hospitals as optional locations for central logistics hubs.

Table E.2: Optional Central Logistics Hubs

Name	Latitude	Longitude
CLH0	26.6849931	87.9908844
CLH1	27.6296267	85.5237477
CLH2	28.806299	81.8383173
CLH3	27.7177784	85.3305038
CLH4	26.9091887	87.9266972
CLH5	29.5688362	80.8017476
CLH6	28.169185	83.037786
CLH7	28.8116311	80.5532168
CLH8	28.0475418	83.7496382
CLH9	26.6525245	87.4493976
CLH10	26.6712262	87.7031023
CLH11	27.6814028	84.4315012
CLH12	26.5380402	86.7428030
CLH13	27.4419931	85.0792469
CLH14	27.6699428	85.309812
CLH15	27.9946583	84.6281275
CLH16	27.6744263	85.4037681
CLH17	27.7110160	85.3147438
CLH18	28.1854700	83.17835
CLH19	28.7536724	81.6880453

Table E.3 shows that only a single supply point is included for the simulation. The choice for the supply points is motivated in section 7.1.

Table E.3: Supply Points

ID	Name	Latitude	Longitude
SP0	Tribhuvan International Airport	27.6966	85.3591

ROUTE DURATIONS The model requires input data on the normal route durations between nodes in the model. Route durations between coordinates are retrieved with the Open Source Routing Machine (OSRM). OSRM uses OpenStreetMap data to calculate route durations. OSRM can provide a routing matrix for up to 100 nodes. This is one of the reasons to only include limited nodes for representing optional central logistics hubs.

E.3 STATIC UNCERTAINTY

In this section, the parametrisation of the static uncertainty variables is motivated. For this study, the focus is not on the exact final outcome values, but rather on the proportions between outcome variables. Therefore, the exact values of this parametrisation are not as important as the proportions for the uncertainty ranges.

RELIEF SUPPLIES PER VICTIM To make an estimation of the relief supplies per victim, it is helpful to first get an idea of the impact on humanitarian needs due to the 2015 earthquake. The UN Humanitarian Aid organisation estimates that 8 million people have been affected by the earthquake (ECHO, 2015). According to analyses from the World Food Programme (2015c), 1.4 million people needed food assistance in Nepal. For the parametric values, it is estimated that for the initial response there is a need for 10 kg of food and non-food items for every affected person. The lower and upper limit of needs per person will be set on 5 and 15 kg per person, to reflect the uncertainty regarding this parametric value.

MAXIMUM COVERED DISTANCE The maximum covered distance determines the amount of cities that can be covered with relief goods from the central logistics hubs. If there is very limited supply of relief goods or trucks, it is estimated that the minimum covered distance is one hour from the central logistics hub. If there is sufficient relief goods and trucks available, it is estimated that all demand points within 5 hours (undisrupted travel duration) can be supplied with relief goods. This implies that a driver would take at least 10 hours to drive to those demand points and back, but probably more as the roads can be heavily disrupted. The best estimate value is chosen to be in between the minimum and maximum estimate of the maximum covered distance.

TRANSPORT COSTS Since 2016, the minimum wage in Nepal is 3.74 USD a day (Zeldin, 2016). Assumed that a working day takes about eight hours of work, the minimum costs of hiring a Nepalese driver would be 0.50 USD an hour. A truck uses about 10 to 15 liters per hour. Fuel normally costs 1 USD per liter, but due to the fuel scarcity after the earthquake, these costs had increased immensely (World Food Programme, 2015b). The minimum and maximum price of fuel is estimated on 12 to 3 USD per litre fuel. A truck uses about 10 to 15 litres of fuel per hour, resulting in fuel costs of about 20 - 45 USD per hour. Including a salary of the truck driver this would be 21- 46 USD per truck per hour. The capacity of a truck is about 3000 KG. The minimum and maximum transport costs per 1000 KG per hour are estimated on 7 to 15 USD, with a best estimate of 10 USD.

