Decision support system for a reactive management of disaster-caused supply chain disturbances

Zur Erlangung des akademischen Grades eines

Doktors der Wirtschaftswissenschaften

(Dr. rer. pol.)

von der Fakultät für Wirtschaftswissenschaften

des Karlsruher Instituts für Technologie (KIT)

genehmigte

DISSERTATION

von

Dipl.-Wi.-Ing. Frank Schätter

Tag der mündlichen Prüfung: 11. Mai 2016

Referent: Prof. Dr. rer. pol. Frank Schultmann

Korreferentin: Prof. Dr. rer. pol. Ute Werner

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AHP	Analytical Hierarchy Process
BCM	Business Continuity Management
BCP	Business Continuity Plan
BOUFLP	Bi-Objective Unconstrained Facility Location Problem
BIA	Business Impact Analysis
BMBF	German Federal Ministry of Education and Research
CRA	Continuity Requirements Analysis
CI	Critical Infrastructure
DW	Data Warehousing
DOM	Disaster Operations Management
DRP	Disaster Recovery Planning
DSS	Decision Support System
IATA	International Air Transportation Association
ICT	Information and Communication Technology
IDC model	Intelligence-Design-Choice model
GSS	Group Support System
IDSS	Intelligent Decision Support System
IT	Information Technology
KMDSS	Knowledge Management-based Decision Support System
LP	Linear Programming
MCLP	Maximal Covering Location Problem
MCDA	Multi-Criteria Decision Analysis
MADM	Multi-Attribute Decision-Making

MAUT	Multi-Attribute Utility Theory
MAVT	Multi-Attribute Value Theory
MILP	Mixed Integer Linear Programming
MODM	Multi-Objective Decision-Making
MS	Management Sciences
NSS	Negotiation Support System
NGO	Non-Governmental Organization
NP-hard	Non-deterministic Polynomial-time hard
OR	Operations Research
P-hard	Polynomial-time hard
P-SC	Public safety critical Supply Chain
PDSS	Personal Decision Support System
ReDRiSS	Reactive Disaster and supply chain Risk decision Support System
SC	Supply Chain
SCCM	Supply Chain Crisis Management
SCM	Supply Chain Management
SCRM	Supply Chain Risk Management
SEAK	scenario-based decision support to manage food supply disruptions
UFLP	Uncapacitated Facility Location Problem

1 Introduction

A crucial part of the economic environment is characterized by networks of *supply chains* (SCs) that, in a nutshell, steer the provision of supplies (e.g. trade goods, services) from points of origin to points of consumption. An SC is built on various entities (e.g. companies) at different functional stages (e.g. production, distribution) that are, from the perspective of a specific entity, either located in its upstream (supply side) or downstream (demand side) (Arnold et al. 2008; Pfohl 2010; Christopher 2011). The focus of this research contribution is on SCs which are part of a *critical infrastructure* (CI)[1] network in a community or society. A CI network comprises different sectors such as food, water, health care, or energy. As the well-functioning of these sectors is essential to guarantee public safety, CI networks have been described as "backbones" of the society or community they belong to (Kröger 2008). In the following, the term *public safety critical SCs* (P-SCs) is used to express the relevance of these SCs for public safety.

Well-functioning P-SCs must ensure both the *security* and the *availability* of *public safety critical supplies* to be provided for the population. Regarding the first, for example, a cryptosporidium (which refers to a type of parasite) outbreak caused a failure of the water treatment system - as a functional stage of the water P-SC - in Milwaukee, USA, in 1993. The outbreak resulted in contaminated water that was consumed by 800,000 people for two weeks causing 54 deaths (Hoxie et al. 1997; Yates 2014). Regarding the second, for example, a strike of 30,000 tanker drivers in Greece in 2010 interrupted the distribution of fuel - as a functional stage of the energy P-SC - to the gas stations. Unavailable fuel also restricted the distribution within food P-SCs and triggered short-term food shortages in several regions of Greece (Die Welt

[1] The European Commission defines CIs as "physical and information technology facilities, networks, services and assets which, if disrupted or destroyed, would have a serious impact on the health, safety, security, or economic well-being of citizens or the effective functioning of governments in the European Union (EU) countries" (European Commission 2004).

2010). The Greek government intervened by instructing the military to manage the delivery of fuel to hospitals, power plants, airports, and harbors (manager magazin 2010).

The focus of this research contribution is on the latter task of P-SCs to guarantee the availability of public safety critical supplies for the population. In this regard, a well-functioning SC in general (including P-SCs) requires a balance of demand and supply from the perspective of any included entity (Oke & Gopalakrishnan 2009). A mismatch of demand and supply might cause an *SC disturbance* which, in turn, might lead to an unavailability of supplies (Jüttner et al. 2003; Rice 2003; Knemeyer et al. 2009). Triggering events of an SC disturbance might have an internal or external source. For example, IT-related events are frequently internally caused; market events or natural disasters, in turn, refer to external sources (Natarajarathinam et al. 2009). Internal and external sources can overlap. The range of consequences of an SC disturbance depends on the triggering event. It might be possible that just business processes of one or several entities are disturbed. Alternatively, it is imaginable that a disturbance cascades through the functional stages of the overall SC network in a spatial and/or temporal dimension (Rose & Lim 2002; Merz 2011).

In the case that a triggering event disturbs one or more P-SCs, public safety is threatened as the sound provision of public safety critical supplies and, thus, the satisfaction of a population with basic needs is not guaranteed. Such a P-SC disturbance might even be amplified when the triggering event additionally impacts further CI sectors (e.g. unavailable roads as part of the transportation infrastructure) or when it cascades through interrelated P-SC networks (e.g. strikes of tanker drivers affecting distributions within food and health care P-SCs). The past has shown that *disasters*[2] in particular have been responsible for causing large-scale P-SC disturbances. For example, climate change

[2] There is a distinction between natural and man-made disasters. While the first arise due to natural or physical phenomena (e.g. geophysical, hydrological, climatological, biological), the latter are caused by humans (e.g. terrorism, war, industrial, nuclear or transportation accidents) (Bournay 2005; ICDRM/GWU 2010; IFRC 2015).

causes more and more natural disasters, such as heat waves, droughts, wildfires, and floods. Moreover, population growth, urbanization, and concentration have exposed more people and assets to disasters in general. Because of the significant increase in disasters in the past decades, the twenty-first century has been termed the "century of disasters" by the Financial Times which included *disaster management* in the top 10 challenges facing science in June 2011 (Cookson 2011).

Both developing countries and industrial nations have been affected by *disaster-caused P-SC disturbances* in the past. In the aftermath of the tsunami disaster in Southeast Asia in 2004, for example, humanitarian aid was required to compensate the unavailability of food supplies in the Maldives. As the Maldives consist of a number of relatively small islands, the availability of food supplies depends on the functioning of imports which were, however, disrupted due to the tsunami. Humanitarian organizations were obliged to fly in food supplies to compensate the P-SC disturbance (Samii & Van Wassenhove 2010). Unavailable food supplies could also be observed in Syria since 2012. The civil war which started in 2011 caused severe interruptions within the production and distribution of foodstuff which resulted in a near collapse of the food P-SC network (Neue Züricher Zeitung 2012; Zeit online 2014). In the USA, disturbances of water and health care supplies occurred in the aftermath of Hurricane Katrina in 2005. The destruction of 170 drinking water facilities caused severe disturbances of water supplies in the city of New Orleans. Additionally, several large hospitals were destroyed or rendered inoperable (The White House 2006).

1.1 Preventive and reactive disaster management

An event that might cause a P-SC disturbance poses a *risk* for the persons responsible within this P-SC. Typically, risks are assessed in a quantitative manner by predicting the occurrence probability of an event and its possible impact (Bertsch 2008; ICDRM/GWU 2010; Comes 2011). Basically two stereotypical categories of risks can be distinguished: high probability low impact risks and low probability high impact risks. Disasters refer to the latter category which might affect entities in major ways (Chopra & Sodhi 2004; Kleindorfer & Saad 2005; Oke & Gopalakrishnan 2009). However, *risk management* mainly focusses on the development of preventive plans to protect against high probability low impact risks as these are the ones which recur (e.g. demand variabilities) (Chopra & Sodhi 2004).

The reason for this asymmetry in treatments of risk lies in the characteristics of disasters. While high probability low impact risks are predictable to a certain degree, disasters might be unpredictable and uncontrollable (Charles et al. 2010; Johnson 2013). According to Sowinski (2003), the challenge of managing disasters is that one does not know when and where they will occur and who will be affected. This lack of knowledge also refers to the estimation of their caused consequences (e.g. extent of damage). Taleb et al. (2009) underline the mistake of executives of risk management to think that low probability high impact risks can be managed by *predicting* them. This is not possible as a practically unlimited number of possible specifications of disasters exist (e.g. types and characteristics of the event, caused consequences). Hence, standard instruments/tools of risk management (e.g. statistical analyses) to forecast the occurrence of specific P-SC disturbances are futile if they continue to try to predict something that cannot be predicted (Taleb et al. 2009).

However, also reactively estimating the consequences of a disaster to manage a P-SC disturbance is challenging. This is because the post-disaster situation cannot typically be analyzed in a deterministic manner. Limited information and, thus, knowledge about consequences and causes, as well as continuous changes of the situation might hinder the development of reactive plans by *crisis management*. The rise of modern information and communication technology (ICT) systems has led to a high availability of information which stems from various sources and can provide helpful guidance in decision situations (Turoff et al. 2009; Yates & Paquette 2011). However, the information available is very heterogeneous in terms of format, quality, and uncertainty, or may even be completely lacking (Wybo & Lonka 2003; Comes et al. 2011). Additionally, the disaster itself as well as the information about it may evolve dynamically. Decision-makers are under pressure to make their decision quickly, which may cause cognitive overload to occur and biases to be reinforced (Maule et al. 2000; Ariely & Zakay 2001; Comes et al. 2012). Despite these challenges, decision-makers of crisis management must respond quickly in the immediate aftermath of an occurring disaster (which is denoted *disaster response*) while acknowledging that their current decision will impact future decisions.

Reactive crisis management must process a range of *logistical decision problems* to maintain the provision of public safety critical supplies in the case of a disaster-caused P-SC disturbance. The characteristic of an arising logistical decision problem required depends on the extent of the disturbance. Basically two stereotypical severity levels can be distinguished in this regard: a *destruction* or *disruption* of a disturbed P-SC. An example of a disaster-caused P-SC destruction could be observed in the aftermath of the earthquake in Nepal in 2015. According to the United Nations, food shortages were faced by 1.5 million people (The Independent 2015). The United Nations World Food Programme intervened to deliver foodstuff to Nepal including areas that were hardest to reach. To compensate the destructed P-SC network, one logistical decision problem that occurred referred to the establishment of field logistics hubs (World Food Programme 2015). In turn, a disaster-caused P-SC disruption was faced by New York City, USA, in the aftermath of Hurricane Sandy in 2012. Food retail companies were forced to close several flooded stores (e.g. in Brooklyn) or to manage physical challenges occurring within the stores. In lower Manhattan, food retail companies had to deal with the logistical decision problem of distributing foodstuff to the stores under the restriction of several closed bridges and tunnels. This caused delays of countless deliveries of foodstuff (The Atlantic Citylab 2013).

1.2 Objectives and structure

The main objective of this research contribution is to develop a post-disaster *decision support system* (DSS) that provides aid for decision-makers of reactive crisis management to solve logistical decision problems in order to manage P-SC disturbances (disruptions and destructions). In literature, DSSs are described as software-based tools assisting the decision-making process (Pearson & Shim 1995; Mattiussi 2012). The usage of such a DSS requires efforts of preventive risk management. Rather than predicting disasters to proactively reduce disaster risks, one major objective of preventive risk management must be the implementation/customization of a DSS to a specific decision situation that is able to estimate and manage consequences of the disaster ex post. This can be understood as an innovative measure of disaster risk reduction. In fact, the threat of mismanaging consequences in disaster response is mitigated as a tool is available that aids decision-makers reactively. To achieve the main objective, varying requirements must be fulfilled from the (methodological) decision theoretic perspective and the (conceptual) perspective of managing P-SC disturbances.

In the extreme, a decision situation in the aftermath of a disaster equals, from a decision theoretic perspective, a decision situation under *ignorance* and *complexity*. A state of ignorance is triggered by fundamental uncertainty due to limited information about the current decision situation. Complexity refers, in the context of disasters, mainly to dynamic developments affecting the decision situation (e.g. secondary disasters occurring over time). Under these conditions, uncertainty cannot be appropriately handled by sound statistical analyses alone (e.g. based on historical data from past disasters). Innovative approaches are therefore needed to aid decision-makers in handling ignorance and complexity arising in a disaster-caused decision situation.

The requirement of decision-making in general is that a made decision must lead to an appropriate result under the varying circumstances which might confront the decision situation. This ability is addressed by the concept of *robustness*. Basically, the concept has been linked to different fields of research such as robust optimization as a domain of operations research (OR) (e.g. Kouvelis & Yu 1997; Ben-Tal et al. 2009; Schöbel 2011) or supply chain management (SCM) (e.g. Snyder 2003; Wallace & Choi 2011; Vlajic et al. 2012). To guarantee an optimal provision of public safety critical supplies for the population in the case of a P-SC disturbance, the robustness of a decision recommendation as the output of a DSS is an important requirement in particular. This is because the current state of the disaster-affected environment might not be known or even in a constant flux due to the ignorance and complexity which arises.

The DSS should address two groups of relevant decision-makers. *Internal decision-makers* refer to the entities (e.g. companies) of the disturbed P-SC itself. Their crisis management must be able to strengthen or restore their own affected business processes to manage the P-SC disturbance. With respect to the example stated above, food retail companies have managed the distribution of foodstuff to their stores in New York City in the aftermath of Hurricane Sandy in 2012. *External decision-makers* are located outside the disturbed P-SC. They might be entities (e.g. companies) of further P-SCs or of SCs of other branches, or (independent) public authorities which intervene when a P-SC disturbance cannot be handled by the internal decision-makers. For example, the United Nations World Food Programme provided Nepal's earthquake-affected population with foodstuff in 2015 (humanitarian aid). As varying logistical decision problems might arise and must be processed by reactive crisis management, it is important that the DSS is generic and adaptive in nature and to be useable by both groups of decision-makers in different decision situations (e.g. arising in a specific country) and logistical decision problems (e.g. resource allocation planning). The implementation/customization of the DSS to a decision situation must be the task of preventive risk management.

To fulfill these requirements, the decision support system *ReDRiSS* (*Reactive Disaster and supply chain Risk decision Support System*) is developed. The remainder of this research contribution is organized into eight chapters. Chapter 2 and chapter 3 provide the methodological and conceptual background by presenting theory and models that are relevant to operating in the interface of decision-making under uncertainty and complexity and reactive crisis management of disaster-caused P-SC disturbances. ReDRiSS is developed in chapter 4. To verify its applicability, two case studies are presented in chapter 5 and chapter 6 that differ in the type of the P-SC disturbance (destruction and disruption) and the responsible decision-makers (external and internal decision-makers). Findings are concluded in chapter 7. The structure of the research contribution is highlighted in Figure 1-1; the rationale of each chapter is briefly outlined in the following paragraphs.

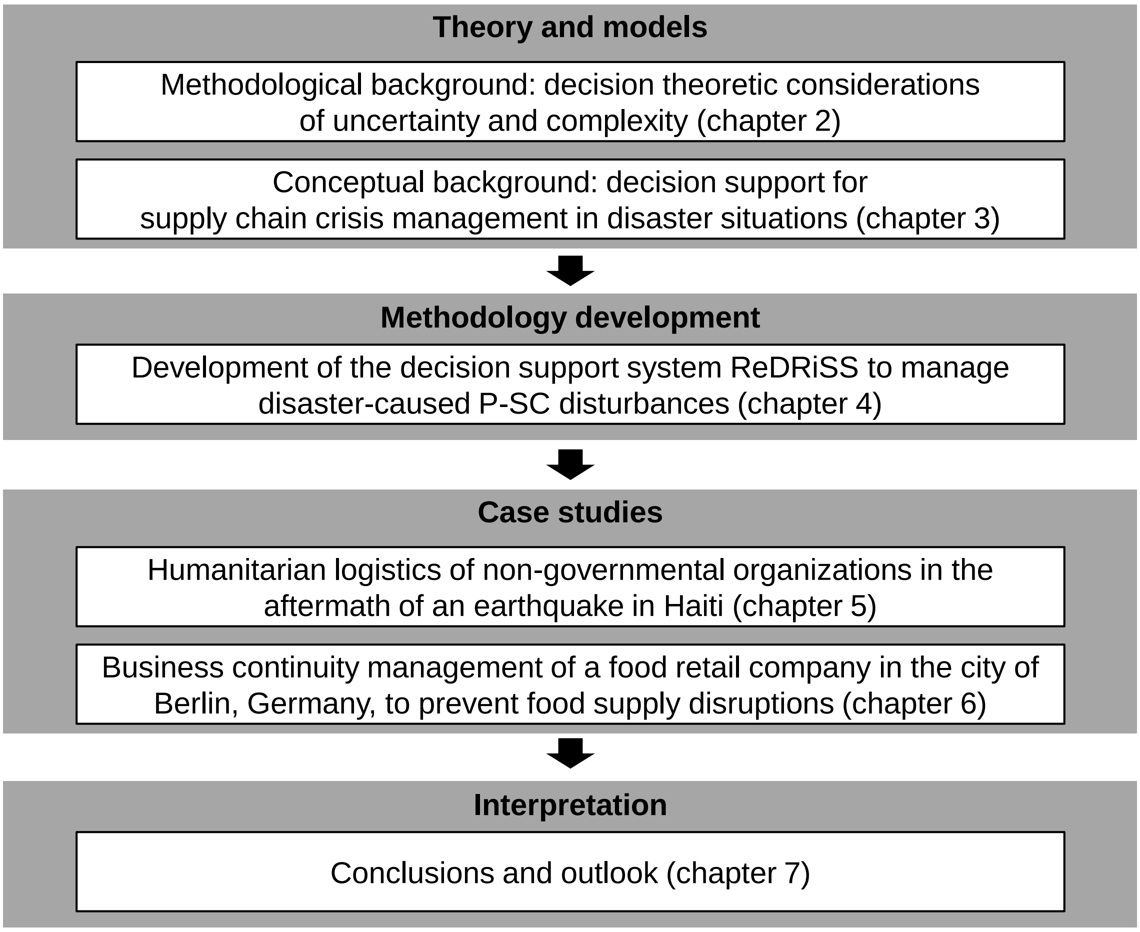


Figure 1-1: Structure

Chapter 2 provides the methodological background of the research by discussing uncertainty (risk and ignorance) and complexity from a decision theoretic perspective. Section 2.1 presents definitions and classifications of uncertainty in general as well as the theoretic decision-making process under uncertainty. One way to handle (non-quantifiable) uncertainty is provided through scenario techniques. The application of scenario-based approaches is highlighted from two perspectives: decision theory and mathematical programming. Section 2.2

focusses on decision situations under complexity. After providing definitions in this regard, the respective decision-making process is outlined. To assist decision-makers, DSSs have become an important field of research. Section 2.3 therefore highlights the general objectives and rationale of DSSs.

The objective of chapter 3 is to provide the conceptual background of this research. In section 3.1, definitions and terminologies of logistics/SCM and disaster theory are given. Section 3.2 discusses the role of SCM in a disaster situation. Thereby, possibilities to manage disaster-caused SC disturbances are discussed as well as the relevance of different SC strategies to hedge against such disturbances. Decision-makers of reactive SC crisis management must make decisions to mitigate consequences of a disturbance. Section 3.3 discusses the scope of decision-making in this regard and the relevance of uncertainty and complexity in the aftermath of a disaster. Research articles dealing with methods of operations research (OR) and management sciences (MS) to support decision-making in a disaster situation in general and in SCM in particular are finally reviewed. Based on the findings, research objectives are revealed in section 3.4.

Chapter 4 presents ReDRiSS which is developed to reactively manage a disaster-caused P-SC disturbance. Therefore, the scope of ReDRiSS is outlined in section 4.1 from the perspective of preventive SC risk management and reactive SC crisis management. With respect to the insights of chapter 2 and 3, the requirements that must be met by ReDRiSS are listed. In section 4.2, the parts and processing steps that specify ReDRiSS are summarized. ReDRiSS consists of four parts whose rationales and mathematical descriptions are presented in-depth in the forthcoming sections: implementation and application of a two-stage scenario technique (section 4.3), stress test (section 4.4), and robustness measurement (section 4.5). Chapter 4 closes with a summary and discussion in section 4.6.

Chapter 5 applies ReDRiSS in a case study that focusses on humanitarian logistics in Haiti. The case study considers destructions of P-SCs of the CI sector “health care” that are caused by an earthquake. To compensate these destructions, humanitarian relief SCs must be established. This is the task of an association of different non-governmental organizations (NGOs) (external decision-maker). The logistical decision problem of facility location planning arises in terms of opening health care facilities in Haiti that are needed to store medicine or medical equipment. Section 5.1 introduces the field of humanitarian logistics and outlines the relevance of facility location planning. In section 5.2, the implementation of ReDRiSS according to the decision situation is discussed. ReDRiSS is applied in section 5.3 and the results are presented and interpreted in section 5.4. Chapter 5 closes with a summary and discussion of the findings in section 5.5.

Chapter 6 presents a case study where ReDRiSS is used by a company as a reactive measure of business continuity management (BCM) to manage its disrupted critical business processes. The case study focusses on disruptions of food P-SCs in Berlin, Germany. In fact, a food retail company (internal decision-maker) is considered whose critical business processes refer to the smooth operation of its stores. A flu pandemic that spreads in the middle-eastern part of Europe causes a large-scale staff absence which forces the food retail company to close several stores. The logistical decision problem arises of allocating the available staff members to the stores. Thereby, decision-making is confronted with an unknown and fluctuating purchasing behavior of diseased customers. Section 6.1 introduces the field of BCM and the relevance of ReDRiSS in this regard. ReDRiSS is adapted to the depicted decision situation in section 6.2. Its application is outlined in section 6.3 and the results are presented in section 6.4. In section 6.5, the findings of the case study are summarized and discussed.

Chapter 7 synthesizes the main aspects of the developed decision support methodology and reveals the major contributions of the research. Section 7.1 includes a critical appraisal regarding the achievement of the pursued research objectives (see section 3.4). The cases of application of ReDRiSS and the requirements that must be thereby fulfilled are discussed in section 7.2. Chapter 7 closes with a presentation of the possible fields of future research in section 7.3.

Chapter 8 summarizes the most important findings of the research.

The eight chapters are complemented by two appendences. Appendix A and appendix B provide input and result data sets of the case studies in chapter 5 and chapter 6.

Parts of this research have been published using contributions of the author: (Comes, Schätter, Schultmann 2013; Schätter, Schultmann, Comes 2013; Schätter, Meng, Wiens, Schultmann 2014; Comes, Schätter, Schultmann 2014; Schätter, Wiens, Schultmann 2015; Schätter, Hansen, Herrmannsdörfer, Wiens, Schultmann 2015). They are not explicitly referenced in the following.

2 Decision theoretic considerations of uncertainty and complexity

The objective of the following chapter is to provide the methodological background of this research. Therefore, the terms *uncertainty* and *complexity* are discussed from a decision theoretic perspective. The Oxford dictionary defines uncertainty as "the state of being uncertain" where uncertain stands for "not able to be relied on; not known or definite" (Stevenson 2010; Liberatore et al. 2013). In a decision situation, uncertainty is related to unknowingness about its characteristics in terms of the state of the underlying decision environment[3]. A state of knowledge and, thus, certainty is achievable when relevant information describing these characteristics becomes available. Consequently, uncertainty is related to a lack of knowledge that is caused by a lack of information. Complexity is an interrelated concept to uncertainty that may characterize a decision situation or, more generally, a system under consideration. A complex system is associated with an uncertain future and the difficulty of predicting the properties of the system (Flach 2012; Hollnagel 2012). The forthcoming sections discuss the fields of decision-making under uncertainty (section 2.1) and complexity (section 2.2) by providing definitions, classifications, and concepts of their management. Moreover, the field of *decision support systems* (DSS), which aim at assisting decision-makers in handling uncertainty and complexity, is introduced (section 2.3).

2.1 Decision situations under uncertainty

This section considers decision situations under uncertainty. At first, definitions and classifications are provided. Secondly, the decision-making process under uncertainty is highlighted. A common measure

[3] The decision environment includes all relevant elements of an environment that might influence the decision-making.

to operationalize the decision-making process in a decision situation under uncertainty is to apply scenario-based approaches. Finally, these approaches are discussed from two methodological perspectives: decision theory and mathematical programming.

2.1.1 Definitions and classifications

The state of a decision situation depends on the availability of information that can be either deterministic or subject to uncertainty (Bertsch 2008). In fact, decision situations might arise under certainty, risk, or ignorance (Knight 1921; Rosenhead et al. 1972; Luce & Raiffa 1989; Kouvelis & Yu 1997; Snyder 2003; Comes 2011). While the first assumes that all relevant aspects of the decision situation are known, the latter two imply that several aspects are affected by uncertainty. To understand the difference of the two possible specifications of uncertainty – risk and ignorance – let $a_1, a_2 \in A$ be two *alternatives* (decision options) of a set of alternatives A that may be used to handle a decision situation. The decision is made under (Luce & Raiffa 1989):

- *certainty*, when a_1 and a_2 invariably lead to the deterministic outcomes $x(a_1)$ and $y(a_2)$.
- *risk*, when a_1 and a_2 lead to a set of probabilistic outcomes $X(a_1)$ and $Y(a_2)$. Each outcome $x(a_1) \in X(a_1)$ occurs with a known probability $p\big(x(a_1)\big) \in [0,1]$ and each outcome $y(a_2) \in Y(a_2)$ occurs with a known probability $p\big(y(a_2)\big) \in [0,1]$ where $\sum p\big(X(a_1)\big) = \sum p\big(Y(a_2)\big) = 1$.
- *ignorance*, when a_1 and a_2 lead to a set of indeterministic outcomes $X(a_1)$ and $Y(a_2)$ in the sense that the probability of each $x(a_1) \in X(a_1)$ and $y(a_2) \in Y(a_2)$ is unknown.

A decision situation under certainty is characterized by available and complete information that covers all relevant aspects of the decision situation in a deterministic manner (Scholl 2001). The outcome of each alternative is known (Rommelfanger & Eickemeier 2002). An (uncertain) decision situation under risk is characterized by information that is principally complete because there is a probability distribution per possible outcome at the decision-makers' disposal (Zimmermann 2000). This information is, however, not sufficient to characterize the decision situation deterministically. As outcomes depend on random influences (Wiens 2013), decision-makers must manage a "qualitative" lack of information in a decision situation under risk (Zimmermann 2000). In an (uncertain) decision situation under ignorance, probability distributions cannot be used (Wiens 2013) as just the set of possible outcomes of alternatives is known (Rommelfanger & Eickemeier 2002). Decision-makers are confronted with a "quantitative" lack of information in this case (Zimmermann 2000).

The term *uncertainty* has been widely discussed in literature which is associated with a large variety of suggested classifications (Sluijs et al. 2005; Bertsch 2008). A classification that has been particularly referenced by authors operating in the field of model-based decision-making (where uncertainty is handled by a model) follows the so-called "*location" of uncertainty* (Bertsch et al. 2007; Bertsch 2008; Comes 2011). This classification outlines the sources/types of uncertainty that are relevant in the context of scientific analyses. In fact, it is distinguished between uncertainty of the decision-makers (preferential uncertainty) and uncertainty that arises in the process of methodological knowledge production (data uncertainty, model uncertainty).

- *Preferential uncertainty* refers to indefinite preferences of the decision-makers (e.g. regarding objectives) (Bertsch et al. 2007; Bertsch 2008; Comes 2011). It occurs because preference-related information is insufficient, unknown, or simply not communicated by the decision-makers. Triggers of preferential uncertainty might be, inter alia, subjective judgment, disagreement between decision-makers, and linguistic impression (Morgan & Henrion 2007). In model-based decision-making, it is suggested to treat preferential uncertainty parametrically by repeating the analysis (of the model) for different values of the uncertain preferential parameters (e.g. Monte Carlo methods, sensitivity analyses) (Bertsch 2008).
- *Model uncertainty* is a feature of the model itself and affects the translation of input information into results (Draper 1995;

Comes 2011). It comprises the two sub-types *model structure uncertainty* and *model technical uncertainty*. The first is about model abstractions, formulations, and constraints and concerns all elements that are required to formulize the model. The latter refers to operational uncertainty when computing the model. It impacts, for example, values of the model's parameters or generated results of decision variables (French 1995; Walker et al. 2003; Morgan & Henrion 2007; Comes 2011). As they are inherently embedded within any model that simplifies the reality, no standard approaches exist for the management of model uncertainty (Bertsch 2008).

- *Data uncertainty* (or uncertainty of the decision-analytic model input) affects information that describes the considered decision situation and the variables that drive changes within this situation (Walker et al. 2003; Comes 2011). According to Zimmermann (2000), sources of data uncertainty refer to a lack of information, abundance of information, conflicting evidence, ambiguity, measurement, and belief. In general, information that is affected by data uncertainty is not appropriate to describe, prescribe, or predict the system, its behavior and further characteristics in a deterministic manner (Zimmermann 2000). An in-depth classification of data uncertainty is to distinguish between *foreseen uncertainty* and *unforeseen uncertainty* (De Meyer et al., 2002). While the first is principally identifiable and manageable by sufficient analyses, the challenge of handling the latter is that one is not even aware of its existence. Unforeseen uncertainty arises due to interaction of elements of the decision situation that are not anticipatable although each single element might be basically foreseeable (De Meyer et al., 2002). Methods to treat data uncertainty are outlined in the forthcoming sections.

Another possibility to classify uncertainty is to focus on the "*nature" of uncertainty* (Walker et al. 2003). This classification has been especially used by authors operating in the field of risk analysis (Bedford & Cooke 2001; Paté-Cornell 2002; Bertsch 2008; Merz 2011; Senge et al. 2014).

- *Aleatory uncertainty* refers to inherent variations of the decision situation which affect, inter alia, external input data, parameters, or model structures (Walker et al. 2003). Exemplary sources causing aleatory uncertainty are the randomness of nature, specific types of human behavior, social, economic, and cultural dynamics, and technical surprise (Walker et al. 2003). Neither research nor development can provide sufficient knowledge to reduce aleatory uncertainty (Hora 1996; Walker et al. 2003; Bertsch 2008; Senge et al. 2014).
- *Epistemic uncertainty* is associated with unknowingness about the decision situation which arises because of limited or inaccurate information, measurement errors, imperfect models, and subjective judgements (Walker et al. 2003). It is described as a systematic type of uncertainty that can be eliminated by sufficient study (Hora 1996; Walker et al. 2003; Senge et al. 2014). Hence, epistemic uncertainty indicates how much could be principally controlled if required (Bedford & Cooke 2001; Comes 2011).

2.1.2 The decision-making process under uncertainty

Decision-making always implies that decision-makers deliberately select an alternative that fits to their objectives and take this alternative as decision (Rommelfanger & Eickemeier 2002). The rationale of making such a selection is denoted the *decision-making process*. Different concepts have been proposed in literature to operationalize the decision-making process. One concept that has been particularly referenced by authors operating in the field of DSSs is the *intelligence-design-choice* (IDC) model of Simon (1977) (see Figure 2-1) (Hall 2008; Pick 2008; Mattiussi 2012; Mattiussi et al. 2014).

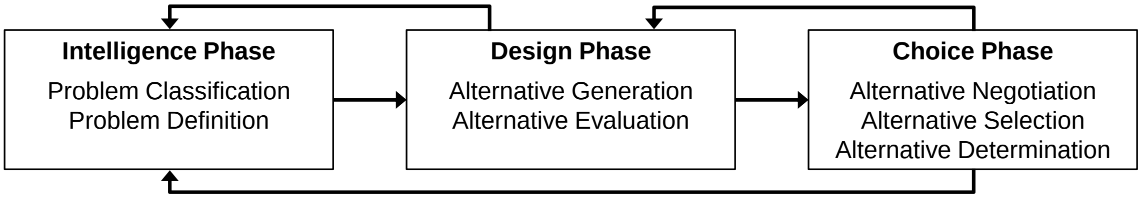


Figure 2-1: Simon's IDC model (adapted from Simon 1977; Hall 2008)

The IDC model describes the decision-making process consisting of three phases that are cyclically-ordered: intelligence, design, and choice (Mattiussi 2012). In the following these phases are briefly summarized based on the considerations of Hall (2008).

- The *intelligence phase* firstly identifies, defines, and classifies a decision problem which principally arises when a deviation of a desired state and a current state is observed in the considered system. It is imaginable that the decision problem is either of a unique manner, similar to other known problems, or routine. The second task of the intelligence phase is to gather appropriate, timely, and relevant information that is required for analyses.
- The *design phase* concentrates on the generation and evaluation of alternatives. Any alternative should be respected that is able to solve the decision problem. Thus, decision-makers obtain a breadth of alternatives which they can choose from. The evaluation of alternatives requires that decision-makers separate what must necessarily be achieved from what can potentially be achieved.
- The *choice phase* steers the process of negotiating alternatives and selecting one alternative that should be implemented as decision. Therefore, it is important to carefully compare, analyze, and contrast evaluated alternatives by respecting the preferences of the decision-makers.

The application of the decision-making process is challenging when the decision situation is affected by uncertainty. As highlighted by Kouvelis & Yu (1997), decision-making under uncertainty requests for the acceptance of uncertainty, strong efforts to structure and to understand uncertainty, and the integration of uncertainty into the decision-making reasoning. With respect to the IDC model and the classification of uncertainty by its “location” (see section 2.1.1), uncertainty might affect any phase. In the intelligence phase, data uncertainty (e.g. caused by a lack of information) might be particularly crucial when the decision problem is unique. In this case, decision-makers are unable to draw on past relevant experiences (Hall 2008). Data uncertainty might additionally affect the design phase when generating and evaluating alternatives under an uncertain state of the underlying decision environment. Decision-makers are forced to evaluate alternatives rather by their instinct than through a sound analysis (Hall 2008). The choice phase might be complicated by preferential uncertainty in terms of, for example, unclear preferences of objectives of the decision-makers. All phases might be additionally affected by model uncertainty.

As outlined in the previous section, preferential uncertainty is typically handled parametrically whereas model uncertainty should be accepted as being inherently embedded within each model simplifying the reality (Bertsch 2008). In turn, widespread measures to *handle data uncertainty* have been proposed in literature which refer to approaches of probability theory, fuzzy-based approaches, and scenario-based approaches (Comes 2011). Their applicability depends on whether the (uncertain) decision situation is affected by risk or by ignorance.

- *Approaches of probability theory* quantify data uncertainty by a probability measure $P \in [0,1]$ in a decision situation under risk. Basically two approaches can be distinguished in probability theory. According to the *frequentist approach*, P is objective and refers to the long-term frequency of occurrence to which an uncertain element of the decision situation is characterized by a specific feature when the process is repeated for an infinite number of times. In the *Bayesian approach*, P is subjective and specified according to one's current information and, thus, knowledge (Walley & Fine 1982; French 1986; Fienberg 2006; Morgan & Henrion 2007; French et al. 2009).
- *Fuzzy-based approaches* quantify data uncertainty in a decision situation under risk where distributional information is imprecise. In fact, *fuzzy sets* allow the modelling of vague information, e.g. to quantify expressions such as "strongly influencing" or "much larger than" (Comes 2011). Major drawback of fuzzy-based approaches is that decision-makers are forced to make multiple assumptions on probabilities which often exceed their capabilities (Zadeh 1975; Lempert et al. 2002; Comes 2011).

- *Scenario-based approaches* allow the handling of data uncertainty that is not necessarily quantifiable. Therefore, they have proven to be an appropriate measure in a decision situation under ignorance[4] (Bunn & Salo 1993; Comes 2011). The DSS which is developed in the course of this research contribution (see chapter 4) uses scenarios for data uncertainty handling. Therefore, scenario-based approaches are highlighted in-depth in the next section.

2.1.3 Scenario-based approaches to handle data uncertainty

Scenarios offer the possibility to explore plausible descriptions of a decision situation and its possible developments (Schoemaker 1993; Walker et al. 2003; Comes 2011). They help to overcome cognitive biases such as overconfidence or misjudgments of probabilities when applying approaches of probability theory or fuzzy-based approaches (Goodwin & Wright 2009; Comes 2011). The set of constructed scenarios should contain likely and unlikely events (Hites et al. 2006) to improve prediction and understanding of causal links of the decision situation (Harries 2003; Wright & Goodwin 2009). In the forthcoming sections, a *scenario typology* and an overview of *scenario construction techniques* is provided. Moreover, scenario-based approaches that operationalize the handling of data uncertainty in the decision-making process are outlined from two perspectives: decision theory by *decision rules* and mathematical programming by *scenario-based optimization models*.

2.1.3.1 Scenario typology and scenario construction techniques

Originally, scenarios arise from the field of future studies where they are used to systematically explore future trends. Amara (1981) highlights three major assumptions that must be achieved by scenarios in this regard: as the future is unpredictable, one needs to ask the question "what is possible/feasible?"; as the future is not predetermined,

[4] Scenario-based approaches can be additionally applied in a decision situation under risk where distributional information is available.

one needs to ask the question “what is probable?”; as choices have an impact on the future, one needs to ask the question “what is desirable?”. Börjeson et al. (2006) transfer these assumptions of future studies into a generic scenario typology that has been referenced by various authors dealing with decision-making (e.g. Höjer et al. 2008; Nowack et al. 2011; De Smedt et al. 2013). In fact, authors distinguish between predictive scenarios, explorative scenarios, and normative scenarios.

- *Predictive scenarios* describe most *probable* events within the decision situation that are expected by the scenario designers (Börjeson et al. 2006). They comprise the sub-types *forecast scenarios* and *what-if scenarios* (Börjeson et al. 2006). The first anticipates what will happen if the most likely event within the decision situation unfolds; the latter explores impacts of probable near-future events (Makridakis et al. 1997; Börjeson et al. 2006; Höjer et al. 2008).
- *Explorative scenarios* capture a widespread range of *possible* events within the decision situation (Börjeson et al., 2006). They comprise the sub-types *external scenarios* and *strategic scenarios*. The first focus on external factors that are beyond the control of the scenario designers; the latter describe consequences of a possible decision when events unfold in the decision situation (Börjeson et al. 2006).
- *Normative scenarios* include *preferable* events within the decision situation (Börjeson et al. 2006). They comprise the sub-types *preserving scenarios* and *transforming scenarios*. The first cover an efficient achievement of a specific objective; the latter focus on an objective in the future which is unreachable if the ongoing event continues (Höjer 2000). By backtracking from the respective objective, constructed scenarios reveal necessary changes to achieve this objective (Börjeson et al. 2006).

Table 2-1 summarizes the scenario typology of Börjeson et al. (2006) including all sub-types and key questions that must be answered during their construction.

Table 2-1: Scenario typology (Börjeson et al. 2006)

Type of scenario	Key question
Predictive scenarios	What will happen?
- Forecast scenarios	What will happen, on the condition that the likely development unfolds?
- What-if-scenarios	What will happen, on the condition of some specified events?
Explorative scenarios	What can happen?
- External scenarios	What can happen to the development of external factors?
- Strategic scenarios	What can happen if we act in a certain way?
Normative scenarios	How can a specific target be reached?
- Preserving scenarios	How can the target be reached, by adjustments to current situation?
- Transforming scenarios	How can the target be reached, when the prevailing structure blocks necessary changes?

Although there is no consensus on how to define and classify scenario construction techniques (Börjeson et al., 2006), scenarios have become an important measure in decision-analytic settings. When used to handle data uncertainty in a decision situation, the quality of constructed scenarios may influence the quality of a recommended decision. Hence, there is a need for an appropriate scenario construction process (Stewart et al., 2013).

A large variety of terms regarding scenario construction techniques exist, e.g. scenario thinking, scenario planning, scenario generation, or scenario analysis (Bradfield et al. 2005). Many techniques develop scenarios in a descriptive story-like form. Wright & Goodwin (2009) apply scenarios to develop a range of plausible futures as pen-pictures by focusing on key data uncertainty and certainty. Comes et al. (2012) use story-like scenarios to follow up data uncertainty and to achieve a deeper understanding of relevant interdependencies of a certain decision problem. Scenario construction is also possible using the Delphi method where experts' opinions are integrated. The method assumes that judgments of a group of experts are more valid than judgments from individuals (Linstone & Turoff 1975). According to Bañuls &

Turoff (2011), key characteristics of the Delphi method are that the process is repetitive, maintains the participants' anonymity, provides controlled feedback, and represents a group statistical response. Another way to construct scenarios is using scenario trees. This method is widely used for financial optimization in terms of discrete approximations to a continuous distribution (Geyer et al., 2013). Further "soft" scenario construction techniques are surveys as well as interviews and workshops to include different actors as scenario designers into the scenario construction process (e.g. decision-makers, stakeholders, and experts) (Börjeson et al. 2006).

Bishop et al. (2007) offer an overview of scenario construction techniques which are listed below. For in-depth information and examples regarding these techniques, reference is made to the contribution of Bishop et al. (2007) and to a summary which is provided by Comes (2011).

- *Judgement techniques* construct scenarios in contribution with experts and stakeholders.
- *Baseline scenario techniques* construct one scenario by extrapolating analyzed prevailing trends to the future.
- *Elaborations of fixed scenarios* detail and shape a set of predetermined basic scenarios.
- *Event sequences* explore event chains with associated probabilities.
- *Backcasting* defines an envisioned future and investigates paths resulting in the desired end state.
- *Dimensions of uncertainty* constructs scenarios based on most important sources of data uncertainty.
- *Cross impact analysis* describes plausible futures combined with quantified probabilities.
- *Modelling techniques* quantify interdependencies between most relevant variables which are partly used to calculate the value of an objective function.

2.1.3.2 Decision rules

One task of the decision-making process is the evaluation of alternatives that might solve the considered decision problem. The challenge of this evaluation is that the state of the underlying decision environment is not definite in a decision situation under uncertainty (risk, ignorance). When using scenarios to capture data uncertainty, the evaluation of alternatives requires testing their outcomes in any constructed scenario. Therefore, decision theory provides a variety of *decision rules* whose applicability depends on whether the uncertain decision situation arises under risk or ignorance. In a decision situation under risk, the occurrence probability of each scenario and, thus, of each outcome is assumed to be known. Probabilities are not available in a decision situation under ignorance where it is just ensured that one scenario and outcome will be realized (Rommelfanger & Eickemeier 2002).

Let $A = \{a_1, \dots, a_i, \dots, a_I\}$ be a finite set of available alternatives and $S = \{s_1, \dots, s_j, \dots, s_J\}$ a finite set of constructed scenarios. The function $g: A \times S \to E$ assigns an outcome $g(a_i, s_j) \in E$ to each tuple $(a_i, s_j) \in A \times S, i = 1, \dots, I, j = 1, \dots, J$ (Scholl 2001; Rommelfanger & Eickemeier 2002). In the following it is exemplarily assumed that the objective of the decision problem is to maximize the outcome of $a_i \in A$ when it is applied to a scenario $s_j \in S$. A *decision rule* follows a *decision criterion* $\phi(a_i)$ that is calculated per $a_i \in A$ to steer the evaluation of its set of outcomes $\{g(a_i, s_j) | j = 1, \dots, J\}$. An alternative is evaluated best that reaches the top (minimal or maximal) score of the set $\{\phi(a_i) \, | i = 1, \dots, I\}$.

<u>Decision rules under risk</u>

In a decision situation under risk, the occurrence probability $p_j \in [0,1]$ of each scenario $s_j \in S$ is assumed to be available. All decision rules that are highlighted in the following assume that the alternative $a^* \in A$ is selected which reaches the maximal score regarding the calculated decision criterion; in fact, $a^* = (a_i \in A: \phi(a_i) = \max\{\phi(a_i) | i = 1, \dots, I\})$.

The μ *criterion* (see [2-1]) prescribes the calculation of the expected value of a set of outcomes $\{g(a_i, s_j) | j = 1, \dots, J\}$ per $a_i \in A$. An alternative is evaluated best when it achieves the highest expected value.

$$\phi(a_i) = \mu(a_i) = \sum_{j=1}^{J} p_j \cdot g(a_i, s_j) \qquad [2\text{-}1]$$

The decision rule assumes that outlier outcomes are compensated by the expected value due to the law of the large numbers. This, however, requires the availability of a necessarily large set of scenarios. In this regard, a major point of criticism is that it cannot be excluded that an alternative that achieves a high expected value leads to a worse result in hindsight than an alternative that is specified by a low expected value (Pfohl & Braun 1986; Scholl 2001).

To eradicate this drawback, various advanced decision rules have been suggested that respect the specific characteristics of the underlying distributional information (regarding the set of outcomes). The (μ, σ) *criterion* integrates the statistical measure of variance (see [2-2]) into the evaluation process; the (μ, ρ) *criterion* uses the semivariance (see [2-3]) by explicitly considering negative and, thus, undesired deviations from the expected value (Schneeweiß 1966; Scholl 2001).

$$\sigma^2(a_i) = \sum_{j=1}^{J} p_j \cdot \left(\mu(a_i) - g(a_i, s_j)\right)^2 \qquad [2\text{-}2]$$

$$\rho^2(a_i) = \sum_{j=1}^{J} p_j \cdot \left(\max\{0, \mu(a_i) - g(a_i, s_j)\}\right)^2 \qquad [2\text{-}3]$$

The formulation of the decision criterion $\phi(a_i)$ depends in this case on the risk preferences of the decision-makers. For example, let them choose between alternatives that achieve the same expected values. With respect to the (μ, σ) *criterion*, risk averse (risk seeking) decision-makers prefer the alternative that is characterized by the lowest (highest) variance.

The *Hodge-Lehmann criterion* (see [2-4]) assumes that probabilities are unreliable and decision-makers do not completely trust in distributional information. As, however, such information is still available and should not be neglected within the evaluation process (Rommelfanger & Eickemeier 2002), the Hodge-Lehmann criterion suggests a compromise of the *μ criterion* and the *maximin criterion* (see decision rules under ignorance, [2-6]). In fact, a reliability parameter $\lambda \in [0,1]$ is introduced which describes a weighting parameter. This parameter is under the control of the decision-makers and specifies the relative importance of the expected value of outcomes (μ criterion) compared to the worst outcome that is achieved by an alternative across all scenarios (maximin criterion). When decision-makers trust in the reliability of the underlying distributional information, they follow the expected value ($\lambda \rightarrow 1$). If they do not trust in this information, they rather base their decision on the worst outcome ($\lambda \rightarrow 0$) (Rommelfanger & Eickemeier 2002; Wiens 2013).

$$\phi(a_i) = \lambda \cdot \mu(a_i) + (1 - \lambda) \cdot \min\{g(a_i, s_j) | j = 1, \dots, J\} \quad [2\text{-}4]$$

Decision rules under ignorance

The occurrence probability $p_j \in [0,1]$ of a scenario $s_j \in S$ is assumed to be unavailable in a decision situation under ignorance. Varying decision rules have been suggested that are applicable when distributional information is lacking. The following decision rules assume the selection of the alternative $a^* \in A$ whose score of the calculated decision criterion is maximal: $a^* = (a_i \in A: \phi(a_i) = \max\{\phi(a_i) | i = 1, \dots, I\})$.

The *Laplace criterion* (see [2-5]) prescribes the calculation of the sum of all outcomes per alternative across all scenarios. Although the decision rule is seen as applicable in a decision situation under ignorance, distributional information is inherently assumed in terms of equal probabilities (Scholl 2001; Rommelfanger & Eickemeier 2002).

$$\phi(a_i) = \sum_{j=1}^{J} g(a_i, s_j) \quad [2\text{-}5]$$

The *maximin criterion* (see [2-6]) determines the worst (minimal) outcome per alternative across all scenarios. That alternative is evaluated best whose worst (minimal) outcome is best (maximal) in comparison of all other alternatives (Scholl 2001; Rommelfanger & Eickemeier 2002). The opposite pole of the maximin criterion is the *maximax criterion* (see [2-7]). Here, the best (maximal) outcome is determined per alternative across all scenarios and decision-makers choose the alternative that achieves the best (maximal) of these best outcomes (Scholl 2001; Rommelfanger & Eickemeier 2002). Decision-makers who select the maximin criterion behave in a rather pessimistic manner and aim at hedging against everything that is likely enough to happen (specified by the set of scenarios). In turn, decision-makers choosing the maximax decision rule are characterized as optimistic.

$$\phi(a_i) = \min\{g(a_i, s_j) | j = 1, \dots, J\} \quad [2\text{-}6]$$

$$\phi(a_i) = \max\{g(a_i, s_j) | j = 1, \dots, J\} \quad [2\text{-}7]$$

The possibility to trade-off the maximin and the maximax criteria and, thus, the degree of optimism and pessimism of the decision-makers' behavior is provided by the *Hurwicz criterion* (see [2-8]). An optimism/pessimism parameter λ is introduced which specifies the relative importance of the *maximin criterion* and the *maximax criterion*. In the two extreme cases of $\lambda = 0$ and $\lambda = 1$, the Hurwicz criterion corresponds to the maximin and maximax criterion (Scholl 2001; Rommelfanger & Eickemeier 2002).

$$\phi(a_i) = (1 - \lambda) \cdot \min\{g(a_i, s_j) | j = 1, \dots, J\} + \lambda \cdot \max\{g(a_i, s_j) | j = 1, \dots, J\} \quad [2\text{-}8]$$

An additional compromise decision rule that has been outlined above (see decision rules under risk), but that can also be applied in a decision situation under ignorance, is the *Hodge-Lehmann criterion* (see [2-4]). The criterion assumes equal occurrence probabilities of the scenarios ($p_m = p_n, \forall m, n \in J$).

Further decision rules exist that follow the indicator of *regret*. The regret indicates the (absolute or relative) deviation of the outcome an alternative achieves in a scenario from the best outcome in this scenario that is reached by any other alternative (Scholl 2001). The higher the regret, the more the outcome of an alternative deviates from the scenario-optimal outcome and the worse the alternative performs in this scenario. Both regret-based decision rules that are outlined below prescribe to select the alternative $a^* \in A$ whose score regarding the calculated decision criterion is minimal: $a^* = (a_i \in A: \phi(a_i) = \min\{\phi(a_i)|i = 1, \dots, I\})$.

The *absolute minimax-regret criterion* (see [2-9]) and *relative minimax-regret criterion* (see 2-10]) determine the worst (maximal) absolute or relative regret per alternative across all scenarios. An alternative is evaluated best whose worst (maximal) regret is best (minimal) across all alternatives (Scholl 2001; Rommelfanger & Eickemeier 2002).

$$\phi(a_i) = \max\left\{\max\left\{g\left(a_i, s_j\right)|i = 1, \dots, I\right\} - g\left(a_i, s_j\right)|j = 1, \dots, J\right\} \quad [2\text{-}9]$$

$$\phi(a_i) = \max\left\{\frac{\max\left\{g\left(a_i, s_j\right)|i = 1, \dots, I\right\} - g\left(a_i, s_j\right)}{\max\left\{g\left(a_i, s_j\right)|i = 1, \dots, I\right\}}|j = 1, \dots, J\right\} \quad [2\text{-}10]$$

2.1.4 Scenario-based optimization models

Decision rules are applied to evaluate a finite set of alternatives. The field of *operations research* (OR) defines alternatives by the mathematical formulation of an optimization model that is used to solve a decision problem. Alternatives refer to the decision variables included in such a model and differ in their specifications. Optimization models consist of objective functions that must be either minimized or maximized (to solve the decision problem) and feasible solutions (alternatives) which are defined by constraint functions. Feasible alternatives are evaluated or, more generally, the optimization model is solved by using an algorithm (exact algorithm, heuristic).[5] Optimization models can be classified by distinguishing between (Neumann & Morlock 2002; Domschke & Drexl 2007; Rader 2010):

- *Linear* and *nonlinear optimization models*: while the first comprises linear objective and constraint functions, the latter assumes that at least one function is nonlinear. *Integer* and *mixed-integer optimization models* allow that all or several decision variables take integer values. *Binary* and *mixed-binary optimization models* prescribe that all or several decision variables take binary values.
- *Single*- and *multi-objective optimization models*: while the first includes one objective function, the latter respects multiple objective functions simultaneously.
- *Polynomial-time hard* (P-hard) and *non-deterministic polynomial-time hard* (NP-hard) *optimization models*: depending on its size, an optimization model might be solvable in polynomial time (P-hard) or not (NP-hard).

The application of an optimization model in a decision situation under uncertainty (risk or ignorance) requires the consideration of data uncertainty affecting the model's parameters (included across all objective functions and constraint functions) (Kouvelis & Yu 1997; Goerigk & Schöbel 2013) (see section 2.1.1). Data uncertainty handling is an important topic of OR literature. Even small perturbations of fixed parameter specifications can cause computed solutions to become completely meaningless from a practical viewpoint when they are taken as decisions (Ben-Tal et al., 2009).

[5] For in-depth information regarding classifications of optimization models, algorithms, and heuristics, reference is made to Neumann & Morlock (2002) and Domschke & Drexl (2007).

The following highlights the rationale of optimization models that process scenarios to represent data uncertainty. Such models are denoted *scenario-based optimization models* (Dembo 1991). A scenario is in this regard defined as a vector in $\mathbb{R}^n$ which includes one discrete specification of the n uncertain parameters where the i^{th} coordinate of the vector specifies the value for the i^{th} uncertain parameter (Hites et al. 2006). The combination of one discrete specification per parameter describes a scenario (regardless whether this parameter is modeled discretely or continuously) (Snyder 2006). Each scenario is used to specify a deterministic sub-model (sub-formulation) of the actual optimization model. The challenge when solving a scenario-based optimization model is that an alternative which is feasible in one of the sub-models (in terms of fulfilling the constraint functions) might not be feasible in the further sub-models. Moreover, it is not guaranteed that an alternative exists that is both feasible and the optimal solution in each sub-model (Hites et al., 2006). To solve a scenario-based optimization model, it must be distinguished whether the uncertain decision situation arises under risk or ignorance. Scenarios can be processed in a decision situation under risk by *stochastic optimization models* and in a decision situation under ignorance by *robust optimization models* (Snyder 2006).

<u>Stochastic optimization models</u>

In a decision situation under risk it is assumed that probability distributions describing possible specifications of the uncertain parameters are known (Rosenhead et al. 1972; Kouvelis & Yu 1997; Snyder 2006). Scenario-based optimization models can therefore be solved in a stochastic manner. To solve (scenario-based) *stochastic optimization models*, a deterministic equivalent of an optimization model is typically formulated. In fact, there is a distinction between deterministic equivalents of the objective functions and of the constraint functions (Kall & Wallace 2003; Snyder 2006; King & Wallace 2013).

Possibilities to formulate such deterministic equivalents have been summarized by Scholl (2001). Regarding the objective functions, the deterministic equivalent might be, inter alia, based on the expected value, variance, or semivariance. The determination of a deterministic equivalent of the constraint functions is required as the intersection of feasible alternatives across all sub-models may be small. Different approaches have been suggested in this regard which do not necessarily request for a feasibility of an alternative across all sub-models. *Fat solution models* postulate that an alternative must be feasible in any scenario which implies the threat of an empty or small solution space (alternatives that are feasible in all sub-models). *Chance-constraint models* allow violations of constraint functions by pre-defining probabilities to which an alternative must be feasible in each constraint function. *Recourse models* allow balancing out violations. For in-depth information of these possibilities, reference is made to Scholl (2001). After defining the deterministic equivalent of objective and constraint functions, the optimization model can be solved numerically.

Following the considerations of Ben-Tal et al. (2009), three requirements must be fulfilled to solve scenario-based optimization models in a stochastic manner:

- stochastic data must be available to specify each uncertain parameter
- therefore, it must be possible to point out the associated probability distribution or at least a “narrow” family of distributions which the “true” parameter specification belongs to
- the decision-makers must accept and, thus, trust in probabilistic guarantees

Ben-Tal et al. (2009) highlight the restrictive character of these requirements. Even when it is possible to achieve stochastic data, it is difficult to properly identify the underlying distributions as this requires a rather unrealistic number of observations in many cases (Ben-Tal et al. 2009). This is associated with the considerations of Thiele (2010) who claims that the accurate estimation of scenario probabilities is difficult in practice. Finally, determining probability distributions is far away from a trivial exercise and distributional assumptions are frequently inappropriate in a system which consists of many elements (Kouvelis & Yu 1997).

Robust optimization models

The concept of *robustness* has gained importance in the OR literature as a “counterpart” to optimality (Bertsimas & Sim, 2004). A robust solution performs sufficiently well across all scenarios instead of being the generic optimal solution in any scenario. Thus, the robust solution can to a certain degree be understood as immune to data uncertainty (Bertsimas & Sim, 2004). The strived degree of robustness depends on the risk preferences of the decision-makers. Typically, “robustness” is associated with the assumption of risk averse decision-makers (Goerigk & Schöbel 2013). *Robust optimization models* have become an appropriate measure in the case that no distributional information is available as the decision situation is affected by ignorance (Rosenhead et al. 1972; Kouvelis & Yu 1997; Snyder 2006).

Following the considerations of Kouvelis & Yu (1997), the rationale of robust optimization can be generalized by three basic tasks. This is firstly the *definition of scenarios* representing data uncertainty, secondly the selection of a *degree of robustness* according to the risk preferences of the decision-makers, and thirdly the formulation and solution of the so-called *robust counterpart* (see also Goerigk & Schöbel 2013; Ben-Tal et al. 2009). Particularly the second task, the selection of the degree of robustness, is crucial as it determines how conservative a finally generated robust solution will be. The degree of conservatism shows how much optimality needs to be “given up” to ensure robustness (Bertsimas & Sim 2004). Frequently, the maximin and minimax-regret criteria have been used in this regard (Kouvelis & Yu 1997; Snyder 2006; Ben-Tal et al. 2009). For an extensive review of concepts that can be used to specify the degree of robustness, reference is made to Goerigk & Schöbel (2013).

In the following, the rationale of robust optimization is exemplarily summarized when the degree of robustness follows the maximin criterion which is described as *strict robustness* or *classical robustness* in literature (Kouvelis & Yu 1997; Ben-Tal et al. 2009; Goerigk & Schöbel 2013). Let therefore again $S = \{s_1, \dots, s_j, \dots, s_J\}$ be a finite set of scenarios, $A = \{a_1, \dots, a_i, \dots, a_I\}$ be the total set of (not necessarily feasible) alternatives, f an objective function, and G a set of constraint functions. The optimization model is exemplarily given in the form of a maximization problem.

1. Determine for each $s_j \in S$ the set of feasible alternatives $B(s_j) \subseteq A$ that fulfil the constraint functions in the sub-model regarding s_j:

$$B(s_j) = \{\forall a_i \in A: G(a_i, s_j) \text{ is fulfilled}\} \qquad [2\text{-}11]$$

2. Determine the intersection of feasible alternatives $B(S)$ across all scenarios of S.

$$B(S) = \bigcap_{j=1,\dots,J} B(s_j) = \{\alpha_1, \dots, \alpha_n, \dots, \alpha_N\} \qquad [2\text{-}12]$$

3. Determine the minimal (worst) objective function value in each scenario $s_j \in S$ that is achieved by any alternative $\alpha_n \in B(S)$ and denote this alternative α^{s_j}:

$$f_{min}^{s_j} = \min\big(f(\alpha_n, s_j) | n = 1, \dots, N\big) \qquad [2\text{-}13]$$

$$\alpha^{s_j} = \big(\alpha_n \in B(S): f(\alpha_n, s_j) = f_{min}^{s_j}\big) \qquad [2\text{-}14]$$

4. Determine the scenario $s_j \in S$ in which the calculated minimal (worst) objective function value is maximal (best) compared to all other scenarios. The underlying alternative is the strictly robust alternative α^{robust}.

$$\alpha^{robust} = \big(\alpha^{s_j}: f_{min}^{s_j} = \max\{f_{min}^{s_1}, \dots, f_{min}^{s_J}\}\big) \qquad [2\text{-}15]$$

2.2 Decision situations under complexity

In the previous section it was highlighted that at least one possible set of outcomes of an alternative is available in a decision situation under ignorance. The forthcoming sections focus on decision situations where this assumption is not necessarily fulfilled. This is because the decision situation or, more generally, the system under consideration is faced by *complexity*. In the following, complexity and complex systems are defined, properties of complex systems are presented, and the decision-making process under complexity is outlined.

2.2.1 Complex systems

The term of *complexity* has been defined in different fields, ranging from biology to philosophy and mathematics (Grisogono 2006; Grauwin et al. 2012; Hollnagel 2012). Most authors agree in a close relationship between complexity and uncertainty. Flach (2012) states that a system is complex if its future is uncertain. Hollnagel (2012) associates complexity with a difficulty of predicting properties of the system.

To define complex systems from the perspective of decision-making (where the decision situation equals a complex system), the *Cynefin framework* of Snowden & Boone (2007) can be used (see Figure 2-2). The term "Cynefin" has a Welsh origin and implies that multiple factors in the environment exist and people's experiences influence them in ways which they cannot understand (Snowden & Boone 2007). Following the Cynefin framework, a decision situation may refer to one of four types of systems "simple", "complicated", "complex", and "chaotic". Simple and complicated systems imply an ordered system state, complex and chaotic systems imply an unordered system state.

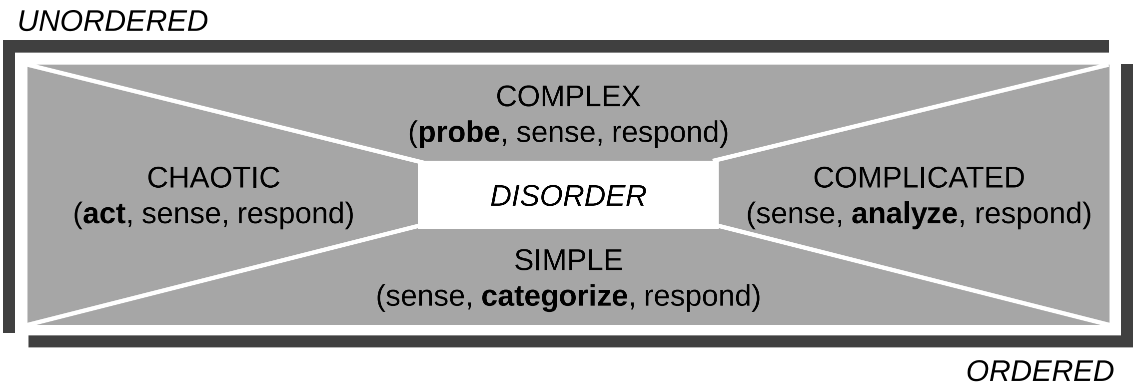


Figure 2-2: Cynefin framework (adapted from Snowden & Boone 2007)

Cause-effect relations of the system's elements are clear and behave in a predictive manner in a *simple system*. The system offers stability for decision-makers because elements are described as "known knowns". This implies that the best decision is self-evident or can be devised more or less easily. All involved decision-makers are on the same level of understanding. An example of a simple system is a bicycle. Processes that govern the system's behavior are known and understood. It is possible to predict the system's reaction to a cause such as pushing the pedals or moving the handlebars. Decision-making in a simple system must particularly "categorize" to facilitate straightforward management and monitoring (Snowden & Boone 2007).

It is possible to identify the best decision by analyses in a *complicated system*. This decision is, however, not directly available for the decision-makers. Although aspects of the system are knowable, as cause-effect relations of the system's elements are clear, not all of them are known yet. Decision-makers are confronted with "known unknowns". An example of a complicated system is the mail delivery system. While the delivery points, speed of the postman and other parameters are known, the optimal route might not be directly obvious but requires further examination. Decision-making in a complicated system is described as time-consuming as decision-makers particularly need to "analyze" (Snowden & Boone 2007).

It is not possible to identify the best decision by analyses in a *complex system*. This is because it is characterized by dynamics and unpredictability. Decision-makers are not just confronted with "known unknowns" but with "unknown unknowns". Elements of the system are not just misunderstood; it is even difficult to be aware of their existence at all as events become clear in retrospect. The elements of a complex system may, especially over time, constrain each other. This causes difficulties in predicting or forecasting what is currently happening or what will happen in future. An example of a complex system is a supply chain network. Various software systems are applied by suppliers, carriers, distributors, second carriers, and customers to organize information flows (Ireland et al., 2014). To optimize the SC network, relevant information occurring at different stages of the SC must be shared by the supply chain partners. Because of the various software systems, this is, however, a difficult venture. As additionally manual processes are required to transfer information, the management of the network of supply chain partners (to optimize the whole supply chain) is prone to uncertain or lacking information. The network can be therefore understood as a complex system (Ireland et al., 2014). Decision-making in a complex system must primarily “probe” in the system to carefully observe its response to possible actions. Subsequently, actions can be adapted to attain a satisfactory result (Snowden & Boone 2007). The decision-making process under complexity should be inspired by *pattern-based management* (Snowden & Boone 2007) whose rationale is outlined in section 2.2.3.

The search of the best decision is even described as pointless in a *chaotic system*. It is characterized by constant shifts and turbulences. Elements of a chaotic system do not follow any knowable rules and are therefore “unknowable”. The events in New York City on September 11th 2001 illustrate a chaotic system. Because of simultaneously occurring individual elements such as the attacks themselves, the behavior of victims and further affected people, and the behavior of individual rescuers, the situation was not immediately comprehensible. Decision-making in a chaotic system requires that decision-makers directly “act” to firstly establish some sense of order (Snowden & Boone 2007).

2.2.2 Properties of complex systems

Although widespread properties of complex systems have been discussed in literature, no unique list exists (Grisogono 2006; Grauwin et al. 2012; Hollnagel 2012). The following provides a substantial overview of properties that *might* characterize a complex system. Properties are assigned to the categories elements and interactions, dynamic nature, and irreducible uncertainty.

Elements and interactions

According to Flach (2012), a complex system is characterized by a high *dimensionality* of its elements in terms of variables, states and behaviors. It is not described as “monolithic” but comprises multiple interacting systems. A complex system can be therefore understood as a so-called *system of systems* which implies that the system’s elements are systems on their own which participate in the larger system (Ireland et al. 2014). Elements (or sub-systems) might be *agents* which follow their own intentions and possess some degree of free will (Ramalingam et al. 2008). This might be a challenge for decision-making as the decision-making process of agents is often a complex system itself.

Complex systems are typically described as *open systems*. As opposed to closed systems, there is no impermeable or sharp boundary between the systems’ elements and their environments. Open systems are faced by a permeable boundary. Interconnections arise between elements and the environment and modifications within the environment may interact with the elements’ behaviors (Manson 2001; Grisogono 2006; Flach 2012). Hence, the behavior of the complex system is more than just a linear aggregation of the elements’ behaviors (Grisogono 2006). *Non-linear interactions* imply that minor changes to elements can produce disproportionally major consequences (Snowden & Boone 2007). Roughly speaking, non-linear interactions lead to a disproportional response of an element in comparison to the size of the triggers. Large triggers can have no or negligible effects whereas small triggers may cause severe effects on the elements. Because of the interconnectedness of elements, non-linear behavior on an individual scale can translate to non-linear behavior on a system-wide scale.

In this regard, complex systems may be characterized by *critical states*. Under normal circumstances, a system is more or less stable to disturbances and either responds in a linear fashion or even compensates the disturbance and returns to a stable state (Helbing & Lämmer 2008). In the case that the system is at a critical state, a minor disturbance can be enough to set a process in motion that will move it to a different state. This is expressed by the term *phase transition* which can leads to *failure cascades* (Helbing & Lämmer 2008). A phase transition is the non-linear behavior on the system scale exactly at the critical state where the system responds to a tiny disturbance with a very large phase transition (Helbing & Lämmer 2008).

Dynamic nature

A complex system is described as in a constant flux where it is difficult, if not impossible, to gain an accurate picture of the system's state at one distinct point of time (Flach 2012). *Dynamic changes* cause the system's state to be greater than the sum of its elements and solutions cannot be imposed but rather arise from the circumstances (Snowden & Boone 2007). Moreover, although each system possesses a "history" which is coherent in retrospect, hindsight does not necessarily lead to foresight in a complex system. This is because conditions constantly change and equal initial conditions will not necessarily result in equal end states (Snowden & Boone 2007). A complex system will rarely return to the exact state again and history will not repeat itself exactly in the same way.

With respect to the dynamic nature of a complex system, the collective property of elements in terms of *emergence* has been mentioned by various authors (Mikulecky 2001; Grisogono 2006; Urry 2006; Snowden & Boone 2007; Grauwin et al. 2012). There is some disagreement in literature about the exact meaning of this property. Basically, two definitions can be distinguished. Firstly, emergence may refer to the appearance of phenomena that arise from an interaction of individual elements. These phenomena are not apparent when studying a single element but only emerge when one studies the system as a whole (e.g. movements of swarms of fish) (Grisogono 2006). Secondly, emergence is the discovery, appearance, or occurrence of previously unknown properties, patterns or events over time (so-called *dynamic emergence*) (Mikulecky 2001; Grisogono 2006; Cavallo 2010). In this regard, a specific property of emergence is the so-called *self-organized criticality* (e.g. Bak et al. 1987; Bak 1990). This property implies that a system naturally moves towards critical states or tipping points without any special interference. Such a movement is repeated sequentially and the system thus moves sooner or later towards another unstable state. Over the course of time, self-organized criticality has been proposed to be present in a wide range of systems that have been denoted "complex" such as, inter alia, in earthquakes or turbulences in liquids (Bak 1990).

Irreducible uncertainty

It is difficult to draw a perfect picture of the complex system's current state. As a result of the previously presented properties, a real-world complex system is typically subject to irreducible uncertainty because of occurring unforeseeable "*unknown unknowns*" (Snowden & Boone 2007). As opposed to "known unknowns" which typically characterize a complicated system (see section 2.2.1) and which can be handled by sufficient analyses, "unknown unknowns" cannot be reduced or incorporated into the choice of strategy (Snowden & Boone 2007). This is because the level of uncertainty itself is not known or it is not possible to be aware of its existence at all. Moreover, there remains a possible source for unanticipated large impact events in terms of so-called *Black Swan* events. Such events lie outside the realm of regular expectation because nothing in the past can convincingly point to their possibility. Furthermore, they carry extreme impacts (Taleb 2007; Johnson 2013). In some cases, a disaster can be a Black Swan event where the caused situation is characterized as *unpredictable* and not at all *controllable* (Johnson 2013) (see chapter 3).

With respect to irreducible uncertainty, the *Butterfly Effect*[6] has been described as an additional property of complex systems. The property highlights the importance of past events for the system's current and future states and goes back to the work of the meteorologist Edward Lorenz in 1963. He discovered that small variations in the initial conditions of a system can create immensely different outcomes in the long run (Lorenz 1963). The term Butterfly Effect is a metaphor for a butterfly flapping its wings at one place and causing a large disturbance at some time in the future and in a completely different place. An example is a weather event that is caused in the atmosphere and that triggers a hurricane in the long run. Butterfly Effects are, thus, associated with the sensitivity to initial conditions (Schmidt 2011).

[6] This property has been also described in "chaos theory" which underlines the blurred boundary between complex and chaotic systems.

2.2.3 The decision-making process under complexity

Grisogono (2006) outlines five restrictions that must be respected when making a decision in a complex system. The restrictions are compliant to the considerations of further authors of the field of complexity science (e.g. Snowden & Boone 2007; Helbing & Lämmer 2008). First, complex systems are faced with networked causalities which lead to the unavailability of cause-effect relations. This implies that making a decision in a complex system might trigger varying consequences (in terms of outcomes). In this regard Cavallo (2010) underlines the irreversibility of a complex system: an early system state cannot return to an earlier state by retracing the processes that led to the current state. Second, a large number of alternatives might exist when making a decision. Therefore, generating one best alternative in a reasonable amount of time is challenging. Third, the complex system's behavior is coherent. This implies, fourth, that recurring patterns and trends in the complex system are not fixed. Something that worked yesterday may not do so tomorrow. Fifth, predictability is limited and it is difficult to precisely determine all consequences (in terms of outcomes) of a given alternative (Grisogono 2006).

According to the second and fifth restrictions, there might be the absence of an alternative that provides a "global optimum" (best state) of the complex system. Decision-making must rather choose between different alternatives leading to "local optima" (frustrated states) (Helbing & Lämmer 2008). A selected alternative might not realize the best state but just improve the ability of dealing with the complex system. Hence, it is difficult to control a complex system by deciding which alternative is the most beneficial one. The selection of an alternative requires knowledge about the future state of the complex system given the assumption that a specific alternative was taken as action. Thus, decision-making is confronted with the challenge of forecasting hypothetic situations. Limitations in facilitating such forecasts lead to a hindered ability of making good decisions. In conclusion, decision-making needs to move from deterministic and reductionist approaches to more adaptive and holistic ways (Snowden & Boone 2007; Ramalingam et al. 2008; Cavallo 2010).

Snowden & Boone (2007) propose a decision-making process that follows the rationale of *pattern-based management*. The term originates from information sciences where patterns are concise representations of data that are rich in semantics (Maddalena 2005). They result from the application of techniques of data reduction to produce knowledge artifacts (e.g. clusters or rules) such as data mining, pattern recognition, and knowledge extraction (Maddalena 2005). When addressing the field of model-based decision analysis, pattern-based management is defined as the opposite of *fact-based management* (Snowden & Boone 2007). Rather than conducting different analyses, pattern-based management requests for a three step process of probing, sensing, and responding. Probing in a complex system is important to observe emergent patterns by creating environments or experiments that encourage interactions between the system's elements and that facilitate instructive patterns to emerge rather than looking for facts (Snowden & Boone 2007). According to Gartner (2008), pattern-based management comprises the three pillars *pattern seeking* to explore in new ways and beyond traditional places, *pattern modelling* to analyze identified patterns, and *pattern adapting* to capture the benefits. These steps should be interconnected in a cyclical manner (see Figure 2-3).

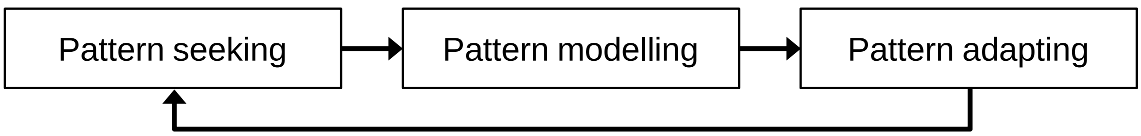


Figure 2-3: Process of pattern-based management

Hence, the decision-making process under complexity must include elements of interaction, communication, and reflection of decision-makers. Falling back into a command-and-control management should be avoided (Snowden & Boone 2007). Creative and innovative approaches are required to explore the potential of "unknown unknowns". However, the human mind is insufficiently equipped to store and process all the information necessary to forecast the complex system's future behavior. Computable models of the complex system are helpful to cope with unstable behaviors and emergent patterns (Hooker 2011). The complex system itself must therefore be quantified, data must be accessible, and processes must be representable by a computable algorithm (Cavallo 2010; Schmidt 2011).

2.3 Decision support systems

Predicting consequences (in terms of outcomes) of alternatives is difficult in a decision situation that is affected by uncertainty (risk, ignorance) and/or complexity (Vahidov & Kersten 2004). The need for computable models to assist decision-makers arises (Hooker 2011). In this regard, research of *decision support systems* (DSS) has considerably intensified in recent years (Burstein & Holsapple 2008). The following sections define DSSs, highlight their basic components, and provide an overview of types of DSSs.

2.3.1 Characteristics of decision support systems

A DSS is defined as a computer technology solution that supports decision-makers in solving a decision problem (Shim et al. 2002). Holsapple (2008) states that a DSS is a computer-based system that represents and processes knowledge in a way that allows the decision-making process to be more productive, agile, innovative, and reputable. Mattiussi (2012) defines a DSS as a software-based tool that assists the decision-making process by interacting with decision-makers and databases while implementing standardized or specific algorithms to solve the decision problem. The quality of decisions received by applying a DSS should be higher than without. Nevertheless, the objective of a DSS is to aid decision-makers within the decision-making process rather than replacing it (Er 1988). Making and implementing a decision is still the task of the decision-makers.

An early approach to characterizing DSSs is provided by Blanning (1979). The author suggests that a DSS must perform at least one of these tasks: data selection, data aggregation, parameter estimation in a probability distribution, simulation of decisions, equalization of decisions, or optimization of decisions. Many DSSs process more than one task. It is, thus, important to define the tasks a specific DSS should process and to map the relationships between these tasks and the responsibility of decision-makers who implement the DSS (Blanning 1979).

Shim et al. (2002) highlight three components a DSS should consist of. This is firstly a sophisticated *data management* capability with access to internal and external data, information, and knowledge ("a database"). The second component concentrates on *model management* to steer modeling functions ("a model"). Thirdly, a DSS should integrate powerful *dialogue management* that facilitates interactive queries, reporting, and graphing functions ("a user interface"). The interplay of these components improves the effectiveness of decision support. As highlighted in Figure 2-4, the three components must operate in an environment of factors which might influence them. As many factors as possible should be taken into consideration because a segmented approach cannot provide an understanding of the relationships between a system and the DSS environment (Pearson & Shim 1995). This consideration should be the task of the *DSS development process* (Pearson & Shim 1995). The DSS development process must respect three aspects (Gachet 2003). Firstly, the development time should be as short as possible. Secondly, a DSS should have a high pre-customization. This implies that it should be tailored for a specific decision situation including the underlying decision problem, decision environment, and decision-makers. Thirdly, the DSS must be characterized by a high customizability so that it can be adjusted to a changing decision environment.

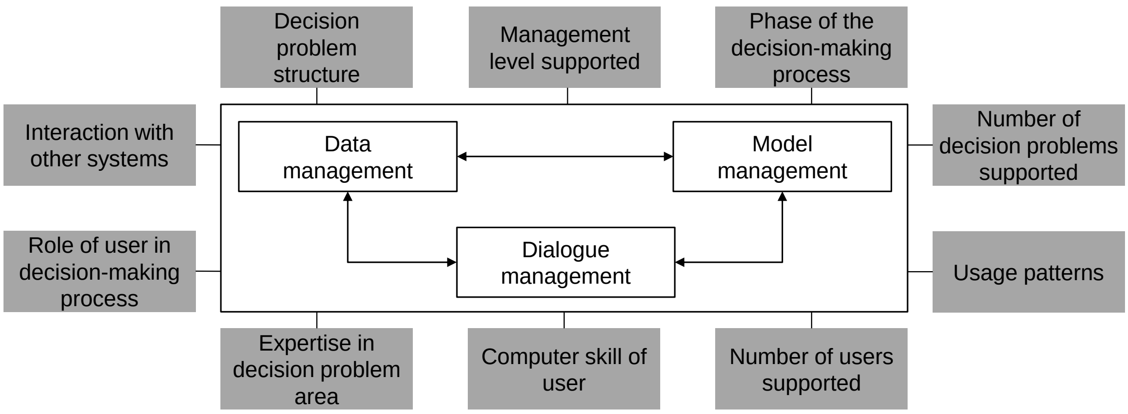


Figure 2-4: Environment of a decision support system (Pearson & Shim 1995)

Decision-makers never had more access to decision-relevant information than today (e.g. "big data"). This information access is not always beneficial as causing the pre-decision (before starting the actual decision-making process) of what information is useful to deal with the decision situation (Djamasbi 2007). Particularly in decision situations where speed is a crucial factor (e.g. in disaster management, see chapter 3), decision-makers are forced to make decisions under tremendous time pressure by just receiving a narrow window of time where they must test/check a number of alternatives. A DSS is targeted at structuring information to reduce uncertainty and complexity of the decision situation (Sojda 2007). Instead of necessarily providing a perfect solution for the decision-makers, a DSS rather aims at obtaining a good solution in an acceptable amount of time. Moreover, a DSS must complement the ability and expertise of the decision-makers by providing information in an efficient manner to guide decision-makers towards their objectives (Hall 2008). Although technological advances allow a DSS to become more proactive and autonomous, support still depends on the decision-makers who use it (Hall 2008).

2.3.2 Types of decision support systems

DSSs have been developed in various directions so that one cannot talk about a homogenous field of application or research. Many different branches have emerged with specific characteristics and tools. According to Arnott & Pervan (2008), seven sub-fields of DSSs can be distinguished: personal decision support systems (PDSS), group support systems (GSS), negotiation support systems (NSS), intelligent decision support systems (IDSS), knowledge management-based decision support systems (KMDSS), data warehousing (DW), and enterprise reporting and analysis systems. PDSS and GSS differ in the number of users applying the DSS: while GSS are used by groups, PDSS are developed for single decision-makers. The objective of an NSS is to assist decision-makers in negotiation situations. An IDSS focuses on artificial intelligence techniques to solve decision problems. Both, a KMDSS and a DW provide a data infrastructure for decision support. In addition, KMDSSs ensure access to organizational and individual knowledge to support the decision-making process. Enterprise reporting and analysis systems mostly assist the top-management level of organizations by delivering a tailored amount of information (Arnott & Pervan 2008).

A further possibility to classify DSSs is provided by Power (2008) and referenced by further authors dealing with DSSs such as Mattiussi (2012). In fact, DSSs are differentiated by their function which implies five types of DSSs. They are summarized in the following based on the considerations of Power (2008). *Model-driven DSSs* use quantitative models such as optimization or simulation models to analyze a decision situation. They are rather based on limited data and parameters provided by the decision-makers while a large data base is not required to operate a model-driven DSS. The management of such large databases is the scope of *data-driven DSSs* to process internal, external, and real-time data. Examples of data-driven DSSs are data warehouses and file systems. Network and communication technology are dominant architectural components in *communication-driven DSSs* (e.g. groupware, video conferencing). Their major objective is to facilitate decision-relevant collaboration and communication (Power 2008). *Document-driven DSSs* refer to computer storage and processing technologies to provide document retrieval and analysis. An example of a document-driven DSS is a database that includes, inter alia, scanned documents, images, or videos. *Knowledge-driven DSSs* recommend actions to decision-makers. They are typically person-computer systems that are characterized by a specialized problem-solving expertise in terms of knowledge about a decision problem, skills of understanding a decision problem and/or skills of solving a decision problem. The highlighted types of DSSs might overlap to a certain degree.

2.4 Summary

Chapter 2 provided the methodological background of this research. Section 2.1 introduced the field of decision situations under uncertainty by presenting definitions and classifications of as well as concepts to deal with uncertainty. The relevance of scenario-based approaches to handle decision situations under risk and ignorance has been discussed from the two perspectives of decision theory and mathematical programming. Decision rules are measures to operationalize the evaluation of alternatives as tasks of the decision-making process. Scenario-based optimization models formulate objective and constraint functions to solve a decision problem. The advantage of both measures is that they bring a high analytic accuracy into the decision-making process. Section 2.2 focused on the field of decision situations under complexity. The section highlighted the fact that complex systems are not uniformly defined in literature and provided a substantial list of possible properties. It became obvious that the decision-making process under complexity requests for handling these properties using innovative approaches. These must be especially able to capture the dynamic behavior and the irreducible uncertainty of elements that are interacting within a complex system. Hence, the need for DSSs arises to aid decision-makers in decision situations under uncertainty and/or complexity. Therefore, section 2.3 outlined the field of DSSs by presenting key components and types.

The focus of this research contribution is on *disaster-caused* decision situations (see chapter 3). Assigning an occurring decision situation unambiguously to one of the categories of decision situations provided in this chapter – risk, ignorance, or complexity – is hard to achieve from a practical viewpoint. In fact, it might be possible that elements of the decision situation refer to different categories. For example, historical data from similar past events (e.g. distributional information) might be available to handle several elements (in the sense of risk). The behavior of further elements might be unknown (in the sense of ignorance), interrelated, or dynamically changing (in the sense of complexity). As opposed to decision situations under ignorance, dynamic developments lead to an incomplete set of alternatives available in a decision situation under complexity. This is, however, an assumption that the highlighted analytical approaches (from the fields of decision theory and mathematical programming) operationalizing the decision-making process are functioning well.

This research develops a DSS that integrates an interdisciplinary scenario-based methodology by combining approaches from both fields. Thereby, the objective is to take into consideration uncertainty in terms of risk and ignorance as well as dynamic developments in the decision environment characterizing a decision situation under complexity.

3 Decision support for supply chain crisis management

A *disaster* is defined as a large-scale event that threatens public safety of a community or society (Oloruntoba & Gray 2006; Kovács & Tatham 2009; Tandler & Essig 2013). Apart from the direct impacts of a disaster, it might disturb the functioning of all *supply chains* (SCs) operating in the affected community or society (Natarajarathinam et al. 2009). This chapter provides the conceptual background of the research by discussing implications of decision support to aid decision-makers in managing disaster-caused SC disturbances. Thereby, the focus is on SCs whose functioning is essential to guarantee public safety. Those are SCs that refer to any *critical infrastructure* (CI) as being responsible for the supply of food, water, health care, and energy. In section 3.1, definitions are given from the perspectives of *supply chain management* (SCM) and disaster research. Subsequently, general directives and concepts of SCM in the context of disasters are outlined in section 3.2. When the focus is on the reactive decision-making in the aftermath of a disaster, *supply chain crisis management* (SCCM) (as a subdivision of SCM) bears responsibility to protect public safety. Therefore, section 3.3 outlines the rationale of decision-making in SCCM and reviews existing decision support approaches in literature to determine the research objectives of the subsequent analysis.

3.1 Definitions

This section provides definitions from the fields of logistics/SCM and disaster research. Those terms are unambiguously used in literature and they provide the notational basis for section 3.2 where the directives of SCM in disaster situations are outlined.

3.1.1 Logistics and supply chain management

The Council of Logistics Management (CLM) defines *logistics* as the "process of planning, implementing, and controlling the efficient, cost-effective flow and storage of raw-material, in-process inventory, finished goods, and related information from point of origin to point of consumption for the purpose of conforming to customer requirements" (Cooper et al. 1997; Pfohl 2010). Logistical operations ensure that the right supplies (e.g. trade goods, services) are delivered in the right quantities with the right qualities to the right locations at the right time (Beamon & Balcik 2008; Pfohl 2010; Bowersox et al. 2012). Supplies are managed by a network of different entities (e.g. organizations, plants) and functional stages (see below) (Sheperd & Günter 2006; Beamon & Balcik 2008). This network, stretched from the points of origin to the points of consumption, and its included entities and functional stages, is denoted the *supply chain* (SC).

Supply chain management (SCM) considers multi-relationships across a possibly large number of involved entities and integrated value-added processes of an SC (Christopher, 2011). Each entity refers to a specific functional stage in the SC regarding the categories suppliers (e.g. raw material supplier; general: tier n to tier 1 supplier), manufacturers, customers (e.g. wholesalers; general: tier 1 to tier n customers), and end customers. From the perspective of a specific entity, functional stages are either located in the upstream (supply side) or in the downstream (demand side) (Arnold et al. 2008; Pfohl 2010; Christopher 2011).

Different flows are involved in an SC and need to be coordinated by SCM. Beside *physical flows* organizing the spatial-temporal transformation of goods, there are *information flows* to manage physical flows, and *financial flows* such as credits, payment schedules, and consignment arrangements (Kleindorfer & Van Wassenhove 2004; Van Wassenhove 2006). Information flows proceed in the opposite direction to physical flows and have become a crucial challenge for SCM, particularly because of an increased global interconnectedness of entities. Information and communication technology (ICT) systems to gather and process information have become an essential element of SCM to manage physical flows and logistical operations systematically within an entity or across entities (Arnold et al. 2008).

Logistics systems can be classified by the phases that become relevant for an entity. *Procurement logistics* refers to the entity's upstream activities of acquiring goods (e.g. raw material, semi-finished goods). *Production logistics* is located inside an entity to manage the stream of goods from procurement warehouses (e.g. raw material) to production processes, the interim storage of goods (e.g. semi-finished goods), and the stream of produced goods to distribution warehouses (e.g. finished goods). *Distribution logistics* comprises downstream activities to provide customers with produced goods. *Sales logistics* handles downstream transactions (e.g. demand forecasts). It is not mandatory that an entity operates in all logistics systems. While a trading company just disregards production logistics, a service company exclusively focusses on procurement logistics (e.g. the provision of working materials) (Arnold et al. 2008; Pfohl 2010).

Logistical decision problems (planning tasks) that arise in SCM can be classified depending on the logistics system and planning horizon or management level they refer to (Günther & Tempelmeier 2011). Strategic decisions are concerned with the design of an SC and have a long-term focus, tactical decisions concentrate on the planning of the SC network with a mid-term focus, and operational decisions deal with the execution of logistical operations with a short-term focus (Hertel et al. 2011). An overview of logistical decision problems is provided by the *SC planning matrix* in Table 3-1 (Rohde et al. 2000; Fleischmann et al. 2004; Kannegiesser 2008).

Table 3-1: Supply chain planning matrix

	Strategic decisions	Tactical decisions	Operational decisions
Procurement logistics	- material programme - supplier selection - cooperation	- personnel planning - material requirements planning - contracts	- personnel planning - ordering materials
Production logistics	- plant location - production system	- master production scheduling - capacity planning	- lot-sizing - machine scheduling - shop floor control
Distribution logistics	- physical distribution planning	- distribution planning	- warehouse replenishment - transport planning
Sales logistics	- product programme - strategic sales planning	- mid-term sales planning	- short-term sales planning

3.1.2 Terminologies of disaster research

Disaster research is intuitively associated with the anticipation that something “bad” happens. The potential or the actual occurrence of such an event is implied by the term *hazard* which is defined as a “threatening event or probability of occurrence of a potentially damaging phenomenon within a given time period and area” (IFRC 2015). A hazard can be caused by a force, a physical condition or an agent; possible consequences might be injury and death of affected people, damage to property, the environment, CI, agriculture, and disturbances of business operations (DHS 2010; ICDRM/GWU 2010). Hazards can be classified by *natural hazards* and *man-made hazards*. Causes of natural hazards are natural or physical phenomena (e.g. geophysical, hydrological, climatological, biological) that trigger a rapid or slow onset event (IFRC 2015). Man-made hazards are caused by humans (e.g. terrorism, war, industrial, nuclear or transportation accidents) (Bournay 2005; ICDRM/GWU 2010; IFRC 2015).

Further classifications of hazards can be found in literature. For instance, man-made hazards are frequently split into technological and intentional hazards (ICDRM/GWU 2010; Kõlves et al. 2013). Technological hazards are produced by man-made technology or unplanned and non-malicious actions; intentional hazards are created by threatened or executed actions with the intention to harm people or organizations (ICDRM/GWU 2010). With respect to the summary provided by Merz (2011), natural hazards can be classified by (classic) natural hazards (e.g. tectonic or climatic events) and socio-natural hazards (e.g. events caused by the climate change). As opposed to technological and intentional hazards, natural hazards are not avoidable in advance as they are not man-made. Their occurrence is, thus, to a certain degree random in terms of aleatory uncertainty (see chapter 2) (Schenker-Wicki et al. 2010).

Hazard is one element that is required to operationalize the decision theoretic definition of risk (as it has been outlined in chapter 2) for disaster research. Basically, *risk* aims at preventively indicating and assessing if and to what extent a hazard may occur and threaten a system (Hamani & Boudjema 2013). It refers to the product of the occurrence probability of a hazard and its possible impact (Bertsch 2008; ICDRM/GWU 2010; Comes 2011).

The occurrence probability is typically captured by the historical frequency of an occurring hazard in the past where it affected a specific region at a specific time with a specific intensity (Bogardi & Birkmann 2004; Villagrán de León 2006; Merz 2011). Potential consequences depend on a system's *vulnerability* which indicates its sensitivity when it is hit by a hazard (Tobin & Montz 1997; Gall 2007; Merz 2011). Hence, risk can be understood as a function of the two elements hazard and vulnerability (UNDP 2004). There is abundant literature discussing definitions and features of the term vulnerability. This research contribution refers to the definition of vulnerability as a "characteristic of design, location, security posture, operation, or any combination thereof, that renders an asset, system, network, or entity susceptible to disruption, destruction, or exploitation" (DHS 2010; ICDRM/GWU 2010). A brief example highlights the importance of vulnerability on the determined degree of risk: a weak earthquake in a metropolitan area may rather lead to severe consequences than a strong earthquake in an uninhabited city. This is because the metropolitan area is more vulnerable to earthquakes than the uninhabited place (Schenker-Wicki et al. 2010).

Further extensions of the quantitative risk formulation have been proposed in literature. They respect additional aspects such as *exposure*, *elements at risk*, *coping capacity*, or *resilience* (Crichton 1999; Granger et al. 1999; Villegas et al. 2006; Bertsch 2008; Merz 2011). The quantitative risk definition does not neglect these aspects as they are implicitly contained within the term vulnerability (Merz 2011). Various authors rather suggest using the concept of risk to understand how a certain system behaves under scrutiny and interacts with its environment than as an instrument that just generates a certain number indicating "the risk" (Haimes et al. 2002; Comes 2011).

When actually occurring, a hazard can trigger a *disaster* which is defined as "a sudden, calamitous event that seriously disrupts the functioning of a community or society and causes human, material, and economic or environmental losses that exceed the community's or society's ability to cope using its own resources" (IFRC 2015). It is predominantly assumed in literature that a disaster is a large-scale hazardous event (Oloruntoba & Gray 2006; Kovács & Tatham 2009; Tandler & Essig 2013). A disaster can, thus, be understood as a combination of a hazard, vulnerability, and the insufficiency to preventively reduce potential negative consequences of risks (IFRC 2015). Normal conditions of the affected system are disturbed in this case which causes negative consequences on public safety that exceed the capacity of adjustment of the affected community or society (WHO/EHA 2002). The capacity comprises all strengths and resources (e.g. physical, institutional, social, economic, personal) that are available to reduce consequences of the disaster situation (UNISDR 2004b).

According to the definition and classification of hazard, literature distinguishes between *natural disasters* and *man-made disasters* (Natarajarathinam et al. 2009). Rutherford & de Boer (1982) even suggest various ways to classify disasters: the duration of development in the cause of disaster (e.g. short, relatively long, or long), the extent of the disaster area (e.g. radius [km]), the number of casualties (e.g. number of death or injured people), the pathology (e.g. type of injuries), and the time until aid is provided.

The welfare of a community or society and, therefore, public safety depends to a great extent on the well-functioning of SCs that are responsible for the supply of basic needs of the population. An occurring disaster might affect thousands of people's lives and all SCs that are included in the community or society (Natarajarathinam et al. 2009). Dysfunctional SCs are in particular then crucial for public safety when these SCs are part of the CI network. Definitions of CI have been primarily proposed by national governments and international institutions (Abou El Kalam et al. 2009). The European Commission defines CIs as "physical and information technology facilities, networks, services and assets which, if disrupted or destroyed, would have a serious impact on the health, safety, security, or economic well-being of citizens or the effective functioning of governments in the European Union (EU) countries" (European Commission 2004). The European Commission distinguishes between CI sectors of energy, ICT, finance, health care, food, water, transportation, production, storage and transport of dangerous goods, and government (European Commission 2004). National governments and international institutions support programs and activities for the protection of CI sectors (European Commission 2004; BMI 2011). This is because the frequency of disaster-caused CI disturbances has increased in recent years (Kleindorfer & Saad 2005; Helbing et al. 2006).