Table E.4: Overview of Estimations of Uncertain Variables

Variable	Lower Limit	Best Estimate	Upper Limit
Maximum Covered Distance (Hours)	1	3	5
Transport Costs (USD/1000KG/Hour)	7	10	15
Needs per Person (KG)	5	10	15

E.4 DYNAMIC UNCERTAINTY: DISRUPTION FACTORS

E.4.1 Uncertainty ranges of the Disruption Factors

Directly after the earthquake it is assumed that there is no information on how hard each area is hit. The disruption factor for each node in the country can be 1 (the minimum) or 2 (the maximum). The best estimate for every node in the country is estimated to be in between at 1.5.

Table E.5: Initial Parametrisation Dynamic Uncertainty Factors

Variables	Lower Limit	Best Estimate	Upper Limit
Disruption Factors Central Logistics Hubs	1	1.5	2
Disruption Factors Supply Points	1	1.5	2

E.4.2 Ground Truth of the Disruption factors

For each node n from the set of all nodes N (demand points, central logistics hubs, and supply points) considered in the facility location model, the distance to the epicentre is calculated based on the spherical geometry.

$$distance\_to\_epicentre_n = f(epicentre, coordinates_n) \quad \forall n \tag{E.1}$$

The ranges of the disruption factors and the distances to the epicentre are calculated to be able to assign the maximum disruption factor to the closest node and the minimum disruption factor to the furthest node. The closest node receives the maximum disruption value of 1.9 and the furthest node gets the minimum disruption value of 1.1

$$\begin{aligned} disruption\_range &= max\_disruption - min\_disruption \\ &= 1.9 - 1.1 \end{aligned} \tag{E.2}$$

$$\begin{aligned} distance\_range &= max\_distance - min\_distance \\ &= \max_{\forall n \in N} f(epicentre, coordinates_n) - \min_{\forall n \in N} f(epicentre, coordinates_n) \end{aligned} \tag{E.3}$$

The disruption factor for each n is calculated based on a radial function where each node is assigned a value proportionally to their distance from the epicentre.

$$disruption_n = ((\frac{distance_n - min\_distance}{disruption\_range}) * disruption\_range) + min\_disruption \quad \forall n \tag{E.4}$$

Table E.6: Disruption Factors of Demand Points

Demand Point	Disruption Factors
Kathmandu	1.520
Pokhara	1.291
Pātan	1.520
Biratnagar	1.900
Birgañj	1.495
Dharān	1.878
Bharatpur	1.379
Janakpur	1.674
Dhangadhi	1.398
Butwāl	1.225
Mahendranagar	1.478
Hetauda	1.487
Madhyapur Thimi	1.532
Triyuga	1.788
Inaruwa	1.870
Nepalgunj	1.213
Siddharthanagar	1.246
Gulariyā	1.260
Titahari	1.886
Panauti	1.557
Tikāpur	1.301
Kirtipur	1.514
Tulsīpur	1.100
Rājbirāj	1.814
Lahān	1.759
Birendranagar	1.232
Panauti	1.556
Gaur	1.576
Siraha	1.723
Tānsen	1.228
Bardiyā	1.258
Rāmechhāp	1.660
Salyān	1.136
Bhaktapur	1.539
Achhām	1.325

Table E.7: Disruption Factors of Optional Central Logistics Hubs

Central Logistics Hub	Disruption Factor
CLH0	1.900
CLH1	1.489
CLH2	1.187
CLH3	1.457
CLH4	1.879
CLH5	1.391
CLH6	1.100
CLH7	1.354
CLH8	1.209
CLH9	1.822
CLH10	1.858
CLH11	1.324

CLH12	1.728
CLH13	1.431
CLH14	1.456
CLH15	1.344
CLH16	1.470
CLH17	1.455
CLH18	1.122
CLH19	1.197

F MOST FREQUENT FACILITY LOCATION DECISIONS AND SEQUENCES

This appendix gives extra insight into the different objective prioritisations as discussed in section 8.2. The four different objective prioritisations which are highlighted in Figure 8.3 are used to zoom in on the facility location decisions and the decision sequences. This appendix presents the analysis and the results.

F.1 FREQUENCY OF FACILITY LOCATION DECISIONS

For each of the four different selected objective prioritisations, four facility locations have been made operational. This analysis looks at which facilities are chosen for multiple of these four objective prioritisations.

Table F.1 shows for each of the four objective prioritisations as selected in section 8.2 which facilities have been made operational. The operational facilities are visualised in Figure 8.3. In the bottom row of the table, the frequency of how often each of the central logistics hubs is chosen for the four selected objective prioritisations.