Although any CI sector is denoted a critical "infrastructure", several sectors are not "infrastructures" in the proper meaning of the word; rather, they are SCs that are responsible for the delivery of "essential products or services" (European Commission 2004). These SCs are denoted *public safety critical SCs* (P-SCs) in this research contribution. When P-SCs are disturbed (disrupted or destructed), the vital welfare of people in the affected community or society is threatened (Braubach 2011; Lin et al. 2011; Herlin & Pazirandeh 2012). P-SCs mainly arise within the CI sectors food, water, health care, and energy. Parts of a P-SC might be highly interconnected to parts of further CI sectors such as built assets (e.g. roads referring to the CI sector of transportation are required for distribution logistics of a food P-SC), ICT (e.g. as any P-SC is based on information flows) and social infrastructure (e.g. personnel to operate medical facilities). Moreover, a specific role is given to the CI sector energy. Although disturbances of energy SCs will not directly impact public safety, the supply of food, water, and health care SCs can only function when the provision of energy supplies is intact.

3.2 Supply chain management in the context of disasters

This research contribution focusses on disaster-caused disturbances of P-SCs. The concept of *disaster operations management* (DOM) provides assistance to handle (possible and actual) consequences of a disaster prior to (preventively) or in the aftermath (reactively) of its occurrence. In the following sections, general implications of managing SC disturbances are highlighted. Therefore, the interface of SCM and DOM is analyzed and SC strategies are provided that are beneficial to achieve an increased resistance against disturbances.

3.2.1 Management of supply chain disturbances

An SC disturbance implies a failed functioning of any of its entities. From the perspective of the SC, consequences might arise locally where just one entity is affected or globally where various entities of the SC are impacted simultaneously. In the latter case, the disturbance propagates through interrelated SC networks (Craighead et al. 2007; Ziegenbein 2007; Merz 2011). Natarajarathinam et al. (2009) introduce three dimensions of an SC disturbance: the disturbance of one entity of the SC, the disturbance of the SC as a whole, and the disturbance of varying SCs on a regional level. An SC disturbance is basically characterized by a (temporal) interruption of any flow within or across entities. This triggers a mismatch between supply and demand (Rice 2003; Jüttner et al. 2003; Knemeyer et al. 2009; Merz 2011). On the supply side, failures of suppliers in the upstream might cause a dissatisfaction of customer demands (e.g. problems in transportation and inventory, insufficient product qualities). A disturbance on the demand side leads to failures of customer processes in the downstream such as fluctuations in demand or instable sales prices (Zsidisin 2003; Tang 2006; Merz 2011; Srinivasan et al. 2011).

An SC disturbance might be caused by different sources. Natarajarathinam et al. (2009) distinguish between external and internal sources. *External sources* are located outside the SC and can be, inter alia, disasters, or market, economy, or political issues. *Internal sources* are located inside the SC and refer to employee-, criminal-, infrastructure-, IT-, or finance-related events. Sources might overlap across both categories; an exact assignment is frequently just possible ex-post (in the aftermath of the SC disturbance) (Natarajarathinam et al. 2009). SCM becomes relevant at two points in time to handle an SC disturbance. Firstly, SCM is required prior to the disturbance by developing preventive measures that mitigate risks caused by internal and external sources. Secondly, SCM must reactively handle consequences of an already occurring SC disturbance. Hence, two subdivisions of SCM must be respected: *supply chain risk management* (SCRM) in the forerun and *supply chain crisis management* (SCCM) in the aftermath of an SC disturbance.

Concepts of risk management include, in varying disciplines, different steps that are ordered in a cyclical manner. In a nutshell, the first step typically refers to measures of risk identification. Identified risks are quantified by risk assessment or risk analysis. Finally, risk mitigation treats, controls, and communicates the assessed risks. Back loops exist between all steps to continuously evaluate and update findings (Hölscher 1999; Rosenkranz & Missler-Behr 2005; Zsidisin & Ritchie 2008; DHS 2010; ICDRM/GWU 2010). Risk management aims at reducing risk, transferring responsibilities of risk, controlling risk to a rational level, or (temporarily) accepting risk (DHS 2010; ICDRM/GWU 2010). The objective of risk management can never be the total avoidance of all risks. This would require the elimination of either or both occurrence probabilities themselves or caused negative consequences which is, however, not possible. With respect to an SC disturbance, risk can be defined in an event-oriented manner. In fact, SCRM is described as the process of identifying triggering events of a possible SC disturbance and of assessing their occurrence probabilities (Heckmann et al. 2015). Depending on the classification of internal and external sources of an SC disturbance, internal SC risks and external SC risks can be distinguished. An additional category refers to network-related risks which concentrate on interactions of entities included within the SC (Jüttner et al. 2003; Natarajarathinam et al. 2009).

Whereas SCRM deals with the proactive handling of risks regarding an SC disturbance, the objective of SCCM is to reactively implement measures that mitigate consequences of an SC disturbance ex-post. A crisis is a situation that features severe threat, uncertainty, and sense of urgency. It is defined as the "turning point that leads to an unstable situation in which an abrupt or decisive change is imminent" (Rosenthal & Pijnenburg 1991; ICDRM/GWU 2010). An SC crisis arises "when one or more supply chain member's activities are interrupted, resulting in a major disruption of the normal flow of goods or services" (Natarajarathinam et al. 2009). In the following, SC disturbances are considered where the source of the crisis is external in terms of a natural or man-made disaster. When a crisis is caused by such a disaster, its handling requests for a change from routine management towards a management that explicitly takes into account strong uncertainty and complexity of the situation (ICDRM/GWU 2010).

The concept of *disaster operations management* (DOM) provides a framework for handling disasters in the forerun and aftermath of their occurrences. Disaster operations represent activities that are needed before, during, and after a disaster in order to diminish its impact (Altay & Green 2006; Galindo & Batta 2013). DOM is defined as the sequence of operations to prevent or to reduce negative consequences resulting from a disaster (Hoyos et al. 2015). It comprises the four phases mitigation, preparedness, response, and recovery (McLoughlin 1985; Altay & Green 2006; Natarajarathinam et al. 2009; Galindo & Batta 2013). Nomenclatures of these phases are not uniformly defined in literature. For example, Van Wassenhove (2012) substitutes the phase of preparedness with preparation and recovery with reconstruction; Crondstedt (2003) uses the term of prevention instead of mitigation. However, implications of the four phases are the same across authors: while mitigation and preparedness refer to preventive measures, response and recovery focus on the reactive handling of a disaster in its aftermath. In combination with the distinction of SCRM and SCCM as highlighted above, SCRM focusses on mitigation and preparedness while SCCM operationalizes response and recovery in the case of a disaster-caused SC disturbance (see Figure 3-1) (Natarajarathinam et al. 2009).

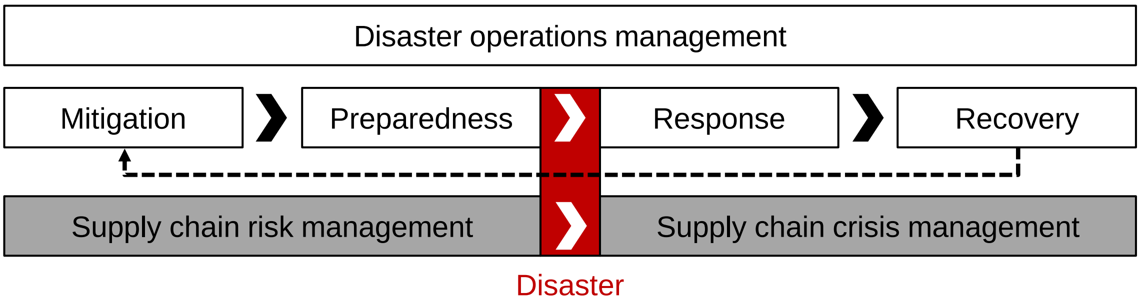


Figure 3-1: Phases and concepts to manage a disaster-caused supply chain disturbance

In the *mitigation* phase, the focus of SCRM is on the identification and assessment of possible (external) risks. The objective is to develop measures that help to reduce and/or eliminate the identified risks (Natarajarathinam et al. 2009). So-called "soft" measures are important such as the analysis of lessons learned from experiences of past disasters. This is important to create safer SCs in future (ICDRM/GWU 2010; Kumar & Havey 2013). A disaster can be already impending in the *preparedness* phase. SCRM must therefore prepare measures that can be conducted in the immediate aftermath of the disaster's occurrence, the response phase (NFPA 2004; Van Wassenhove 2012). Specific preparedness measures refer to, inter alia, the resourcing of capabilities and capacities (e.g. pre-positioned resources) or the development and setting up of ICT systems and business continuity plans (DHS 2010; ICDRM/GWU 2010; Van Wassenhove 2012; Kumar & Havey 2013). An important measure of SCCM in the *response* phase is the conduction of an immediate impact analysis. Based on the results of this analysis, measures that have been developed by SCRM can be adapted and applied quickly (Natarajarathinam et al. 2009; ICDRM/GWU 2010; Caymaz et al. 2013). The *recovery* phase specifies measures to re-establish the former situation (Rosenthal & Pijnenburg 1991). The focus of SCCM is thereby the long-term reparation and restoration of the disturbed SC to regain pre-disaster conditions (Natarajarathinam et al. 2009; ICDRM/GWU 2010).

3.2.2 Strategies for supply chain disturbances

To create SCs that are able to withstand disturbances, at least to a certain degree, various strategies have been proposed in literature. Although these strategies are inconsistently interpreted among authors (Klibi et al., 2010), they basically aim at protecting an SC from negative consequences of an SC disturbance (Husdal 2010). In the following, the three major strategies of *robustness*, *flexibility*, and *resilience* are briefly introduced.

The term *robustness* has been defined in different fields of research (Bundschuh et al., 2006; Qiang et al., 2009). In SCM, the strategy of robustness addresses the ability of an SC to withstand internal or external shocks (Snyder 2003; Wallace & Choi 2011; Vlajic et al. 2012). It is defined as an "SC configuration that provides an attractive outcome while considering many sources of uncertainty" (Mo & Harrison 2005; Vlajic et al. 2012). The level of robustness is determined by the weakest entity of the SC (Kleindorfer & Saad 2005). Most authors underline the feature of a robust SC to perform in a stable manner despite uncertain conditions of its environment (Rice 2003). Robustness measurement is typically based on key outcome indicators such as, inter alia, cost, service level, or lead time. Stable values of these key outcome indicators confirm robustness (Vlajic et al. 2012). One prominent measure to design a robust SC is to embed redundancies into the SC. Redundancies are reserves or back-up options (e.g. multiple sourcing, large inventory stocks) to continue logistical operations while managing an SC disturbance (e.g. large inventory stocks) (Sheffi 2005; Stewart et al. 2009; Charles et al. 2010; Klibi et al. 2010) As stated by Sheffi (2005), however, redundancies just provide some "breathing room" for the SC during a disturbance, are an expensive measure (e.g. cost of additional stocks), and therefore only temporarily useful.

The strategy of *flexibility* describes the ability of an SC to manage changes in its environment (Correa 1994; De Toni & Tonchia 2005; Wallace & Choi 2011). SC flexibility is defined as "the possibility to react to disturbances with few consequences in time, effort, cost, or outcome" (De Toni & Tonchia 2005; Charles et al. 2010). The strategy may address any logistics system (procurement, production, distribution, and sales flexibility) which takes into account varying outcome measures (e.g. quality, product, cost, and service flexibility) (Slack 1992; De Toni & Tonchia 2005; Charles et al. 2010). Beamon & Balcik (2008) distinguish between range flexibility and response flexibility. The former specifies to what extent logistical operations can be changed; the latter considers losses in time and cost that go along with these changes. Furthermore, state flexibility and action flexibility can be differentiated (Mandelbaum 1978; De Toni & Tonchia 2005). State flexibility is the ability of the SC to remain working despite changes. The objective is to maintain a stable functioning of the SC. Action flexibility refers to the ability of taking action during changes.

Adaptability is the feature of a flexible SC to manage medium- or long-term disturbances (e.g. for several months) (Sheffi 2004; Charles et al. 2010; Gatignon et al. 2010). An adaptable SC is able to "meet structural shifts in markets [and to] modify SC strategies, products and technologies" (Lee 2004). In turn, *agility* is the feature of a flexible SC to respond quickly and smoothly to short-term disturbances (e.g. for several hours, days, or weeks) (Lee 2004). An agile SC is able to "thrive and prosper in an environment of constant and unpredictable change" (Maskell 2001; Sheffi 2004; Oloruntoba & Gray 2006; Van Wassenhove 2012).

The term *resilience* has been defined multidisciplinarily (Bhamra et al., 2011). Its conception originates from material sciences where a resilient material recovers its original shape after a deformation (Sheffi 2005). Transferred to SCM, the strategy of resilience implies the ability of an SC "to return to its original state or move to a new, more desirable state after being disturbed" (Christopher & Peck, 2004). A resilient SC is able to recover from a large disturbance (e.g. long-term, severe consequences) (Sheffi 2005). To establish a resilient SC, two capabilities are required: the SC must firstly be robust and secondly be flexible in terms of adaptability (Rice 2003; Sheffi 2005; Charles et al. 2010; Vlajic et al. 2012).

In summary, robustness is the ability of a disturbed SC to quickly regain stability, flexibility is the ability to appropriately react to an SC disturbance, and resilience is the ability to survive an SC disturbance (Husdal 2010). From a comprehensive perspective, flexibility and resilience can be understood as specific features of robustness itself (Scholl 2001). In fact, flexibility describes the short-term, resilience the long-term feature of a robust SC. The distinction between the strategies lies in the detail: a robust SC endures a disturbance without severe impacts because of existing redundancies (Ku 1995; Husdal 2004); a flexible (agile, adaptable) SC accommodates a disturbance by modifying courses or targets which requires the willingness of SCM to change tracks and being open to deviation from the initial course (Husdal 2004; Husdal 2009); a resilient SC even survives a large-scale disturbance and is able to return to the original state or to move towards a new desirable state over time (Husdal 2008; Husdal 2009).

3.3 Decision-making in supply chain crisis management

The scope of this research contribution is on the reactive management of disaster-caused P-SC disturbances. SCCM must therefore process varying logistical decision problems (see section 3.1.1) to quickly help affected P-SCs to recover from the shock by handling arising uncertainty and complexity of the decision situation. The following section discusses uncertain and complex properties that might characterize a disaster situation. Subsequently, the scope of decision-making in SCCM is outlined. The section closes with a literature review regarding existing concepts and approaches of decision support in disaster-caused decision situations.

3.3.1 Uncertain and complex properties of disaster situations

SCM is basically confronted with inherent and exogenous uncertainty. *Inherent uncertainty* is embedded into any SC (e.g. P-SCs). This is because the SC is characterized by interrelations of entities and functional stages which requires the management of multiple information flows (van der Vorst & Beulens 2002). Triggers of inherent uncertainty are, inter alia, unclear or non-communicated objectives of entities, non-existing control actions, or the unpredictability of consequences of available control action alternatives. To handle inherent uncertainty, SC strategies must be modified such as the configuration of the SC (van der Vorst & Beulens 2002). *Exogenous uncertainty* is related to external sources of SC disturbances such as changes in markets, products, or technology (van der Vorst & Beulens 2002). According to Sowinski (2003), exogenous uncertainty is particularly crucial when it is caused by a disaster whose occurrence is rare and random. It is difficult to predict when and where it will happen and who will be affected. This highlights the criticality of a disaster-caused SC disturbance: while inherent uncertainty is predictable to a certain degree (e.g. fluctuations on the demand or supply side of an SC follow roughly regular patterns of occurrence), exogenous uncertainty is associated with strong uncertainty and unpredictability (van der Vorst & Beulens 2002; Charles et al. 2010).

The criticality of exogenous uncertainty for disaster-caused decision-making in SCCM to manage P-SC disturbances has been addressed by various authors in the past few years (de la Torre et al. 2012; Das & Hanaoka 2013; Liberatore et al. 2013; Rennemo et al. 2014). Exogenous uncertainty is basically associated with indefinite consequences of the disaster (Liberatore et al. 2013). Sparse or lacking information (e.g. regarding the state of the environment) causes unknowingness about the behavior of the demand side and the supply side of a P-SC. On the demand side, exogenous uncertainty results in unknown spatial demand distributions (e.g. demand locations in remote areas) or demand mixes and volumes (e.g. product specifications and quantities) (de la Torre et al. 2012; Rennemo et al. 2014). On the supply side, exogenous uncertainty refers to indefinite logistical operations of procurement and distribution, e.g. delays of supplies or increased product prices due to product scarcities or non-available suppliers (de la Torre et al. 2012; Liberatore et al. 2013).

The higher the degree of exogenous uncertainty, the more difficult it is to predict the consequences on CI sectors (Liberatore et al. 2013). In particular cascading effects are crucial in this regard as interdependencies between CI sectors do not often become obvious before a certain CI sector is disturbed. In recent years, indirect consequences of disasters have increased (Kleindorfer & Saad 2005). While in the past, the impact of a disaster occurred mostly locally, it might now propagate through highly interconnected CI sectors (Rinaldi et al. 2001). For example, the functioning of P-SCs especially depends on the intactness of the CI sector of transportation (de la Torre et al. 2012; Liberatore et al. 2013; Rennemo et al. 2014). Transportation infrastructures comprise all nodes and edges in the transportation network (e.g. roads, railroads, airports, ports) as well as all transportation modes of public and economic mass transits and long-distance traffic (Fletcher 2002; European Commission 2004). Exogenous uncertainty implies unclear states and conditions of any part of this infrastructure (Hamedi et al., 2012). As most logistical operations within and across P-SCs depend on functioning transportation infrastructures, their states in a disaster situation determine to a significant degree how robust, flexible, or resilient P-SCs can be (Madhusudan & Ganapathy 2011).

Cascades of consequences are prominent: while the disaster causes an increase in demands for public safety critical supplies, P-SCs may be hampered by direct and indirect impacts that result from the impairment of physical and information flows or by damaged interrelated CI sectors (Merz 2011). Consequences of a disaster on P-SCs are, thus, hard to predict (The World Bank 2010). To increase predictability in a disaster situation, ICT systems (as a CI sector itself) are needed to provide the right information in the right format at the right time to the right people (e.g. decision-makers) (Fletcher 2002). From the IT perspective, ICT systems gather, synthesize, and interpret information; from the communication perspective, ICT systems transmit this information to responsible persons (e.g. decision-makers) (Leidner et al., 2009). It is expected that information in a disaster situation, if available, is heterogeneous in terms of format, quality, and quantity (Comes et al. 2011). ICT systems must prepare information arising from multiple sources by filtering and structuring valid information and communicating this information to decision-makers (Turoff et al. 2009).

Sparse or lacking information triggers a lack of knowledge about the current state of the environment, developments of this state, and cause-effect chains (Helbing et al. 2006). Disasters are characterized by uncertain and unpredictable surroundings (e.g. location, consequences) where logistical activities must be performed in rapidly changing environments (Natarajarathinam et al. 2009; Rennemo et al. 2014). Time pressure, particularly in the response phase, means that decisions have to be made near real time which forestalls the possibility of further investigations or waiting until more or better information is available. This challenge is also amplified by dynamic developments of the environment in the disaster-affected community or society. An example is the dynamic development of the socioeconomic behavior (e.g. population movements) that might trigger demand fluctuations over time and hamper demand estimations (de la Torre et al. 2012; Rennemo et al. 2014). Moreover, it is often unclear if the disaster's cause (e.g., a natural hazard) will be unique or if it will cause further replicas or secondary disasters (Hoyos et al. 2015).

In summary and with respect to the considerations of chapter 2, exogenous uncertainty might trigger a decision situation under ignorance which depends on the actual extent of available information in a disaster situation. Dynamic developments caused by cascading effects of P-SCs and CI sectors, socioeconomic changes, and secondary disasters might even complement such a decision situation by properties that evolve to a complex system (Prelipcean & Boscoianu 2011).

3.3.2 Scope of decision-making in supply chain crisis management

Managing disaster-caused P-SC disturbances might be the task of SCCM of both for-profit P-SCs and public P-SCs (Natarajarathinam et al. 2009). Organizations (e.g. food retail companies of the food sector) and public authorities (e.g. public hospitals of the health care sector) bear responsibility to protect public safety in the affected community or society. SCCM is in both cases forced to make reactive decisions in the aftermath of a disaster to ensure the intactness of public safety critical supplies. The following discusses the scope of decision-making in a disaster situation from two perspectives: decision-makers that refer to an internal entity of the disturbed P-SC and those that are located outside this P-SC.

Internal decision-makers are organizations and public authorities of the disturbed P-SC themselves. SCCM must implement measures that strengthen or restore their own disturbed business processes. Organizations are often buffeted by events that have not been registered as real possibilities prior to their occurrence and which might have a considerable impact on their fortunes (Feduzi & Runde 2014). However, as stated by Benoit (1997), an organization's survival during a disaster (triggered by any source) depends greatly on its speed of response. In recent years, organizations have increasingly strengthened their efforts in establishing departments of *business continuity management* (BCM)[7] (von Rössing 2005). BCM originates from disaster recovery planning (DRP). While several authors use the concepts of BCM and DRP synonymously (e.g. Watters & Watters 2014), further sources understand DRP as the part of BCM that concentrates on IT failures (e.g. Elliot et al. 2010). The major objective of BCM is to keep business processes within an organization alive while considering effects of an SC disturbance (Hiles & Barnes 2010). BCM can be understood as the subdivision of SCRM that explicitly concentrates on the development of measures to hedge against SC disturbances. Examples of preventive BCM measures are, inter alia, supplier audits, changes of the supplier strategy to multiple sourcing, and an increase in safety stocks (Naujoks

[7] Further information on BCM is provided in the case study in chapter 6.

2003; Zsidisin 2003). Despite its proactive scope, BCM also becomes relevant in SCCM. An example is the development of business continuity plans (for pre-defined cases) that are preventively developed by SCRM and reactively conducted by SCCM (BSI 2008).

External decision-makers are organizations and public authorities that are located outside the disturbed P-SC. They might be entities of further P-SCs or of SCs of other branches, or (independent) public authorities. In difference to organizations of the private sector, public authorities are obliged to intervene due to their jurisdictions to ensure public safety. External decision-makers assume responsibility in the case that a P-SC disturbance (and therefore public safety) cannot be handled internally by the affected entities themselves. For example, further P-SCs of the same CI sector and whose functioning is still intact might overtake supply responsibilities of a disturbed P-SC. Alternatively, it might be possible that SCs of other branches make their own infrastructures accessible (e.g. warehouses) to establish logistical replacement structures. Coordinating the establishment of these structures might be additionally the task of public authorities. In this regard, *humanitarian logistics*[8] has become a prominent field where especially disaster-caused P-SC disturbances in terms of destruction are addressed. The objective of humanitarian logistics is to maintain the provision of public safety critical supplies to disaster-affected people (Van Wassenhove 2012). In humanitarian logistics, developed preventive measures of SCRM are essential for a successful reactive SCCM. This is particularly the case as logistical replacement structures must be established quickly to compensate the destructed P-SCs (Balcik & Beamon 2008).

Logistical decision problems that must be processed by SCCM of both internal and external decision-makers can principally arise on any management level. For example, a strategic decision might refer to the distribution structure of warehouse locations, a tactical decision might be the planning of personnel, and an operational decision might deal with modifications of transportation routes. In real-world disaster

[8] Further information on humanitarian logistics is provided in the case study in chapter 5.

situations, most common logistical decision problems focus on resource allocation which comprises all activities of locating resources (Hoyos et al. 2015). An overview of logistical decision problems in disaster response is provided by Rennemo et al. (2014). The authors highlight the importance of resource allocation problems, facility location and routing problems, vehicle routing and tour covering problems, network flow problems, and single commodity allocation problems.

Regardless of the type of decision-makers, a disturbed P-SC must be strengthened or replaced under the restriction that it functions under uncertain and complex conditions of the underlying environment. In this regard, the highlighted SC strategies in section 3.2.2 gain importance. In disaster response, decision-making must facilitate a robust and flexible provision of public safety critical supplies. This provision must be intact although the environment might still be affected by dynamic shifts. Therefore, robustness in the sense of state flexibility (see section 3.2.2) must be established to guarantee that P-SCs remain working despite changes (Mandelbaum 1978; De Toni & Tonchia 2005).

3.3.3 Literature review: decision support based on operations research and management sciences

The suitability of methods of *operations research* (OR) and *management sciences* (MS) to support decision-makers in SCCM and DOM has been widely discussed in literature. Altay & Green (2006) synthesize views of different OR-related communities (e.g. The Association of European Operational Research Societies (EURO) or the US counterpart of EURO, INFORMS) and define OR/MS as "a scientific approach to aid decision-making in complex systems". OR/MS methods refer to classical analytical techniques such as mathematical programming, simulation, and probability and statistics, but also to OR/MS related areas like decision theory, system dynamics, multi-criteria decision-making, and expert systems (Altay & Green 2006; Galindo & Batta 2013). As the importance of OR/MS methods for decision support across all phases of DOM (mitigation, preparedness, response, and recovery) and both subdivisions of SCM (SCRM and SCCM) has increased in recent years, various reviews/surveys focusing on the interface of both fields have been contributed. The large number of articles found by those reviews underlines the momentum that research in that topic has gained (Hoyos et al. 2015).

Altay & Green (2006) point out the increasing need for studying OR/MS issues in DOM. The authors investigate 109 peer-reviewed research articles. They do not explicitly address decision situations arising in SCM but provide a broad view on disaster research (e.g. including decisions of evacuation plans). Results of the review show that most articles use mathematical programming to support decision-making (30%), followed by probability and statistics (19%), simulation (11%), and decision theory and multi-attribute utility theory (MAUT) (10%). Articles mainly focus on the pre-disaster period (mitigation: 44%, preparedness: 21%, response: 24%, recovery: 11%). The authors use a classification scheme to distinguish between articles of theory, model, and application. Theory articles (27%) present reflections, frameworks, or principles about a specific area; models (58%) refer to articles that develop analytical models; applications (15%) embed models into an applicable product such as DSSs. Altay & Green (2006) outline major future research directions. The first refers to the specific conditions of disaster situations. Although good planning is important in such situations, some room for improvisation due to the unusual challenges should be left. A change from routine management is required to successfully provide decision support. This can be achieved by developing or combining interdisciplinary techniques that take into account the inherent structure of disaster situations where knowledge is incomplete and uncertainty cannot be easily resolved. Moreover, the authors conclude that most articles concentrate on external decision-makers (according to the distinction introduced in section 3.3.2). Therefore, future research must strengthen the focus on BCM (internal decision-makers) by considering company-level post-disaster logistical decision problems.

An extension of the contribution of Altay & Green (2006) is provided by Galindo & Batta (2013). The authors review 155 papers of OR/MS research in DOM. They refer to the classification scheme developed by Altay & Green (2006). Their results show that mathematical programming (33%) is still the most frequently applied methodology. Simulation (18%) and decision theory and MAUT (18%) remain relatively stable compared to the former review. A significant decrease can be observed regarding probability and statistics (6%). Research on the pre-disaster period is still the major scope of research. While between each 23% and 33% of research concentrates on mitigation, preparedness, and response, just 3% considers disaster recovery. Findings regarding the distinction of theory, model, and application confirm the trend shown by Altay & Green (2006): while about 76% of articles concentrate on models, the amount of application articles, including DSSs, is very small (5%). A significant change affects the considered type of disaster which is more generic (70%) compared to the previous review (38%). Authors recommend future research of application studies that provide tools for taking theoretical and analytical research into practice. They explicitly highlight the need for supporting decision-making in quick and efficient ways by intensifying research on DSSs regarding all phases of DOM. As articles again mainly address external decision-makers, a lack of research regarding BCM in disaster situations is revealed.

The interface of SCM and DOM is addressed by the survey of Natarajarathinam et al. (2009). The authors explore research trends of managing SCs in times of crisis prior to and in the aftermath of an SC disturbance. They investigate 118 peer-reviewed articles in 48 journals that concentrate on OR/MS and SCM research. As opposed to the previously outlined review articles, authors respect all internal and external sources that might impact an SC. Although disasters are the main (external) source of SC disturbances (63% of reviewed articles), also articles focusing on internal sources (e.g. financial issues) are identified (17%). SC disturbances caused by a combination of both internal and external sources is the scope of 20% of articles. Research mainly focusses on disturbances that affect the whole SC (41%) or that occur regionally (41%). Findings show that research is typically about proactive approaches and, thus, rather on the phases of mitigation and preparedness than on response and recovery. 69% of articles consider SC disturbances from an analytical or conceptual perspective; just 22% suggest an application (e.g. DSSs). Moreover, authors highlight a lack of applications that are targeted at strengthening SC robustness.

Hrisridis et al. (2010) consider the management and analysis of data in disaster situations. They explicitly address challenges of DSSs to be operable in disaster situations. Decision models are typically developed to handle specific needs of decision-making. This is, however, critical in disaster management where one single model might not be sufficient. Authors therefore outline the need for research to combine or to aggregate individual decision models (Meissner et al. 2002). Moreover, Hrisridis et al. (2010) highlight the dynamic property of disaster situations (Schneid & Collins 2000). It is necessary to adapt decision models to the dynamic needs of disaster management. This is associated with the challenge of making decisions under the restriction of uncertain data and varying sources of uncertainty. Future research should develop DSSs that are appropriate to process time-evolving and uncertain data. The relevance of DSSs in disaster situations is confirmed by Schryen et al. (2015). The authors highlight the need for improving communication using transparent and easily understandable decision support tools (Comfort 2007). This is particularly crucial when supporting decision-makers in the response phase where response plans must be executed (Mendonca et al. 2007).

Rennemo et al. (2014) review measures of OR/MS that have been applied in disaster response. Authors explicitly focus on external decision-makers (e.g. of humanitarian logistics). An important requirement of decision-making is uncertainty handling. Results of the survey show that uncertainty is mainly handled in a stochastic manner. This refers to varying logistical decision problems such as, inter alia, facility location and covering tour problems (e.g. Balcik & Beamon 2008), resource allocation and vehicle routing problems (e.g. Van Hentenryck et al. 2010), and network flow and facility routing problems (e.g. Mete & Zabinsky 2010). The relevance of stochastically processing uncertainty has also been addressed by Hoyos et al. (2015). The authors build on the contributions of Altay & Green (2006) and Galindo & Batta (2013).

They review 101 articles that use an OR/MS model with some stochastic component to improve the decision-making process in DOM. Results show that mathematical programming with stochastic components is the most popular methodology in this domain (48%), followed by probability and statistical models (20%) and expert systems (12%). Particularly models of two-stage and scenario-based stochastic programming can be found, for example processing facility location problems (e.g. Chang et al. 2007) or distribution problems (e.g. Tricoire et al. 2012). Further articles develop, inter alia, two-stage, dynamic, and scenario-based stochastic programming models for the prepositioning and allocation of facilities and commodity distribution after a disaster event (Rawls & Turnquist 2012). Integrating stochastic components into decision theory can be, furthermore, found in terms of Bayesian probabilistic networks, analytical hierarchy process (AHP), multi-criteria decision-making and multi-attribute evaluation. An example is the contribution of Frey & Butenuth (2011) who apply a dynamic Bayesian network to assess the functionality of infrastructural objectives in the aftermath of an occurring natural disaster. Hoyos et al. (2015) conclude a lack of research focusing on scenario planning as a measure to cope with non-quantifiable uncertainty. Most models assume distributional information without any previous analysis. This might trigger mistakes when applied in disaster response. Moreover, Hoyos et al. (2015) highlight the need for combining models in a multidisciplinary manner (e.g. by combining methods of mathematical programming and decision theory).

Yao et al. (2009) provide an approach that handles uncertainty non-stochastically through a scenario-based robust optimization model to support decision-making in transportation planning. Their focus is on demand uncertainty and they use the strictly robust counterpart to develop a robust solution. A related approach is suggested by Ben-Tal et al. (2011). They apply a scenario-based robust optimization model to dynamically assign emergency response and evacuation traffic flow problems with a pre-defined time dependent (dynamic) demand uncertainty.

Most articles on SCCM and DOM take the perspective of external decision-makers (Sahebjamnia et al. 2015). A topical review of academic and practitioner journals in the field of humanitarian logistics is provided by Kovács & Spens (2007). They conclude that the importance of logistics is still underestimated in disaster operations from a generic viewpoint. Based on this paper, Caunhye et al. (2012) review optimization models of emergency logistics to identify research gaps and to suggest future research directions. The authors consider different decision problems. With respect to facility location problems, they propose to switch the focus from pre-disaster positioning to post-disaster modelling that takes into account the dynamic and uncertain disaster environment. Moreover, the authors address the limitation of optimization models in general. One aspect in this regard refers to the availability of information. Even if such information is available, optimization models may take too long to solve to optimality. Authors underline that it is rather essential to make models more practical. A further review of humanitarian logistics is provided by Liberatore et al. (2013). They find out that mostly stochastic programming is applied within decision models to process uncertainty. However, these studies are not typically integrated within systems or tools that are appropriate to provide decision support for practitioners. The authors therefore recommend intensifying the development of DSSs that are able to manage uncertainty.

As stated by various authors (e.g. Altay & Green 2006; Natarajarathinam et al. 2009; Galindo & Batta 2013), there is a lack of decision support aiding internal decision-makers. As explicitly discussed by Galindo & Batta (2013), there are virtually no articles available that are related to BCM in times of disasters. The focus is rather on developing models for helping the affected population in general. Just little attention is paid to business disturbances. A limited number of articles develops models for business continuity and recovery planning (Sahebjamnia et al. 2015). These articles, however, rather focus on the description of general frameworks of BCM in DOM than on the development of decision support models. Bryson et al. (2002), for example, discuss disaster recovery alternatives of organizational crisis management in general. Sahebjamnia et al. (2015) develop an integrated BCM and DRP framework that includes all strategic, tactical, and operational decision levels with different time frames, and various elements at each level.

3.4 Summary and research objectives

Chapter 3 provided the conceptual background of this research. The scope is on P-SCs whose functioning is an essential element to protect public safety of a disaster-affected society or community. Section 3.1 introduced the fields of logistics/SCM and disaster research by defining relevant terminologies and concepts. Section 3.2 discussed general implications of SCM in the case that a disaster causes an SC disturbance. This included the consideration of the subdivisions of SCM (SCRM and SCCM) as well as their assignment to the phases of DOM (mitigation, preparedness, response, and recovery). Major strategies towards SC disturbances – robustness, flexibility, and resilience – have been highlighted. Section 3.3 discussed implications of decision-making in SCCM. Therefore, the importance of uncertainty and complexity in the aftermath of an occurring disaster was discussed and the scope of responsible decision-makers of SCCM was outlined. The section closed with a literature review regarding existing approaches of OR/MS to provide decision support in disaster-caused decision situations.

Following the considerations of this chapter, four *research objectives* (RO1-RO4) arise which are outlined in the following paragraphs:

- RO1: Development of a DSS that takes analytical advantage of OR/MS models by integrating them into an applicable decision support tool.
- RO2: Development of a reactive DSS for SCCM that aids decision-makers in the disaster response phase by providing a robust decision recommendation.
- RO3: Development of an innovative scenario-based approach that allows the processing of uncertainty and complexity in a disaster-caused decision situation.

- RO4: Development of a DSS that is generic in nature, is able to adapt to varying logistical decision problems, and supports either internal or external decision-makers.

The high number of articles dealing with OR/MS research in DOM in general and at the interface of SCM and DOM as illustrated by the literature review in section 3.3.3 underlines the importance of this field of research. Authors state that articles mainly concentrate on the discussion of theories and framework as well as on the development of very decision problem-specific OR/MS models. There is a lack of applications to be used by decision-makers (Altay & Green 2006; Natarajarathinam et al. 2009; Galindo & Batta 2013). As explicitly concluded by Galindo & Batta (2013), this lack mainly affects the unavailability of DSSs. Authors recommend that future research should develop tools that take theoretical and analytical OR/MS research into the practical field. Hence, the *research objective RO1* is to develop a DSS that takes the analytical advantage of OR/MS models by integrating them into an applicable decision support tool.

Most articles that concentrate on the interface of OR/MS models and SCM consider the pre-disaster phases (Natarajarathinam et al. 2009). This is particular true for facility location problems (Caunhye et al. 2012). *Research objective RO2* is to develop a reactive DSS for SCCM that aids decision-makers in the immediate aftermath of a disaster, the response phase. In fact, the DSS should be able to manage P-SC disturbances. Therefore, it must be able to provide a robust decision recommendation when processing a specific logistical decision problem. This is an important prerequisite for a robust P-SC design. Because of dynamics affecting disaster situations, robustness is to be understood in the sense of state flexibility to guarantee that P-SCs work despite changes in the environment (Mandelbaum 1978; De Toni & Tonchia 2005). The lack of applications that respect the need for robust SCs (in general) to hedge against SC disturbances has been highlighted by Natarajarathinam et al. (2009).

The crucial challenge of decision-making in the immediate post-disaster period is that an occurring decision situation might be affected by uncertainty and complexity. Decision support tools must be able to process uncertain data of varying sources (Hrisridis et al. 2010). Schneid & Collins (2000) underline the dynamic behavior of the disaster situation (as the dominant property of a complex system in this regard) which must be appropriately respected by a DSS (Hrisridis et al. 2010). Various authors address the limitations of existing optimization models focusing on disaster situations (Caunhye et al. 2012; Liberatore et al. 2013). When stochastic optimization models are applied to handle uncertainty, probability distributions are needed to specify uncertain parameters. This is, however, rarely the case from a practical viewpoint (Ben-Tal et al. 2011). Non-stochastic robust optimization models might be useful to bypass this problem. Nevertheless, issues might be caused when the disaster situation is faced by dynamic developments. The consideration of dynamic parameters (e.g. demand uncertainty over time) has been addressed by few articles (e.g. Ben-Tal et al. 2011). Authors assume that dynamics can be treated in a predictable manner. In disaster situations it is possible that dynamic developments change the state of the decision environment from scratch (e.g. caused by secondary disasters, changes of the socioeconomic and cascading effects of P-SCs and CI sectors). Such disaster-caused dynamic developments have been described as unpredictable (Johnson 2013). Hence, there is a need for innovative approaches to respect dynamic developments and, thus, complexity by decision-making in disaster situations.

Altay & Green (2006) and Hoyos et al. (2015) highlight the future research needed for combining interdisciplinary techniques that take into account the inherent structure of disaster situations where knowledge is incomplete and uncertainty cannot be easily resolved. As stated by Galindo & Batta (2013), the use of scenarios might be a useful measure for uncertainty handling. Hoyos et al. (2015) underline a lack of research in this regard. The major challenge of applying scenario techniques in a disaster situation is that strong uncertainty might trigger an overwhelming number of possible scenarios (Hoyos et al. 2015). Models of OR/MS frequently use scenario-based approaches, such as stochastic or robust optimization models. Regarding the first, the drawback refers to the unavailability of distributional information (see above). Robust optimization models, in turn, construct scenarios by defining uncertainty sets. In the case that a disaster situation is affected by complexity in terms of disaster-caused dynamic developments (see above), the uncertainty space and, thus, the scenario space (overall number of scenarios) might not be visible. Therefore, *research objective RO3* focusses on the development of an innovative scenario-based approach that allows the processing the relevant aspects of uncertainty and complexity in a disaster-caused decision situation. To be applicable in the response phase, such an approach must be embedded into a system that is transparent and easily understandable by nature (Comfort 2007; Schryen et al. 2015).

Current OR/MS research in DOM and SCM mainly addresses external decision-makers (according to the distinction between internal and external decision-makers of section 3.3.2). As summarized by Galindo & Batta (2013), there are virtually no articles that relate to BCM in times of disaster and, thus, take the perspective of internal decision-makers. Various authors underline the future research to strengthen the focus on BCM in terms of solving company-level post-disaster logistical problems (Altay & Green 2006). When addressing the post-disaster management of P-SC disturbances, both internal and external decision-makers might bear responsibility. From the perspective of SCCM, logistical decision problems that arise in a disaster situation might be similar. Therefore, *research objective RO4* is to develop a DSS that is generic in nature. This implies that the DSS should be able to adapt to varying logistical decision problems. Rather than in-depth analyzing the differences between internal or external decision-makers, the focus of the DSS should be on the similarities affecting both categories of decision-makers: the excessive demand to respect uncertainty and complexity characterizing the disaster-affected decision environment while making a decision.

4 The decision support system ReDRiSS

The previous chapters introduced the fields of decision-making under uncertainty (risk, ignorance) and complexity (chapter 2) and decision support for SCCM in the case of a disaster-caused P-SC disturbance (chapter 3). These chapters provided the methodological and conceptual basis to develop the *Reactive Disaster and supply chain Risk decision Support System ReDRiSS*. Section 4.1 outlines preliminary considerations of the development process. Parts and processing steps of ReDRiSS are summarized in section 4.2 and discussed in the sections 4.3, 4.4, and 4.5. The chapter closes with a summary and discussion in section 4.6.

4.1 Preliminary considerations

The following sections outline the scope of ReDRiSS by discussing the decision situations it focusses on and its relevance for the management of disaster-caused P-SC disturbances. Subsequently, requirements that must be fulfilled by ReDRiSS are listed.

4.1.1 Scope of ReDRiSS

ReDRiSS addresses the post-disaster management of P-SC disturbances. While its application should support reactive SCCM, its establishment (customization to a specific decision situation) is a measure of preventive SCRM which decision-makers can proactively invest in. The following paragraphs briefly highlight the scope of ReDRiSS from two perspectives.

<u>Scope of ReDRiSS 1: decision situations</u>

The insights of chapter 2 and 3 allow the distinction between three stereotypical decision situations arising in SCCM. Decision situations of *category 1* occur on an everyday level and are characterized by a high occurrence probability (e.g. seasonal demand fluctuations). The decision-makers are still aware of this due to the experience and knowledge they have gained from previous situations. This knowledge is associated with the availability of statistical data with a high degree of validity. To be a useful measure in such decision situations, a DSS must be able to handle uncertainty in terms of risk by processing this statistical data ("stochastic uncertainty"). Decision situations of *category 2* are characterized by a low occurrence probability. The situations can be described as "extreme" because the impact might be severe (e.g. an IT failure). Nevertheless, negative consequences are *predictable* to a certain degree and can be captured by applying appropriate measures such as scenario techniques. To assist decision-makers in handling decision situations of category 2, a DSS must be able to process uncertainty in terms of ignorance ("scenario-based uncertainty"). Decision situations of *category 3* are also characterized by a low occurrence probability. As opposed to situations of category 2, however, the feature of being "extreme" is exceeded as parts of the situation are *unpredictable* (e.g. a power blackout for several weeks due to a heat wave). According to the considerations of chapter 2, such decision situations are characterized by properties of a complex system. Table 4-1 summarizes the directives of the stereotypical decision situations.

Table 4-1: Categories of decision situations

Decision situation	Objective of SCCM	Scope of decision support
Category 1	Management of decision situations arising on an everyday level	Management of uncertainty in terms of risk
Category 2	Management of "extreme" and predictable decision situations	Management of uncertainty in terms of ignorance
Category 3	Management of "extreme" and unpredictable decision situations	Management of complexity

The objective of ReDRiSS is to support reactive SCCM in the case of a disaster-caused P-SC disturbance. As it has been discussed in chapter 3, the major challenge is thereby to respect the consequences in the environment caused by the disaster. ReDRiSS includes a scenario technique that primary analyzes uncertainty in terms of ignorance due to sparse or lacking exogenous information arising in disaster response (in terms of a category 2 decision situation). In addition, the scenario technique allows to systematically exploring the most crucial disaster-relevant property of a complex system: dynamic developments in the environment (in terms of a category 3 decision situation). Widespread possibilities of such (unpredictable) dynamic developments exist which can never be respected completely by decision-making. Therefore, ReDRiSS focusses on dynamic developments that are related to the main disaster. This includes secondary disasters in the aftermath of the main disaster (e.g. earthquake aftershocks) and socioeconomic changes (e.g. demand fluctuations due to population movements) (Prelipcean & Boscoianu 2011; Hoyos et al. 2015).

Scope of ReDRiSS 2: managing P-SC disturbances

When a ship on the high seas encounters a severe storm, basically four developments of the situation are imaginable. First, the ship is strong enough to withstand the storm without any difficulty (best case); second, the ship sinks and everyone on board dies (worst case); third, the structure of the ship is severely affected, but when all available capabilities and capacities are used, the ship can get through the storm relatively unscathed; fourth, the ship sinks, but a lifeboat is rapidly made ready and rescues (at least temporarily) passengers and crew.

This metaphor can be transferred to a decision situation where a disaster affects P-SCs. In the best case, P-SCs remain functional without difficulty; in the worst case, P-SCs collapse and trigger negative consequences for public safety. In terms of the third and fourth possibility described in the metaphor, the development of the situation toward the worst case is avoidable when the right measures are implemented. Of course, these four risk cases can, in addition, occur simultaneously or they may switch over time. For example, it is imaginable that a P-SC, despite being not seriously affected in the immediate aftermath of a disaster, is disrupted or delayed because interconnected CI sectors and P-SCs fail and consequences cascade through the network.

Two severity levels in the consequences to disturbed P-SCs can be distinguished: *disruptions* and *destructions* of P-SCs. In the case of the first severity level, the scope of SCCM is to develop *adaptation strategies* whose implementation strengthens the functioning of disrupted P-SCs to avoid a supply interruption. Public safety has not been directly affected; the objective is rather to prevent the society or community from belated consequences. In the case that the second severity level occurs, SCCM needs to reestablish P-SCs rapidly. *Compensation strategies* are required to temporarily bypass unavailable P-SCs with replacement structures (compensating P-SCs) that take over their functionalities. As the disaster has already triggered severe consequences, the objective of compensation strategies is to reduce further deterioration of the situation and to avoid a supply vacuum. In several situations, both adaptation strategies and compensation strategies are required; for example, when non-redundant P-SCs fail and need to be replaced while further P-SCs can be strengthened by adaptation strategies.

The objective of ReDRiSS is to aid SCCM in developing both types of strategies. With respect to the considerations of chapter 3, the development of compensation strategies addresses its application by external decision-makers (e.g. public authorities). The development of adaptation strategies aids internal decision-makers in terms of entities of the disrupted P-SCs themselves (e.g. an affected organization). To verify ReDRiSS, two case studies are conducted in the further chapters. The first refers to the field of humanitarian logistics where the objective of ReDRiSS is to develop compensation strategies (see chapter 5); the second concentrates on the field of BCM focusing on adaptation strategies (see chapter 6) (see Figure 4-1).

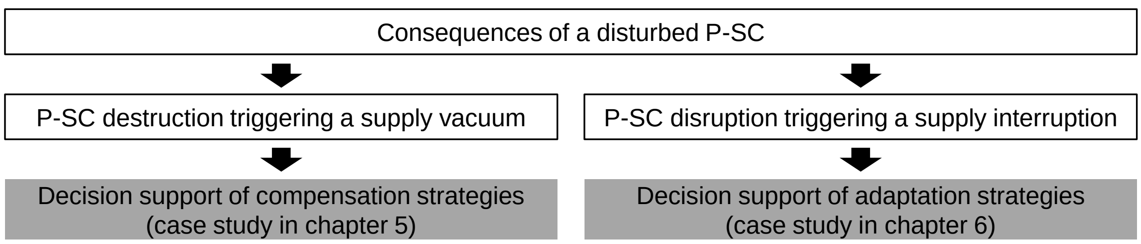


Figure 4-1: Scope of ReDRiSS

Decisions in terms of logistical operations (planning tasks) can be classified according to the planning horizon (see chapter 3) (Günther & Tempelmeier 2011). Strategic decisions concern the strategic design of an SC and have a long-term focus, tactical decisions refer to the planning of the SC network with a mid-term focus, and operational decisions deal with the execution of logistical operations. Specifications of adaptation strategies depend on the situational context and the underlying logistical decision problem. They can be principally required at any management level. Compensation strategies theoretically refer to any logistical decision problem as well; as opposed to adaptation strategies, however, the strategic network design of compensating P-SCs arises from a higher priority than network planning (tactical) and network operation strategies (operational). This is because time is a critical restriction in disaster response, and strategic network design strategies are the foundation of replacement structures, including, inter alia, strategies for identifying the best locations for temporal distribution centers or for supplier selections.

4.1.2 Requirements of ReDRiSS

To address the research objectives that have been identified in section 3.4, ReDRiSS must fulfil the requirements listed below. In fact, ReDRiSS should

- be based on a generic structure to be preventively adaptable to various decision situations (as the task of SCRM) and to provide reactive decision support for SCCM in disaster response
- be able to support both internal and external decision-makers by developing either adaptation strategies or compensation strategies
- include an innovative scenario-based methodology to respect both uncertainty and complexity of the decision situation during a disaster situation
- be holistic in its nature to operationalize all steps of the decision-making process

- achieve a high analytical accuracy by using approaches of OR/MS to solve the underlying logistical decision problem
- be able to respect possible multiple objectives of the decision-makers and operate according to their preferences
- focus on the design of robust (adapted or compensated) P-SCs by providing a robust decision recommendation according to the risk preferences of the decision-makers
- be transparent and easily understandable to provide a practical application for decision-makers

The achievement of the listed requirements is discussed in the final section 4.6.

4.2 Overview of parts and processing steps

Figure 4-2 shows the generic rationale of ReDRiSS which comprises nine processing steps that are conducted across the four parts (A) *implementation*, (B) *two-stage scenario technique*, (C) *stress test*, and (D) *robustness measurement*. Part A describes the implementation process of ReDRiSS in the pre-disaster phases (mitigation or preparedness); processing steps therefore refer to preventive SCRM. The application process of ReDRiSS to support reactive SCCM in the early post-disaster phase (disaster response) comprises processing steps of the parts B, C, and D. In the following paragraphs, a general overview of the involved parts is provided and the basic actions implied by the processing steps are briefly summarized. An in-depth consideration of the processing steps is the scope of the forthcoming sections 4.3 (part A and part B), 4.4 (part C), and 4.5 (part D).

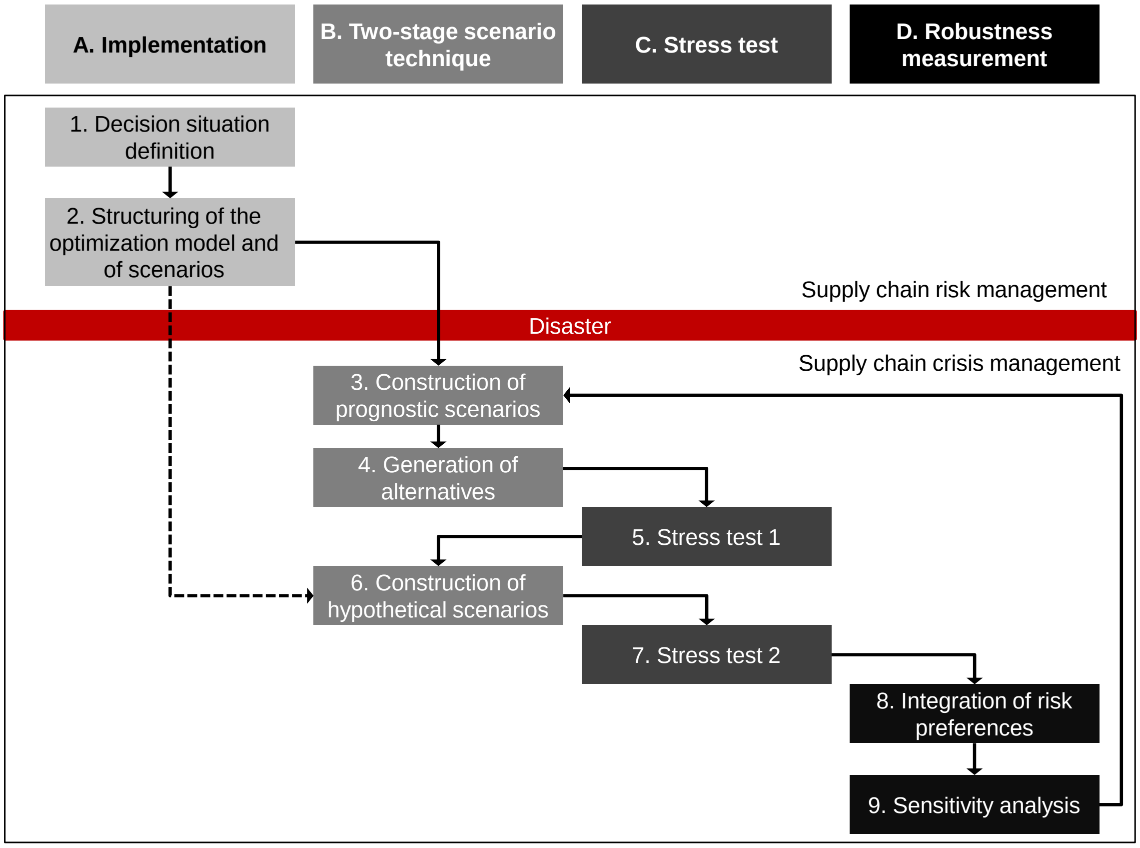


Figure 4-2: Parts and processing steps of ReDRiSS

4.2.1 General overview

The included parts of ReDRiSS operationalize the decision-making process under uncertainty and complexity (see IDC model in section 2.1.2 and pattern-based management in section 2.2.3). In *part A*, the framework of ReDRiSS is set. Therefore, a requirements profile summarizes the decision situation (e.g. decision-makers, logistical decision problem, objectives) and the scope of ReDRiSS to assist the decision-makers. ReDRiSS integrates an *optimization model* (as a measure of mathematical programming) to solve the considered logistical decision problem. The parameters of the optimization model define the decision environment. Thereby, the decision environment includes all elements of the environment that might influence the solution of the decision problem. ReDRiSS constructs *scenarios* to capture uncertainty and complexity regarding the state of the decision environment. The structure of the scenarios is determined by the parameters of the optimization model. In fact, a scenario includes one specification per parameter. In preparation of part B (where the optimization model is applied to scenario techniques), the task of part A is to preventively develop a *specification process* per parameter. Hence, part A operationalizes the intelligence phase of the IDC model by defining the logistical decision problem and it prepares the conduction of the design phase.

Part B includes a *two-stage scenario technique*. Exogenous information about the state of the disaster-affected decision environment is expected to be sparse or lacking in disaster response. Therefore, *prognostic scenarios* (stage 1) are constructed by applying the specification processes that have been developed in part A. Prognostic scenarios describe different specifications of the uncertain parameters and, thus, states of the decision environment. They are used to formulate a number of deterministic optimization sub-models. Solving these sub-models provides a set of *alternatives* (given by the values of the decision variables of the optimization model). As it is assumed that the disaster-affected decision environment might evolve dynamically over time (as a major property of a complex system in the context of disasters), *hypothetical scenarios* are subsequently constructed (stage 2). Their objective is to simulate dynamic developments, caused by critical events, within the states of the decision environment determined by the prognostic scenarios. Hypothetical scenarios are needed to test alternatives as they correspond to deteriorated states of the decision environment. The criticality of dynamic developments might vary across alternatives. Therefore, ReDRiSS provides the opportunity to construct a customized set of hypothetical scenarios per alternative. Hence, part B refers to the design phase of the IDC model in terms of alternative generation under uncertainty. Moreover, the two-stage scenario technique operationalizes the process of pattern-based management: pattern seeking (construction of prognostic scenarios), pattern modelling (generation of alternatives), and pattern adapting (construction of hypothetical scenarios).

Part C includes a *stress test* procedure to evaluate alternatives when they are applied to both prognostic and hypothetical scenario-specific optimization sub-models. The result is a set of outcomes per alternative which refer to the objective function values. Part C is interrelated to the processing steps of part B. In fact, prognostic scenarios and generated alternatives are prioritized prior to the construction of hypothetical scenarios. Just prioritized alternatives (denoted *promising alternatives*) and prioritized prognostic scenarios (denoted *significant scenarios*) are further processed into hypothetical scenarios. This is important for operational and computational reasons. After the construction of hypothetical scenarios, all promising alternatives are tested across the prognostic and the customized hypothetical scenarios. The obtained outcomes provide the input of part D. Hence, part C operationalizes the design phase of the IDC model in terms of alternative evaluation.

The objective of *part D* is to measure robustness of promising alternatives based on the input provided by part C. Robustness refers to the appropriacy of a promising alternative to deal with the varying states of the decision environment specified by the prognostic and hypothetical scenarios. Within robustness measurement, it is important to respect the attitude of the decision-makers. This refers to both their preferences of objectives and their risk preferences. The result of part D is a *robustness ranking* of the promising alternatives. As this ranking directly depends on preferential adjustment screws that are under the control of the decision-makers, sensitivity analyses are finally required to explore the effects of preferential uncertainty. Part D operationalizes the choice phase of the IDC model in terms of alternative selection and action determination.

It is possible to repeat part B, C, and D and, thus, the process of reactive SCCM. This possibility is given when updated exogenous information is gathered from the decision environment over time and the deadline by which a decision has to be made has not been reached yet.

4.2.2 Overview of processing steps

The initiative of decision-makers (of SCRM) is essential to invest in the implementation/customization of ReDRiSS to get assistance in a specific decision situation. In *processing step 1* (part A), the decision situation is structured by defining the logistical decision problem and characterizing the decision environment. Relevant questions that need to be answered are: Which actors are involved in different roles? What are their respective objectives? What decisions are addressed? Which parts of the decision environment characterize its state? The result is a *requirements profile* that summarizes the decision situation and the scope of ReDRiSS.

The requirements profile lays the basis for formulating an *optimization model* in *processing step 2* (part A). This optimization model is required to solve the reported logistical decision problem. The structure of scenarios is associated with this optimization model. In fact, a *scenario* is defined as a vector in $\mathbb{R}^n$ which includes the values of n uncertain parameters; the i^{th} coordinate of the vector specifies the value of the i^{th} uncertain parameter (Hites et al. 2006). Each scenario is, thus, a discrete combination of one specification per parameter. In preparation of part B, it is already important to steer both the process of specifying each parameter (see processing steps 3 and 6) and the process of solving each scenario-specific optimization sub-model (see processing step 4). Moreover, possible sources of exogenous information are determined that must be activated in disaster response to specify the parameters.

Prognostic scenarios are constructed in *processing step 3* (part B). The parameters of the optimization model are specified by using the identified exogenous information sources. In disaster response, exogenous information is expected to be uncertain as lacking or being incomplete so that not all parameters can be specified deterministically. Prognostic scenarios are constructed to overcome this *uncertainty*. Therefore, different specifications of the uncertain parameters are defined based on the developed specification processes of part A (see section 4.3.3). The reason for denoting scenarios "prognostic" is that they aim at describing *probable* and *expected* states of the decision environment. In fact, the construction of prognostic scenarios must follow the question: "what is most likely to happen in the uncertain decision environment?"

Each prognostic scenario defines one optimization sub-model. *Processing step 4* (part B) generates alternatives by solving each optimization sub-model deterministically. An *alternative* is defined by specifications of the optimization model's decision variables. Either exact solvers or heuristics can be used to generate an optimal alternative or a set of Pareto-optimal alternatives per prognostic scenario (see section 4.3.4). The result is an aggregated set of alternatives which have been generated across all prognostic scenarios.[9]

In *processing step 5* (part C), the generated alternatives are tested. The procedure is denoted *stress test 1* as the outcome of an alternative (in terms of objective function values) is determined when it is applied to all prognostic scenario-specific optimization sub-models and in which it is not necessarily the optimal solution ("putting alternatives under stress") (see section 4.4.3.1). Based on these outcomes, the *regret* per alternative and prognostic scenario is calculated. The regret refers to the outcome of an alternative in a scenario compared to the best outcome that can be reached in the scenario by any other alternative (Scholl 2001). Obtained regret data are used to prioritize the set of alternatives toward a set of *promising alternatives*. These promising alternatives achieve minimal regret values across the prognostic scenarios (regarding a regret value threshold that has to be defined by the decision-makers). Additionally, a set of *significant scenarios* is generated per promising alternative. This set includes those prognostic scenarios in which the regret values of the promising alternatives are maximal (regarding a regret value threshold that has to be defined by the decision-makers). A set of significant scenarios, thus, includes the "worst case" prognostic scenarios of the considered promising alternative.[10]

[9] Depending on the case of application, it might also be possible to respect all feasible alternatives.

[10] Depending on the case of application, it might also be possible to further respect all generated alternatives and prognostic scenarios. In such a case, stress test 1 is omitted. The set of promising alternatives equals to the generated set of alternatives (processing step 4) and the set of significant scenarios equals to the set of prognostic scenarios (processing step 3) which is the same for each promising alternative.

Hypothetical scenarios are constructed in *processing step 6* (part B). Their construction follows the question: “what can additionally happen to the decision environment when probable and expected states (specified by prognostic scenarios) unfold and become vulnerable states or states of failure?” Hypothetical scenarios aim at revealing *complexity* by simulating *critical events* in the decision environment (see section 4.3.5). In fact, a critical event triggers a *dynamic development* within the significant scenarios. With respect to the properties of complex systems (see chapter 2), widespread possibilities of such dynamic developments exist. Their relevance in terms of causing negative consequences on outcomes of promising alternatives varies. Therefore, ReDRiSS proposes a methodology to capture dynamic developments by a *customized* set of hypothetical scenarios per promising alternative. Each set, thus, includes promising alternative specific *critical* and *unexpected* states of the decision environment.

In *processing step 7* (part C), promising alternatives are tested and compared when they are applied in each prognostic scenario and hypothetical scenario (*stress test 2*, see section 4.4.3.2). When a customized set of hypothetical scenarios has been generated per promising alternative, the alternative is just tested in its customized set. The objective of stress test 2 is to calculate regret values that can be used for robustness measurement in part D. As opposed to stress test 1, the regret calculations of this part explicitly concentrate on comparing outcomes of promising alternatives. This is because promising alternatives have been assessed as appropriate (compared to all other alternatives) when they are applied to (probable and expected) prognostic scenarios (see stress test 1). The objective of processing step 7 is to provide data that can be analyzed to determine the *robustness* of promising alternatives to *uncertainty* (prognostic scenarios) and *complexity* (hypothetical scenarios).

Based on the regret data, the objective of *processing step 8* (part D) is to generate a *robustness value* per promising alternative. It is assumed that decision-makers in the field of DOM are characterized by risk aversion (Scholl 2001). Decision-makers are interested in receiving a decision recommendation that is *robust* in terms of hedging against threats that are triggered by an uncertain and complex state of the decision environment. The implementation of a robust decision is one step towards a robust design of the (adapted or compensated) P-SC. Being risk averse, decision-makers might operate in a rather *pessimistic* manner. This attitude reflects the question how to evaluate regret data. ReDRiSS distinguishes between the *inter- and intra-scenario degrees of pessimism*. While the first determines the robustness of alternatives when applied to prognostic and hypothetical scenarios, the latter adjusts the evaluation process of regret data within each scenario category. Hence, processing step 8 integrates the personal degree of pessimism of decision-makers to develop one robustness value per promising alternative.[11]

The obtained *robustness ranking* of promising alternatives is influenced by subjective preference parameters and biases of the decision-makers. To explore effects of preferential uncertainty in this regard, *sensitivity analyses* must be conducted in *processing step 9* (part D). Their focus is on both varying preferences of objectives (in the case that the optimization model is of a multi-objective manner) and risk preferences in terms of the inter- and intra-scenario degrees of pessimism. Subsequently, the *robust alternative* can be provided as a decision recommendation for the decision-makers.

4.3 Implementation and application of the two-stage scenario technique

In chapter 2, the relevance of scenarios for uncertainty handling in both disciplines of OR/MS, decision theory and mathematical programming, has been discussed. ReDRiSS includes a *two-stage scenario technique* in part B to process *uncertainty* and *complexity* affecting the state of the decision environment. In the following, definitions are provided and the rationale of implementing and applying the two-stage

[11] Robustness measurement in ReDRiSS respects the degree of pessimism of the decision-makers. Although robustness measurement is thereby based on regret data, the concept of *regret aversion* is not addressed. For further information regarding this concept, see Broll et al. (2013).

scenario technique is summarized and its included processing steps are outlined: structuring of the optimization model and of scenarios (processing step 2), construction of prognostic scenarios (processing step 3), generation of alternatives (processing step 4), and construction of hypothetical scenarios (processing step 6).

4.3.1 Definitions

Let in the following be:

- $a = (x_1, \dots, x_J) \in \Omega$ a vector of J decision variables where Ω is the decision space
- $f(a) = \{f_1(a), \dots, f_F(a)\}$ a set of $F \in \mathbb{Z}$ objective functions
- $g(a) = \{g_1(a), \dots, g_G(a)\}$ a set of $G \in \mathbb{Z}$ constraint functions

[4-1] highlights the generic formulation of the *optimization model* as a minimization problem (maximization problems are treated respectively). The formulation refers to a single objective optimization model when $F = 1$ and to a multi-objective optimization model when $F \geq 2$ (Zitzler 1999). An *alternative* a of the decision space Ω is defined by the specifications of all decision variables $x_j \in \{x_1, \dots, x_J\}$.

$$\begin{aligned} \min_{\mathrm{a}} \; & f(a) = \left(f_1(a), \dots, f_F(a)\right) \\ \text{subject to} \; & g(a) = \left(g_1(a), \dots, g_G(a)\right) \leq 0 \\ & a = (x_1, \dots, x_J) \in \Omega \end{aligned} \quad [4\text{-}1]$$

Let $Par = \{par_1, \dots, par_p, \dots, par_P\}$ be the parameters included within $f(a)$ and $g(a)$. A *scenario* is a combination of one discrete *specification* per parameter $par_p \in Par$. The set of scenarios S, thus, refers to the Cartesian product:

$$S = V(par_1) \times \dots \times V(par_p) \times \dots \times V(par_P) \quad [4\text{-}2]$$

where

$$V\left(par_p\right) = \left\{v_1\left(par_p\right), \dots, v_{n_p}\left(par_p\right), \dots, v_{N_p}\left(par_p\right)\right\} \qquad [4\text{-}3]$$

is the set of discrete specifications of $par_p \in Par$ and N_p is the absolute number of specifications of this set. The Cartesian product in [4-2] can be defined as

$$S = \left\{\{v_{n_1}(par_1), \dots, v_{n_P}(par_P)\} | v_{n_p}\left(par_p\right) \in V\left(par_p\right), \right.$$
$$\left. p = 1, \dots, P, n_p \in \left\{1, \dots, N_p\right\}\right\} \qquad [4\text{-}4]$$

Indicator l refers to the l^{th} set included in S which is denoted scenario $s_l \in S$. The total number of scenarios $|S|$ is

$$|S| = |V(par_1)| \cdot \dots \cdot |V(par_P)| = \prod_{p=1}^{P} N_p \qquad [4\text{-}5]$$

4.3.2 Rationale of the two-stage scenario technique

Scenario construction in ReDRiSS is associated with the specification of the parameters of Par. The following types of parameters are distinguished:

- $EV \subseteq Par$ is a set *of environmental variables* which characterizes the state of the disaster-affected decision environment. Their specifications are prone to uncertainty and complexity.
- $PV \subseteq Par$ is a set of *planning variables* which highlights planning assumptions for decision-making. Their specifications are deterministic.

Note that $EV \cup PV = Par$. Let $|EV|$ and $|PV|$ be the absolute numbers of environmental variables and planning variables. To ensure that alternatives are generated and tested under the same planning conditions, it is assumed that *planning information* is available and deterministic. This planning information is captured from the decision-makers or the decision environment (e.g. budget, number of warehouses). Hence, all constructed (prognostic and hypothetical) scenarios contain constant specifications of planning variables. This is an important requirement when testing alternatives as it ensures that any generated alternative is feasible in any scenario-specific optimization sub-model from a planning perspective (see section 4.4). Scenarios exclusively vary in the specifications of environmental variables that characterize the state of the disaster-affected decision environment. Thus, the exploration of effects of uncertainty and complexity by ReDRiSS is always associated with the specifications of the environmental variables. Thereby, the construction of prognostic and hypothetical scenarios differs in the underlying types of information that are processed to determine these specifications.

Prognostic scenarios are developed to close knowledge gaps caused by lacks of *exogenous information* which is gathered from the decision environment in disaster response and that indicates its conditions (e.g. states of roads). In a disaster-affected decision environment, exogenous information is expected to be insufficient to specify all environmental variables in a deterministic manner. Therefore, varying specifications of uncertain environmental variables must be defined.

Hypothetical scenarios aim at exploring dynamic developments in terms of changing states of the decision environment over time (e.g. shifts in population demands, secondary disasters such as earthquake aftershocks). As opposed to prognostic scenarios, the construction of hypothetical scenarios is not necessarily linked to exogenous information. It rather processes *endogenous information* provided by part C of ReDRiSS itself: prioritized alternatives that come into question to solve the decision problem (*promising alternatives*) and “worst case” prognostic scenarios per promising alternative (*significant scenarios*) whose underlying states of the decision environment are modified by simulating dynamic developments.

The distinction between prognostic and hypothetical scenarios is inspired by the scenario classification of Börjeson et al. (2006). The authors distinguish between predictive and explorative scenarios (see section 2.1.3). While prognostic scenarios refer to the class of predictive scenarios and aim at answering the question "what is happening/ what will happen?" hypothetical scenarios are explorative scenarios and imply the question "what can happen?"

In a decision situation under uncertainty (in terms of ignorance), the occurrence probability of any possible state of the decision environment (and, thus, of scenarios and outcomes of alternatives) is unavailable (Camerer & Weber 1992; Wiens 2013). This assumption is intensified in a decision situation under complexity where the state of decision environment is characterized by a constant flux. Here, even the overall scenario space and the existing set of alternatives is unknown. Scenario construction in ReDRiSS follows the *principle of insufficient reason*, a statute that can be traced back to the work of Laplace and Bernoulli (Bamberg & Coenenberg 2006). It implies that any considered state of the decision environment (scenario) has the same occurrence probability. A major point of criticism of this principle is that, under the assumption of equal probabilities of states, each state is indeed characterized by a very specific occurrence probability (Wiens 2013). Additionally, probabilities vary when more or less states are respected.

Nevertheless, ReDRiSS follows the principle of insufficient reason. This is because, as emphasized by Kouvelis & Yu (1997), there is a threat of misjudgments with compulsively defining occurrence probabilities of scenarios. In fact, this principle is in ReDRiSS separately assumed for each scenario category (prognostic and hypothetical scenarios). Although it is not verified to what degree the constructed sets of prognostic and hypothetical scenarios represent the overall scenario space, ReDRiSS assumes the same occurrence probabilities of scenarios of each scenario category. This is crucial to avoid an over- or underestimation of constructed scenarios. Nevertheless, the (subjective) occurrence probability of a (probable and expected) prognostic scenario is principly higher than the occurrence probability of a (critical and unexpected) hypothetical scenario.

4.3.3 Construction of prognostic scenarios

The decision situation is defined as certain if all environmental variable specifications are deterministically as exogenously given. In this case, scenarios are not required as the optimization model in [4-1] can be applied in a deterministic manner. When at least one uncertain environmental variable is identified, prognostic scenarios must be constructed to deal with this uncertainty. The following sections outline the process of constructing prognostic scenarios and their formal mathematical definition.

4.3.3.1 Process of constructing prognostic scenarios

The construction of prognostic scenarios is prepared by SCRM (processing step 2) and conducted by SCCM (processing step 3). Five tasks are therefore required (see Figure 4-3).

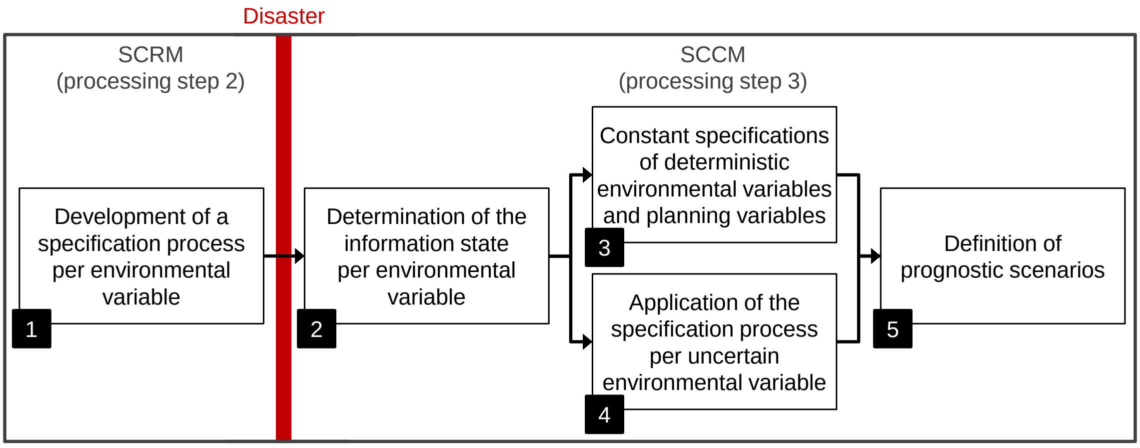


Figure 4-3: Process of constructing prognostic scenarios

When implementing ReDRiSS, parameters of the optimization model must be classified by planning and environmental variables. As any environmental variable might become uncertain in the aftermath of a disaster, it is important to be prepared for the case that all environmental variables must be reactively specified without the availability of any exogenous information. Therefore, a *specification process* per environmental variable is preventively defined (task 1). Widespread possibilities exist for this purpose; the possibility chosen depends on the underlying case of application. For example, it is imaginable to define, per environmental variable, methods (e.g. Monte-Carlo method) or functions (e.g. statistical distributions) that regulate its specification. The task is associated with the need for already capturing available exogenous information (e.g. historical data) or its sources that must be activated when constructing prognostic scenarios by applying specification processes.

The extent of prognostic scenarios is determined by the exogenous *information states* of environmental variables in the aftermath of a disaster (task 2). There is a distinction between the information states *available* and *unavailable*. If the information state of an environmental variable is *unavailable*, it must be respected within the construction process of prognostic scenarios. When its information state is *available*, the question arises whether this information is *complete* or *incomplete*. In the case that the information state is *complete*, the environmental variable can be specified in a deterministic manner. An *incomplete* information state at the most indicates several aspects of this specification (e.g. entries of several matrix cells of an environmental variable). It is assumed that the reliability of all available exogenous information is guaranteed within ReDRiSS; reliability verifications are the task of upstream processes of information gathering, e.g. supported by ICT systems.

For example, an environmental variable might be a matrix highlighting the conditions of a transportation network. Value entries of cells of this matrix refer to the required times to use the routes (e.g. measured in hours). When the information is complete, each cell is specified by a number; when the information is incomplete, several cells cannot be specified as either the conditions of several route connections are not known or exogenous information just indicates difficulties of using the transportation routes. Varying specifications must be defined for the uncertain environmental variable by anticipating expected times.

Hence, an environmental variable is uncertain if its information state is unavailable or available but incomplete. Environmental variables whose information state is available and complete can be specified in a deterministic manner (*deterministic environmental variables*) (task 3).

For the remaining environmental variables (*uncertain environmental variables*), the steered specification processes of processing step 2 must be activated and conducted (task 4). Prognostic scenarios are finally constructed by combining each specification per uncertain environmental variable and the constant specifications of the deterministic environmental variables and planning variables (task 5).

4.3.3.2 Formal definition of prognostic scenarios

Let in the following be:

- $PV = \{pv_1, \dots, pv_m, \dots, pv_M\}$ the set of planning variables
- $EV^{det} = \{ev_1^{det}, \dots, ev_d^{det}, \dots, ev_D^{det}\} \subseteq EV$ the set of deterministic environmental variables
- $EV^{unc} = \{ev_1^{unc}, \dots, ev_u^{unc}, \dots, ev_U^{unc}\} \subseteq EV$ the set of uncertain environmental variables

where $EV^{det} \cup EV^{unc} = EV$. With respect to the formal scenario definition (see section 4.3.1), the *set of prognostic scenarios S^{prog}* is defined as

$$S^{prog} = \left(V(ev_1^{unc}) \times \dots \times V(ev_u^{unc}) \dots \times V(ev_U^{unc})\right) \cup \left\{V\left(ev_d^{det}\right) | d = 1, \dots, D\right\} \cup \{V(pv_m) | m = 1, \dots, M\} \quad [4\text{-}6]$$

where

$$V(ev_u^{unc}) = \left\{v_1(ev_u^{unc}), \dots, v_{n_u}(ev_u^{unc}), \dots, v_{N_u}(ev_u^{unc})\right\} \quad [4\text{-}7]$$

$$V\left(ev_d^{det}\right) = \left\{v_1\left(ev_d^{det}\right)\right\} \quad [4\text{-}8]$$

$$V(pv_m) = \{v_1(pv_m)\} \quad [4\text{-}9]$$

[4-7] is the set of N_u specifications of $ev_u^{unc} \in EV^{unc}$; [4-8] and [4-9] refer to the constant specification per $pv_m \in PV$ and $ev_d^{det} \in EV^{det}$. The l^{th} set included in S^{prog} is denoted prognostic scenario $s_l^{prog} \in S^{prog}$. Moreover, the number of prognostic scenarios L is the number of specifications across all uncertain environmental variables:

$$L = |V(ev_1^{unc})| \cdot \ldots \cdot |V(ev_u^{unc})| \cdot \ldots \cdot |V(ev_U^{unc})| = \prod_{u=1}^{U} N_u \quad [4\text{-}10]$$

4.3.4 Generation of alternatives

Based on S^{prog}, a number of L optimization sub-models is formulated and each of them is solved in a deterministic manner in processing step 4. The aggregated set of generated alternatives per optimization sub-model provides the input for stress test 1 (processing step 5, see section 4.4) which, in turn, prepares construction of hypothetical scenarios (processing step 6, see section 4.3.5). The optimization sub-model of prognostic scenario $s_l^{prog} \in S^{prog}$ is

$$\min_a f\left(a, s_l^{prog}\right) = \left(f_1\left(a, s_l^{prog}\right), \ldots, f_F\left(a, s_l^{prog}\right)\right) \quad [4\text{-}11]$$

$$\text{subject to } g\left(a, s_l^{prog}\right) = \left(g_1\left(a, s_l^{prog}\right), \ldots, g_G\left(a, s_l^{prog}\right)\right) \leq 0$$

$$a = \left(x_1, \ldots, x_J\right) \in \Omega, s_l^{prog} \in S^{prog}$$

The integration of an optimization model into ReDRiSS provides the advantage of mathematically developing alternatives according to the objectives and constraints of decision-makers. Either exact solvers or heuristics can be used to compute an optimal alternative or a set of Pareto-optimal alternatives per optimization sub-model. Pareto-optimal alternatives refer to a set of mathematically equally good alternatives where no objective can be improved without scarifying one or more of the other objectives (Shin & Ravindran 1991; Klamroth & Miettinen 2008). Particularly heuristics have proven as successful when applied in disaster management from a computational perspective. This is highly relevant when the decision-making process is faced with time pressure or when the optimization model is NP-hard and considerable effort is required to solve the problem numerically (Domschke & Drexl 1996).

In the case that the optimization model is of a multi-objective manner ($F \geq 2$), methods of *multi-objective decision-making* (MODM) must be applied to solve each optimization sub-model. MODM is a sub-division of *multi-criteria decision analysis* (MCDA) which provides methods to handle varying objectives within the decision-making process. Methods of MODM assume that all alternatives are feasible that fulfill the constraint functions of a mathematical model (Walther 2010; Geldermann 2014). Objectives are defined by quantifiable objective functions (Geldermann 1999; Geldermann 2014). Because of the potentially conflictive nature of objectives, there is typically not one optimal alternative available that optimizes all objective functions simultaneously. Rather several mathematically equally good alternatives exist which are denoted efficient or Pareto-optimal. To identify the best alternative out of a set of Pareto-optimal alternatives, preference-related information of the decision-makers is required (Zitzler et al. 2000; Marler & Arora 2004; Klamroth & Miettinen 2008; Comes 2011). Three directions are distinguished in this regard (Geldermann 1999; Marler & Arora 2004; Walther 2010; Comes 2011; Geldermann 2014): methods that follow

- an *a priori articulation of preferences* which are elicited at the beginning of the search process (e.g. goal programming),
- a *progressive articulation of preferences* where decision-makers need to iteratively provide preference-related information while solving the mathematical program (e.g. method of Geoffrion et al. 1972), or
- an *a posteriori articulation of preferences* where firstly a set of efficient alternatives is determined and secondly decision-makers are supposed to select the most satisfactory alternative (e.g. generation of the complete solution).

In the case that a method of MODM is applied within ReDRiSS, it is important that the preferences of objectives which are defined by the decision-makers are the same as used in part C (see section 4.4). Let $A(s_l^{prog})$ be the generated set of alternatives based on s_l^{prog}. The *aggregated set of alternatives* A across all prognostic scenarios of S^{prog} is

$$A = A\left(s_1^{prog}\right) \cup \ldots \cup A\left(s_l^{prog}\right) \cup \ldots \cup A\left(s_L^{prog}\right) \\ = \{a_1, \ldots, a_z, \ldots, a_Z\} \qquad [4\text{-}12]$$

4.3.5 Construction of hypothetical scenarios

Input data for the construction of hypothetical scenarios is *endogenous information* which is generated by processing step 5 (see section 4.4):

- A set of *promising alternatives* $\tilde{A} = \{\tilde{a}_1, \ldots, \tilde{a}_b, \ldots, \tilde{a}_B\} \subseteq A$ that is filtered out of A. Just promising alternatives come into question to solve the decision problem.
- A set of *significant scenarios* $S^{si,\tilde{a}_b} \subseteq S^{prog}$ per $\tilde{a}_b \in \tilde{A}$. $S^{si,\tilde{a}_b} = \left\{s_1^{si,\tilde{a}_b}, \ldots, s_w^{si,\tilde{a}_b}, \ldots, s_W^{si,\tilde{a}_b}\right\}$ includes a number of W prognostic scenarios in which $\tilde{a}_b$ performs poorly compared to all other prognostic scenarios.

The following sections outline the construction process of hypothetical scenarios and their formal mathematical definition.

4.3.5.1 Process of constructing hypothetical scenarios

The construction of hypothetical scenarios is prepared by SCRM (processing step 2) and conducted by SCCM (processing step 6). A hypothetical scenario is constructed per promising alternative and significant scenario. The construction implies the modification of the state of the decision environment (specifications of environmental variables) assumed by the significant scenario. This modification is simulated by a *dynamic development* that is caused by a *critical event*. The process of constructing hypothetical scenarios regulates the integration of a critical event into a significant scenario to simulate a dynamic development. Therefore, four tasks are required (see Figure 4-4).

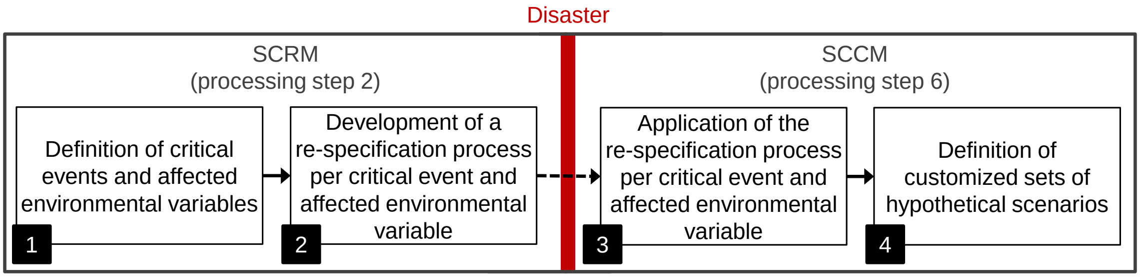


Figure 4-4: Process of constructing hypothetical scenarios

Critical events and their affected environmental variables are identified (task 1). Subsequently, a *re-specification process* per affected environmental variable of a critical event is preventively defined (task 2). Re-specification processes of all affected environmental variables are applied to simulate a dynamic development within the significant scenario (task 3). In fact, their underlying specifications are re-specified. A re-specification process must not necessarily impact all elements of an affected environmental variable (e.g. it might just re-specify several matrix cells). Moreover, again widespread possibilities exist to define a re-specification process which depends on the case of application (e.g. statistical distribution functions). By applying the re-specification process of the affected environmental variables for each critical event in each significant scenario, a *customized set of hypothetical scenarios* is developed per promising alternative (task 4). Hence, the number of hypothetical scenarios within a customized set equates to the multiplication of the number of significant scenarios and critical events (see section 4.3.5.2).

The re-specification process of an affected environmental variable (referring to a critical event) triggers a dynamic development (of this environmental variable) that is either of an *alternative-specific*, *environment-specific,* or *generic* manner:

- *Alternative-specific dynamic development*: the re-specification process depends on the promising alternative itself in terms of its specifications of decision variables. When considering a facility location problem, for example, a promising alternative might contain a binary decision variable that regulates the geographic distribution of facilities. A critical event could be an earthquake that triggers interruptions of roads. The re-specification process of the road network (affected environmental variable) could be managed by simulating interruptions of roads close to the facility locations that are indicated by the decision variable specification.

- *Scenario-specific dynamic development*: the re-specification process depends on the significant scenario in terms of its state of the decision environment (specifications). Taking the exemplary critical event above, the re-specification process could dictate the interruption of all main roads of the considered road network (affected environmental variable) by doubling the required times to use these main roads as it is assumed within the significant scenario.
- *Generic dynamic development*: the re-specification process pretends a modified state of an environmental variable. Taking the exemplary critical event above, the re-specification process could define a new state of several roads of the road network (affected environmental variable). Re-specifications in this case do not depend on the promising alternative itself and/or on the specification of the environmental variable assumed by the significant scenario.

Combinations of these types are possible. For example, elements of an affected environmental variable (e.g. matrix cells) whose specifications are modified might be identified in an alternative-specific manner while the actual re-specification of these elements is scenario-specific. Moreover, constructed hypothetical scenarios always vary in the specifications of environmental variables (of the significant scenarios) that are not affected by the dynamic development (and critical event). In the special case that a generic dynamic development is simulated by defining a new state of *all* environmental variables and *all* of their elements, the critical event triggers exactly one hypothetical scenario that is the same regarding any promising alternatives and significant scenarios. The number of hypothetical scenarios in the generic (and not customized) set equates to the number of critical events in this case. Hence, the basis for developing *customized* hypothetical scenarios per promising alternative is the possibility of defining re-specifications in an alternative-specific and/or scenario-specific manner and/or the fact that an already customized set of significant scenarios is respected.

Hypothetical scenarios are explicitly used to explore the individual vulnerabilities of a promising alternative (caused by the promising alternative itself or its significant scenario to which it is vulnerable). They are not used to increase the set of alternatives by solving hypothetical scenario-specific optimization sub-models. This is because generated alternatives would then particularly hedge against possible but rather "unlikely" (as critical and unexpected) states. A generation of alternatives that is based on prognostic scenarios, in turn, increases the chance of obtaining alternatives that perform appropriately under probable and expected states of the decision environment.

4.3.5.2 Formal definition of hypothetical scenarios

Let, in the following, be:

- k a critical event
- K the maximal number of critical events
- $EV_k^{crit} = \{ev_{k,1}^{crit}, \dots, ev_{k,t}^{crit}, \dots, ev_{k,T}^{crit}\} \subseteq EV$ the set of T environmental variables that must be modified due to k

A *single* hypothetical scenario refers to a critical event k, a promising alternative $\tilde{a}_b \in \tilde{A}$, and one of its significant scenarios $s_w^{si,\tilde{a}_b} \in S^{si,\tilde{a}_b}$. The re-specification $V_w^{\tilde{a}_b}(ev_{k,t}^{crit})$ of $ev_{k,t}^{crit} \in EV_k^{crit}$ in $s_w^{si,\tilde{a}_b}$ is:

$$V_w^{\tilde{a}_b}(ev_{k,t}^{crit}) = \{v_1(ev_{k,t}^{crit})\} \quad [4\text{-}13]$$

Hypothetical scenario $s_{w,k}^{hyp,\tilde{a}_b} \in S^{hyp,\tilde{a}_b}$ simulates a dynamic development within $s_w^{si,\tilde{a}_b}$ by integrating the re-specification $V_w^{\tilde{a}_b}(ev_{k,t})$ of each $ev_{k,t}^{crit} \in EV_k^{crit}$:

$$s_{w,k}^{hyp,\tilde{a}_b} = \left(s_w^{si,\tilde{a}_b} \setminus \left\{v_{n_i}(ev_i) \middle| \forall ev_i \in EV \cap EV_k^{crit}, i \in \{1, \dots, |EV|\}, n_i \in \{1, \dots, N_i\}\right\}\right) \cup \left\{V_w^{\tilde{a}_b}\left(ev_{k,t}^{crit}\right) \middle| t = 1, \dots, T\right\} \quad [4\text{-}14]$$

$S^{hyp,\tilde{a}_b}$ is the set of hypothetical scenarios regarding $\tilde{a}_b$:

$$S^{hyp,\tilde{a}_b} = \left\{s_{1,1}^{hyp,\tilde{a}_b}, \dots, s_{1,K}^{hyp,\tilde{a}_b}, \dots, s_{W,1}^{hyp,\tilde{a}_b}, \dots, s_{W,K}^{hyp,\tilde{a}_b}\right\} \quad [4\text{-}15]$$

The set of hypothetical scenarios S^{hyp} is:

$$S^{hyp} = \left\{S^{hyp,\tilde{a}_1}, \dots, S^{hyp,\tilde{a}_b}, \dots, S^{hyp,\tilde{a}_B}\right\} \quad [4\text{-}16]$$

The number of hypothetical scenarios $|S^{hyp}|$ is defined by the number of promising alternatives B, the number of significant scenarios per promising alternative W, and the number of critical events K:

$$\left|S^{hyp}\right| = B \cdot W \cdot K \quad [4\text{-}17]$$

The rationale of construction of hypothetical scenarios is illustrated in Figure 4-5 in terms of the $\tilde{a}_b$-specific transformation process of $S^{si,\tilde{a}_b}$ into $S^{hyp,\tilde{a}_b}$.

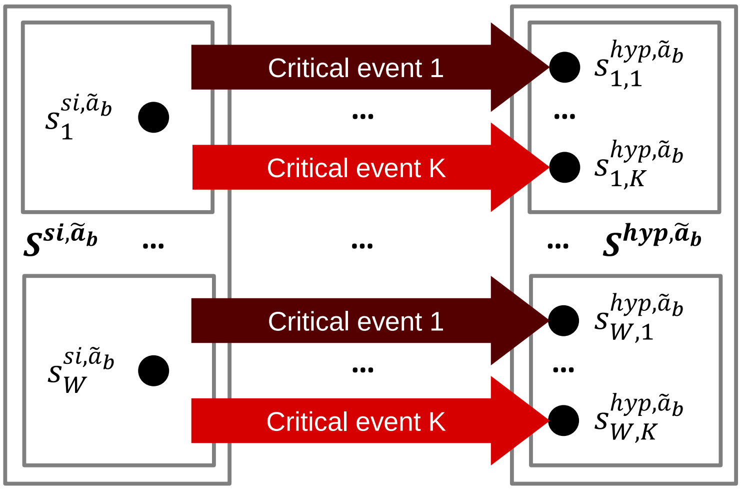


Figure 4-5: Rationale of hypothetical scenarios

4.4 Stress test

Stress test is in literature defined as a technique to assess the vulnerability of an object under observation to major changes in the environment in terms of exceptional but still plausible events (Blaschke et al. 2001). The technique is applied to gather information about sources and effects of risks. It has proven particularly successfully in the financial sector to assess an institution's portfolio regarding potential loss exposures (Hu et al. 2014; Yu et al. 2014). Part C of ReDRiSS proposes a stress test related approach to generate and evaluate outcomes of an alternative when it is applied to the states of the decision environment defined by prognostic and hypothetical scenarios. This stress test is required for two reasons: to prepare the construction of hypothetical scenarios (part B, processing step 6) and to prepare the robustness measurement of alternatives (part D, processing steps 8 and 9). In the following section, concepts are outlined that are included within part C. Subsequently, the stress test approach is presented and its application within stress test 1 (processing step 5) and stress test 2 (processing step 7) is discussed.

4.4.1 Applied concepts

In ReDRiSS, outcomes of alternatives correspond to objective function values when they are applied to varying scenario-specific optimization sub-models. Outcomes are evaluated to determine the robustness of alternatives. Therefore, they must be transformed into a suitable indicator. The choice of such an indicator depends on the underlying concept of robustness. In ReDRiSS, robustness measurement follows the concept of *optimality robustness* which is measured by the indicator of *regret*. Moreover, the optimization model might be of a multi-objective manner. In such a case, a number of outcomes per alternative and scenario exists which equates to the number of objective functions. To respect multiple objectives while determining optimality robustness of an alternative, ReDRiSS includes an approach that is inspired by the method of *multi-attribute value theory* (MAVT).

4.4.1.1 Stress test in literature

Stress test techniques distinguish between *sensitivity tests* and *scenario tests*. Sensitivity tests aim at stressing one single parameter without relating the considered shock to the other parameters. Scenario tests explore consequences of shocks by stressing various parameters simultaneously (Blaschke et al. 2001; Yu et al. 2014). Two approaches of scenario tests exist: the *historical scenario approach* and the *hypothetical scenario approach* (Blaschke et al. 2001; Alexander & Baptista 2009; Hu et al. 2014). The historical scenario approach assumes that future events will be similar to past ones without taking into account dynamic changes that may happen in future; the hypothetical scenario approach explores impacts of extreme but plausible changes in the external environment regardless of historical experiences (Hu et al. 2014). According to Hu et al. (2014), existing approaches of scenario tests are faced with three problems. Firstly, most approaches are probability-based (e.g. value-at-risk). Secondly, scenario designers must frequently imagine or anticipate “rare events” without receiving any structural support. Thirdly, plausibility of scenarios is often not guaranteed.

The stress test approach of ReDRiSS is inspired by the aforementioned classifications and in particular by scenario tests. In a nutshell, the behavior of an alternative is explored when it is applied to states of the decision environment assumed by prognostic and hypothetical scenarios. Particularly the latter concentrate on unexpected states (“rare events”) of the decision environment as they “stress” the specifications of environmental variables assumed within prognostic scenarios. ReDRiSS answers the aforementioned challenges of scenario tests (Hu et al. 2014) as follows: occurrence probabilities of scenarios are not assumed due to an uncertain and even complex decision environment (principle of insufficient reason, see section 4.3.2). To support scenario designers, each scenario is of an equal formal structure and constructed using a clear procedure. According to Comes (2011), plausibility is in practice a subjective concept and must be guaranteed by human judgement. This is ensured by a close cooperation with decision-makers when ReDRiSS is applied.