Table F.1: Frequency of Facility Location Decisions

CLH: / **Objective Prioritisation**	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
Lowest Max. Travel Time				X				X					X							X
Lowest # Uncovered Demand Points & Total Uncovered Demand				X				X				X	X							
Low Costs, relatively low # Uncovered Demand Points				X				X				X								X
Lowest Costs		X		X											X		X			
Frequency:	0	1	0	4	0	0	0	3	0	0	0	2	2	0	1	0	1	0	0	2

F.2 DECISION SEQUENCES

After four decision-making periods, each decision pathway has contains four operational central logistics hubs. This means that for each combination of four logistics hubs, there could be different decision pathways that end up at the same result, but with a different sequence of decisions.

Multiple decision pathways can lead to the same outcome when facility locations are chosen in different sequences.

This analysis looks at which facility locations are chosen at the different decision-making periods.

Before the results are presented, the methodology of how the sequences are determined is described. Different decision pathways end up at the different selected objective prioritisations. For each of the four resulting sets, this analysis looks at which order the facilities are chosen most frequently. This is algorithmically determined by following the following steps:

1. Which location is most often chosen at the first decision-making period.
2. Which of the remaining locations is most often chosen at the first and second decision-making period?
3. Which of the remaining locations is most often chosen at the first, second, and third decision-making period?
4. Which location is remaining?

When at any decision-making period two locations are chosen equally often, both are selected for that period, and the next period is skipped.

Table F.2: Most Frequent Decision Sequences

Objective Prioritisation	**First**	**Second**	**Third**	**Fourth**	**# Paths**
Lowest Max. Travel Time	3	19	12	7	8
Lowest # Uncovered Demand Points & Total Uncovered Demand	3,11	-	7,12	-	12
Low Costs, relatively low # Uncovered Demand Points	11	3	19	7	14
Lowest Costs	3,14	-	16	1	2

Table F.2 shows the results of the analysis. From the table, it appears that for three of the four objective prioritisations, central logistics hub 3 is chosen first. For the remaining case, it is chosen second. This suggests that this location is a good choice for any of the objective prioritisations. Figure F.1 shows the location of this central logistics hub, which is located close to Kathmandu and Tribhuvan International Airport. The results are further described in 8.2.3.

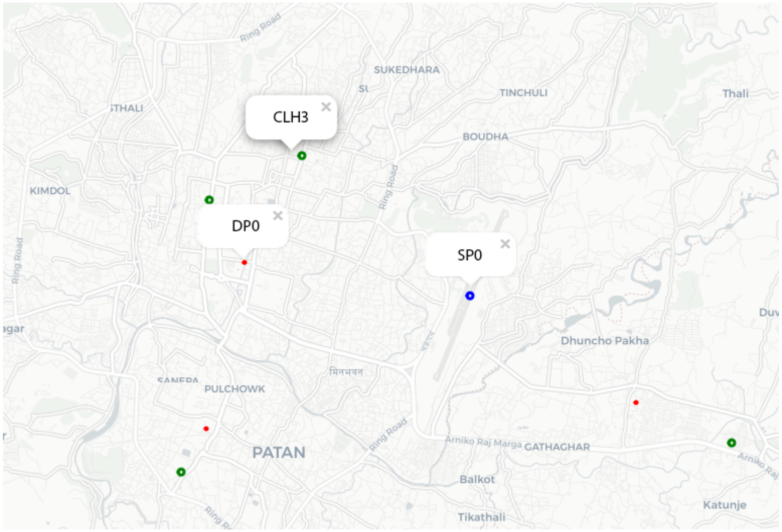


Figure F.1: CLH3
Green Circles: Demand points
Red Dots: Optional Central Logistics Hubs
Blue Circles: Supply Points

G | SCENARIO DISCOVERY PEELING TRAJECTORIES

In this appendix, the peeling trajectory is given for each of the boxes as is found for the scenario discovery analyses for each of the objectives. For each peeling trajectory, the selected point as is used for the box is indicated.