4.4.1.2 Optimality robustness and regret

Robust decision-making distinguishes between evaluating the robustness of the solution and the robustness of the model that is used to generate the solution (Mulvey et al. 1995; Kouvelis & Yu 1997). Scholl (2001) splits this distinction into the interconnected concepts of *solution robustness*, *optimality robustness*, *feasibility robustness*, *information robustness*, *planning robustness*, and *assessment robustness*. In ReDRiSS, robustness measurement requests for comparing outcomes of alternatives across scenarios. As the concepts of feasibility robustness, solution robustness, and optimality robustness explicitly concentrate on outcomes, they are principally applicable using ReDRiSS. The further listed concepts rather focus on robustness of the decision-making process itself, such as on temporal effects across different steps of the planning process (planning robustness), the appropriacy of information (information robustness), or the suitability of the underlying model (assessment robustness). Feasibility robustness, solution robustness, and optimality robustness follow the same rationale: an alternative should perform well – according to the risk attitude of the decision-makers (see section 4.5) – in any scenario. A measure of "well" might be the deviation of an outcome from being not feasible (feasibility robustness), from a given outcome threshold (solution robustness), or from the scenario-optimal outcome that can be reached by any alternative in the considered scenario (optimality robustness).

As scenarios might greatly differ in their assumptions (in ReDRiSS: specifications of environmental variables), robustness measurement of alternatives must respect scenario-specific characteristics. Following the considerations of Scholl (2001), the concept of *optimality robustness* is suitable in this case and therefore used by ReDRiSS. Optimality robustness is measured by the indicator of *regret*. The regret of an alternative in a scenario is defined as the absolute or relative deviation of the outcome of an alternative in a scenario from the best outcome that can be reached by any other alternative in this scenario (Scholl

2001). Equations [4-18] and [4-19] show the absolute and relative regret of an alternative $alt \in Alt$ in a scenario $scen \in Scen$ regarding objective i; $f_i(alt, scen)$ is the outcome of alt when it is applied in $scen$ and $f_i^*(Alt, scen)$ is the optimal outcome of $scen$ that can be achieved by any alternative of Alt.[12]

$$ra_i(alt, scen) = f_i(alt, scen) - f_i^*(Alt, scen) \qquad [4\text{-}18]$$

$$rr_i(alt, scen) = \frac{f_i(alt, scen) - f_i^*(Alt, scen)}{f_i^*(Alt, scen)} \qquad [4\text{-}19]$$

An alternative is denoted "totally robust" when it is the generic optimal alternative in any scenario (Scholl 2001). In fact, alt performs totally robustly in $scen$ and regarding objective i if $f_i^*(Alt, scen) = f_i(alt, scen)$ as $ra_i(alt, scen) = rr_i(alt, scen) = 0$. A totally robust alternative rarely exists when multiple objectives are respected as many real-world problems do $(ra_i(alt, scen) = rr_i(alt, scen) = 0, \forall scen \in Scen, \forall i)$. Robust decision-making should therefore rather focus on alternatives whose regret values are acceptable across scenarios and objectives (Scholl 2001). In fact, an absolute or relative threshold RA_i or RR_i can be defined where an alternative is denoted robust if $ra_i(alt, scen) \leq RA_i, \forall scen \in Scen, \forall i$ or $rr_i(alt, scen) \leq RR_i, \forall scen \in Scen, \forall i$ (Scholl 2001).

4.4.1.3 Multi-attribute value theory (MAVT)

MAVT is a method of *multi-attribute decision-making* (MADM) which is the sub-division of MCDA that includes methods to evaluate a discrete number of alternatives regarding the achievement of objectives (Geldermann 1999; Haase 2011). The purpose of MAVT is to determine a normalized outcome of an alternative (e.g. in a scenario) that respects preferences of the decision-makers regarding all considered objectives. As stated by several authors, MAVT has proven to be successful in the

[12] [4-18] and [4-19] highlight the case of a minimization problem. When a maximization problem is considered, $ra_i(alt, scen) = f_i^*(Alt, scen) - f_i(alt, scen)$ and $rr_i(alt, scen) = \frac{f_i^*(Alt,scen) - f_i(alt,scen)}{f_i^*(Alt,scen)}$.

context of disaster management as the method is clear and transparent in its nature (French 1996; Papamichail & French 2000; Geldermann et al. 2007; Bertsch 2008). The MAVT process comprises four steps where back-loops between all steps exist (Belton & Stewart 2002; Bertsch 2008). In the following, a summary of the MAVT process is provided; for in-depth information reference is made to Bertsch (2008).

- *Problem structuring*: objectives are structured by criteria, e.g. in a hierarchical manner. A decision table is set up to highlight the outcome of each alternative regarding each criterion.
- *Preference elicitation*: *inter-criteria preferences* and *intra-criteria preference*s are integrated by processing preference-related information of the decision-makers. Inter-criteria preferences are defined by the relative weight of each criterion to highlight its relative importance. Intra-criteria preferences focus on the normalization of each objective specific outcome to the interval [0,1]. This is important to make possibly varying units of the criteria comparable. Therefore, a *value function* per criterion is defined. Different types of value functions are imaginable in this regard (e.g. linear, exponential). The "best" and "worst" outcome corresponds to 1 and 0 respectively.
- *Aggregation*: one aggregated outcome per alternative is calculated by adding up the multiplication of the criterion-specific normalized value of the alternative (according to the intra-criteria preferences) and the relative weight of this criterion (according to the inter-criteria preferences).
- *Sensitivity analysis*: as the aggregated outcome per alternative follows subjective attitudes, sensitivity analyses explore the effects when relative weights (inter-criteria preferences) and value functions (intra-criteria preferences) are modified. If results are highly sensitive, decision-makers should check whether weights accurately reflect their preferences (Belton & Vickers 1990).

An advancement of MAVT is provided by the method of *multi-attribute utility theory* (MAUT). This method determines the utility of an alternative based on *utility functions* by assuming that outcomes are uncertain due to random external factors (Belton & Stewart 2002; Bertsch 2008). MAUT respects uncertain outcomes by means of probability distributions and expectations of the decision-makers. This makes MAUT difficult to use in practice as such probability distributions are not typically known (Belton & Stewart 2002; O'Hagan & Oakley 2004; Geldermann et al. 2009). For in-depth information regarding differences and similarities between MAVT and MAUT, see Bertsch (2008).

4.4.2 Stress test approach

Let the input of the stress test be:

- $Alt = \{alt_1, \dots, alt_j, \dots, alt_J\}$ a set of alternatives
- $Scen = \{scen_1, \dots, scen_k, \dots, scen_K\}$ a set of scenarios

The stress test approach of ReDRiSS, as it is applied within stress test 1 and stress test 2, comprises five tasks which are highlighted in Figure 4-6.

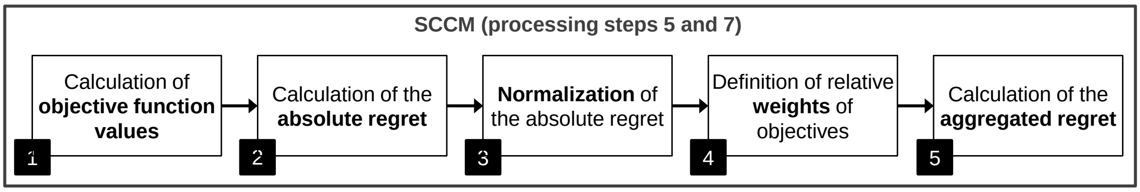


Figure 4-6: Stress test process

Let the optimization model correspond to the minimization problem highlighted in [4-11] (see section 4.3.4). Per $alt_j \in Alt$ and $scen_k \in Scen$, the outcome (objective function value) regarding each objective $i = 1, \dots, F$ is calculated by using the $scen_k$-specific optimization sub-model (task 1). The result is a matrix of outcomes of all alternatives of Alt per $scen_k \in Scen$:

$$f(Alt, scen_k) = \begin{pmatrix} f_1(alt_1, scen_k) & \cdots & f_1(alt_J, scen_k) \\ \vdots & \ddots & \vdots \\ f_F(alt_1, scen_k) & \cdots & f_F(alt_J, scen_k) \end{pmatrix} \quad [4\text{-}20]$$

The absolute regret is used as an indicator to compare outcomes. In preparation to the calculation, the best (minimal) outcome of all alternatives of Alt per $scen_k \in Scen$ and per $i = 1, \ldots, F$ is determined:

$$f_i^*(Alt, scen_k) = \min\left(f_i(Alt, scen_k) = \left\{f_i(alt_1, scen_k), \ldots, f_i\left(alt_J, scen_k\right)\right\}\right) \quad [4\text{-}21]$$

The *absolute regret* of alt_j in $scen_k$ and regarding i is (task 2):

$$ra_i\left(alt_j, scen_k\right) = f_i\left(alt_j, scen_k\right) - f_i^*(Alt, scen_k) \quad [4\text{-}22]$$

The result is a set of absolute regret values of all alternatives of Alt per $scen_k \in Scen$ and per $i = 1, \ldots, F$:

$$ra_i(Alt, scen_k) = \left\{ra_i(alt_1, scen_k), \ldots, ra_i\left(alt_J, scen_k\right)\right\} \quad [4\text{-}23]$$

Tasks 3, 4, and 5 include a process that is inspired by MAVT. The objective of this process is to generate an aggregated absolute regret value (across all objectives $i = 1, \ldots, F$) per $scen_k \in Scen$ and $alt_j \in Alt$ that is normalized to the interval [0,1]. Therefore, values of each set $ra_i(Alt, scen_k), i = 1, \ldots F, k = 1, \ldots, K$ (see [4-23]) are normalized (task 3), a relative weight of each objective $i = 1, \ldots, F$ is defined (task 4), and an aggregated regret value per $scen_k \in Scen$ and $alt_j \in Alt$ is calculated (task 5).

With respect to the MAVT process, the *normalization* of sets of absolute regret values (see [4-23]) requires the integration of intra-criteria preferences that are elicited from the decision-makers. Therefore, an individual value function vf_i is defined per $i = 1, \ldots, F$. Value functions, thus, might vary across the objectives (e.g. linear or exponential value functions).

$$vf_i: \begin{cases} \mathbb{R} \rightarrow [0,1] \\ ra_i(alt_j, scen_k) \mapsto vf_i\left(ra_i(alt_j, scen_k)\right) = ra_i^{norm}(alt_j, scen_k) \end{cases} \quad [4\text{-}24]$$

An alternative is defined as totally robust in a scenario when it achieves the absolute regret of 0. The "best" (minimal) and "worst" (maximal) normalized regret value of $ra_i(Alt, scen_k)$, thus, corresponds to 0 and 1 respectively.

$$vf_i\left(\min(ra_i(Alt, scen_k))\right) = 0 \quad [4\text{-}25]$$

$$vf_i\left(\max(ra_i(Alt, scen_k))\right) = 1 \quad [4\text{-}26]$$

Inter-criteria preferences are elicited from the decision-makers (task 4) by *relative weights of objectives* $we_i \in [0,1], i = 1, \dots, F$ where:

$$\sum_{i=1}^{F} we_i = 1 \quad [4\text{-}27]$$

Based on the normalized absolute regret values $ra_i^{norm}(alt_j, scen_k), i = 1, \dots, F, j = 1, \dots, J, k = 1, \dots, K$ and the relative weights of objectives $we_i \in [0,1], i = 1, \dots, F$, the *aggregated regret* $ra^{agg}(alt_j, scen_k) \in [0,1]$ is calculated (task 5):

$$ra^{agg}(alt_j, scen_k) = \sum_{i=1}^{F} we_i \cdot ra_i^{norm}(alt_j, scen_k) \quad [4\text{-}28]$$

The result is a matrix of aggregated regret values across all alternatives of Alt and all scenarios of $Scen$:

$$ra^{agg}(Alt, Scen) = \begin{pmatrix} ra^{agg}(alt_1, scen_1) & \cdots & ra^{agg}(alt_1, scen_K) \\ \vdots & \ddots & \vdots \\ ra^{agg}(alt_J, scen_1) & \cdots & ra^{agg}(alt_J, scen_K) \end{pmatrix} \quad [4\text{-}29]$$

A special note has to be made on the question of feasibility of alternatives when they are tested against different scenario-specific optimization sub-models. According to decision theory, the stress test approach follows the assumption that alternatives are applicable under different conditions of the decision situation and lead to a result in any of them (Neumann & Morlock 2002). Equal specifications of planning variables ensure that the decision space is identical from the planning perspective (see section 4.3.2). Each generated alternative is, thus, principly feasible in any scenario. In turn, specifications of environmental variables vary across scenarios. Their assumed specifications in a scenario describe the state of the decision environment. It is possible that constraints including environmental variables might be violated when testing an alternative in an optimization sub-model. Such violations are basically tolerated by ReDRiSS. This is because the behavior of alternatives is explored under environmental conditions that are not under the control of the decision-makers. When an alternative is taken as action, it has to cope with any environmental conditions although a constraint is not fulfilled. Hence, the purpose of constraints is explicitly to regulate the *generation of alternatives* where constraints are not allowed to be violated.

For example, a constraint can postulate a scenario-specific objective function threshold that must be reached by an alternative to be feasible. This threshold might not be reached by another alternative that, in turn, has achieved the threshold in a further scenario and that has been therefore added to the set of alternatives. The drawback of an alternative that does not reach the threshold in a scenario is reflected by an inferior regret value. For simplification reasons, it is generically assumed in the following that an alternative clearly provides one objective function value per scenario and objective without explicitly considering violations of constraints.

In some cases it might be possible that an alternative adapts to a certain degree to the scenario-specific state of the decision environment. Such a potential of an alternative is described in literature as its *flexibility* as a feature of robustness itself (see section 3.2.2). Whether an alternative adapts or not depends on its underlying decision variables.

For example, a location planning problem typically includes decision variables that reflect strategic, tactical, or operational sub-decisions. Strategic decision variables (e.g. whether to establish a facility or not) are frequently (depending on the situational context) not adaptable to changed states of the decision environment. Tactical or operational decisions (e.g. the allocation of facilities to the sales areas) may be adaptable to such changes. ReDRiSS assumes that an alternative always adapts to the scenario-specific conditions (e.g. switching allocations of facilities to the sales areas when roads are inaccessible). In this way, it is ensured that the flexibility of alternatives is inherently respected by ReDRiSS.

4.4.3 Stress test application

The following outlines the result processing when applying the stress approach by stress test 1 and stress test 2.

4.4.3.1 Stress test 1

Input of *stress test 1* is:

- The set of prognostic scenarios S^{prog} (see [4-6], section 4.3.3.2)
- The set of alternatives A (see [4-12], section 4.3.4)

The stress test approach (see section 4.4.2) is conducted based on this input. As result, a set of aggregated regret values is generated:

$$ra^{agg}(A, S^{prog}) = \begin{pmatrix} ra^{agg}\left(a_1, s_1^{prog}\right) & \cdots & ra^{agg}\left(a_1, s_L^{prog}\right) \\ \vdots & \ddots & \vdots \\ ra^{agg}\left(a_Z, s_1^{prog}\right) & \cdots & ra^{agg}\left(a_Z, s_L^{prog}\right) \end{pmatrix} \quad [4\text{-}30]$$

Aggregated regret values are needed for two purposes. Firstly, a subset of *promising alternatives* $\tilde{A} = \{\tilde{a}_1, \dots, \tilde{a}_b, \dots, \tilde{a}_B\} \subseteq A$ is filtered. This subset includes alternatives that perform robustly in all prognostic scenarios in comparison to the further alternatives. Secondly, a customized subset of *significant scenarios* $S^{si,\tilde{a}_b} = \left\{s_1^{si,\tilde{a}_b}, \dots, s_w^{si,\tilde{a}_b}, \dots, s_W^{si,\tilde{a}_b}\right\} \subseteq S^{prog}$ is filtered per $\tilde{a}_b \in \tilde{A}$. This subset includes those prognostic scenarios in which $\tilde{a}_b$ is characterized by the maximal "worst" aggregated regret values. $\tilde{A}$ and $S^{si,\tilde{a}_b}, b = 1, \dots, B$ provides the input of processing step 6 (part B). The reason for prioritizing alternatives and scenarios is computational: as there might be a large number of alternatives and prognostic scenarios available, computational issues might be caused if all alternatives and prognostic scenarios are considered within the construction of hypothetical scenarios.

A threshold $TS \in [0,1]$ is defined by the decision-makers to filter $\tilde{A}$. An alternative is a *promising alternative* if all of its aggregated regret values are below this threshold in any prognostic scenario. Hence, $\tilde{A}$ is:

$$\tilde{A} = \left\{\forall a_z \in A: \max_{\forall l}\left(\left\{ra^{agg}\left(a_z, s_l^{prog}\right)\right\}\right) \leq TS\right\} \qquad [4\text{-}31]$$

Significant scenarios represent customized prognostic "worst case" scenarios. Let be:

- $ra^{agg}(\tilde{a}_b, S^{prog}) = \left\{ra^{agg}\left(\tilde{a}_b, s_1^{prog}\right), \dots, ra^{agg}\left(\tilde{a}_b, s_L^{prog}\right)\right\} \subseteq ra^{agg}(A, S^{prog})$ the subset of aggregated regret values of $\tilde{a}_b \in \tilde{A}$ regarding all prognostic scenarios of S^{prog}
- $ra^{met}(\tilde{a}_b, S^{prog}) = \{ra^{met,1}(\tilde{a}_b), \dots, ra^{met,R}(\tilde{a}_b)\}, R = L$ the metrical ordered equivalent of $ra^{agg}(\tilde{a}_b, S^{prog})$.

The identification of significant scenarios is steered by the *n-quantile* $q_n(\tilde{a}_b)$ of the set $ra^{met}(\tilde{a}_b, S^{prog})$ where n must be defined by the decision-makers. The aggregated regret of $\tilde{a}_b$ in each $s_w^{si,\tilde{a}_b} \in S^{si,\tilde{a}_b}$, $ra^{agg}\left(\tilde{a}_b, s_w^{si,\tilde{a}_b}\right)$, must be higher (worse) than $q_n(\tilde{a}_b)$. Thus, the number of significant scenarios is the same of each promising alternative: $\left|S^{si,\tilde{a}_j}\right| = \left|S^{si,\tilde{a}_k}\right|, \forall \tilde{a}_j, \tilde{a}_k \in \tilde{A}, j \neq k$. Hence, $S^{si,\tilde{a}_b}$ is:

$$S^{si,\tilde{a}_b} = \left\{\forall s_l^{prog} \in S^{prog}: ra^{agg}\left(\tilde{a}_b, s_l^{prog}\right) > q_n(\tilde{a}_b)\right\} \qquad [4\text{-}32]$$

Figure 4-7 exemplarily visualizes the stress test 1 results (promising alternatives and significant scenarios) for the input data $A =$

$\{a_1, a_2, a_3\}$, $S^{prog} = \{s_1^{prog}, \ldots, s_{10}^{prog}\}$, $TS = 0.7$, and $n = 0.8$. The results of this example are:

- $\tilde{A} = \{\tilde{a}_1 = a_2, \tilde{a}_2 = a_3\}$
- $S^{si,\tilde{a}_1} = \{s_1^{si,\tilde{a}_1} = s_{10}^{prog}, s_2^{si,\tilde{a}_1} = s_5^{prog}\}$
- $S^{si,\tilde{a}_2} = \{s_1^{si,\tilde{a}_2} = s_3^{prog}, s_2^{si,\tilde{a}_2} = s_5^{prog}\}$

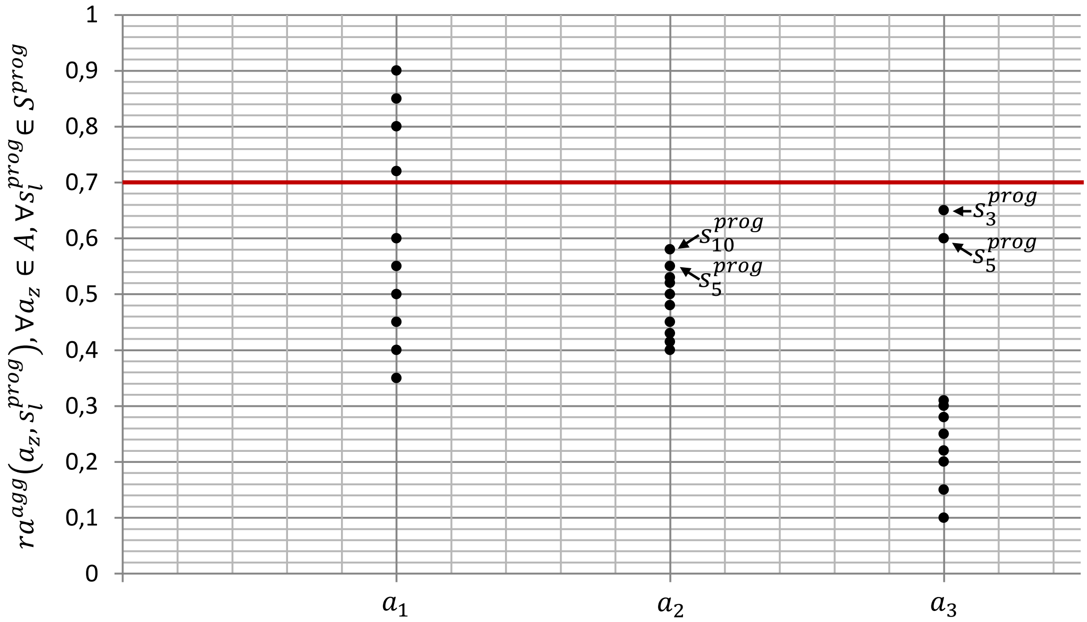


Figure 4-7: Visualization of exemplary stress test 1 results

4.4.3.2 Stress test 2

Input of *stress test 2* is:

- The set of prognostic scenarios S^{prog} (see [4-6], section 4.3.3.2)
- The set of promising alternatives $\tilde{A}$ (see [4-31]), section 4.4.3.1)
- The customized sets of hypothetical scenarios $S^{hyp,\tilde{a}_b}, \forall \tilde{a}_b \in \tilde{A}$ (see [4-32] , section 4.4.3.1)

The objective of stress test 2 is to provide data that is sufficient for measuring the robustness of each $\tilde{a}_b$ in part D (see section 4.5). Therefore, the stress test approach is separately conducted for:

- each $\tilde{a}_b \in \tilde{A}$ in each $s_l^{prog} \in S^{prog}$
- each $\tilde{a}_b \in \tilde{A}$ in each $s_{w,k}^{hyp,\tilde{a}_b} \in S^{hyp,\tilde{a}_b}$

Results are the sets of aggregated regret values:

$$ra^{agg}(\tilde{A}, S^{prog}) = \begin{pmatrix} ra^{agg}\left(\tilde{a}_1, s_1^{prog}\right) & \cdots & ra^{agg}\left(\tilde{a}_1, s_L^{prog}\right) \\ \vdots & \ddots & \vdots \\ ra^{agg}\left(\tilde{a}_B, s_1^{prog}\right) & \cdots & ra^{agg}\left(\tilde{a}_B, s_L^{prog}\right) \end{pmatrix} \quad [4\text{-}33]$$

$$ra^{agg}\left(\tilde{A}, S^{hyp,\tilde{A}}\right) = \begin{pmatrix} ra^{agg}\left(\tilde{a}_1, s_{1,1}^{hyp,\tilde{a}_1}\right) & \cdots & ra^{agg}\left(\tilde{a}_1, s_{W,K}^{hyp,\tilde{a}_1}\right) \\ \vdots & \ddots & \vdots \\ ra^{agg}\left(\tilde{a}_B, s_{1,1}^{hyp,\tilde{a}_B}\right) & \cdots & ra^{agg}\left(\tilde{a}_B, s_{W,K}^{hyp,\tilde{a}_B}\right) \end{pmatrix} \quad [4\text{-}34]$$

The *expected aggregated regret* and the *maximal aggregated regret* are calculated per $\tilde{a}_b \in \tilde{A}$. As occurrence probabilities of scenarios are not assumed, the expected aggregated regret RE is

$$RE(\tilde{a}_b, S^{prog}) = \frac{1}{L}\sum_{l=1}^{L} ra^{agg}(\tilde{a}_b, s_l^{prog}) \quad [4\text{-}35]$$

$$RE(\tilde{a}_b, S^{hyp,\tilde{a}_b}) = \frac{1}{W \cdot K}\sum_{w=1}^{W}\sum_{k=1}^{K} ra^{agg}(\tilde{a}_b, s_{w,k}^{hyp,\tilde{a}_b}) \quad [4\text{-}36]$$

The maximal aggregated regret RM refers to the scenario per scenario category in which $\tilde{a}_b$ performs worst. It is defined as:

$$RM(\tilde{a}_b, S^{prog}) = \max_{\forall l}\left(ra^{agg}\left(\tilde{a}_b, s_l^{prog}\right)\right) \quad [4\text{-}37]$$

$$RM\left(\tilde{a}_b, S^{hyp,\tilde{a}_b}\right) = \max_{\forall w,k}\left(ra^{agg}\left(\tilde{a}_b, s_{w,k}^{hyp,\tilde{a}_b}\right)\right) \quad [4\text{-}38]$$

The result of stress test 2 is a matrix including the expected and maximal aggregated regret values regarding both scenario categories (see Table 4-2). This matrix provides the input for the robustness measurement in part D.

Table 4-2: Result matrix of stress test 2

	Prognostic scenarios		Hypothetical scenarios	
	Expected regret	Maximal regret	Expected regret	Maximal regret
$\tilde{a}_1$	$RE(\tilde{a}_1, S^{prog})$	$RM(\tilde{a}_1, S^{prog})$	$RE(\tilde{a}_1, S^{hyp,\tilde{a}_1})$	$RM(\tilde{a}_1, S^{hyp,\tilde{a}_1})$
...	...	...	...	...
$\tilde{a}_b$	$RE(\tilde{a}_b, S^{prog})$	$RM(\tilde{a}_b, S^{prog})$	$RE(\tilde{a}_b, S^{hyp,\tilde{a}_b})$	$RM(\tilde{a}_b, S^{hyp,\tilde{a}_b})$
...	...	...	...	...
$\tilde{a}_B$	$RE(\tilde{a}_B, S^{prog})$	$RM(\tilde{a}_B, S^{prog})$	$RE(\tilde{a}_B, S^{hyp,\tilde{a}_B})$	$RM(\tilde{a}_B, S^{hyp,\tilde{a}_B})$

4.5 Robustness measurement

Although there might be a large set of alternatives available, decision-making implies taking *one* alternative as action to solve a decision problem. In ReDRiSS, the selection of such an action depends on the decision-makers' perception of the effect of uncertainty and complexity. This perception is described by the terms *risk attitude* or *risk preference* which are ambiguously used in literature (Wiens 2013). Most authors agree in assuming the two extreme types of *risk-averse* and *risk-seeking* decision-makers. With respect to Hillson & Murray-Webster (2007), risk-averse decision-makers are characterized as uncomfortable with potentially negative consequences triggered by a decision ex post. They prefer to avoid or at least to reduce as many threats as possible. Risk-seeking decision-makers welcome uncertainty. They are less interested in avoiding or reducing threats but rather in exploiting opportunities (e.g. offered by alternatives). Part D of ReDRiSS measures robustness of promising alternatives by respecting the risk preferences of the decision-makers (processing step 8). The final processing step of ReDRiSS proposes a sensitivity analysis (processing step 9) to explore the impact of preferential uncertainty on the robustness of promising alternatives.

4.5.1 Integration of risk preferences

Decision-makers in SCM principally tend to operate in a risk-averse manner (Scholl 2001). This risk aversion reflects all levels of decision-making in SCM, strategic, tactical, and operational decisions. The reason for this risk aversion is not necessarily the personal risk attitude of decision-makers. They would rather bear responsibility to operate in the name of an organization and must be aware of justifying negative consequences of a decision ex post. However, decision-makers must also try to exploit existing potentials of alternatives to avoid wastes of resources.

Hence, ReDRiSS assumes a *principle risk aversion* of decision-makers. They are not just confronted with a decision situation that threatens the objectives of the organizations they are operating in the name of (e.g. private companies, public authorities). In both fields of application of ReDRiSS, the development of compensation strategies and adaptation strategies, public safety is threatened or even already affected.

Input data of processing step 8 is the aggregated regret matrix provided by stress test 2 (see Table 4-2). Based on this data, the objective is to determine one *robustness value* per promising alternative. To measure robustness while respecting risk preferences, an in-depth consideration of the principle risk aversion of decision-makers is required: their personal *degree of pessimism* which explores whether they perform in a rather *neutral* or *pessimistic* manner within their principle risk aversion. The task of integrating the degree of pessimism into ReDRiSS is associated with weighting the effect of uncertainty and complexity captured by prognostic and hypothetical scenarios. Therefore, two aspects must be respected: the *inter-* and *intra-scenario degrees of pessimism*.

Regarding the inter-scenario degree of pessimism, neutral decision-makers would rather aim at measuring robustness of a promising alternative based on the set of prognostic scenarios. This is because prognostic scenarios are defined as probable and expected. In turn, pessimistic decision-makers might be interested in hedging against critical and unexpected dynamic developments of the decision environment specified by customized hypothetical scenarios. ReDRiSS respects the inter-scenario degree of pessimism by a relative weight of each scenario category, $we^{prog}, we^{hyp} \in [0,1]$, where:

$$we^{prog} + we^{hyp} = 1 \qquad [4\text{-}39]$$

Regarding the intra-scenario degree of pessimism, neutral decision-makers understand a promising alternative as robust if it achieves a small aggregated regret in any scenario of a considered scenario category. Pessimistic decision-makers aim at hedging against that single scenario in which a promising alternative performs worst and, thus, achieves the highest aggregated regret. This is even true when this promising alternative is characterized by a very small aggregated regret in any other scenario of the considered scenario category.

ReDRiSS respects the intra-scenario degree of pessimism through a procedure that is inspired by the *Hodge-Lehmann criterion* (see section 2.1.3.2). The criterion suggests combining the *μ criterion* and the *minimax criterion*[13]. Thereby, the reliability parameter $\lambda \in [0,1]$ reflects the relative importance of the expected value of the considered set of outcomes (*μ criterion*) compared to the worst value of this set (*minimax criterion*) (Zimmermann & Gutsche 1991; Scholl 2001; Rommelfanger & Eickemeier 2002; Wiens 2013). ReDRiSS adapts the rationale of the *Hodge-Lehmann criterion* to integrate the intra-scenario degree of pessimism separately for each scenario category. Therefore, a reliability parameter per scenario category, $\lambda^{prog}, \lambda^{hyp} \in [0,1]$, is defined. Neutral decision-makers totally trust in the quality of the set of aggregated regret values and follow the expected value of this set ($\lambda^{prog}, \lambda^{hyp} \to 1$). Pessimistic decision-makers do not trust in the quality of the set of aggregated regret values and follow the maximal value of this set ($\lambda^{prog}, \lambda^{hyp} \to 0$). Hence, the intra-scenario degree of pessimism is respected within ReDRiSS by calculating the criterion $\phi^{prog}(\tilde{a}_b), \forall \tilde{a}_b \in \tilde{A}$:

$$\phi^{prog}(\tilde{a}_b) = \lambda^{prog} \cdot RE(\tilde{a}_b, S^{prog}) + (1 - \lambda^{prog}) \cdot RM(\tilde{a}_b, S^{prog}) \qquad [4\text{-}40]$$

[13] The minimax criterion is the equivalent of the maximin criterion (see section 2.1.3.2). It is applied when the objective of the decision situation is to minimize outcomes of alternatives.

$$\phi^{hyp}(\tilde{a}_b) = \lambda^{hyp} \cdot RE\left(\tilde{a}_b, S^{hyp,\tilde{a}_b}\right) + (1 - \lambda^{hyp}) \cdot RM(\tilde{a}_b, S^{hyp,\tilde{a}_b}) \qquad [4\text{-}41]$$

An alternative decision rule that has been explicitly suggested in literature to steer the specification of risk preferences follows the Hurwicz criterion (see section 2.1.3.2). In this case, the parameter λ regulates the degree of pessimism by aggregating the minimin criterion[14] and the minimax criterion. The reason for not using a procedure within ReDRiSS that is related to the Hurwicz criterion lies in the assumed principle risk aversion of decision-makers. In fact, the Hurwicz criterion allows decision-makers to even operate in an optimistic manner by following the minimin criterion ($\lambda = 1$). This would be, however, not a wise behavior in disaster management. Moreover, by considering just extreme values by trading-off the minimin and minimax criteria, the medium range of values might be neglected. This might imply the threat of making contra-intuitive decisions (Bamberg & Coenenberg 2006; Wiens 2013).

Based on the adjusted inter- and intra-scenario degree of pessimism, a *robustness value* is calculated per $\tilde{a}_b \in \tilde{A}$:

$$RV(\tilde{a}_b) = we^{prog} \cdot \phi^{prog}(\tilde{a}_b) + we^{hyp} \cdot \phi^{hyp}(\tilde{a}_b) \qquad [4\text{-}42]$$

The result of processing step 8 is a set of *robustness values* $\{RV(\tilde{a}_b) | \forall \tilde{a}_b \in \tilde{A}\}$. Finally, the promising alternative is denoted *robust alternative* $\tilde{a}$, and is provided as decision recommendation to the decision-makers, that achieves the minimal robustness value in this set:

$$\tilde{a} = \left(\tilde{a}_b \in \tilde{A}: RV(\tilde{a}_b) = \min_{\forall \tilde{a}_b \in \tilde{A}}(\{RV(\tilde{a}_b)\})\right) \qquad [4\text{-}43]$$

[14] The minimin criterion is the equivalent of the maximax criterion (see section 2.1.3.2). It is applied when the objective of the decision situation is to minimize outcomes of alternatives.

4.5.2 Sensitivity analysis

The objective of sensitivity analyses in decision-making typically is to examine the impact of preferential parameters on initial results (Bertsch 2008). Chosen specifications of preferential parameters might be subjective in their nature. It is, thus, valuable to explore whether or not differences in the judgments of decision-makers matter in terms of the results (Belton & Vickers 1990; French 2003; Bertsch 2008). Sensitivity analyses are conducted as the final step of the decision-making process. The objective is to test the robustness of initial results to perturbations of preferential parameter specifications (Saltelli et al. 2008; Comes 2011). Sensitivity analyses may observe effects of varying specifications of just one parameter or multiple parameters simultaneously (Butler et al. 1997; Geldermann et al. 2005; Bertsch 2008; Hiete et al. 2010; Comes 2011).

In ReDRiSS, the objective of the sensitivity analysis in processing step 9 is to explore the *preferential robustness* of robustness values of promising alternatives themselves. As stated by Bertsch (2008), obtained result rankings that remain stable compared to initially used parameter specifications can be understood as robust. When, in turn, results of sensitivity analyses indicate that rankings are sensitive, decision-makers should carefully check if parameter specifications accurately reflect their preferences (Belton & Vickers 1990; Bertsch 2008). Hence, the objective is to explore whether ReDRiSS results that have been proven as robust to *data uncertainty* are additionally robust to *preferential uncertainty*. Sensitivity analyses do not explore further scenarios or alternatives. This goes along with the considerations of Comes (2011) who claims from the perspective of disaster management that the purpose of sensitivity analyses is rather to observe the effect of preferential uncertainty than to identify new development paths for analyses.

Two sensitivity analyses are conducted in ReDRiSS to explore the effect of varying preferential parameter specifications. This is firstly the variation of preferences of objectives ($we_i, i = 1, \dots, F$) that have been used in stress test 2 (processing step 7). Secondly, variations of chosen risk preferences in processing step 8 are investigated. This concerns both a changed inter-scenario degree of pessimism (we^{prog},we^{hyp}) and intra-scenario degree of pessimism (λ^{prog},λ^{hyp}). Whether sensitivities of (parameters of) preferences and risk preferences should be explored separately or simultaneously depends on the case of application. In any case, it is important to report interpretations of results by using appropriate visualizations (Bertsch 2008). These visualizations should be enriched by explanations, e.g. by natural language reports, to stimulate discussions of decision-makers (Geldermann et al. 2009). The actual characteristics of such visualizations and explanations depend again on the case of application. Examples of visualizations of results of sensitivity analyses can be found in the case studies of this research (see chapters 5 and 6).

4.6 Summary and discussion

Chapter 4 presented ReDRiSS, a DSS which aims at aiding decision-makers of SCCM in the post-disaster management of P-SC disturbances. Based on the methodological and conceptual insights provided by chapters 2 and 3, the scope of ReDRiSS and the requirements it must fulfil have been outlined in section 4.1. The rationale of ReDRiSS has been discussed from a top-down perspective. While section 4.2 summarized the general functioning and interactions of included parts and processing steps, an in-depth consideration into each processing step has been undertaken by sections 4.3, 4.4, and 4.5. Firstly, processing steps regarding the implementation and application of a two-stage scenario technique (part A and part B) have been discussed in section 4.3. Secondly, a stress test approach (part C) has been presented in section 4.4. This approach provides, in interaction with the two-stage scenario technique, endogenous information that is sufficient to, thirdly, measure robustness of alternatives to solve the considered logistical decision problem (part D, section 4.5). In the following paragraphs, the achievement of the requirements listed in section 4.1 is verified.

1. ReDRiSS should be based on a generic structure to be preventively adaptable to various decision situations (as the task of SCRM) and to *provide reactive decision support for SCCM in disaster response*. The crucial challenge of ReDRiSS is support decision-makers in the exploration of effects of uncertainty and complexity facing a disaster-caused decision environment. ReDRiSS includes a generic methodology that is adaptable to varying decision situations. The interchangeable element of this methodology is an optimization model to solve a logistical decision problem. This optimization model directly determines the specification of alternatives (decision variables) and of scenarios (parameters). The pre-disaster implementation of ReDRiSS (part A) as the task of SCRM requires the definition of the optimization model and its adaptation to be applicable within parts B, C, and D or, in general, by post-disaster SCCM. This adaptation requires the selection of an appropriate solution algorithm, the classification of parameters of the optimization model, and the preparation of scenario construction by developing specification processes of parameters. The post-disaster process of ReDRiSS is the same in any decision situation. A two-stage scenario technique (part B) is coupled with a stress test approach (part C). In there, alternatives are tested and endogenous information (regret data) is provided to be evaluated by a standardized robustness measurement (part D).

2. ReDRiSS should be able to support both internal and external decision-makers by developing either adaptation strategies or compensation strategies. Most approaches that have been proposed at the interface of SCM and DOM focus on the development of compensation strategies, in particular regarding the field of humanitarian logistics (see chapter 3). These approaches concentrate on the establishment of logistical compensation structures in the case that the disaster causes destructions of P-SCs. There is a lack of approaches that consider the possibility that P-SCs (or several of their entities) can, although they are severely affected, be kept alive by implementing the right decisions. ReDRiSS is able to support decision-makers in "repairing" disrupted P-SCs. This is because the application of ReDRiSS mainly depends on the optimization model that is used to generate and test alternatives. Rather than differentiating between compensation strategies and adaptation strategies, ReDRiSS places the focus on the similarities that affect both internal and external decision-makers: the excessive demand of respecting uncertainty and complexity in a disaster-affected decision environment while making a decision.

3. ReDRiSS should include an innovative scenario-based methodology to respect both uncertainty and complexity of the decision situation during a disaster situation. With respect to the previous two requirements, ReDRiSS suggests a two-stage scenario technique to explore uncertainty and complexity (in terms of dynamic developments caused by secondary disasters or socioeconomic changes) within the disaster-affected decision environment. Explorations differ in the type of information processed. Uncertainty refers to a lack of knowledge about the post-disaster state of the decision environment. Available exogenous information (from the decision environment) is, thus, the trigger to construct prognostic scenarios. They close lacks of exogenous information by defining probable and expected states of the decision environment. Complexity, in turn, is captured by analyzing vulnerabilities of these states. Therefore, endogenous information which is provided by ReDRiSS itself (outcomes of alternatives across prognostic scenarios) is used to simulate critical and unexpected dynamic developments within prognostic scenarios. This simulation implies that the state of a prognostic scenario changes toward a vulnerable state or a state of failure. This state of the decision environment is denoted hypothetical scenario. As widespread possibilities of dynamic developments affecting a decision environment exist, hypothetical scenarios are constructed in a customized manner (per promising alternative). In fact, a dynamic development either simulates the weakness of a promising alternative itself (when it is hypothetically taken as decision in a prognostic scenario) or the weakness of a state of the decision environment in which the promising alternative performs poorly compared to further alternatives (significant scenario). Hence, ReDRiSS iteratively scans uncertainty and complexity facing the decision environment: uncertainty is processed to close lacks of exogenous information by prognostic scenarios, endogenous information in terms of alternatives and outcomes is generated, and complexity is simulated via dynamic developments within hypothetical scenarios.

4. ReDRiSS should be holistic in its nature to operationalize all steps of the decision-making process. Following the IDC model (see chapter 2), ReDRiSS operationalizes the steps of the decision-making process under uncertainty that arise across the phases intelligence, design, and choice. Part A refers to the intelligence phase whose objective is to classify and to define the logistical decision problem. Moreover, the conduction of the design phase is prepared. Part B focusses on the design phase by generating alternatives under uncertainty. In part C, alternatives are evaluated (design phase) and negotiated (choice phase). Part D refers to the choice phase in terms of selecting an alternative and determining an action. Regarding the decision-making process under complexity, literature suggests following the rationale of pattern-based management (see chapter 2). ReDRiSS operationalizes this approach using the two-stage scenario technique (part B). Prognostic scenarios reveal uncertainty of the decision environment (pattern seeking). Endogenous information in terms of alternatives and outcomes is generated based on prognostic scenarios (pattern modelling). Weaknesses of promising alternatives and significant scenarios are further explored by simulating dynamic developments within hypothetical scenarios (pattern adapting). Hence, the rationale of ReDRiSS respects the requirements of both the decision-making process under uncertainty and complexity.

5. ReDRiSS should achieve a high analytical accuracy by using approaches of OR/MS to solve the underlying logistical decision problem. Approaches of both fields of OR/MS, mathematical programming and decision theory, are used by ReDRiSS to ensure its analytical accuracy. ReDRiSS includes an optimization model to solve the underlying logistical decision problem by applying an appropriate algorithm (e.g. exact algorithm, heuristic). The optimization model is solved in a scenario-based manner to generate and test alternatives. Outcomes of alternatives are evaluated with respect to optimality robustness by using the regret as indicator. The evaluation of regret data is facilitated by a process that is inspired by MAVT as a method of MADM. In fact, outcomes are normalized and aggregated (across all objectives) by integrating inter- and intra-objective preferences of the decision-makers. Risk preferences of decision-makers are respected and a final (optimality) robustness value per promising alternative is generated by a process that is inspired by the Hodge-Lehmann decision criterion.

6. ReDRiSS should be able to respect possible multiple objectives of the decision-makers and must operate according to their preferences. The optimization model that is integrated into ReDRiSS might be of a single- or multi-objective manner. In the latter case, methods of MODM can be used to generate compromise alternatives (by respecting preferences in an a priori, a posteriori, or progressive manner). Alternatively, all Pareto-optimal solutions (regarding multiple objectives) or all feasible alternatives (if possible) might be respected. The actual integration of preferences of objectives is the task of the stress test approach. An aggregated regret value per (relevant) alternative and scenario is generated via a process that is inspired by MAVT. When preferences have already been defined during the generation process of alternatives (in the sense of MODM), it is important to use the same preferences within the stress test approach.

7. ReDRiSS should focus on the design of robust (adapted or compensated) P-SCs by providing a robust decision recommendation according to the risk preferences of the decision-makers. The objective of designing robust (adapted or compensated) P-SCs has been the trigger for the development of ReDRiSS. Therefore, ReDRiSS provides a platform on which threats in a disaster-affected decision environment can be systematically explored via scenarios. Measuring robustness based on the concepts of optimality robustness and regret allows the respect for scenario-specific characteristics. ReDRiSS includes a novel process of robustness measurement that additionally integrates the risk preferences of the decision-makers. This affects the question whether decision-makers prefer to hedge against probable and expected states of the decision environment (prognostic scenarios) or against critical and unexpected states and, thus, more abstract eventualities (hypothetical scenarios). ReDRiSS assumes a principle risk aversion of decision-makers. It is, thus, ensured that they can never perform in an optimistic manner (regarding hedging against threats) in the disaster-caused decision situation.

8. ReDRiSS should be transparent and easily understandable to provide a practical application for decision-makers. Decision-makers participate in any part of ReDRiSS. In preventive SCRM, they define the decision problem and are involved when formulating the optimization model and determining a solution algorithm. Moreover, they are integrated into the development of specification processes of environmental variables in preparation for scenario constructions. In reactive SCCM, decision-makers steer the process of ReDRiSS by setting preferential adjustment screws (preferences of objectives, risk preferences).

ReDRiSS fulfills the general requirements of a DSS highlighted in chapter 2. It includes a “model” of parts and processing steps, a “database” of exogenous and endogenous information, and a “user interface” to integrate preferences of objectives and risk preferences of the decision-makers. This integration of decision-makers into ReDRiSS is crucial as it aims at technically *aiding* decision-makers but never *replacing* them (see chapter 2). In fact, respecting the (risk) preferences of the decision-makers is important for two reasons. Firstly, although robustness measurement is always associated with the identification of an alternative that hedges against threats caused by uncertainty and complexity, the degree of robustness additionally depends on the decision-makers’ perception of the decision situation. The degree of robustness must therefore be adjusted according to these perceptions. Secondly, by providing the opportunity for the decision-makers to actively steer the decision-making process, their trust in the DSS might increase. This is an important requirement to push the subsequent practical implementation of the obtained decision recommendation.

5 Case study 1: humanitarian logistics in Haiti

This chapter presents a case study that applies ReDRiSS in a decision situation arising in the field of *humanitarian logistics*. Haiti is hit by an earthquake which causes destructions of P-SCs. Therefore, logistical replacement structures in terms of *humanitarian relief SCs* must be established from scratch in disaster response. The focus of the case study is on the establishment of a humanitarian relief SC that compensates the functions of destructed P-SCs of the CI sector "health care". Thereby, the logistical decision problem is considered where in Haiti to set up temporary health care facilities to store medicine and medical equipment. Solving the facility location problem is a step toward defining the distribution structure of the humanitarian relief SC. ReDRiSS is applied to aid decision-makers in reactively identifying robust locations of the health care facilities. In section 5.1, the field of humanitarian logistics is introduced. The structure and assumptions of the case study are outlined in section 5.2, the logistical decision problem is solved in section 5.3, and the results are discussed in section 5.4. The chapter closes with a summary and discussion in section 5.5.

5.1 Humanitarian logistics in disaster response

Disasters are characterized by a sudden occurrence which might challenge the ability of the affected society or community to handle the triggered situation using its own resources (UNISDR 2004a). To mitigate human pain, threat of life, disease, hunger, damage of logistical structures, or losses of property, reactive operations of *humanitarian relief* provide aid for the disaster-affected area (ICDRM/GWU 2010). When the disaster causes destructions of P-SCs, logistical replacement structures must be established rapidly to compensate their failures.

The most extensive part of overall humanitarian relief refers to *humanitarian logistics*. About 80 percent of humanitarian relief operations have a logistical background (Van Wassenhove 2006; Kovács & Spens 2007). Humanitarian logistics comprises the "processes of planning, implementing and controlling the efficient and cost-effective flow and storage of goods and materials, as well as related information, from point of origin to point of consumption for the purpose of alleviating the suffering of vulnerable people" (Thomas & Kopczak 2005).

The compensation of destructed P-SCs is the task of *humanitarian relief SCs*. They distribute relief supplies (e.g. foodstuff, water, medicine) from different sources to the destinations where they are needed (Eßig & Tandler 2010; Afshar & Haghani 2012). Particularly in the disaster response phase, which usually comprises the first 72 hours after an occurring disaster, relief supplies must be provided quickly for the beneficiaries to minimize human suffering and death (Balcik & Beamon 2008). Due to a potentially large number of victims, "fast" decisions are required to establish humanitarian relief SCs. This is also the case when decisions are strategic, have a long term impact, and are irreversible in the short term. An example of such a decision is the choice of locations for warehouses, camps of dislocated people, or field hospitals (Altay & Green 2006).

The objective of *humanitarian relief SCM* is to steer the effective provision of relief supplies to as many beneficiaries as possible. However, inefficient procedures lead to wastes of resources that could have helped further people if they had been used appropriately (Tomasini & Van Wassenhove 2009). Humanitarian relief SCM must, therefore, respect both objectives of *effectiveness* and *efficiency* (Balcik & Beamon 2008; Bölsche 2009). Effectiveness aims at creating humanitarian relief SCs that provide relief supplies for those in need. Efficiency refers to the humanitarian relief SC's capacity to perform in an appropriately organized manner; the scope is on the minimization of resources (e.g. duration, costs). The objectives of effectiveness and efficiency typically conflict and must be balanced out in the design of a humanitarian relief SC (Kotabe 1998). Although effectiveness has been considered as the dominant objective in humanitarian relief SCM, longer term operations illustrate the need for additionally respecting the objective of efficiency. This is important to avoid a wasting of scarce resources and to prepare a fast recovery (Beamon & Balcik 2008).

As immediate response is required in the aftermath of a disaster, humanitarian relief SCs must be designed and deployed at once. However, the capability of decision-makers might be affected because of very limited knowledge about the state of the decision environment. Lacks of knowledge arise due to sparse exogenous information about consequences such as needs of the population or states of CI sectors (e.g. transportation infrastructure), and about available resources (Ozel 2001). Beside this uncertainty, the interconnectedness of CI sectors, possible occurrences of secondary disasters over time, and socioeconomic changes also cause a state of complexity within the decision environment (see section 3.3.1).

External decision-makers bear responsibility in humanitarian logistics (see section 3.3.2) such as representatives of governments, military, aid agencies, donors, non-governmental organizations (NGOs), or private companies (Van Wassenhove 2012). They must evaluate strengths and drawbacks of different SC designs while respecting uncertainty and complexity characterizing the decision environment. Determining an appropriate design requires, inter alia, the definition of the distribution structure of the humanitarian relief SC (see Figure 5-1).

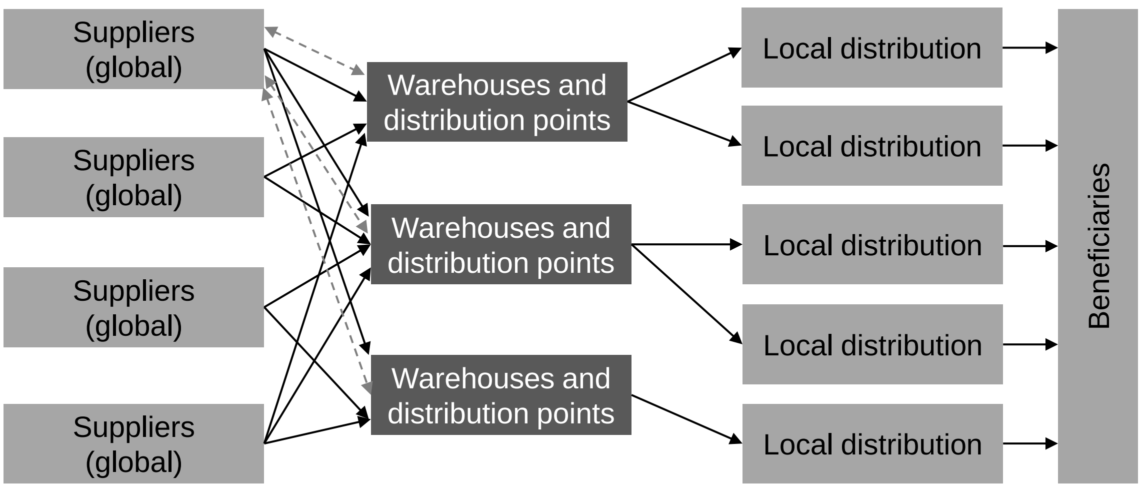


Figure 5-1: Distribution structure of humanitarian relief supply chains (adapted from Balcik et al. 2010)

A crucial logistical decision problem arising in this regard is *facility location planning*. Facilities (e.g. warehouses) act as intermediate buffers between incoming supplies and local distribution. Incoming supplies should be easily accessible and provide sufficient capacity; local distribution should be fast and correspond to the needs of the beneficiaries. While the flow of goods is directed (highlighted by black lines in Figure 5-1), the flows of information are bidirectional (highlighted by gray dotted lines, only shown for one supplier for the sake of clarity).

In analogy to business SCs, the distribution structure of a humanitarian relief SC comprises a vertical and a horizontal component (Domschke & Schildt 1994; Bölsche 2009). The vertical distribution structure includes the stages at which facilities are established. Beneficiaries whose demands must be satisfied are located at the final stage of this vertical distribution structure. The horizontal distribution structure highlights the number and locations of facilities per stage as well as their relations (e.g. the allocation of local distribution to beneficiaries' demands). Bölsche (2009) distinguishes between four types of warehouses regarding the vertical distribution structure (PAHO 2001):

- *General delivery warehouses* are central warehouses that are characterized by high capacities. As their locations are of strategic importance, they are typically established preventively.
- *Slow rotation warehouses* are central or regional warehouses. They are needed for the storage of relief supplies whose delivery is not time sensitive (e.g. EDP-supplies).
- *Quick rotation warehouses* are regional warehouses near airports or harbors. They are needed for the storage of relief supplies whose delivery is time sensitive (e.g. foodstuff, water, health care).
- *Temporary collection sites* are local warehouses near the beneficiaries. They are located in on-hand facilities (e.g. schools, gyms) and are needed for the final delivery of relief supplies.

5.2 Implementation of ReDRiSS

The forthcoming sections provide a general description of the decision situation (*ReDRiSS part A*, *processing step 1*). Moreover, the optimization model is formulated that is applied to process the logistical decision problem (*ReDRiSS part A*, *processing step 2*). This optimization model refers to an adaptation of the bi-objective unconstrained facility location problem (Revelle & Laporte 1996; Villegas et al. 2006; Daskin 2013).

5.2.1 General description of the decision situation

In January 2010, a severe earthquake of the magnitude 7.0 hit Haiti. Its epicenter was about 17 km west of the country's capital, Port-au-Prince (WHO 2010). The earthquake was followed by about 70 severe aftershocks, two of them with a magnitude of 6.0 or higher and sixteen with a magnitude of 5.0 (UNC 2010). In summary, the direct and indirect consequences of the 2010 earthquake were disastrous: the death toll was high, and destroyed infrastructure as well as a lack of coordination and planning hampered the effective and efficient distribution of disaster relief goods and services (Rencoret et al. 2010).

Due to the experiences of this previous disaster in Haiti, an association of different NGOs (external decision-makers, in the following denoted *NGO association*) decides to preventively invest in an implementation of ReDRiSS to be prepared for the case of another earthquake in Haiti in future. The first task of implementing ReDRiSS is to develop a requirements profile that summarizes the depicted decision situation and the scope of ReDRiSS (*ReDRiSS part A, processing step 1*).

The NGO association concentrates on the compensation of destructed P-SCs of the CI sector "health care" by quickly establishing a *temporary health care SC* (as a humanitarian relief SC). To define the vertical distribution structure of this SC, the logistical decision problem of locating health care facilities (warehouses) in Haiti arises. Health care facilities refer to the category of quick rotation warehouses (see section 5.1) and are required for the storage of medicine or medical equipment.

They operate as trading centers to supply temporary collection sites which, in turn, organize the final provision of supplies for the beneficiaries.

As the epicenter location and the earthquake's intensity are unknown prior to the occurrence of an earthquake, the decision problem must be solved reactively in disaster response. Solving the decision problem is restricted by an unknown extent of health care demands and states of the transportation infrastructure, as well as the possibility of secondary disasters occurring over time in terms of earthquake aftershocks. Uncertain health care demands restrict analyses to determine suitable locations of the health care facilities; interruptions of transportation infrastructures obstruct the exchange of supplies between regions. The possibility of secondary disasters triggers the threat of dynamic developments within the decision environment over time which might make an implemented alternative (the chosen health care facility locations) futile in retrospect. Widespread alternatives exist to solve the decision problem. The characteristics of the decision environment might affect the ability of decision-makers to compare these alternatives by analyzing their advantages and drawbacks in terms of withstanding the aforementioned threats. Hence, ReDRiSS should aid the NGO association reactively in identifying *robust* locations of health care facilities.

The analysis of possible health care facility locations should respect both relevant objectives of humanitarian logistics, effectiveness and efficiency. Effectiveness is measured by the *service level* that is achieved by an alternative in terms of the extent of satisfied health care demands (or of temporary collection sites as a preliminary stage prior to the provision of beneficiaries, see section 5.1). Efficiency is measured by the *costs* that are required to achieve this service level. The consideration of efficiency in addition to effectiveness aims at avoiding wastes of resources (e.g. money) that could have helped further people if they had been used appropriately. Objectives of effectiveness and efficiency operate in contrary directions: an increase in service level (increase of effectiveness) typically causes an increase in costs (decrease of efficiency) and vice versa.

The scope of ReDRiSS in case study 1 is summarized by the *requirements profile* highlighted in Table 5-1.

Table 5-1: Requirements profile (case study 1)

Disaster type	Earthquake
Location	Haiti
Decision-makers	NGO association of the CI sector "health care"
Decision support	Compensation strategy
Logistical decision problem	Location planning of quick rotation warehouses (health care facilities) to define the vertical distribution structure of a temporary health care SC
Objectives	Identification of robust locations of health care facilities to achieve an effective and efficient distribution of medicine and medical equipment
Challenges	Unknown health care demands and states of the transportation infrastructure (uncertainty), dynamic developments in terms of aftershocks over time (complexity)

5.2.2 Adaptation of the bi-objective unconstrained facility location problem to the decision situation

ReDRiSS integrates an optimization model to process the decision problem. This optimization model must be preventively formulated (*ReDRiSS part A*, *processing step 2*). An appropriate optimization model of facility location planning to respect both objectives of effectiveness and efficiency is provided by the *bi-objective unconstrained facility location problem* (BOUFLP). ReDRiSS integrates an adapted version of the BOUFLP to the depicted decision situation.

Basically, the BOUFLP is a hybrid of the mathematical programming formulations of the *maximal covering location problem* (MCLP) and the *uncapacitated facility location problem* (UFLP) and refers to the class of mixed integer linear programming (MILP) (Revelle & Laporte 1996; Villegas et al. 2006, Daskin 2013). The MCLP focusses on the objective of effectiveness. With respect to the assumed decision situation, the objective is to open health care facilities that maximize satisfied health care demands (service level). The objective of efficiency is addressed by the UFLP by opening health care facilities that minimize required costs (sum of transportation and fixed costs) to satisfy health care demand. The following paragraphs present the adapted formulation of the BOUFLP.

Let $I = \{1,2, \dots\}$ be the set of possible locations where health care facilities can be opened (built) and $J = \{1,2, \dots\}$ the set of locations where health care demands might arise. The health care demand in location $j \in J$ is b_j. When opening a health care facility in location $i \in I$, fixed costs f_i arise. G is the predetermined number of health care facilities to open according to planning information provided by the NGO association. Moreover, let h_{ij} be the shortest road distance [km] between location i and location j; the associated transportation cost of using this road connection is indicated by c_{ij}.

$$c_{ij} = b_j \cdot h_{ij} \qquad [5\text{-}1]$$

D_{max} is the maximal covering road distance [km]; a health care facility can just serve health care demands at locations within this distance. Locations of health care facilities that are able to meet b_j are summarized by the set Q_j.

$$Q_j = \left\{ i \in I: h_{ij} \leq D_{max} \right\} \qquad [5\text{-}2]$$

Binary decision variable y_i indicates whether a health care facility is opened in location i ($y_i = 1$) or not ($y_i = 0$); binary decision variable x_{ij} indicates whether b_j is met by a health care facility in location i ($x_{ij} = 1$) or not ($x_{ij} = 0$). Table 5-2 provides an overview of parameters and decision variables of the adapted BOUFLP (Villegas et al. 2006).

Table 5-2: Parameters and decision variables (case study 1)

Parameter	Description	Range of values
b_j	Health care demand at location j	$\in \mathbb{R}_0^+$
f_i	Fixed cost of opening a health care facility at location i	$\in \mathbb{R}_0^+$
h_{ij}	Road distance [km] between location i and location j	$\in \mathbb{R}_0^+$
c_{ij}	Transportation cost of serving health care demand at location j by health care facility at location i	$\in \mathbb{R}_0^+$
D_{max}	Maximal covering road distance [km]	$\in \mathbb{R}^+$
G	Number of health care facilities to be built	$\in \mathbb{N}^+$
Q_j	Set of locations of all health care facilities that are able to meet health care demand at location j within D_{max}	
Decision variable	**Description**	**Range of values**
y_i	1: health care facility is opened at location i, 0: otherwise	$\in \{0,1\}$
x_{ij}	1: health care demand at location j is met by health care facility at location i, 0: otherwise	$\in \{0,1\}$

Equations [5-3] to [5-9] show the mathematical formulation of the adapted BOUFLP. The objective functions [5-3] and [5-4] and the constraint functions [5-5] to [5-9] are discussed in the following paragraphs.

$$\max z_1 = \sum_{j \in J} b_j \sum_{i \in Q_j} x_{ij} \qquad [5\text{-}3]$$

$$\min z_2 = \sum_{i \in Q_j} \sum_{j \in J} c_{ij} x_{ij} + \sum_{i \in I} f_i y_i \qquad [5\text{-}4]$$

subject to

$$\sum_{i \in I} x_{ij} = 1 \qquad \forall j \in J \qquad [5\text{-}5]$$

$$x_{ij} \leq y_i \qquad \forall i \in I, \forall j \in J \qquad [5\text{-}6]$$

$$\sum_{i \in I} y_i = G \qquad [5\text{-}7]$$

$$x_{ij} \in \{0,1\} \qquad \forall i \in I, \forall j \in J \qquad [5\text{-}8]$$

$$y_i \in \{0,1\} \qquad \forall i \in I \qquad [5\text{-}9]$$

Equations [5-3] and [5-4] represent the objective functions of the MCLP and UFLP. [5-3] measures the service level of an alternative as the sum of satisfied health care demands that are met by opened health care facilities within the maximal covering distance D_{max}. The first term of [5-4] represents the associated transportation costs of meeting those health care demands (arising within D_{max}). The second term highlights fixed costs of opening the health care facilities. Constraint function [5-5] guarantees that each health care demand is met by just one health care facility; [5-6] forces health care demands to be assigned to open health care facilities; [5-7] proposes to open a number of G health care facilities; [5-8] and [5-9] define the decision variables as binary (Villegas et al. 2006).

In the adapted version of the BOUFLP, the calculation of both service level and costs just respect those health care demands that are maximally distanced by D_{max} from an opened health care facility. Hence, objective function values of an *alternative* (which is defined by the binary values of decision variables $y_i, i \in I$ and $x_{ij}, \forall i \in I, \forall j \in J$) indicate its achieved maximal service level and associated minimal costs.

Haiti is divided into 10 départements which comprise 42 arrondissements (see Figure 5-2, section 5.3). The occurrence of the earthquake might trigger a health care demand b_j in any arrondissement j of the set $J = \{1, \dots, 42\}$. As health care facilities are quick rotation warehouses, a fast import of medicine and medical equipment stored in these warehouses is essential. Therefore, they should be located near airports (Bölsche 2009). Haiti possesses 15 airports that are registered by the international air transportation association (IATA). The case study assumes that just an arrondissement that includes such an airport is allowed to host a health care facility. Thus, the set of possible locations is $I = \{1, \dots, 15\} \subseteq J$.

The case study refers to the population distribution of Haiti in 2012. Therefore, the total population of Haiti is assumed to be 10,413,212 (IHSI 2012). About 25% of this population lives in arrondissement 5 (the capital city Port-au-Prince) whose underlying département Ouest (arrondissement 5, 6, 25, 27, and 28) includes 36% of the total population. The département Arbitonite (arrondissements 15, 30, 31, 33, 34) achieves a ratio of 15% (IHSI 2012). The exact location of a health care facility to be opened in an arrondissement always refers to its most populated city. Country specific information has been attached to appendix A.1.

To deliver medicine and medical equipment from the health care facilities to the temporary collection sites (and finally to the beneficiaries), the road network (transportation infrastructure) must be intact. The case study respects states of larger tarred roads like highways or interstates as those are the only roads traversable by trucks. On the basis of the inland road network, road distances [km] for road connections between Haiti's arrondissements are calculated with the help of GPS data. As the most populated city of each arrondissement specifies the possible health care facility location, the road network between these cities is considered by analyses.

A specific assumption is made regarding arrondissement 6 (Gônave, département Ouest). This arrondissement refers to an island which is separated from the inland road network. A waterway connection must be used to access arrondissement 6. The shortest waterway connection to this island starts in arrondissement 5 (Port-au-Prince, département Ouest). As both most populated cities of the arrondissements 5 and 6, Port-au-Prince and Anse-à-Galets, possess harbors, the waterway connection [km] is added to the infrastructure network. Road (waterway) distances across arrondissements have been attached to appendix A.2.

5.3 Solving the logistical decision problem

This section outlines the application of ReDRiSS in an occurring decision situation. Haiti is hit by an earthquake. Exogenous information indicates that its epicenter is located in département Nord-Est. As exogenous information does not specify the exact epicenter location within this département, arrondissements 11, 12, 40, and 42 define the possible epicenter area (see Figure 5-2).

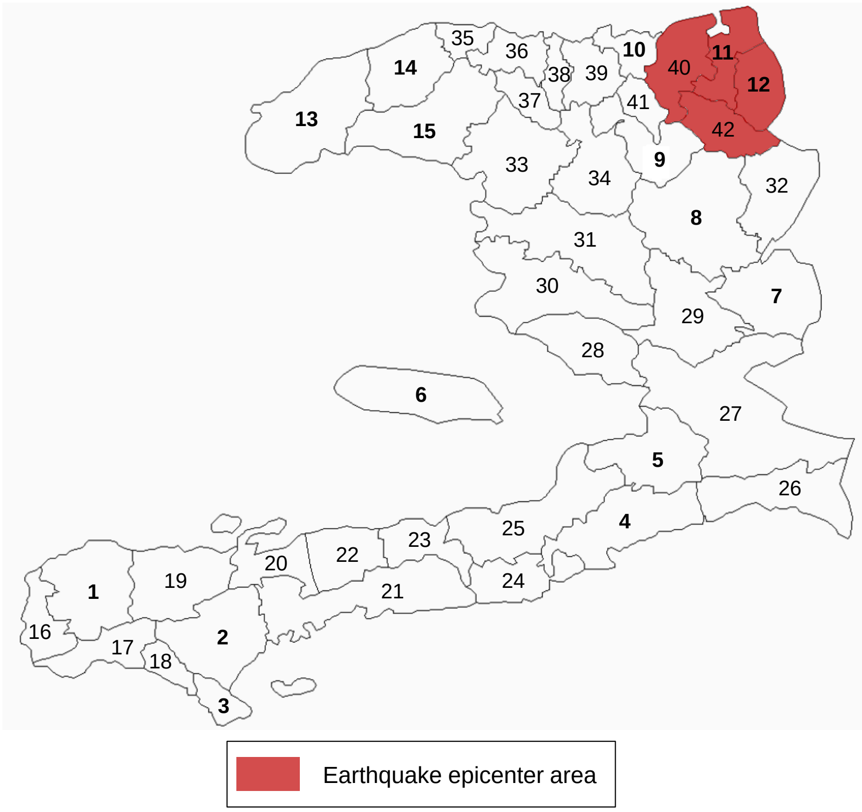


Figure 5-2: Geographic representation of Haiti and epicenter area

5.3.1 Prognostic scenarios

Because of a lack of exogenous information arising in the immediate aftermath of the earthquake, the state of the decision environment is unknown. *Prognostic scenarios* are therefore constructed to describe probable and expected states. The following sections outline the construction process of prognostic scenarios (*ReDRiSS part B*, *processing step 3*).[15]

[15] The construction of prognostic scenarios is based on specification processes of environmental variables which are actually developed in ReDRiSS part A, processing step 2. For the sake of clarity, specification processes are presented in this section.

5.3.1.1 Classification of parameters

To construct prognostic scenarios, parameters of the adapted BOUFLP must be specified. Parameters refer to *planning variables* and *environmental variables*. Planning information that is required to specify the planning variables is assumed to be deterministic. The specification of each planning variable is, thus, constant in any constructed prognostic scenario. In the depicted decision situation it is assumed that fixed costs that might accrue for, inter alia, imports of material that is required to physically construct the health care facilities or permission fees to use a certain location in Haiti do not arise. It is rather assumed that the NGO association pre-allocates material to set up an exact number of G health care facilities. All possible locations are made accessible by Haiti's government without raising any additional fee. Hence, all *alternatives* (locations of health care facilities) are equal in their fixed costs which can be, thus, disregarded by analyses. Moreover, the NGO association defines a maximal covering distance according to its experiences from past disasters. In summary, the following planning variables and their specifications are defined:

- $D_{max} = 100$ km as the maximal covering distance
- $G = 5$ as the number of health care facilities to be opened
- $f_i = 0, \forall i \in I$ as disregarded fixed costs

Environmental variables refer to those parameters whose specifications depend on environmental factors and are, thus, prone to uncertainty. The environmental variables are:

- $B = (b_1, \dots, b_j, \dots, b_{42})$ as the vector of health care demands where $b_j \in B$ specifies the health care demand at location $j \in J$
- $H = \begin{pmatrix} h_{1,1} & \cdots & h_{1,42} \\ \vdots & \vdots & \vdots \\ h_{42,1} & \cdots & h_{42,42} \end{pmatrix}$ as the matrix of shortest road distances across all arrondissements (including one waterway distance, see section 5.2.2)

- $C = \begin{pmatrix} c_{1,1} & \cdots & c_{1,42} \\ \vdots & \vdots & \vdots \\ c_{42,1} & \cdots & c_{42,42} \end{pmatrix} = \begin{pmatrix} b_1 \cdot h_{1,1} & \cdots & b_{42} \cdot h_{1,42} \\ \vdots & \vdots & \vdots \\ b_1 \cdot h_{42,1} & \cdots & b_{42} \cdot h_{42,42} \end{pmatrix}$ as the matrix of transportation costs across all arrondissements
- $Q = \{Q_1, \ldots, Q_j, \ldots, Q_{42}\}$ where the set $Q_j \in Q$ includes health care facilities that are able to meet $b_j, j \in J$

Exogenous information is assumed to be inappropriate to specify any environmental variable deterministically. Therefore, a *specification process* must be applied per environmental variable. This primarily affects B and H which are faced by unknown distributions of health care demands of the population and failures of the road network. The specifications of the uncertain environmental variables C and Q can be directly calculated based on the developed specifications of B and H (see [5-1] and [5-2]).

It is assumed that the extent of damage in an arrondissement (health care demands and road failures) depends on the linear distance between this arrondissement and the earthquake's epicenter arrondissement.[16] The uncertain location of the epicenter arrondissement (11, 12, 40, or 42) must, thus, be respected by the specification processes. Linear distances across Haiti's arrondissements have been attached to appendix A.3.

5.3.1.2 Specification of health care demands

The distribution of Haiti's population is used to specify B (see appendix A.1) It is assumed that the relative share of the population in an arrondissement $j \in J$ needing health care decreases with the linear distance $dist_j$ between j and the epicenter arrondissement. To calculate this relative share in j, a *health care demand ratio function* $d(dist_j)$ is formulated.

The NGO association fears a health care demand in the epicenter arrondissement that equates to 100% of its population pop_j

[16] The *harvesine formula* is used to calculate the linear distance between two points on a sphere. Geographic locations of the points refer to their latitudes and longitudes.

($d(0) = 100\%$). It is assumed that health care demands principally arise in any arrondissement that is located within the maximal linear distance $dist_{dmax}$ from the epicenter arrondissement. The equation [5-10] shows the linear formulation of the health care demand ratio function as used in the case study. If expertise is available, alternative formulations can be taken (e.g. exponential courses).

$$d(dist_j) = \begin{cases} d(0) - \dfrac{d(0)}{dist_{dmax}} \cdot dist_j, \text{if } dist_j < dist_{dmax} \\ 0, \text{else} \end{cases} \quad [5\text{-}10]$$

In the depicted decision situation, $dist_{dmax}$ is unknown. Therefore, a number of eight heath care demand ratio functions $d_n(dist_j), n = 1, \ldots, 8$ are used where $dist_{dmax} = n \cdot 50$ and $d_n(dist_{dmax}) = 0$ (see Figure 5-3).

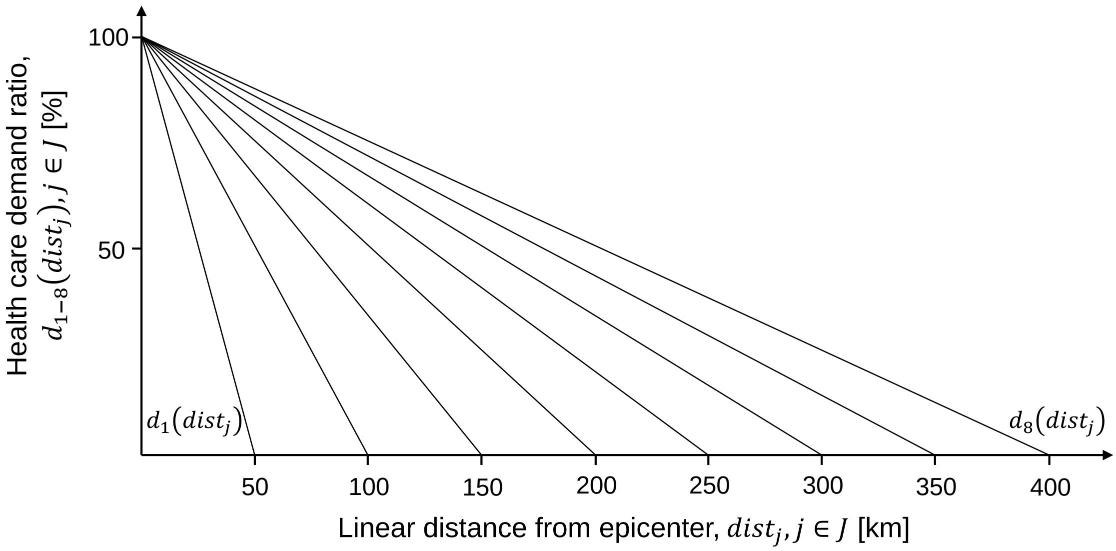


Figure 5-3: Health care demand ratio functions

Based on $d_n(dist_j)$ and pop_j, b_j is calculated by:

$$b_j = pop_j \cdot d_n(dist_j), n \in \{1, \ldots, 8\} \quad [5\text{-}11]$$

Hence, eight specifications of B are generated per possible epicenter arrondissement (11, 12, 40, or 42). The total number of obtained specifications is $4 \cdot 8 = 32$.

5.3.1.3 Specification of states of the road network

To specify H, it is assumed that the probability of a road failure depends on the linear distance of the considered road from the epicenter arrondissement. Let $j, m \in J$ be two neighbored arrondissements where a direct road connection between j and m exists that doesn't cross any further arrondissement. The road distance between j and m is denoted by $h_{jm} = h_{mj}$. Moreover, it is assumed that the linear distance $dist_m$ between m and the epicenter arrondissement exceeds $dist_j$; in fact $dist_j \leq dist_m$. The probability of a failure of the road connection between j and m depends on $dist_j$ (as it is closer to the epicenter). This probability is specified by a *road failure probability function* $p\left(dist_j\right)$.

It is assumed that the failure probability of a single road that is located within the epicenter arrondissement is 50% ($p(0) = 50\%$). Let $dist_{pmax}$ be the maximal linear distance from the epicenter arrondissement where road failures are principally possible. The equation [5-12] highlights the linear formulation of the road failure probability function. If expertise is available, alternative formulations can be taken (e.g. exponential courses).

$$p\left(dist_j\right) = \begin{cases} p(0) - \dfrac{p(0)}{dist_{pmax}} \cdot dist_j, \text{if } dist_j < dist_{pmax} \\ 0, \text{else} \end{cases} \qquad [5\text{-}12]$$

In the depicted decision situation, $dist_{pmax}$ is unknown. Therefore, a number of eight road failure probability functions $p_t\left(dist_j\right), t = 1, \ldots, 8$ are used where $dist_{pmax} = t \cdot 50$ and $p_t\left(dist_{pmax}\right) = 0$ (see Figure 5-4). To specify H by assuming a specific epicenter arrondissement and $t \in \{1, \ldots, 8\}$, the following steps must be conducted.

1. For all neighbored arrondissements $j, m \in J$
    a. calculate $p_t(dist_j)$.
    b. generate a random number $rand \in [0,100]$.

c. when $rand \leq p_t(dist_j)$, set $h_{jm} = h_{mj}$ to a default value to simulate a failure of the road connection between j and m.

2. Apply *Dijkstra's algorithm*[17] to calculate H which includes all shortest road distances $h_{ou} = h_{ou}, \forall o, u \in J, o \neq u$.

Hence, eight specifications of H are generated per possible epicenter arrondissement (11, 12, 40, or 42). The total number of obtained specifications is $4 \cdot 8 = 32$.

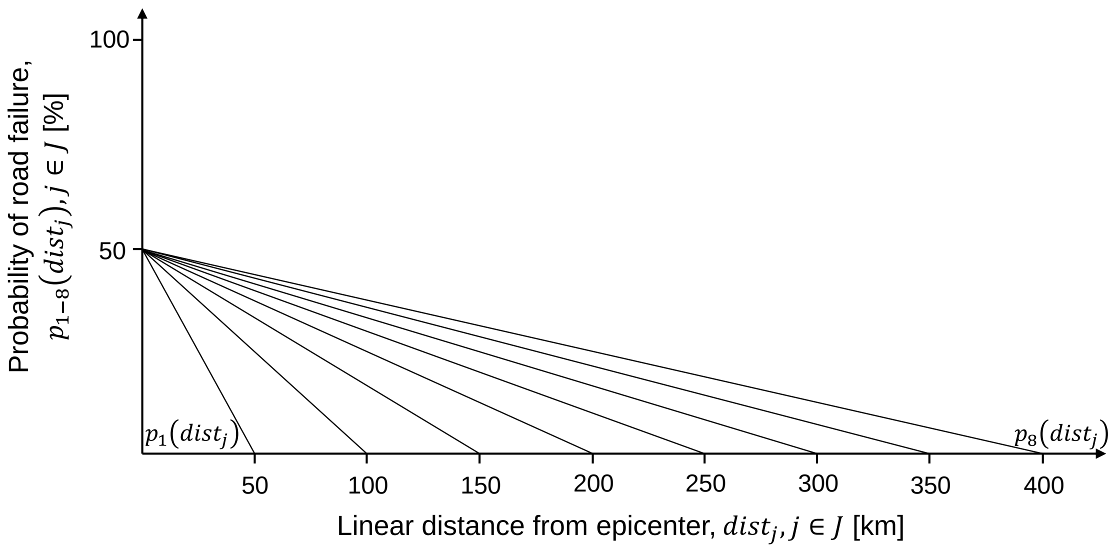


Figure 5-4: Road failure probability functions

5.3.1.4 Construction of prognostic scenarios and example

Each prognostic scenario includes one specification of B and H, the resultant specifications of C and Q, and the constant specifications of D_{max}, G, and f_i. In total, 256 prognostic scenarios are constructed (4 epicenter arrondissements · 8 health care demand vectors · 8 matrices of shortest road distances) and summarized by the set $S^{prog} = \{s_1^{prog}, \dots, s_{256}^{prog}\}$.

Figure 5-5 exemplarily illustrates $s_{83}^{prog} \in S^{prog}$ which refers to epicenter arrondissement 12, $n = 3$ ($dist_{dmax} = 150$ km), and $t = 3$ ($dist_{pmax} = 150$ km). The left-hand side representations of Haiti in

[17] For detailed information about *Dijkstra's algorithm* to calculate shortest paths within a network, reference is made to Neumann & Morlock (2002).

Figure 5-5 show the calculated health care demand ratios (upper representation) and road failure probabilities (lower representation) across all arrondissements. The right-hand side representations of Haiti visualize the resultant specifications of B (upper representation) and road failures as respected by H (lower representations). The health care demand in s_{83}^{prog} is 23.25% of Haiti's total population. Although arrondissement 5 is characterized by a small health care demand ratio, it is characterized by the highest relative share of the overall health care demand. This is because arrondissement 5 refers to Port-au-Prince which includes 25.29% of Haiti's total population.

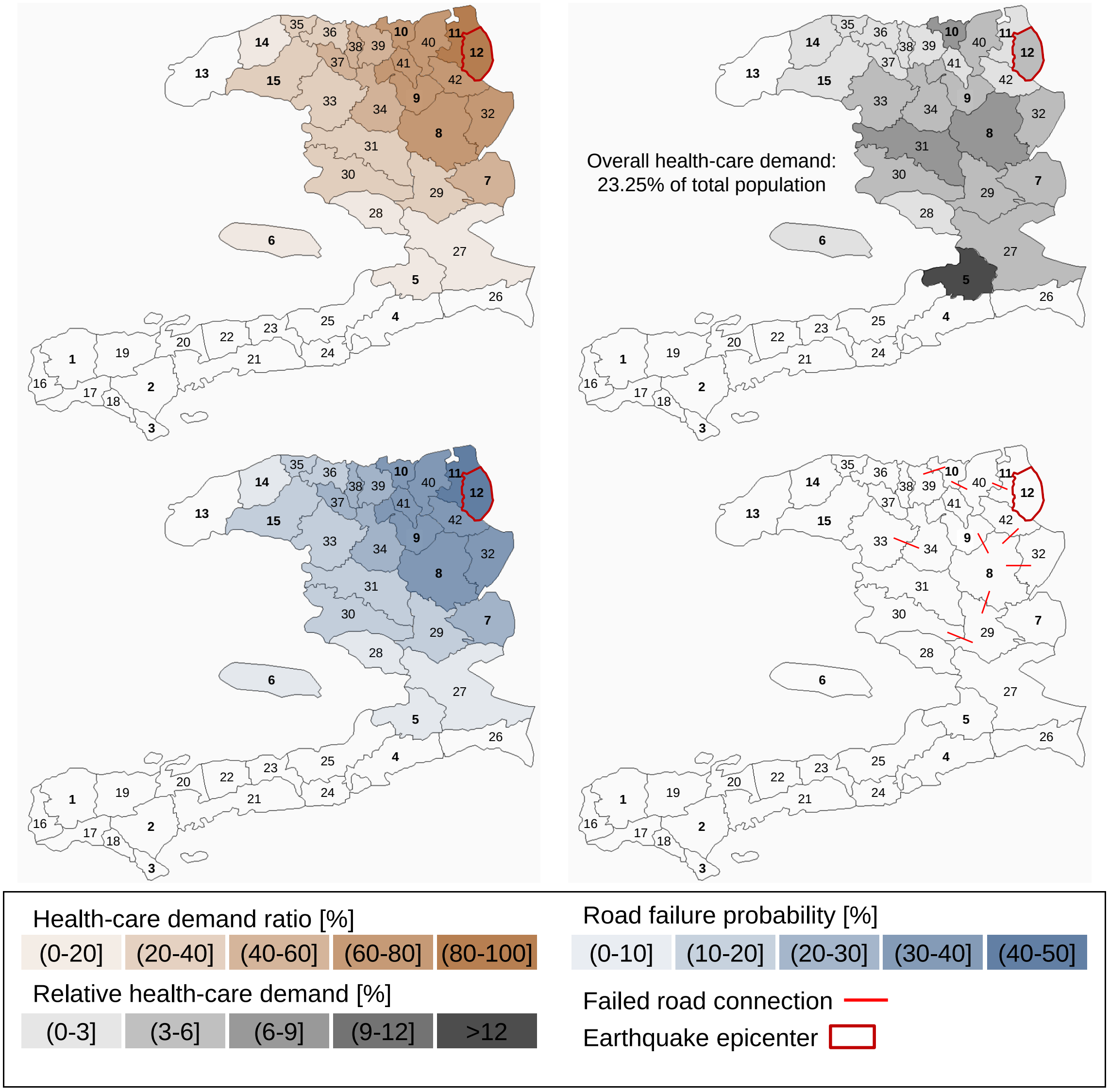


Figure 5-5: Exemplary visualization of a prognostic scenario

5.3.2 Alternatives

An alternative is defined by the binary values of decision variable $y_i, \forall i \in I$ (the binary values of decision variable $x_{ij}, \forall i \in I, \forall j \in J$ are adaptable to scenario-specific conditions, see below). These values indicate whether a health care facility is opened in arrondissement $i \in I$ ($y_i = 1$) or not ($y_i = 0$). As $I = \{1, \dots, 15\}$ and $G = 5$, the feasible space of alternatives comprises 3003 alternatives[18]. All alternatives of this space are respected in the following. Hence, no solution algorithm is applied in the case study to generate the optimal alternative per scenario-specific optimization sub-model (*ReDRiSS part B*, *processing step 4*). The set of feasible alternatives is denoted $A = \{a_1, \dots, a_{3003}\}$.

Each $a_z \in A$ is tested in each $s_l^{prog} \in S^{prog}$ by using the respective scenario-specific optimization sub-model (*ReDRiSS part C*, *processing step 5*). Thereby, the binary values of $x_{ij}, \forall i \in I, \forall j \in J$ are adapted to the specifications of the environmental variables as assumed by s_l^{prog}. Health care demand b_j is met by health care facility i when c_{ij} is minimal (compared to all opened health care facilities of a_z) and when h_{ij} does not exceed D_{max} (then, $x_{ij} = 1$; $x_{ij} = 0$ else). The adaptation of $x_{ij}, \forall i \in I, \forall j \in J$ is required as prognostic scenarios vary in H and B.

Based on the binary values of the decision variables $y_i, \forall i \in I$ and the adapted binary values of $x_{ij}, \forall i \in I, \forall j \in J$, objective function values z_1 (service level) and z_2 (costs) are calculated. Subsequently, the *normalized regret* of a_z in s_l^{prog} is determined by comparing, per objective, the calculated objective function value and the best (z_1: maximum; z_2: minimum) objective function value that can be achieved by any other alternative of A in s_l^{prog}. The normalization of the calculated regret per objective is exemplarily regulated by a linear value function. Let $r_{z_1}(a_z, s_l^{prog})$ and $r_{z_2}(a_z, s_l^{prog})$ be the normalized regret of a_z in s_l^{prog} and regarding z_1 and z_2. Alternative a_z performs best in s_l^{prog} when $r_{z_1}(a_z, s_l^{prog}) = r_{z_2}(a_z, s_l^{prog}) = 0$.

[18] $\binom{|I|}{G} = \binom{15}{5} = \frac{15!}{(15-5)! \cdot 5!} = 3003$

$$r_{z_1}\left(a_z, s_l^{prog}\right) = \frac{z_1^{max}\left(A, s_l^{prog}\right) - z_1\left(a_z, s_l^{prog}\right)}{z_1^{max}\left(A, s_l^{prog}\right) - z_1^{min}\left(A, s_l^{prog}\right)} \quad [5\text{-}13]$$

$$r_{z_2}\left(a_z, s_l^{prog}\right) = \frac{z_2\left(a_z, s_l^{prog}\right) - z_2^{min}\left(A, s_l^{prog}\right)}{z_2^{max}\left(A, s_l^{prog}\right) - z_2^{min}\left(A, s_l^{prog}\right)} \quad [5\text{-}14]$$

With respect to preference-related information provided by the NGO association, the *relative weights of objectives* $we_{z_1} = 0.7$ and $we_{z_2} = 0.3$ are chosen in the case study to calculate the *aggregated regret* of each $a_z \in A$ and $s_l^{prog} \in S^{prog}$. Hence, the NGO association prioritizes the objective of effectiveness more highly than the objective of efficiency. The aggregated regret of a_z in s_l^{prog} is

$$r\left(a_z, s_l^{prog}\right) = 0.7 \cdot r_{z_1}\left(a_z, s_l^{prog}\right) + 0.3 \cdot r_{z_2}\left(a_z, s_l^{prog}\right) \quad [5\text{-}15]$$

The result is a 3003×256 matrix of aggregated regret values. This matrix is used to filter a set of *promising alternatives* $\tilde{A} \subseteq A$ and a customized set of *significant scenarios* $S^{sig}(\tilde{a}_b) \subseteq S^{prog}$ per promising alternative $\tilde{a}_b \in \tilde{A}$. To determine $\tilde{A}$, alternatives of A are ranked by the maximum (worst) aggregated regret value achieved by each $a_z \in A$ across all prognostic scenarios of S^{prog}. Based on this ranking, the best 31 promising alternatives are filtered (1%[19] of all feasible alternatives) and denoted $\tilde{A} = \{\tilde{a}_1, \dots, \tilde{a}_{31}\}$. Hence, promising alternatives are characterized by a maximal aggregated regret that decreases the maximal aggregated regret of all alternatives of the set $A \backslash \tilde{A}$.

Subsequently, prognostic scenarios of S^{prog} are ranked per promising alternative $\tilde{a}_b \in \tilde{A}$ by the aggregated regret that is achieved by $\tilde{a}_b$ in the prognostic scenarios. Based on this ranking, the "worst" 13 prognostic scenarios are filtered (5%[20] of all prognostic scenarios) that are

[19] This value has been exemplarily chosen in this case study. Depending on the preferences of the decision-makers, more or less alternatives can be added to the set of promising alternatives.

[20] This value has been exemplarily chosen in this case study. Depending on the preferences of the decision-makers, more or less prognostic scenarios can be added to the set of significant scenarios.

characterized by the highest values. For example, s_{83}^{prog} is a significant scenario of promising alternative $\tilde{a}_2 = a_{307} = [5, 8, 10, 11, 12]$; thus, $\tilde{a}_2$ performs relatively badly in s_{83}^{prog} compared to in all further prognostic scenarios of S^{prog}. The customized set of significant scenarios of $\tilde{a}_b$ is denoted $S^{si,\tilde{a}_b} = \{s_1^{si,\tilde{a}_b}, \dots, s_{13}^{si,\tilde{a}_b}\}$.

Table 5-3 provides an overview of the obtained promising alternatives and corresponding health care facility locations (arrondissements). Additional information regarding calculated aggregated regret values and the customized sets of significant scenarios has been attached to appendix A.4.

Table 5-3: Promising alternatives

Alternative	Locations	Alternative	Locations
$\tilde{a}_1 = a_{321}$	[5, 8, 9, 10, 12]	$\tilde{a}_{17} = a_{281}$	[5, 9, 10, 12, 15]
$\tilde{a}_2 = a_{307}$	[5, 8, 10, 11, 12]	$\tilde{a}_{18} = a_{156}$	[6, 9, 10, 12, 14]
$\tilde{a}_3 = a_{287}$	[5, 9, 10, 11, 12]	$\tilde{a}_{19} = a_{157}$	[6, 9, 10, 12, 13]
$\tilde{a}_4 = a_{175}$	[6, 8, 10, 12, 15]	$\tilde{a}_{20} = a_{282}$	[5, 9, 10, 12, 14]
$\tilde{a}_5 = a_{301}$	[5, 8, 10, 12, 15]	$\tilde{a}_{21} = a_{283}$	[5, 9, 10, 12, 13]
$\tilde{a}_6 = a_{302}$	[5, 8, 10, 12, 14]	$\tilde{a}_{22} = a_{356}$	[5, 7, 9, 10, 12]
$\tilde{a}_7 = a_{303}$	[5, 8, 10, 12, 13]	$\tilde{a}_{23} = a_{412}$	[5, 6, 9, 10, 12]
$\tilde{a}_8 = a_{371}$	[5, 7, 8, 10, 12]	$\tilde{a}_{24} = a_{706}$	[4, 5, 9, 10, 12]
$\tilde{a}_9 = a_{427}$	[5, 6, 8, 10, 12]	$\tilde{a}_{25} = a_{1036}$	[3, 5, 9, 10, 12]
$\tilde{a}_{10} = a_{721}$	[4, 5, 8, 10, 12]	$\tilde{a}_{26} = a_{1531}$	[2, 5, 9, 10, 12]
$\tilde{a}_{11} = a_{1051}$	[3, 5, 8, 10, 12]	$\tilde{a}_{27} = a_{2246}$	[1, 5, 9, 10, 12]
$\tilde{a}_{12} = a_{1546}$	[2, 5, 8, 10, 12]	$\tilde{a}_{28} = a_{622}$	[4, 6, 9, 10, 12]
$\tilde{a}_{13} = a_{2261}$	[1, 5, 8, 10, 12]	$\tilde{a}_{29} = a_{177}$	[6, 8, 10, 12, 13]
$\tilde{a}_{14} = a_{176}$	[6, 8, 10, 12, 14]	$\tilde{a}_{30} = a_{1447}$	[2, 6, 9, 10, 12]
$\tilde{a}_{15} = a_{637}$	[4, 6, 8, 10, 12]	$\tilde{a}_{31} = a_{511}$	[4, 8, 10, 12, 15]
$\tilde{a}_{16} = a_{155}$	[6, 9, 10, 12, 15]		

One can see in Table 5-3 that all promising alternatives suggest opening a health care facility in arrondissements 10 and 12. While the first (Ouanaminthe) is part of the epicenter area, the latter (Cap Haïtien) refers to the most populated arrondissement in the north-eastern part of Haiti. Two promising alternatives suggest opening an additional health care facility in the epicenter area (arrondissement 11). A facility is located in Haiti's most populated arrondissement 5 (Port-au-Prince) in 21 promising alternatives. Locations in arrondissements of the southern-western part of Haiti, which is furthermost distanced by roads from the epicenter area (arrondissements 1, 2, 3, and 4), are part of 12 promising alternatives.

5.3.3 Hypothetical scenarios

Prognostic scenarios are constructed to close lacks of exogenous information in terms of an uncertain epicenter area and unknown consequences of the earthquake regarding health care demands and states of the road network. *Hypothetical scenarios* are constructed to simulate dynamic developments caused by critical events affecting the states of the decision environment as assumed by prognostic scenarios over time. The case study explores critical events by secondary disasters in terms of *earthquake aftershocks*.

Hypothetical scenarios are constructed in a customized manner per promising alternative. It is assumed that the extent of the caused consequences by an aftershock depends on both its epicenter location and intensity. Critical aftershock epicenter locations are identified per promising alternative to simulate *alternative-specific dynamic developments* (see section 4.3.5). Both these locations and the intensities of the caused aftershocks also depend on the state of the decision environment as assumed by its significant scenarios; hypothetical scenarios therefore additionally highlight *scenario-specific dynamic developments* (see section 4.3.5). The following sections discuss the process of developing and simulating critical aftershock events via hypothetical scenarios (*ReDRiSS part B*, *processing step 6*).[21]

5.3.3.1 Identification of critical aftershock epicenter locations

The case study explores the possibility of *critical aftershock events* whose epicenter locations might principally refer to any arrondissement. Just as the main earthquake did, the aftershock causes health

[21] The construction of hypothetical scenarios is based on re-specification processes of environmental variables which are actually developed in ReDRiSS part A, processing step 2. For the sake of clarity, re-specification processes are presented in this section.

care demands and failures within the road network. The extent of these consequences in an arrondissement is again influenced by its linear distance from the aftershock's epicenter arrondissement.