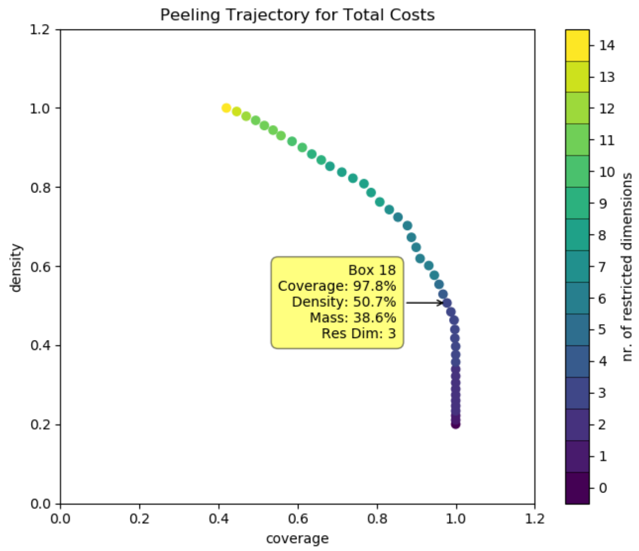


Figure G.1: Peeling Trajectory for the first box for Total Transport Costs

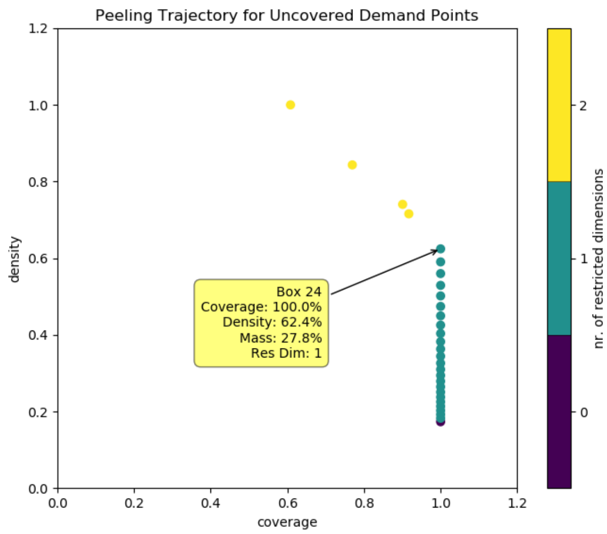


Figure G.2: Peeling Trajectory for the first box for Number of Uncovered Demand Points