The ability of a promising alternative to handle consequences (in terms of achieving an acceptable service level and/or transportation costs) depends on the area where these consequences occur. Thus, the criticality of the epicenter location varies across the promising alternatives. *Critical epicenter locations* (arrondissements) are developed by exploring critical changes of the states of B and H. Each two critical epicenter locations are determined per $\tilde{a}_b \in \tilde{A}$ and $s_w^{si,\tilde{a}_b} \in S^{si,\tilde{a}_b}$. In fact, the ability of $\tilde{a}_b$ is explored

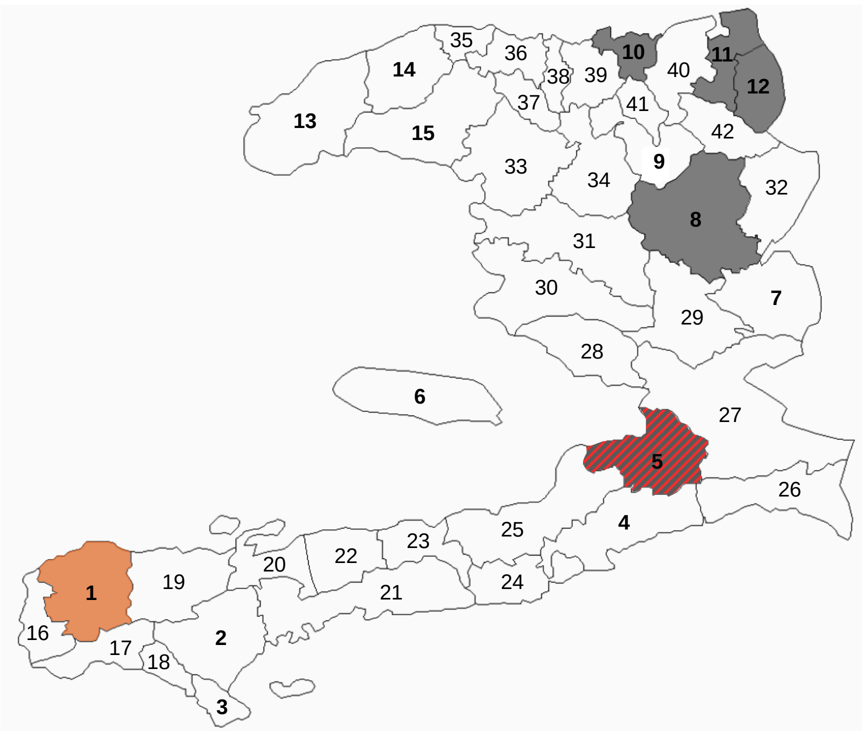
- to manage critical shifts of health care demands (B) caused by the aftershock in $s_w^{si,\tilde{a}_b}$
- to react to critical additional failures within the road network (H) caused by the aftershock in $s_w^{si,\tilde{a}_b}$

Regarding the first it is assumed that the criticality of shifts of health care demands (caused by the aftershock) increases when arrondissements are affected that cannot be accessed easily via roads by the health care facilities (of $\tilde{a}_b$). Hence, *aftershock epicenter 1* in $s_w^{si,\tilde{a}_b}$ refers to the arrondissement whose shortest road distance to the closest opened health care facility (of $\tilde{a}_b$) is maximal. When an aftershock occurs in this arrondissement, difficulties might be triggered to satisfy additional health care demands arising further afield. This is enhanced by road failures in the aftershock-affected area.

Regarding the second, it is assumed that road failures near the health care facilities (of $\tilde{a}_b$) mostly impact the performance of $\tilde{a}_b$. Therefore, *aftershock epicenter 2* refers to the arrondissement containing the health care facility that satisfies most health care demands in $s_w^{si,\tilde{a}_b}$ (which is indicated by the adapted binary values of decision variable $x_{ij}, \forall i \in I, \forall j \in J$). An occurring aftershock within this arrondissement might cause that other arrondissements are isolated from the included health care facility because of additional (and probable) road failures.

This threat is intensified by the additional health care demands in the aftershock-affected area.

Figure 5-6 exemplarily illustrates the two identified aftershock epicenter locations with respect to promising alternative $\tilde{a}_2 = a_{307}$ and significant scenario $s_{12}^{si,\tilde{a}_2} = s_{83}^{prog}$ (which has been visualized in Figure 5-5, section 5.3.1.4). The maximal road distance between any health care facility (of $\tilde{a}_2$) and all arrondissements is the one between arrondissement 5 (Port-au-Prince) and 1 (Jérémie). Thus, the latter specifies aftershock epicenter 1. Arrondissement 5 satisfies most health care demands in $s_{12}^{si,\tilde{a}_2}$ and is taken as aftershock epicenter 2. The aftershock epicenter locations of all promising alternatives and significant scenarios have been attached to appendix A.5.



Aftershock epicenter 1	Aftershock epicenter 2	$\tilde{a}_2 = a_{307} = [5, 8, 10, 11, 12]$

Figure 5-6: Exemplary visualization of aftershock epicenter arrondissements

5.3.3.2 Simulation of aftershocks within significant scenarios

Based on the aftershock epicenter locations, every two aftershocks are simulated within each $s_w^{si,\tilde{a}_b} \in S^{si,\tilde{a}_b}$, $\tilde{a}_b \in \tilde{A}$. It is assumed that the *in-*

tensity of the aftershock is below the intensity of the main earthquake. This is reflected by the ratio of caused health care demands and probability of road failures. In fact, the aftershock's intensity is set to 75% of the main earthquake in $s_w^{si,\tilde{a}_b}$. To simulate the aftershock, again health care demand ratio and road failure probability functions are used (see section 5.3.1). The modified maximal health care demand ratio in the aftershock epicenter arrondissement is 75% ($d(0) = 75\%$) and the maximal road failure probability in the aftershock epicenter arrondissement is 37.5% ($p(0) = 37.5\%$). Furthermore, the maximal linear distances ($dist_{dmax}$ and $dist_{pmax}$), where health care demands or road failures are principally possible, is set to 75% as in $s_w^{si,\tilde{a}_b}$.

Let $d_{n,w}(dist_j), n \in \{1, \dots, 8\}$ and $p_{t,w}(dist_j), t \in \{1, \dots, 8\}$ be the calculated health care demand ratio and road failure probability in arrondissement j and $s_w^{si,\tilde{a}_b}$. Regarding the modified state of the road network, it is assumed that a failed road in $s_w^{si,\tilde{a}_b}$ remains failed in the constructed hypothetical scenario. Roads that are still intact, in turn, receive a second chance to fail by the probability $p_{t,w}(dist_j)$. The process of specifying H equates to the process that has been outlined in section 5.3.1.3.

To calculate the modified health care demand based on $d_{n,w}(dist_j)$, health care demand in $s_w^{si,\tilde{a}_b}$, $b_{j,w}$, must be respected. The maximal additional health care demands ($pop_j - b_{j,w}$) can principly arise. Hence, the modified health care demand b_j is

$$b_j = b_{j,w} + (pop_j - b_{j,w}) \cdot d_{n,w}(dist_j), n \in \{1, \dots, 8\} \qquad [5\text{-}16]$$

5.3.3.3 Construction of hypothetical scenarios and example

According to section 4.3.5, each two critical events ($K = 2$) are simulated in each of 13 significant scenarios ($W = 13$) per each of 31 promising alternatives ($B = 31$). The total number of hypothetical scenarios, thus, is $2 \cdot 13 \cdot 31 = 806$. Each 26 customized hypothetical scenarios are constructed per promising alternative $\tilde{a}_b \in \tilde{A}$ and are summarized by the set $S^{hyp,\tilde{a}_b} = \{s_{1,1}^{hyp,\tilde{a}_b}, s_{1,2}^{hyp,\tilde{a}_b}, \dots, s_{13,1}^{hyp,\tilde{a}_b}, \dots, s_{13,2}^{hyp,\tilde{a}_b}\}$.

Figure 5-7 exemplarily shows the two hypothetical scenarios that have been constructed based on $\tilde{a}_2 = a_{307}$ and significant scenario $s_{12}^{si,\tilde{a}_2} = s_{83}^{prog}$ (which has been visualized in Figure 5-5, section 5.3.1.4). Explanations of the Figure 5-7 are provided below.

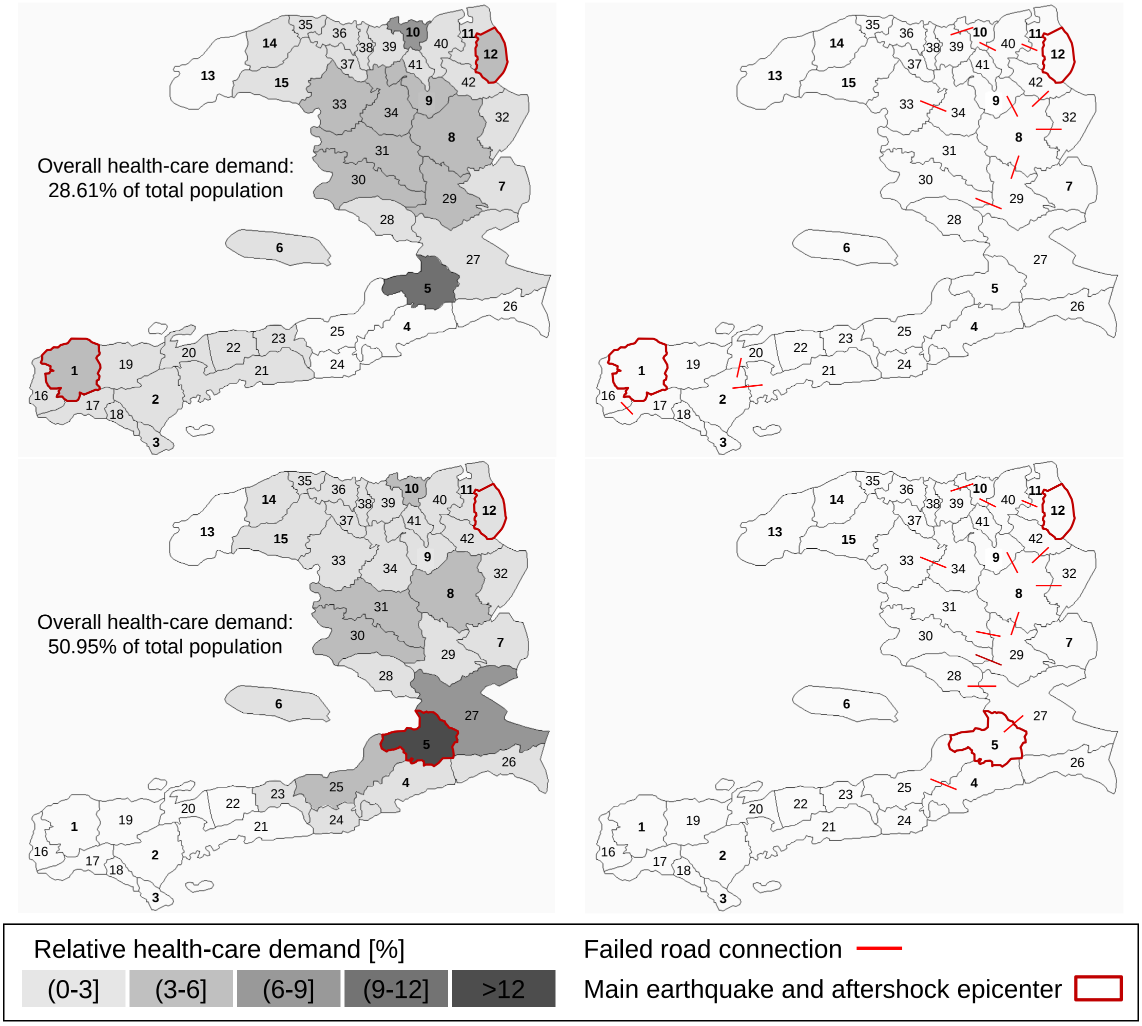


Figure 5-7: Exemplary visualization of hypothetical scenarios

The representations on the upper level show the health care demand distribution and state of the road network as assumed in hypothetical scenario $s_{12,1}^{hyp,\tilde{a}_2}$ which simulates an aftershock in epicenter 1 (arrondissement 1). On the lower level, $s_{12,2}^{hyp,\tilde{a}_2}$ is illustrated that has been constructed based on aftershock epicenter 2 (arrondissement 5). It becomes obvious that $s_{12,1}^{hyp,\tilde{a}_2}$ includes additional health care demands and road failures that are widely distanced from the closest health care facility of $\tilde{a}_2$ in $s_{12}^{si,\tilde{a}_2}$ (arrondissement 5). In $s_{12,2}^{hyp,\tilde{a}_2}$, additional road failures and health care demands arise near the health care facility that satisfies most health care demands in $s_{12}^{si,\tilde{a}_2}$ (arrondissement 5).

5.4 Results

ReDRiSS provides a robust decision recommendation (promising alternative) for the NGO association. Robustness measurement implies the testing of promising alternatives in all prognostic scenarios and customized hypothetical scenarios and the evaluation of the obtained results (aggregated regret data) by integrating the degree of pessimism of the NGO association. The following sections discuss the process and results of robustness measurement.

5.4.1 Robustness measurement

Each promising alternative $\tilde{a}_b \in \tilde{A}$ is tested in each prognostic scenario $s_l^{prog} \in S^{prog}$ and in each hypothetical scenario $s_{w,k}^{hyp,\tilde{a}_b} \in S^{hyp,\tilde{a}_b}$ by using the respective optimization sub-models (*ReDRiSS part C*, *processing step 7*). The aggregated regret $r\left(\tilde{a}_b, s_l^{prog}\right)$ and $r\left(\tilde{a}_b, s_{w,k}^{hyp,\tilde{a}_b}\right)$ are calculated based on the process outlined by equations [5-13], [5-14], and [5-15] (see section 5.3.2). As opposed to this process, the regret compares the objective function values of $\tilde{a}_b$ and the further promising alternatives of $\tilde{A}$ in a scenario. By again using the relative weights of objectives $we_{z_1} = 0.7$ and $we_{z_2} = 0.3$, the result is a $31 \times (256 + 26)$ matrix of aggregated regret values. Based on this matrix, the expected and maximal normalized aggregated regret of $\tilde{a}_b$ in each scenario category is determined. The *expected aggregated regret* of $\tilde{a}_b$ per scenario category is

$$RE(\tilde{a}_b, S^{prog}) = \frac{1}{256}\sum_{l=1}^{256} r(\tilde{a}_b, s_l^{prog}) \qquad [5\text{-}17]$$

$$RE\left(\tilde{a}_b, S^{hyp,\tilde{a}_b}\right) = \frac{1}{26}\sum_{w=1}^{13}\sum_{k=1}^{2} r(\tilde{a}_b, s_{w,k}^{hyp,\tilde{a}_b}) \qquad [5\text{-}18]$$

The *maximal aggregated regret* of $\tilde{a}_b$ per scenario category is

$$RM(\tilde{a}_b, S^{prog}) = \max_{l=1,\dots,256}\left(r\left(\tilde{a}_b, s_l^{prog}\right)\right) \qquad [5\text{-}19]$$

$$RM\left(\tilde{a}_b, S^{hyp,\tilde{a}_b}\right) = \max_{w=1,\dots,13,k=1,2}\left(r\left(\tilde{a}_b, s_{w,k}^{hyp,\tilde{a}_b}\right)\right) \qquad [5\text{-}20]$$

The result matrix of expected and maximal aggregated regret values has been attached to appendix A.6. This matrix provides the basis for measuring the robustness of promising alternatives by integrating risk preferences of the decision-makers (*ReDRiSS part D*, *processing step 8*). Risk preferences are reflected by the *inter- and intra-scenario degrees of pessimism* of the NGO association. The following values are assumed according to preference-related information provided by the NGO association:

- Inter-scenario degree of pessimism: $we^{prog} = 0.8, we^{hyp} = 0.2$
- Intra-scenario degree of pessimism: $\lambda^{prog} = 0.8, \lambda^{hyp} = 0.2$

The values imply that the NGO association primarily aims at respecting prognostic scenarios for robustness measurements of promising alternatives ($we^{prog} = 0.8$) and using the expected aggregated regret ($\lambda^{prog} = 0.8$). Although hypothetical scenarios are less used for robustness measurement ($we^{hyp} = 0.2$), the evaluation of aggregated regret values in this scenario category follows the maximal aggregated regret ($\lambda^{hyp} = 0.2$). Hence, the NGO association operates rather *neutrally* in its principle risk aversion; however, it is aware of threats simulated within hypothetical scenarios and respects them through robustness measurement. The *robustness value* $RV(\tilde{a}_b)$ is

$$RV(\tilde{a}_b) = 0.8 \cdot \left(0.8 \cdot RE(\tilde{a}_b, S^{prog}) + 0.2 \cdot RM(\tilde{a}_b, S^{prog})\right) + 0.2 \cdot \left(0.2 \cdot RE\left(\tilde{a}_b, S^{hyp,\tilde{a}_b}\right) + 0.8 \cdot RM\left(\tilde{a}_b, S^{hyp,\tilde{a}_b}\right)\right) \qquad [5\text{-}21]$$

The obtained robustness ranking of the ten most robust promising alternatives is shown in Table 5-4 (the extensive ranking of all promising alternatives has been attached to appendix A.6). Promising alternative $\tilde{a}_{17} = a_{281}$ achieves the best robustness value and is provided as decision recommendation $\tilde{a}$ for the NGO association. The difference between the two most robust promising alternatives, $\tilde{a}_{17}$ and $\tilde{a}_5$, in their robustness values is very small (0.002). This is because they differ in just one arrondissement ($\tilde{a}_{17}$: 9, $\tilde{a}_5$: 8). The insights provided by the robustness ranking are interpreted in section 5.4.3 after conducting three sensitivity analyses to explore the effects of preferential uncertainty (see section 5.4.2).

Table 5-4: Robustness ranking (case study 1)

Number	Alternative	Locations	Robustness value
1	$\tilde{a}_{17} = a_{281}$	[5, 9, 10, 12, 15]	0.475
2	$\tilde{a}_5 = a_{301}$	[5, 8, 10, 12, 15]	0.477
3	$\tilde{a}_1 = a_{321}$	[5, 8, 9, 10, 12]	0.515
4	$\tilde{a}_{20} = a_{282}$	[5, 9, 10, 12, 14]	0.549
5	$\tilde{a}_3 = a_{287}$	[5, 9, 10, 11, 12]	0.551
6	$\tilde{a}_2 = a_{307}$	[5, 8, 10, 11, 12]	0.565
7	$\tilde{a}_{21} = a_{283}$	[5, 9, 10, 12, 13]	0.579
8	$\tilde{a}_6 = a_{302}$	[5, 8, 10, 12, 14]	0.582
9	$\tilde{a}_{22} = a_{356}$	[5, 7, 9, 10, 12]	0.599
10	$\tilde{a}_7 = a_{303}$	[5, 8, 10, 12, 13]	0.609

5.4.2 Sensitivity analyses

The robustness ranking directly depends on the adjusted preferences of the NGO association in terms of preferences of objectives (we_{z_1}, we_{z_2}) and risk preferences ($we^{prog}, we^{hyp}, \lambda^{prog}, \lambda^{hyp}$). To explore effects of preferential uncertainty on the obtained results, ReDRiSS prescribes *sensitivity analyses* (*ReDRiSS part D, processing step 9*). The following outlines the results of three conducted sensitivity analyses where the values of the inter-scenario degree of pessimism, the intra-scenario degree of pessimism, and the relative weights of objectives have been separately varied. Sensitivity analyses focus on the promising alternatives in Table 5-4. Results are interpreted in section 5.4.3. Data of the sensitivity analyses can be found in appendix A.7.

5.4.2.1 Sensitivity of the inter-scenario degree of pessimism

A robustness value of a promising alternative is calculated based on the discrete value pairs (we^{prog}, we^{hyp}), $we^{prog} = 0.1 \cdot n$, $we^{hyp} = 1 - we^{prog}$, $n = 1, \dots, 10$. The sensitivity analysis assumes the adjusted preferences of objectives $\left(we_{z_1} = 0.7, we_{z_2} = 0.3\right)$ and intra-criteria degree of pessimism $(\lambda^{prog} = 0.8, \lambda^{hyp} = 0.2)$ as used for the generation of initial results. As the expected and maximal aggregated regret value per promising alternative doesn't depend on (we^{prog}, we^{hyp}), obtained robustness values in the range of values $we^{prog} \in [0,1]$, $we^{hyp} = 1 - we^{prog}$ are located on a linear straight line. Results of the sensitivity analysis are shown in Figure 5-8.

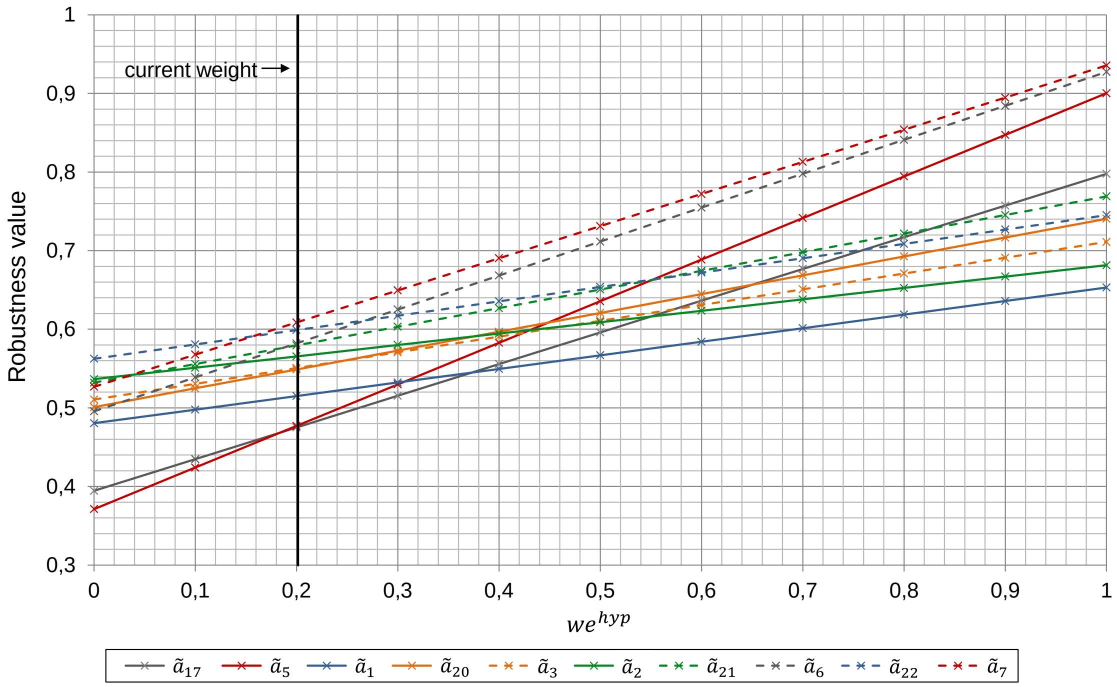


Figure 5-8: Sensitivity of the inter-scenario degree of pessimism (case study 1)

Results indicate that the robust decision recommendation $\tilde{a}$ varies across three intervals of the discrete value pair (we^{prog}, we^{hyp}):

- $\tilde{a} = \tilde{a}_5$ for $(we^{hyp} \in \{0,0.1\}, we^{prog} = 1 - we^{hyp})$
- $\tilde{a} = \tilde{a}_{17}$ for $(we^{hyp} \in \{0.2,0.3\}, we^{prog} = 1 - we^{hyp})$

- $\tilde{a} = \tilde{a}_1$ for $(we^{hyp} \in \{0.4, \ldots, 1\}, we^{prog} = 1 - we^{hyp})$

5.4.2.2 Sensitivity of the intra-scenario degree of pessimism

A robustness value of a promising alternative is calculated for the discrete value pair $(\lambda^{prog}, \lambda^{hyp}), \lambda^{prog} = 0.1 \cdot n, \lambda^{hyp} = 0.1 \cdot m, n = 1, \ldots, 10, m = 1, \ldots, 10$. The sensitivity analysis assumes the adjusted preferences of objectives $(we_{z_1} = 0.7, we_{z_2} = 0.3)$ and inter-criteria degree of pessimism $(we^{prog} = 0.8, we^{hyp} = 0.2)$ as used for the generation of initial results. As the expected and maximal aggregated regret value per promising alternative does not depend on $(\lambda^{prog}, \lambda^{hyp})$, obtained robustness values in the range of values $\lambda^{prog} \in [0,1], \lambda^{hyp} \in [0,1]$ are located on a linear plane surface. Results of the sensitivity analysis are shown in Figure 5-9. For the sake of clarity, just the surfaces of promising alternatives achieving a best robustness value in any value pair $(\lambda^{prog}, \lambda^{hyp})$ are colored.

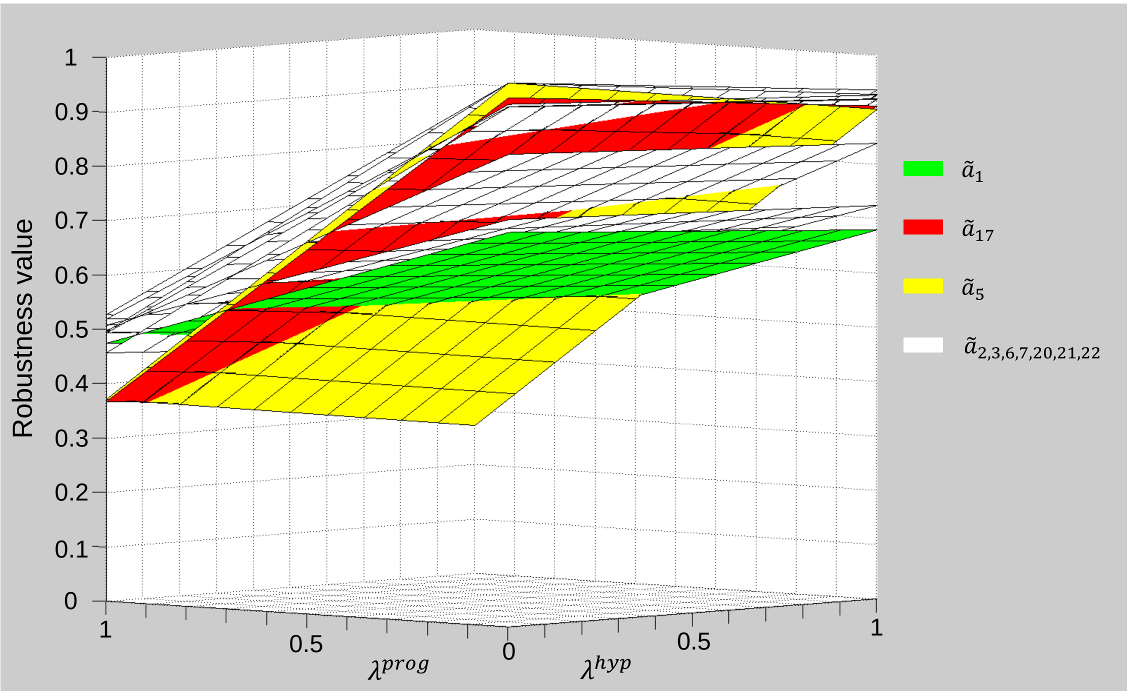


Figure 5-9: Sensitivity of the intra-scenario degree of pessimism (case study 1)

Results indicate that the robust decision recommendation $\tilde{a}$ varies across three intervals of the discrete value pair $(\lambda^{prog}, \lambda^{hyp})$:

- $\tilde{a} = \tilde{a}_5$ for ($\lambda^{prog} = 0.6, \lambda^{hyp} = 1$) or ($\lambda^{prog} = 0.7, \lambda^{hyp} \in \{0.4, \dots, 1\}$) or ($\lambda^{prog} = 0.8, \lambda^{hyp} \in \{0.3, \dots, 1\}$) or ($\lambda^{prog} \in \{0.9, 1\}, \lambda^{hyp} \in \{0.2, \dots, 1\}$)
- $\tilde{a} = \tilde{a}_{17}$ for ($\lambda^{prog} \in \{0.7, \dots, 1\}, \lambda^{hyp} \in \{0, 0.1\}$) or ($\lambda^{prog} \in \{0.7, 0.8\}, \lambda^{hyp} = 0.2$) or ($\lambda^{prog} = 0.7, \lambda^{hyp} = 0.3$)
- $\tilde{a} = \tilde{a}_1$ for ($\lambda^{prog} \in \{0, \dots, 0.5\}, \lambda^{hyp} \in \{0, \dots, 1\}$) or ($\lambda^{prog} = 0.6, \lambda^{hyp} \in \{0, \dots, 0.9\}$)

5.4.2.3 Sensitivity of preferences of objectives

A robustness value of a promising alternative is calculated for the discrete value pair $(we_{z_1}, we_{z_2}), we_{z_1} = 0.1 \cdot n, we_{z_2} = 1 - we_{z_1}, n = 1, \dots, 10$. The sensitivity analysis assumes the adjusted inter-criteria degree of pessimism ($we^{prog} = 0.8, we^{hyp} = 0.2$) and intra-criteria degree of pessimism ($\lambda^{prog} = 0.8, \lambda^{hyp} = 0.2$) as used for the generation of initial results. As the expected and maximal aggregated regret value per promising alternative depend on (we_{z_1}, we_{z_2}), robustness values in the range of values $we_{z_1} \in [0,1], we_{z_2} \in [0,1]$ are not necessarily located on a linear straight line. Results of the sensitivity analysis are shown in Figure 5-10. For the sake of clarity, robustness values are connected via trend lines.

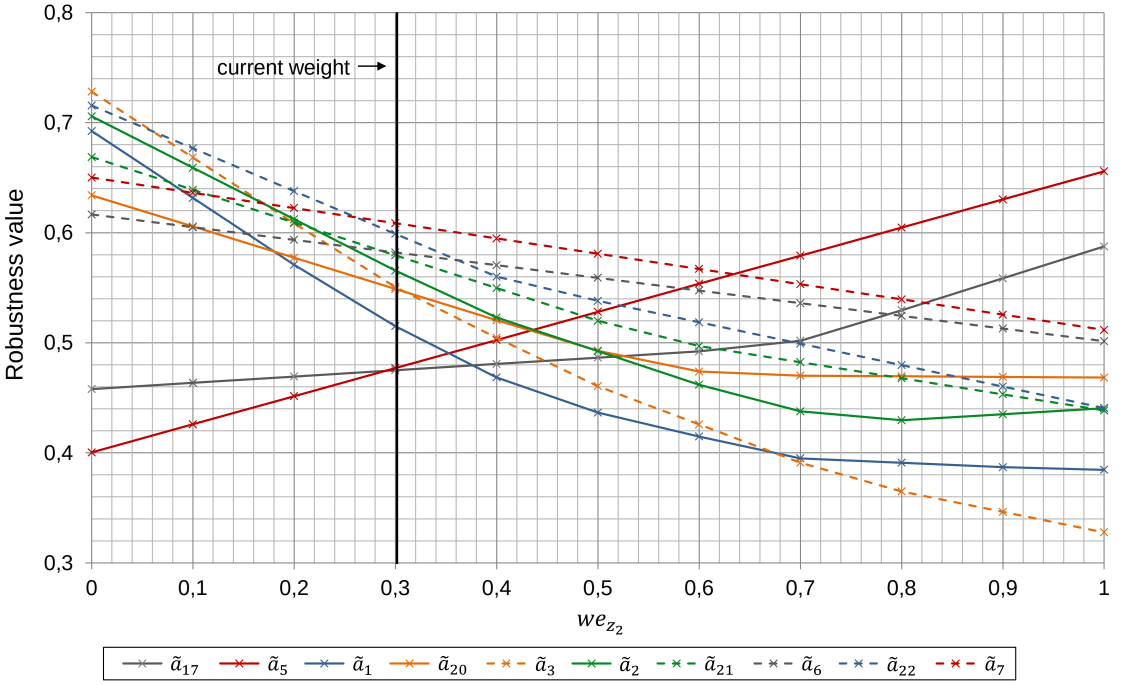


Figure 5-10: Sensitivity of preferences of objectives

Results indicate that the robust decision recommendation $\tilde{a}$ varies across four intervals of the discrete value pair $\left(we_{z_1}, we_{z_2}\right)$:

- $\tilde{a} = \tilde{a}_5$ for $\left(we_{z_1} \in \{0.8,0.9,1\}, we_{z_2} = 1 - we_{z_1}\right)$
- $\tilde{a} = \tilde{a}_{17}$ for $\left(we_{z_1} \in \{0.7\}, we_{z_2} = 1 - we_{z_1}\right)$
- $\tilde{a} = \tilde{a}_1$ for $\left(we_{z_1} \in \{0.4,0.5,0.6\}, we_{z_2} = 1 - we_{z_1}\right)$
- $\tilde{a} = \tilde{a}_3$ for $\left(we_{z_1} \in \{0, \dots, 0.3\}, we_{z_2} = 1 - we_{z_1}\right)$

5.4.3 Interpretation of results

Initial results (see Table 5-4) indicate that three of five health care facility locations of the ten most robust promising alternatives are identical (arrondissements 5, 10, 12). Those locations can be, thus, understood as *totally robust*. Arrondissement 5 (Port-au-Prince) is Haiti's most populated arrondissement; arrondissement 10 (Cap Haïtien) is the most populated arrondissement of Haiti's north-eastern part; arrondissement 12 (Ouanaminthe) is the most populated arrondissement of the main earthquake's epicenter area. Any scenario is characterized by a high health care demand in these arrondissements, even when their underlying health care demand ratios are low. Hence, opening health care facilities in these arrondissements provides the advantage of increasing the service level by reducing the associated transportation costs. Regarding the remaining two health care facility locations that must be opened, the results show three regional clusters of arrondissements: a health care facility in an arrondissement of Haiti's north-western part (13, 14, 15), central part (7, 8, 9), or the main earthquake's epicenter area (11). Figure 5-11 visualizes the findings of the robustness ranking.

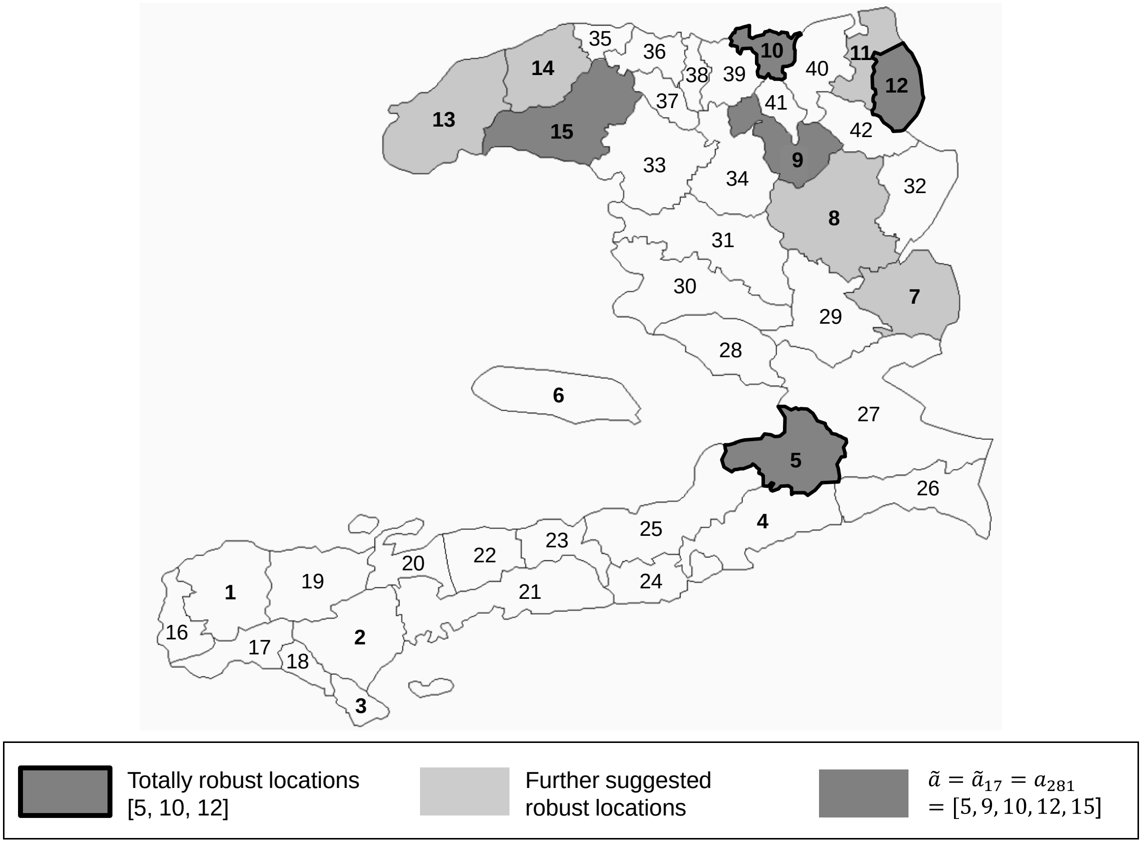


Figure 5-11: Visualization of the robustness ranking

Promising alternative $\tilde{a} = \tilde{a}_{17} = [5, 9, 10, 12, 15]$ is provided as the robust decision recommendation for the NGO association. With respect to the insights provided by the sensitivity analyses (see section 5.4.2), further promising alternatives exist that achieve a best robustness value when different adjustments of preferential parameters are used (preferences of objectives and risk preferences). These are $\tilde{a}_1$ which suggests opening health care facilities in arrondissements 8 and 9 and

$\tilde{a}_5$ which proposes facilities in arrondissements 8 and 15. The following paragraphs explore differences between $\tilde{a}_1$, $\tilde{a}_5$, and $\tilde{a}_{17}$.

Promising alternative $\tilde{a}_5$ is assessed as most robust when decision-makers operate neutrally in their principle risk aversion. They choose a low inter- and intra-scenario degree of pessimism ($we^{prog} \rightarrow 1, \lambda^{prog} \rightarrow 1$). Robustness measurement is mainly based on the expected aggregated regret a promising alternative achieves across prognostic scenarios. In turn, $\tilde{a}_1$ is most robust when decision-makers operate pessimistically in their principle risk aversion. Therefore, a high inter- and intra-scenario degree of pessimism is selected ($we^{prog} \rightarrow 0, \lambda^{hyp} \rightarrow 0$). Robustness measurement is mainly based on the maximal aggregated regret a promising alternative achieves across hypothetical scenarios.

Adjustments of preferential parameters as used in the case study ($we^{prog} = 0.8, \lambda^{prog} = 0.8, \lambda^{hyp} = 0.2$) indicate a rather neutrally operating NGO association in its principle risk aversion. However, decision-makers are aware of the possibility of occurring threats within the decision environment caused by critical events and respect them through robustness measurements. The most robust promising alternative $\tilde{a}_{17}$ can therefore be understood as a “compromise” of $\tilde{a}_1$ and $\tilde{a}_5$. In fact, $\tilde{a}_{17}$ is assessed as most robust when prognostic scenarios are more highly prioritized than hypothetical scenarios ($we^{prog} > we^{hyp}$) and when the expected aggregated regret is taken to evaluate promising alternatives in prognostic scenarios and the maximal aggregated regret is used to evaluate promising alternatives in hypothetical scenarios ($\lambda^{prog} \rightarrow 1, \lambda^{hyp} \rightarrow 0$). Hence, decision-makers principly trust in the set of prognostic scenarios. However, they are interested in implementing a decision that performs robustly to deteriorated states of the decision environment specified by hypothetical scenarios. To understand the effects of changing preferential parameter values, differences between $\tilde{a}_1, \tilde{a}_5$, and $\tilde{a}_{17}$ are visualized in Figure 5-12 and are discussed in the following paragraphs.

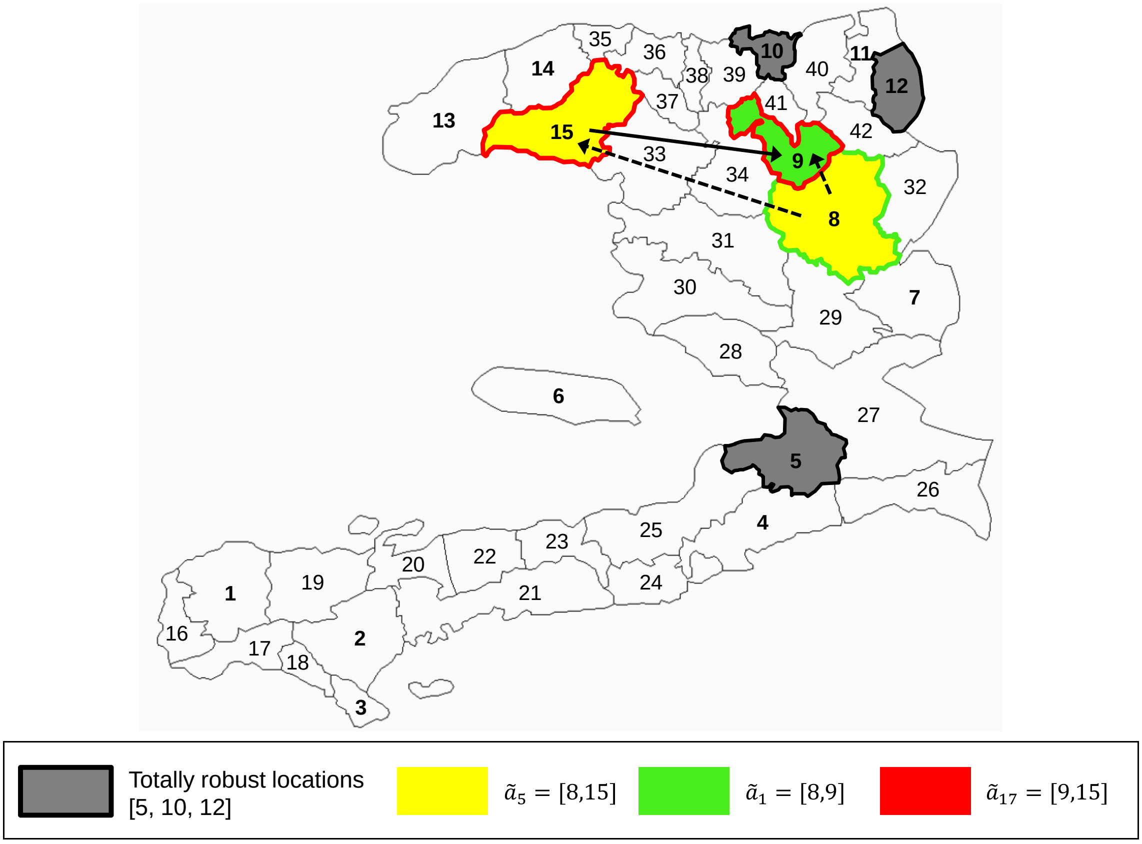


Figure 5-12: Visualization of robust promising alternatives

Both $\tilde{a}_1$ and $\tilde{a}_5$ suggest a health care facility in arrondissement 8 and, thus, differ in just one health care facility location. Promising alternative $\tilde{a}_5$ opens this facility in arrondissement 15. This is because prognostic scenarios indicate that the north-western part of Haiti is most likely to be affected by the main earthquake. In turn, $\tilde{a}_1$ aims at strengthening the part of Haiti that is located close to the epicenter area by opening the facility in arrondissement 9. The reason is that mostly hypothetical scenarios are respected by robustness measurement. In many significant scenarios (of the promising alternatives), the majority of health care demands is satisfied by the facility in arrondissement 8. Decision-makers, therefore, aim at strengthening the part of Haiti close to this arrondissement (and the epicenter area) by a facility in arrondissement 9 to hedge against additional health care demands and road failures. The "compromise" promising alternative $\tilde{a}_{17}$ opens health care facilities in arrondissements 9 and 15. It suggests protecting the epicenter area by a facility in the closer arrondissement 9 (compared to arrondissement 8). As, however, prognostic scenarios are mainly respected for robustness measurement, health care demands that might arise in Haiti's north-western part are covered by a facility in arrondissement 15. In summary, differences between $\tilde{a}_1, \tilde{a}_5$, and $\tilde{a}_{17}$ concentrate on the distribution of facilities in Haiti's northern part. The southern part, in turn, is always understood as well covered by the totally robust health care facility in arrondissement 5. The difference between $\tilde{a}_1$ and $\tilde{a}_5$ (black line) and their differences to $\tilde{a}_{17}$ (black dotted lines) are visualized in Figure 5-12.

The conducted sensitivity analysis of preferences of objectives underlines the robustness of $\tilde{a}_1$, $\tilde{a}_5$, and $\tilde{a}_{17}$ (as stated by the sensitivity analyses of risk preferences). While $\tilde{a}_5$ and $\tilde{a}_{17}$ are most robust when we_{z_1} increases we_{z_2}, $\tilde{a}_1$ is most robust when we_{z_1} and we_{z_2} are almost the same. An additional promising alternative, $\tilde{a}_3$, is assessed as most robust when we_{z_2} increases we_{z_1}. As decision-makers are interested in reducing transportation costs, the epicenter area is strengthened by an additional health care facility in arrondissement 11 in this case.

5.5 Summary and discussion

Chapter 5 applied ReDRiSS in a case study that focused on humanitarian logistics in Haiti. A decision situation has been considered where P-SCs of the CI sector "health care" have been destructed due to an earthquake. ReDRiSS provided analytical support to solve a facility location problem of opening quick rotation warehouses in Haiti to store medicine or medical equipment. Solving the facility location problem is an essential step toward defining the distribution structure of a humanitarian relief SC that takes over the functions of destructed P-SCs.

Section 5.1 introduced the field of humanitarian logistics and outlined the relevance of facility location planning in this regard. The structure and assumptions of the case study have been discussed in section 5.2. An adapted version of the BOUFLP to solve the logistical decision problem has been formulated and the decision situation has been characterized. The post-disaster application of ReDRiSS has been highlighted in section 5.3 by following the processing steps of the two-stage scenario technique. Robustness measurement has been addressed by section 5.4. Generated results have been verified by sensitivity analyses and obtained findings have been interpreted.

The case study shows that robust health care facility locations can be determined even when conditions of the disaster-affected decision environment are uncertain and complex. In fact, three of five health care facility locations are always the same (totally robust) across the ten most robust promising alternatives. Regarding the two remaining locations, regional clusters within Haiti exist whose underlying arrondissements might host these facilities. All clusters refer to Haiti's northern or central part. This underlines a similarity of the investigated promising alternatives as well as their basic robustness. Differences in the obtained robustness values are, therefore, subtle.

The case study highlighted the advantage of ReDRiSS to construct customized sets of hypothetical scenarios. This advantage is captured by simulating *alternative-specific* and *scenario-specific dynamic developments* in terms of earthquake aftershocks. In fact, promising alternatives to solve the facility location problem are identified, their individual worst case prognostic scenarios (significant scenarios) are filtered, and dynamic developments caused by critical events (aftershocks) are simulated within the significant scenarios. Both the criticality of dynamic developments in terms of their caused threats and the ability of promising alternatives to handle these threats vary across promising alternatives. Therefore, dynamic developments are simulated alternative-specifically by developing critical aftershock epicenter locations (arrondissements) from the perspective of a promising alternative. Furthermore, dynamic developments are simulated scenario-specifically in the sense that the aftershock affects the state of the decision environment as assumed within a promising alternative's worst case prognostic scenarios (significant scenarios). In this way, ReDRiSS provides the possibility of exploring individual advantages and weaknesses of promising alternatives by systematically analyzing complexity of the decision situation in terms of changed and deteriorated states of the decision environment.