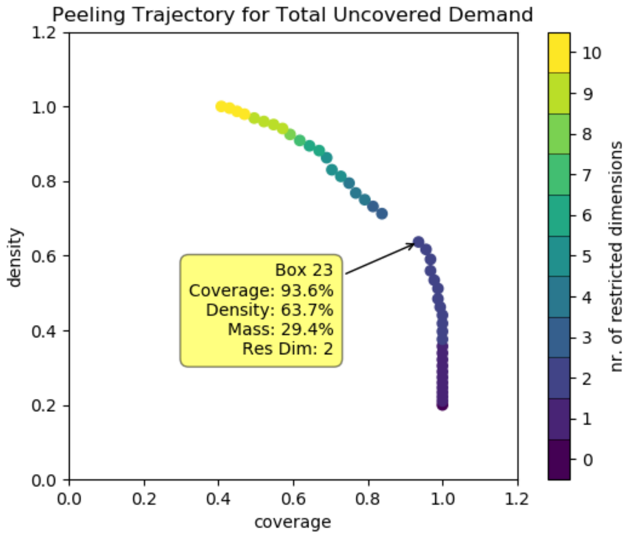


Figure G.3: Peeling Trajectory for the first box for Total Uncovered Demand

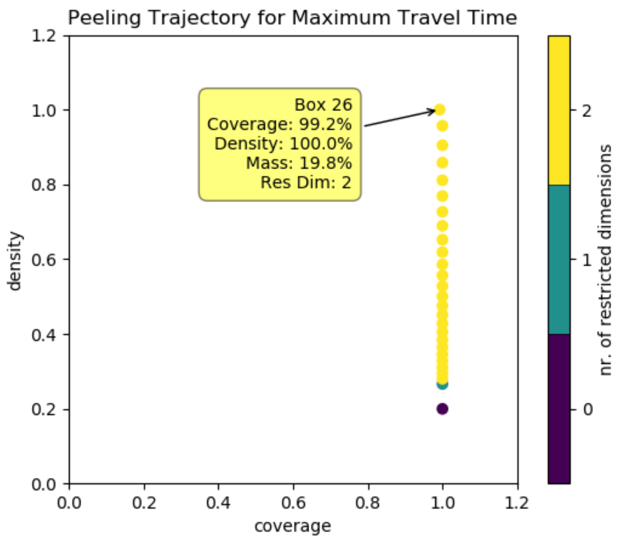


Figure G.4: Peeling Trajectory for the first box for Maximum Travel Time

H RESIDUAL PLOTS FOR SIMPLE LINEAR REGRESSION ANALYSIS

In this appendix the residual plots of the simple linear regression analysis are presented. None of the residual plots seem to imply a non-linear relation between the explanatory and the dependent variable.

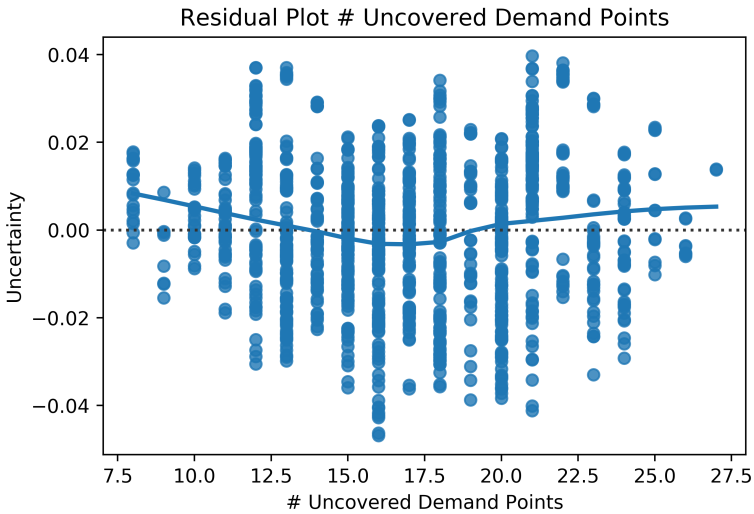


Figure H.1: Residual Plot for number of Uncovered Demand Points

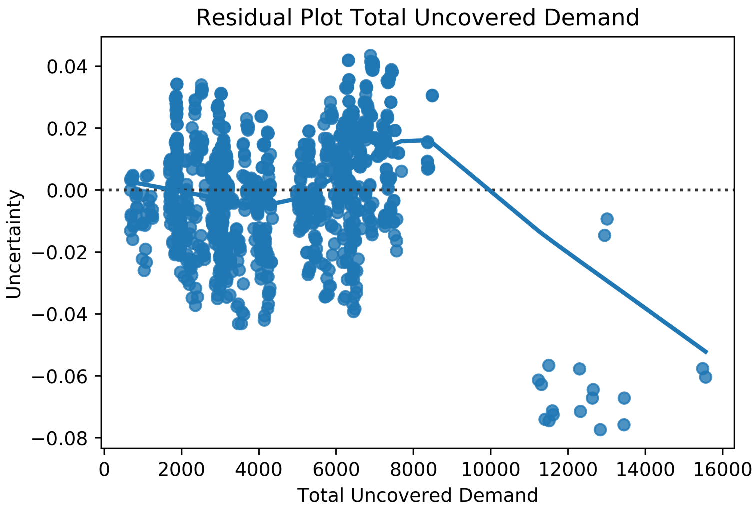


Figure H.2: Residual Plot for Total Uncovered Demand

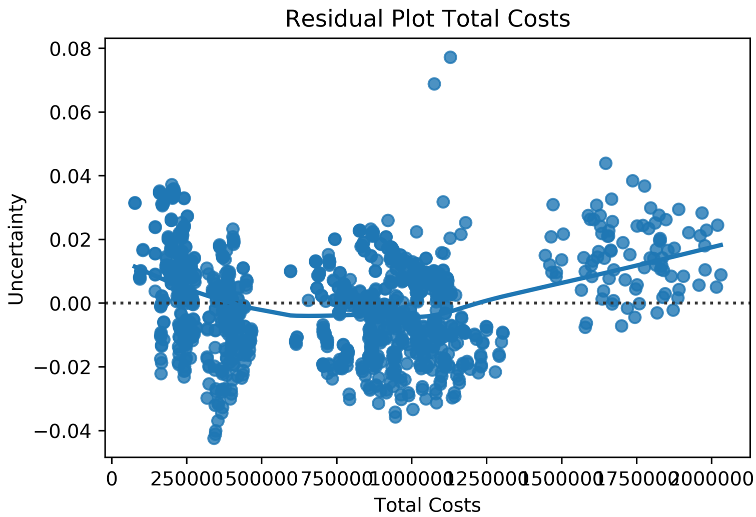


Figure H.3: Residual Plot for Total Transport Costs

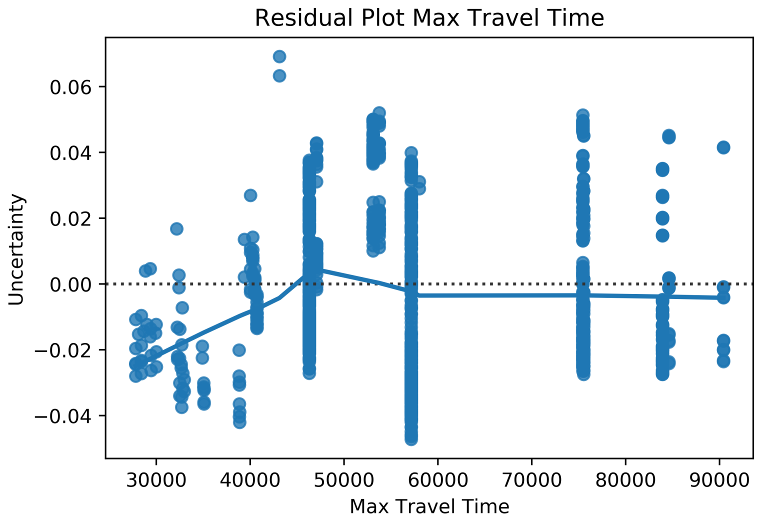


Figure H.4: Residual Plot for Maximum Travel Time

I REDUCTION OF UNCERTAINTY ON OPTIMALITY OF DECISIONS

This appendix looks at the relationship between the reduction of uncertainty and the optimality of the outcomes of the decision-making method to check whether the reduction of uncertainty indeed leads to improved facility location decisions. It does so by correlating the size of the uncertainty space with the optimality of the decision-making method's outcomes of each decision pathway. This appendix elaborates on the used methodology and presents the numeric results. Section 8.4.3 presents the most important outcomes.

I.1 METHODOLOGY

It is possible to look at the effect of uncertainty on the optimality of decisions, by doing a bivariate analysis. To do so, the analysis looks at the last of the four decision-making periods. At this last decision-making period, the decision-making method is run for each decision pathway. The uncertainty space functions as input for this method and results in a set of Pareto optimal robust solutions. In this analysis, the relationship between this size of the uncertainty space will be related to the hypervolume of the resulting Pareto front.

The uncertainty space is quantified by taking the mean of all dynamic uncertain factors. Each of the disruption factors for the demand points and the (optional) facility locations, started with an uncertainty bandwidth of 1. Over time, the uncertainty of each of these disruption factors has reduced because of their closeness to operational central logistics hubs (facility locations). The trajectory of facility locations decisions is different for each decision pathway. Therefore, the disruption factors of each decision pathway have an individual interval. An uncertainty interval of 0.3 means that on average, 70% of the uncertainty is reduced for each disruption factor of that decision pathway. These remaining uncertainty intervals at the last decision-making period are averaged and are represented by the variable "uncertainty bandwidth".

The hypervolume, as introduced in section 8.4.3, is specific for each Pareto front. For each decision pathway, the decision-making period proposes a set of optimised robust solutions. Therefore, the hypervolume is computed for each decision pathway, where the objective scores are normalised with unity-based normalisation, and the reference point is a vector of four ones. (The reference point represents the upper boundaries for the objective scores (Brands, 2015), i.e. $[1, 1, 1, 1]$.)

Initially, no correlation is found between the reduction of uncertainty and the optimality of the decision-making method for each decision pathway. Because a higher cardinality of a Pareto set leads to an easier attainment of higher hypervolumes (Brands, 2015), the hypervolume of each Pareto set is divided by its cardinality. The resulting indicator of optimality for each decision pathway is the "relative hypervolume".

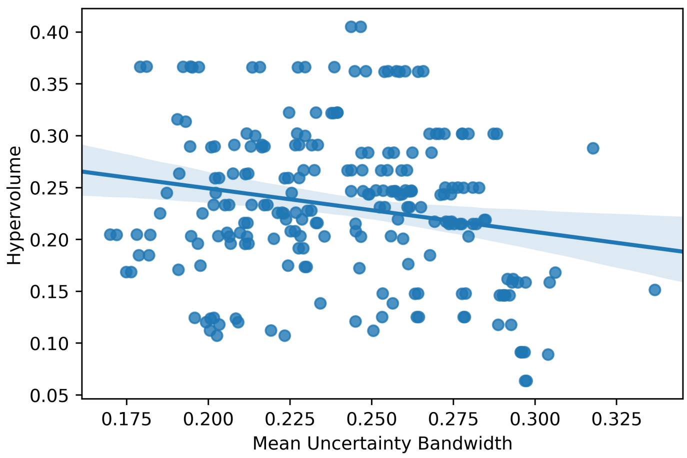
The regression model used for the regression analysis is an Ordinary Least Squares (OLS) regression. The model includes a constant and the uncertainty bandwidth as the single explanatory variable. The linear function used to fit the linear regression model is:

$$RelativeHypervolume = \beta_0 + \beta_1 \cdot MeanUncertaintyBandwidth \tag{I.1}$$

I.2 RESULTS

Figure I.1 shows a scatter graph of the hypervolumes and the mean uncertainty bandwidths of all decision pathways at the last decision-making period. The scatter graph suggests that there is no correlation between the hypervolumes and the uncertainty bandwidths.

Figure I.1: Hypervolumes and mean uncertainty bandwidths for each decision pathway at the last decision-making period: Not corrected for the cardinality of Pareto front



In Figure I.2 a scatter graph is shown where the hypervolumes are corrected for the cardinality of the Pareto front. A negative relationship between the relative hypervolume and the mean uncertainty bandwidth is suggested by the graph.

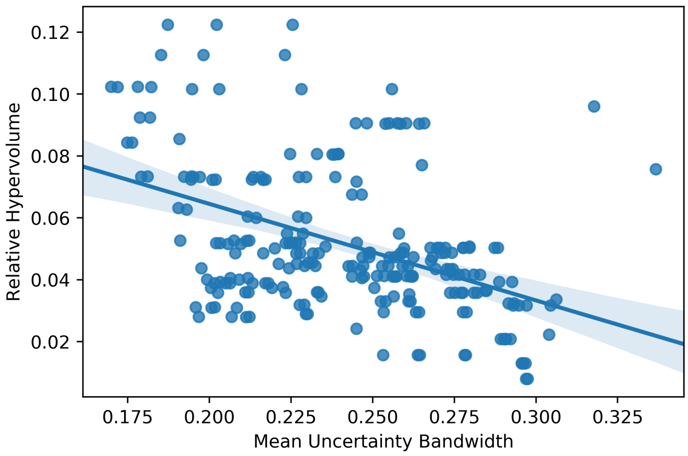
To analyse the relationship between the relative hypervolumes and the mean uncertainty bandwidths statistically, a linear regression is analysis is conducted. The results of the linear regression analysis are shown in Table I.1.

Table I.1: Linear regression results for explaining the relative hypervolumes

R-squared = 0.201 N = 231			
	Coefficient	std err	P-value
Constant	1.0362	0.082	0.000
Mean Uncertainty Bandwidth	-2.5466	0.335	0.000

Table I.1 shows that there is a significant relationship between the mean uncertainty bandwidths and the relative hypervolumes. The Pearson correlation coefficient can be found by taking the square root of the R-squared, which is $\sqrt{\text{R-squared}} = \sqrt{0.201} = 0.449$. A Pearson correlation coefficient of 0.449 is classified as a moderately strong correlation (Evans, 1996). When there is less uncertainty, larger relative hypervolumes are attained by the decision-making method.

Figure I.2: Relative hypervolumes and mean uncertainty bandwidths for each decision pathway at the last decision-making period: corrected for the cardinality of Pareto front



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