A further advantage of ReDRiSS becomes obvious when interpreting the results of robustness measurement that respect risk preferences of the decision-makers. The conducted sensitivity analyses show three promising alternatives that are assessed as most robust for different adjustments of the preferential parameters. Although all of these promising alternatives are basically robust (as all health care facility locations refer to the identified regional clusters of Haiti, see above), they show significant differences regarding the underlying risk preferences of the decision-makers (in terms of their degrees of pessimism). These differences might become important when decision-makers implement a decision by transferring the decision recommendation into practice. Decision-makers operating in disaster management and in particular in the field of humanitarian logistics must make decisions that might trigger severe consequences for beneficiaries. Their trust in an implemented decision is therefore essential. A DSS can just strengthen this trust when offering the opportunity for the decision-makers to influence the decision-making process by adjusting their (risk) preferences.

Various extensions of the case study are possible. This firstly affects the adapted BOUFLP that is used to solve the facility location problem. The optimization model assumes that the number of health care facilities to be opened, G, is predetermined by the decision-makers. This assumption might be modified by just defining a minimum and maximum number of facilities to be set up. To identify the best number of facilities, analyses must trade-off fixed costs (e.g. they increase when more facilities are opened) and transportation costs (e.g. they increase when fewer facilities are opened). Exploring this trade-off allows an in-depth consideration of the objective of efficiency. A second extension of the case study refers to the construction process of prognostic and hypothetical scenarios. It is assumed that consequences caused by the earthquake in terms of health care demands and road failures in an arrondissement depend on its linear distance from the epicenter arrondissement. Linear functions are used to reflect this dependence. Expert interviews might be useful to formulate a more precise function in this regard. Finally, the case study should be adapted to a historical earthquake event (e.g. in 2010). This requires the reconstruction of the past conditions of the decision situation. Extensive tasks are therefore required such as, inter alia, literature reviews, interviews with experts and decision-makers (e.g. NGOs), data collections, restorations of exogenous information flows that arose in the aftermath of the earthquake, or analyses of decisions made. Despite the widespread challenges occurring in this regard, comparing decision recommendations that are generated by ReDRiSS and actually made past decisions is an important step of continuing the verification of the DSS.

6 Case study 2: business continuity management in the food sector

This chapter presents a case study to apply ReDRiSS in a decision situation arising in the field of *business continuity management* (BCM). The case study has been developed within the research project *SEAK* (*scenario-based decision support to manage food supply disruptions*) which was funded by the German Federal Ministry of Education and Research (BMBF) from January 2013 to December 2015. SEAK's major objective was the development of decision support approaches to aid internal decision-makers (companies of the CI sector "food", denoted "food sector" in the following) in managing food SC (P-SC) disruptions.

The depicted decision situation is about a flu pandemic that has spread in the middle-eastern part of Europe. It causes a large-scale staff absence in a food retail company owning stores in Berlin, Germany, which threatens its critical business processes in terms of operating the stores smoothly. To strengthen the functioning of these critical business processes, the logistical decision problem arises of allocating the available staff members to the stores. Therefore, the food retail company implements and applies ReDRiSS as a measure of BCM to develop a robust allocation that withstands uncertain and fluctuating customer food demands within the flu pandemic affected population (customers). In section 6.1, the field of BCM is introduced and its relevance regarding the case study is outlined. Section 6.2 focusses on the implementation of ReDRiSS as a measure of BCM. ReDRiSS is applied in section 6.3 and the results are presented in section 6.4. The chapter closes with a summary and discussion in section 6.5.

6.1 Business continuity management

The following sections provide an introduction into the field of BCM. Definitions and standards are presented and the BCM lifecycle is outlined describing a framework to operationalize BCM within an organization. Furthermore, the relevance of BCM for the topic of this case study is described which is on companies of the food sector that are impacted by a disease-caused staff absence.

6.1.1 Definitions

BCM refers to a set of principles, policies, and tools to support organizations in keeping their critical business processes functioning if the situation arises where they are threatened or already affected by a disruptive event (Peck 2006). The focus is thereby on disruptive events that are characterized by a high impact and a low probability. Such events typically just allow a short timeframe for the decision-makers to react (e.g. disasters) (Zsidisin et al. 2005). Since the year 2012, BCM has been defined by the standard ISO 22301. Thus, organizations have the opportunity to certify their BCM activities. According to ISO 22301, BCM is defined as a "holistic management process that identifies potential threats to an organization and the impacts to business operations those threats, if realized, might cause, and which provides a framework for building organizational resilience with the capability of an effective response that safeguards the interests of its key stakeholders, reputation, brand, and value-creating activities" (ISO 2015). Hence, BCM refers to proactive management process by providing a framework of tools (ISO 2015) with the objective of recovering disrupted critical business processes (Kildow 2011).

Different disciplines that are bundled together by an organization must participate and collaborate within BCM (von Rössing 2005). According to the considerations of chapter 3, efforts of both preventive SCRM and reactive SCCM are required to manage SC disturbances (disruptions or destructions). When disturbances refer to disruptions of critical business processes affecting an organization, BCM bears a particular responsibility in coordinating and, thus, bridging the gap between SCRM and SCCM (Boerse 2014). The interconnectedness of BCM, SCRM, and SCCM becomes directly obvious within the standard ISO 22301. On the one hand, BCM is described as a management process that coordinates the identification and minimization of risks. SCRM therefore builds the foundation of a functioning BCM by identifying critical business processes and risks of disruptive events and their consequences. On the other hand, BCM is described as a management process that provides an action framework to withstand an actually occurring disruption of the critical business processes (von Rössing 2005). It supports SCCM by providing a pre-developed *business continuity plan* (BCP). The task of SCCM is to transfer this BCP into practice to run an appropriate crisis operation with the objective of recovering the normal operation over time (Eren & Schindler 2011). Figure 6-1 visualizes the relationship between BCM, SCRM, and SCCM.

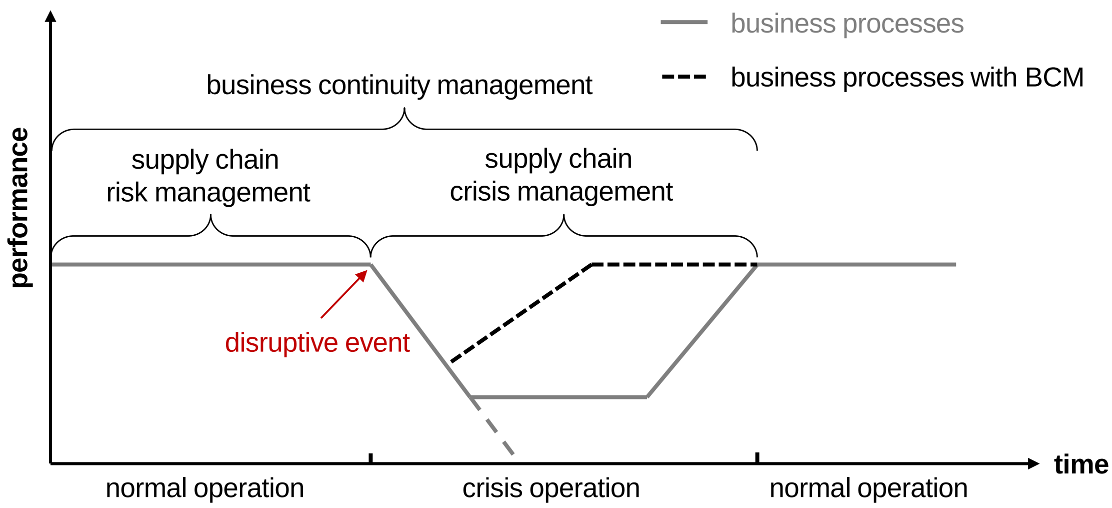


Figure 6-1: Business continuity management (adapted from Lauwe 2007)

A practical framework to operationalize BCM within an organization is provided by the *BCM lifecycle*. In this framework, BCM is described as a cyclically-ordered process that must be continuously repeated by an organization to establish BCM because the market and environmental conditions it operates within typically change over time (von Rössing 2005). The BCM lifecycle indicates the stages of activities an organization must move through and repeat to establish BCM (BCI 2013). It comprises six professional practices (see below) which either refer to management practices (professional practices 1 and 2) or to technical practices (professional practices 3, 4, 5, and 6) (BCI 2013). The management practices follow the objective of disseminating BCM as a whole within the organization; the technical practices aim at developing a BCM strategy and finally a BCP to manage disruptive events affecting critical business processes preventively (by SCRM) and reactively (by SCCM). The following professional practices contribute to the management practices (BCI 2013):

- *Policy and program management* (professional practice 1): the structure of BCM within an organization is based on a BCM policy and program. This describes general principles, guidelines, and conditions of BCM according to the organization's objectives, requirements, responsibilities, and visions (BCI 2010; Eren & Schindler 2011; BCI 2013).
- *Embedding business continuity* (professional practice 2): the BCM policy and program must be sustainably embedded into the organization's everyday business activities and its organizational culture (BCI 2013; BCI 2010). This requires iteratively analyzing the status quo (e.g. by audits) and creating awareness of the staff members (Eren & Schindler 2011).

The objective of technical practices is to develop a BCM strategy and a BCP within the BCM policy and program. Therefore, the following professional practices must be conducted (BCI 2013):

- *Analysis* (professional practice 3): the organization is reviewed regarding its objectives, functioning, and constraints of the environment it operates within (BCI 2010; BCI 2013). Three methods are applied in this regard. Consequences of disruptive events are analyzed via business impact analyses (BIA) with the objective of identifying critical business processes. The resources that are required to keep these critical business processes intact are determined by continuity requirements analyses (CRA). Risk analyses identify and assess risks that might cause a disruption of the critical business processes (BCI 2010; BCI 2013).
- *Design* (professional practice 4): based on the insight provided by the previous professional practice, a BCM strategy is developed that states how continuity and recovery from a disruption of critical business processes could be achieved (BCI 2010; BCI 2013). Such a BCM strategy must include both measures that can be applied prior to the occurrence of the disruption to minimize

risks and an action framework whose focus is on its reactive management (BCI 2010; BCI 2013).

- *Implementation* (professional practice 5): the BCM strategy is executed by developing a concrete BCP that prescribes how to manage the disruption of the critical business processes (BCI 2010; BCI 2013). The BCP is of particular importance (von Rössing 2005) as it comprises all corresponding documents that are required to implement recovery measures in the aftermath of an occurring disruptive event (BCI 2010; BCI 2013).
- *Validation* (processional practice 6): to establish a permanent and effective BCM within the organization, the results of the technical practices, the development of a BCM strategy and a BCP, must be continuously validated. This requires a reflection of the organization to improve its resilience via maintenance, exercise, and review (BCI 2010; BCI 2013).

An organization must conduct the professional practices of the BCM lifecycle prior to the occurrence of a disruptive event threatening its critical business processes. Its focus, however, is on both, the preventive and reactive management of such an event. This underlines the cross-divisional function of BCM to support both SCRM and SCCM (see Figure 6-1).

6.1.2 The relevance of business continuity management in the case study

The companies of the food sector are part of the CI network of a society or community. Thus, an effective BCM of these companies is not just required to protect from own economic losses caused by disruptions of critical business processes. Rather, the management of disruptive events is also relevant to ensure public safety as companies of the food sector bear a particular responsibility in this regard. In today's globalized world, an increasing geographic, economic, and legislative interconnectedness of food SCs triggers the risk of disruptions within any part which propagate through the food sector and, thus, affect various companies simultaneously (Dani & Deep 2010). As opposed to further

CI sectors such as water or energy, intervention measures of public authorities are limited to protecting people from the consequences of a food undersupply. This is mainly because the food sector includes a high number of market players (Dani & Deep 2010).

According to a survey provided by GfK (2014), a trend can be observed in the German population to store fewer private stocks of foodstuff. In turn, companies of the food sector usually refer to a warehousing strategy that allows the satisfaction of customer food demands just for several days (Dalton 2006). This efficiency of food SCs under normal conditions increases their vulnerabilities to be severely affected by disruptive events (Peck 2006). When private stocks are not enough, foodstuff might become quickly scarce and the population might react through so-called “panic purchases”. This purchasing behavior of hoarding larger amounts of foodstuff might further strain the already affected companies (Dalton 2006). In order to manage disruptive events, BCM (of the companies) must manage “priority channels” within the food supply (e.g. to guarantee the provision of food staples). In this regard, it is important to encourage cooperation between companies and between companies and public authorities (Peck 2006).

According to Woodman (2007), who analyzes companies in the United Kingdom regarding their efforts of embedding BCM into their structures, the risk of a *staff absence* is one of the central risks to be considered by BCM. Although a staff absence has been mentioned as a frequent source of business interruptions, however, less than 50% of the surveyed companies have developed preventive strategies to manage this type of risk. The ratio is significantly below further efforts of BCM such as handling industrial fires or failures of ICT systems. Possible sources of a staff absence are widespread. Literature in particular highlights the criticality of outbreaks of epidemics or pandemics[22] (Sikich 2008; Tan & Takakuwa 2011). This is because in such a case, the extent of the staff absence is not just determined by the diseased number of staff members. Rather, healthy staff members might be forced to stay

[22] An epidemic affects a regional area; a pandemic affects countries or even continents simultaneously.

at home to care for, inter alia, family members such as their children when schools or kindergartens close (Dalton 2006). Further staff members might not appear at work to avoid an infection (Dalton 2006). The objective of BCM must be to establish a communication structure within an organization. This includes, for example, the fast provision of information of protective measures to avoid an infection. Companies must take care to not mix different groups of available staff members. This is because several staff members might be characterized by a higher infection risk than others due to their job specifications (e.g. sales representatives) (Dalton 2006).

6.2 Implementation of ReDRiSS

The case study considers a food retail company that owns stores in Berlin, Germany. It conducts the BCM lifecycle to prepare for disruptive events affecting its critical business processes. Those critical business processes refer to the activities its staff members must conduct to operate a store such as, inter alia, activities at the checkout (purchasing) area, the filling up of shelves, or customer advisory services. The food retail company has applied the prescribed management practices according to the BCM lifecycle (see section 6.1.1) and has embedded a BCM policy and program into its everyday business activities and organizational culture. By applying the technical practices according to the BCM lifecycle, a large-scale staff absence has been identified as a major risk disrupting its critical business processes. Thereby, diseases (e.g. epidemics, pandemics) have been determined as the most crucial source (professional practice 3: analysis). When a disease-caused staff absence occurs, the food retail company is forced to operate its stores with a reduced number of staff members which threatens its major objective of profit maximization. This objective is, however, not just affected by a reduced number of staff members. Rather, the objective is also threatened by the uncertain purchasing behavior of the disease-affected customers which is reflected by fluctuations in their food demands. Moreover, the food retail company is aware of its responsibility to protect public safety because it participates in the CI network. Hence, it develops a BCM strategy that prescribes preventively establishing ReDRiSS by SCRM to reactively support SCCM when a disease-caused staff absence enters. The application of ReDRiSS should support SCCM in managing the crisis operation in terms of robustly allocating available staff members to the stores by respecting the uncertain customer food demands (professional practice 4: design). Thus, ReDRiSS is an implemented system that, when it is applied, reactively develops a concrete BCP within the BCM strategy (professional practice 5: implementation). In the following sections, the implementation process of ReDRiSS is outlined. The subsequent need for validating ReDRiSS (professional practice 6: validation) is discussed in the final section 6.5.

6.2.1 General description of the decision situation

The first task of implementing ReDRiSS is the development of a requirements profile that summarizes the depicted decision situation and the scope of ReDRiSS (*ReDRiSS part A*, *processing step 1*).

Figure 6-2 shows the geographical distribution of the 29 stores of the food retail company in Berlin. Further information regarding Berlin's structure (districts I to XII) has been attached to appendix B.1. Food retail stores can be classified by the sizes of their sales area into *consumer markets* $(500 - 4999\,\mathrm{m}^2)$ and *self-service warehouses* $(5000 - 7000\,\mathrm{m}^2)$ (Kotzab & Teller 2005). The size of the sales area comprises the space that is available for the customers when they make their purchases. It includes the goods shelves and the footprints, the corresponding corridors, and the checkout (purchasing) area. Parking spaces and areas that are inaccessible for the customers are excluded from the sales area (e.g. offices, areas of storage, incoming goods). The 29 stores of the food retail company refer to 18 consumer markets and 11 self-service warehouses.

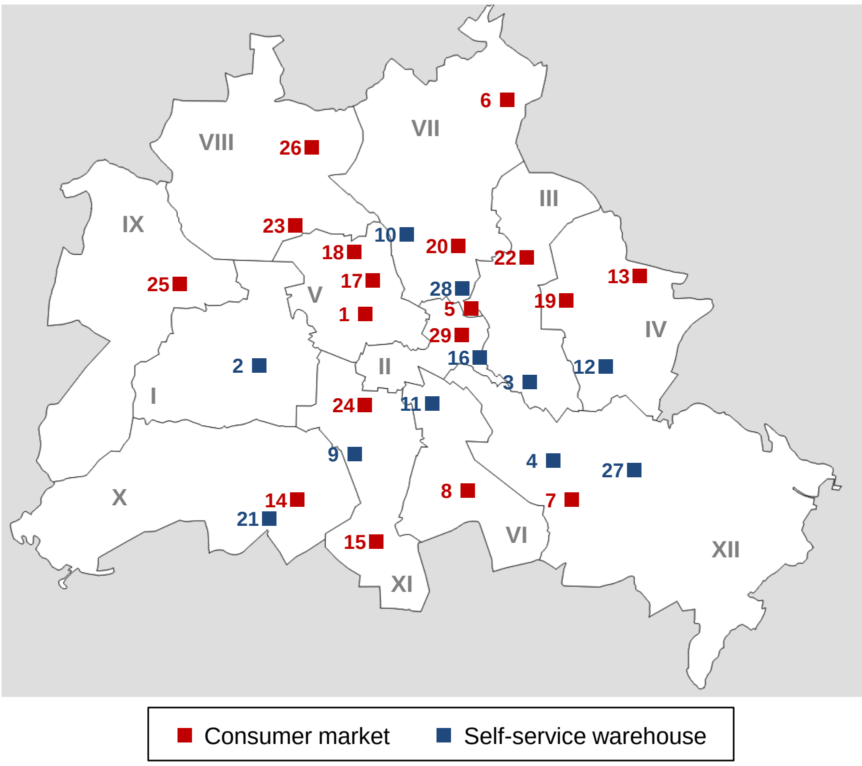


Figure 6-2: Geographic distribution of stores in Berlin[23]

In order to operate a store, a minimum number of staff members is required to be employed in it. If this number is not allocated to a store, this store has to be closed. It is assumed that the food retail stores are highly standardized and a single staff member can potentially work in any of both types of stores (consumer markets and self-service warehouses) without lowering the throughput of foodstuff [kg] he/she is able to generate. The possible throughput of a store is, thus, directly linked to its employed number of staff members.

Decision-makers are located at the management level of the food retail company that supervises the allocations of staff members to the stores and that has the authority to close stores in cases of necessity (decision-makers are denoted "food retail company" in the following). When a large-scale staff absence occurs, the food retail company must organize its crisis operation by distributing available staff members to the stores for the scope of one day. As there is a minimum number of staff members required to operate a store, the allocation of staff mem-

[23] Source of the geographical map of Berlin: (d-maps 2015)

bers might imply that the food retail company is forced to close several stores.

The major objective of the food retail company is profit maximization. It is assumed that average costs are constant in the normal and in the crisis operation of the stores and that disposition costs are negligible. Therefore, the profit that can be achieved by the food retail company on one day is proportional to the aggregated revenue of all stores. To achieve this objective, the food retail company must find a way to turn over the throughput of foodstuff that is principly achievable by the reduced number of employed staff members.

When making a decision of allocating staff members to the stores, information about the extent of the staff absence is required. This information must be provided by all store managers early enough (in the morning). A "safety markup" is added to this aggregated ratio of the staff absence across all stores as several staff members might not report sick in the morning or as they become diseased during the day. Thus, the "safety markup" provides the food retail company some breadth to flexibly re-allocate staff members during the day in order not to be forced to close any additional store. Decisions that can be taken by the food retail company vary. For instance, it is imaginable to keep as many stores open as possible with the minimum required capacity of staff members. Alternatively, stores might be closed and the remaining stores are operated by a higher capacity of staff members (to achieve a higher throughput of foodstuff in the opened stores).

The decision-making is enhanced by the fluctuating character of customer food demands. Such fluctuations arise because the population of Berlin (customers) is also affected by the flu pandemic. It is imaginable that the customer food demands increase as healthy people raise their individual stocks of foodstuff for several days to be prepared for an infection. Alternatively, households whose inhabitants are already infected might not be able to go to the stores which might, in turn, cause a decrease in customer food demands. The mostly unpredictable shift in customer food demand is additionally motivated by the fact that some areas of Berlin are more industrial than others. Moreover, normal consumption behavior is potentially altered when a great part of the customers remain at home diseased, primarily in the more lived-in districts.

Coupling effects between the staff absence and the customer food demands might be severe: while the food retail company might be forced to close several stores because of fewer available staff members, customer food demand might increase and cause a (company-specific) undersupply of foodstuff. Although just one company of the food sector is considered in the case study, public safety might be threatened by the flu pandemic. This is because further companies operating within the area of Berlin and further parts of middle-eastern Europe might be impacted in the same way. Thus, existing redundancies within the food sector are reduced. Table 6-1 shows the requirements profile of the depicted decision situation.

Table 6-1: Requirements profile (case study 2)

Disaster type	Pandemic
Location	Berlin, Germany
Decision-makers	Food retail company
Decision support	Adaptation strategy
Logistical decision problem	Allocation of staff members to the stores
Objective	Identification of a robust allocation of staff members to maximize profit in terms of turning over the achieved throughput of foodstuff by the available staff members
Challenge	Unknown and fluctuating customer food demands due to changed purchasing behaviors of diseased customers

6.2.2 Development of an optimization model for staff allocation planning

The following paragraphs describe the optimization model that is integrated into ReDRiSS (*ReDRiSS part A*, *processing step 2*) to solve the underlying logistical decision problem.

The profit [€] that can be achieved by the food retail company for the scope of one day depends on the aggregated revenue [€] in all stores. This revenue depends on the achieved throughput of the stores by the employed staff members [kg] and, in fact, the share of this throughput that is turned over by the customers [€]. Generally, it is assumed that the achieved throughput of a store increases linearly with the employed number of staff members in this store. A staff absence directly causes losses in the throughput and, thus, losses in the possible revenue and profit. The major influencing factor of whether the achieved throughput is turned over to generate the possible revenue and profit is whether the flu pandemic affected customers satisfy their food demands at the food retail company or not.

In the depicted decision situation, the purchasing behavior is not predictable which is reflected by unknown and fluctuating customer food demands. Hence, the objective of the food retail company must be to create the best conditions that the customers actually make their purchases in its stores. The optimization model, therefore, follows the calculus that the chance of a diseased customer attending a store increases when the purchasing distance (distance between the customer and its next store) decreases. When the staff members are allocated to the stores in a manner that allows that all served customers need a minimum sum of purchasing distances to reach their serving stores, the chance increases that the food retail company turns over the possible throughput and, thus, maximizes its revenue and profit. By following this calculus, the secondary effect enters that the food retail company meets its responsibility in protecting public safety by managing the crisis operation in a people-oriented manner.

Let $J = \{1,2,\dots\}$ be the set of customers that is served by the set of stores $I = \{1,2,\dots\}$. The food demand of customer $j \in J$ is denoted b_j. A number of staff members m is available and must be allocated to the stores. The achieved throughput of a store $i \in I$ depends on its employed number of staff t_i (decision variable). It is assumed that this throughput increases linearly to the number of employed staff members; this additional throughput per staff member is indicated by the constant factor γ. Moreover, let d_{ij} be the purchasing distance between j and i.

An opened store i must employ a minimum number of staff members l_i. The binary decision variable x_i indicates whether store i is opened ($x_i = 1$) or closed ($x_i = 0$) which depends on the specification of t_i. Moreover, let u_i be the maximum number of staff members in this store (during normal operation). The employed number of staff members t_i in an opened store must be between l_i and u_i:

$$l_i \cdot x_i \leq t_i \leq u_i \cdot x_i \tag{6-1}$$

Let $B_{total} = \sum_j b_j$ be the overall customer food demand that can be satisfied by the stores during normal operation where u_i staff members are employed in each store i. Due to the staff absence, the unsatisfied customer food demand B^- is:

$$B^- = B_{total} - \gamma \cdot m \tag{6-2}$$

Each $b_j, j \in J$ can be satisfied by exactly one store. Binary decision variable y_{ij} indicates whether j is served by store i ($y_{ij} = 1$) or not ($y_{ij} = 0$). Table 6-2 provides an overview of parameters and decision variables of the optimization model.

Table 6-2: Parameters and decision variables (case study 2)

Parameter	Description	Range of values
b_j	Food demand [kg] of customer j	$\in \mathbb{R}^+$
d_{ij}	Purchasing distance [km] between store i and customer j	$\in \mathbb{R}_0^+$
l_i	Minimum number of staff members in an opened store i	$\in \mathbb{N}^+$
u_i	Maximum number of staff members in an opened store i	$\in \mathbb{N}^+$
m	Available number of staff members	$\in \mathbb{N}^+$
γ	Throughput per staff member and day [kg]	$\in \mathbb{R}^+$
Decision variable	**Description**	**Range of values**
x_i	1: store i is opened, 0: otherwise	$\in \{0,1\}$
t_i	Number of allocated staff members to store i	$\in \mathbb{N}_0$
y_{ij}	1: store i serves customer j, 0: otherwise	$\in \{0,1\}$

The equations [6-3] to [6-11] show the formulation of the developed optimization model which refers to the class of MILP. In the following paragraphs, the objective function [6-3] and the constraint functions [6-4] to [6-11] are discussed.

$$\min z = \sum_i \sum_j y_{ij} \cdot d_{ij} \qquad [6\text{-}3]$$

subject to

$$\sum_i t_i = m \qquad \forall i > 0 \qquad [6\text{-}4]$$

$$\sum_i y_{ij} = 1 \qquad \forall i, j \qquad [6\text{-}5]$$

$$\sum_j (y_{ij} \cdot b_j) \geq \gamma \cdot t_i \cdot x_i \qquad \forall j, \forall i > 0 \qquad [6\text{-}6]$$

$$t_i \geq l_i \cdot x_i \qquad \forall i \qquad [6\text{-}7]$$

$$t_i \leq u_i \cdot x_i \qquad \forall i \qquad [6\text{-}8]$$

$$x_0 = 0 \qquad [6\text{-}9]$$

$$t_i \in \mathbb{N}_0 \qquad \forall i \qquad [6\text{-}10]$$

$$x_i, y_{ij} \in \{0,1\} \qquad \forall j, \forall i > 0 \qquad [6\text{-}11]$$

The objective function [6-3] prescribes allocating the available number of staff members to the stores so that the sum of the purchasing distances between all serving stores and served customers is minimized. Due to the staff absence, it might be necessary to close stores or to run stores with a lower capacity of staff members. The customer food demands that cannot be satisfied (B^{-}, see [6-2]) are "served" by a "dummy store" ($i = 0$). This "dummy store" does not employ any staff member and is characterized by purchasing distances to all customers of zero ($d_{oj} = 0, \forall j \in J$). The constraint function [6-4] ensures that a number of m staff members are allocated to the "real" stores ($i > 0$). In constraint function [6-5], it is guaranteed that a customer is assigned to exactly one store. The throughput of a store corresponds to the employed number of staff members in this store. This throughput must be achieved with the customer food demands that are served by that store. Therefore, the constraint function [6-6] assumes that the throughput of each store $i > 0$ is at least as high as the throughput capacity that can be achieved by the number of staff members employed in this store (the reason for the "≥"-relation is discussed in the following paragraph). The constraint functions [6-7] and [6-8] ensure that the allocated number of staff members in a store is between the minimum and maximum number of staff members of the store, [6-9] ensures that the "dummy store" is closed, and [6-10] and [6-11] define the feasible range of values of the decision variables.

The "≥"-relation used in the constraint function [6-6] might theoretically allow an overload of the stores (in the sense that the served customer food demands increase the achieved throughput in a store). This overload, however, is directly minimized by the objective function. In fact, customer food demands that trigger an increase of the throughput capacity of a store (defined by employed staff members) are assigned to another store (or the "dummy store") to minimize the objective function. It is, thus, just possible that the "last" customer food demand that is assigned to a store is served although it actually exceeds the remaining throughput capacity of the store. The application of the optimization model shows that this overload is significantly below one per mill and the effect is, thus, negligible. If a "="-relation was used to formulate the constraint function, the assignment of customer food demands to the stores would just be secondarily steered by their purchasing distances. Primarily, this assignment would be regulated by the objective of an equality of the throughput capacity and customer food demands. A further alternative formulation of the constraint function by a "≤"-relation would lead to the trivial solution that all customer food demands are served by the "dummy store". The overall purchasing distance of served customers and the "real" stores ($i > 0$) would be zero in this case.

6.3 Solving the logistical decision problem

A flu pandemic spreads in the middle-eastern part of Europe. The food retail company is affected by a large-scale staff absence which threatens its critical business processes in terms of operating its stores smoothly with the available number of staff members. The BCM department of the food retail company activates ReDRiSS to support SCCM in developing a robust allocation of the available staff members to the stores for the scope of one day.

6.3.1 Prognostic scenarios

To solve the logistical decision problem, parameters of the optimization model presented in section 6.2.2 must be specified. Parameters refer to *planning variables* and *environmental variables*. As not all environmental variables can be specified deterministically (see below), prognostic scenarios are constructed to explore the consequences of the disease-caused staff absence (*ReDRiSS part B*, *processing step 3*).

The specification of each planning variable is constant in any prognostic scenario because deterministic planning information is available. In the depicted decision situation it is assumed that planning information indicating the extent of the staff absence and, thus, the number of available staff members m is provided by the store managers early enough in the morning to flow into the decision-making process. It shows an aggregated ratio of the staff absence (including the "safety markup", see section 6.2.1) across all stores of 60%. Further planning variables refer to the maximum number of staff members u_i that are employed in a store $i \in I$ in the normal operation, the minimum number of staff members l_i that has to be employed in a store $i \in I$ to open this store, and the throughput γ [kg] that is achieved in a store by a staff member per day. The constant specifications of these planning variables are known by the food retail company and are outlined in section 6.3.1.1. Moreover, the constant specification of planning variable $d_{ij}, \forall i \in I, \forall j \in J$ indicating the purchasing distances between all stores and customers is deduced in section 6.3.1.2.

The optimization model integrates one environmental variable which refers to the customer food demands $b_j, \forall j \in J$. As the customers of the food retail company are affected by the flu pandemic, the specification of this environmental variable is prone to uncertainty. It is assumed in the depicted decision situation that there is no exogenous information arising ad-hoc that allows decision-makers to deterministically specify (parts) of the (geographical) customer food demand distribution across the districts of Berlin. Therefore, a specification process is developed and applied as it is presented in section 6.3.1.3.[24]

6.3.1.1 Specification of store characteristics

According to real planning information that is provided by the SEAK project, the considered food retail company is characterized by

- 18 consumer markets and 11 self-service warehouses (see Figure 6-2, section 6.2.1),
- a market share in Berlin of 10.6%,
- a maximum number of staff members of $u = 42$ in a consumer market and of $u = 91$ in a self-service warehouse (thus, the total number of staff members in normal operation is 1757),
- a monetary value density of foodstuff of 3.786 €/kg,
- a monetary sales value per customer of 4.761 €/(person·day),
- and an average throughput per additional staff member employed in a store of $\gamma = 266.1$ kg/day whereby it is assumed that this throughput is equal in a consumer market and in a self-service warehouse.

In the food sector, staff requirements fluctuate in normal operation on a yearly, monthly, and even daily basis (Kirsch et al. 1998). The staff absence causes a situation where the available staff members must keep critical business processes within a store intact in order to operate this store. Therefore, l_i must be employed in a store $i \in I$.

[24] The construction of prognostic scenarios is based on a specification process of the environmental variable which is actually developed in ReDRiSS part A, processing step 2. For the sake of clarity, the specification process is presented in this section.

In order to define l_i in a consumer market and a self-service warehouse, planning information about the personnel structure of the food retail company is required. Although this planning information principly exists, it is not communicated by the considered food retail company for the purpose of this case study. For this reason, the minimum staff is estimated by using the study of Baethge-Kinsky et al. (2006). According to the authors, a large German store chain employs 59% full-time staff members and 41% part-time or marginal staff members in its stores. When a store is under-occupied, staff members must quickly switch their operations to run all critical business processes. It is, however, not ensured that any staff member is appropriately qualified to operate all critical business processes smoothly. Particularly the skills of part-time or marginally employed staff members are frequently not sufficiently pronounced in this regard (Baethge-Kinsky et al. 2006). The authors highlight this using the example of sales activities in a store that are rather threatened by unqualified staff members than improved by implemented management strategies that focus on the enhancement of the skills of the staff members. Moreover, the study highlights just an intermediate level of knowledge of the staff members concerning the operation of the critical business processes. Hence, it is assumed in the following that at least the number of full time employed staff members is required to operate a store. In fact, the minimum number of staff members is rounded up to 60% of the maximum number of staff members and is, thus, $l = 26$ in a consumer market and $l = 55$ in a self-service warehouse.

Table 6-3 summarizes the constant specifications of the planning variables which define the store characteristics. In total, the food retail company employs 1757 staff members (when each store is operated by the maximum number of staff members) whereof not less than 1073 staff members are required to run all 29 stores (by the minimum number of staff members per store). When the staff absence causes the unavailability of more than 684 staff members (40% of the maximum staff) at least one store has to be closed. Following exogenous information indicating a staff absence of 60%, $m = 702$ staff members are available in the depicted decision situation.

Table 6-3: Planning variables regarding store characteristics

Planning variable	Consumer market	Self-service warehouse
Maximum staff $u_i, i \in I$ [persons]	42	91
Minimum staff $l_i, i \in I$ [persons]	26	55
Throughput per staff member and day γ [kg]	266,1	266,1

6.3.1.2 Specification of locations and purchasing distances of customers

The food retail company serves 10.6% of the overall customer food demand of Berlin (see above). As Berlin consists of 2.04 million households (Statistik Berlin Brandenburg 2012), the number of households served by the food retail company (or the company's catchment area) is 216,300. To reduce computational effort within the case study, an aggregation factor of 10:1 is used indicating that one customer represents ten households. Hence, 21,630 customers are considered in the following. To specify the purchasing distances between these customers and the stores to specify planning variable $d_{ij}, \forall i \in I, \forall j \in J$, customer data regarding their locations are required. As this planning information is, however, not communicated by the considered food retail company, a realistic geographic distribution of customer locations must be deduced for the purpose of the case study.[25]

The analysis, generation, and estimation of the catchment area of companies has been the scope of various authors (e.g. Krüger et al. 2013; Koller 2014). These empirical studies refer to and confirm the findings of Huff (1964) who has stated four regularities. Firstly, the ratio of customers patronizing a shopping area varies with the purchasing distance from this shopping area. Secondly, the ratio of customers patronizing various shopping areas is influenced by the product diversity of each shopping area. Thirdly, purchasing distances of customers to various shopping areas are affected by the type of product purchases. Fourthly, the attraction of a shopping area depends on the proximity of rival shopping areas.

[25] It is expected that the food retail company owns customer location data which is discussed in section 6.5.

As the case study considers just one food retail company, the product diversity offered by consumer markets and self-service warehouses is almost identical. Thus, the second and third regularities can be neglected when estimating customer locations. Following the remaining regularities, the catchment area of a store depends on the purchasing distances of customers and on the locations of stores of competing food retail companies.

To estimate the customer locations, customers are cyclically-distributed around the store's locations. Thereby there is no distinction made between housing areas, industrial estates, or undeveloped lands. The number of customers per district is determined by the market share of the food retail company and the population of the districts (Statistik Berlin Brandenburg 2012). A distribution function is defined to specify the purchasing distances of the cyclically-distributed customers. This function is based on empirical data of purchasing distances provided by Krüger et al. (2013) that has been gathered via consumer surveys within the stores of the food sector. The data distinguishes between the monitored region (e.g. rural areas, urban cores) and the company form of the considered food retail companies (e.g. discounter, self-service warehouses, consumer markets) (Krüger et al. 2013). Moreover, the densities of stores of all food retail companies in the districts n [1/km^2] is integrated into the distribution function (according to information provided by the SEAK project, see appendix B.1).

Based on this data, a *district-specific distribution function* $F_n(d)$ of *purchasing distances* d is developed via a regression of the empirical data of Krüger et al. (2013). $F_n(d)$ determines, in dependence of n, the ratio of customers that find a store within the purchasing distance d [km].

$$F_n(d) = \begin{cases} 0 & \text{for } d \leq \dfrac{0.043}{n} \\ 0.189 \cdot \ln(2.6 \cdot d \cdot n) + 0.412 & \text{for } \dfrac{0.043}{n} < d < \dfrac{8{,}633}{n} \\ 1 & \text{for } d \geq \dfrac{8{,}633}{n} \end{cases} \qquad [6\text{-}12]$$

Figure 6-3 highlights $F_n(d)$ for an average density of stores in Berlin of $n = 0.5/\text{km}^2$ in comparison to the empirical data of Krüger et al. (2013).

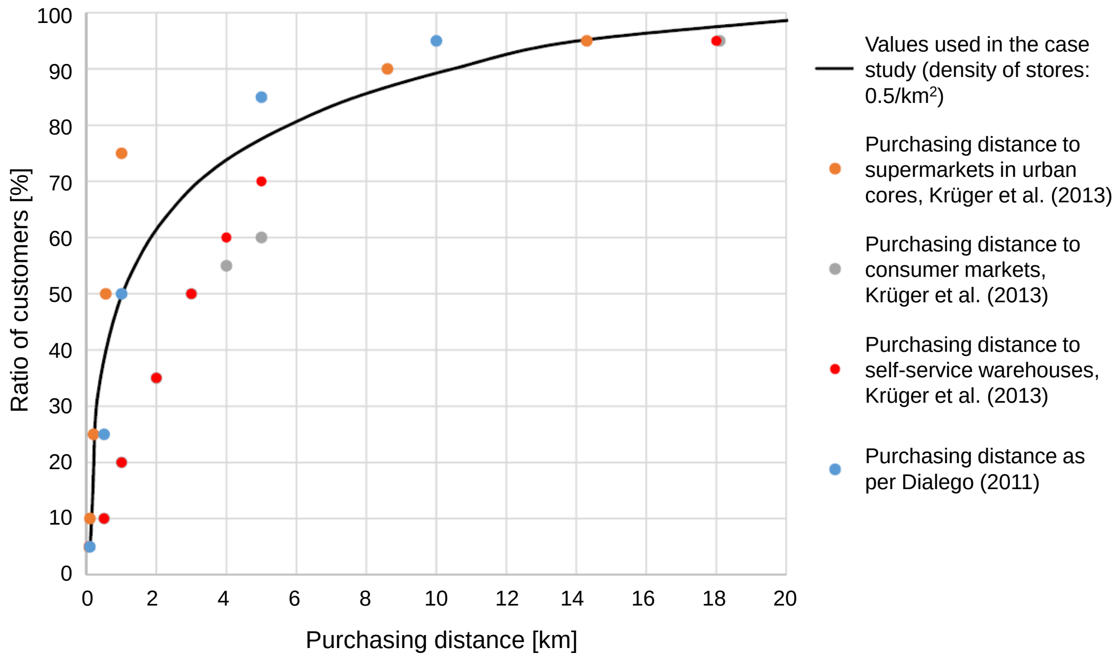


Figure 6-3: Purchasing distances

According to the function highlighted in Figure 6-3, the shortest purchasing distance of a customer to his/her next store is $0.043/0.5 = 0.086\,\text{km}$; the maximum purchasing distance is $8.633/0.5 = 17.266\,\text{km}$. It becomes obvious that the obtained purchasing distances of customers to the consumer markets and the self-service warehouses are basically below the empirical data. The reason therefore is that the latter does not respect regional circumstances such as populations or densities of stores. With respect to the purchasing distances in urban cores, the obtained purchasing distances increase the empirical data. This is because the study of Krüger et al. (2013) does not differentiate between the types of the supermarkets (e.g. consumer markets, self-service warehouses) in the urban core. Hence, empirical data does not respect the larger catchment area of such high capacity supermarkets. To further verify the plausibility of $F_n(d)$, Figure 6-3 additionally shows empirical data of another study provided by Dialego (2011). This study neither differentiates purchasing distances by the company forms of the food retail companies nor by district-specific characteristics.

The number of customers per store is defined by the population of the underlying district. To determine the customer locations by using equation [6-12], the following procedure is conducted:

1. Select a random location of a customer in the urban area of Berlin or its surrounding (defined by a latitude and longitude).
2. Determine the linear distance [km] $dist_1$ of this customer to his/her next store (given by the shortest purchasing distance).[26]
3. Determine the density of stores n of the district this next store is located within (see appendix B.1); calculate the minimum distance $dist_{min} = 0.043/n$ and the maximal distance $dist_{max} = 8.633/n$ a customer is allowed to be distanced from this next store.
4. Select a random distance $dist_2$ by using the density function $f_n(d) = F_n(d)'$.
5. If $dist_1 \leq dist_2$ and if $dist_{min} \leq dist_1 \leq dist_{max}$, accept the customer location; else, go to step 1.

This procedure is repeated until 21,630 customer locations have been determined. A randomly selected customer that is located outside the city boundaries of Berlin, but whose linear distance to his/her next store is between $dist_{min}$ and $dist_{max}$ (which is, thus, a feasible customer location), is assigned to the district this store is located within. The 21,630 generated customer locations are illustrated in the “heat map” in Figure 6-4.

[26] The *harvesine formula* is used to calculate the linear distance between two points on a sphere. Geographic locations of the points refer to their latitudes and longitudes.

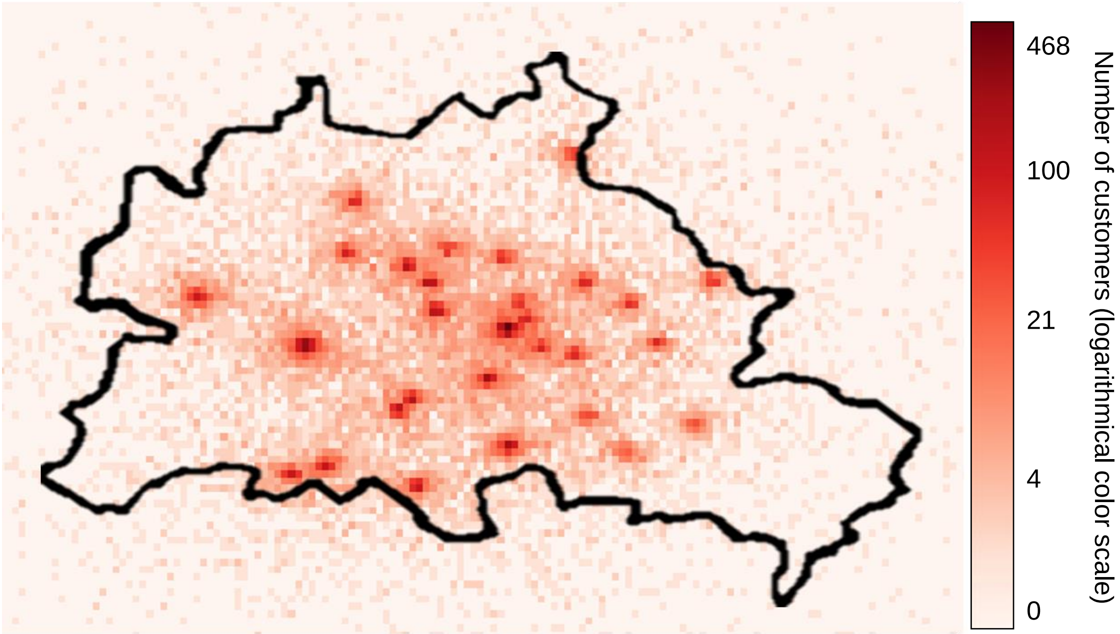


Figure 6-4: "Heat map" of customer locations

To specify planning variable $d_{ij}, \forall i, \forall j$, the linear distances between all customers and their next stores (which is defined by $dist_1$, see above) are calculated. The results show an average purchasing distance (between all customers and stores) of 12.26 km; the range of purchasing distances is between 30 m and about 40 km. More than 50% of the food retail company's customers are located less than 1 km distanced from their next stores. Less than 5% of customers cannot find a store within a radius of 10 km.

6.3.1.3 Specification of costumer food demands

The flu pandemic causes shifts in the customer food demands $b_j, \forall j \in J$ that exceed everyday fluctuations. Different developments are thereby imaginable (see section 6.2.1). As the environmental variable cannot be specified deterministically, a specification process is developed that allows describing different states of the customer food demand. It is assumed that a customer makes purchases every day to satisfy his/her food demands. According to UGW (2014), one third of the German population makes at least three purchases per week; another one third makes on average two purchases per week. Nielsen (2013) even states a number of 180 purchases per person and year. Due to the aggregation of households by the factor 10:1, one purchase per customer and day is seen as realistic.

The specification process is steered by a distribution function. In fact, a *gamma distribution* is used as it has been proven as an appropriate statistical distribution to estimate food consumption data (Battese et al. 1988; Vilone et al. 2014). Furthermore, the gamma distribution is exclusively defined for the positive range of real numbers which avoids the undesired effect of obtaining negative customer food demands. To formulate a gamma distribution, an expected value of customer food demands $\mu_{customer}$ and a realistic standard deviation $sd_{customer}$ must be defined.

Rather than respecting the foodstuff diversity offered by the food retail company, it is assumed that each customer purchases a basket of foodstuff whose relevant criterion is its weight [kg]. The monetary value density of foodstuff is 3.786 €/kg and the monetary sales value per person is 4.761 €/day(d) (see above). Hence, the average food demand μ_{person} [kg/d] is:

$$\mu_{person} = 4.761 \frac{€}{d} \cdot \frac{1\,kg}{3.786\,€} \approx 1.257 \frac{kg}{d} \qquad [6\text{-}13]$$

As one customer represents ten households and a household in Berlin includes on average 1.72 persons (Statistik Berlin Brandenburg 2012), the average food demand of a customer per day, $\mu_{customer}$, is:

$$\mu_{customer} = \mu_{person} \cdot 1.72 \cdot 10 = 21.62 \frac{kg}{d} \qquad [6\text{-}14]$$

Empirical studies indicate a coefficient of variation of 30% regarding both, the human energy consumption and the consumption of food components such as fats, proteins, or vegetables (Hoffmann et al. 2002; Pot et al. 2014). Thus, this coefficient of variation is used to describe realistic fluctuations of the expected food demand μ_{person}. Thus, the standard deviation sd_{person} [kg/d] of a customer [person] of the food retail company is:

$$sd_{person} = \mu_{person} \cdot 0.3 \approx 0.377 \frac{kg}{d} \qquad [6\text{-}15]$$

It is assumed that food demands of different persons are independent which implies that random variables do not correlate. The standard deviation of a customer $sd_{customer}$ cannot be determined by adding up the standard deviations of persons represented by a customer ($sd_{customer} \neq sd_{person} \cdot 10 \cdot 1.72$). Rather, $sd_{customer}$ is calculated by using the variance $Var_{customer}$:

$$Var_{customer} = Var_{person} \cdot 10 \cdot 1.72 \qquad [6\text{-}16]$$

Subsequently, $sd_{customer}$ can be calculated by:

$$\begin{aligned} sd_{customer} &= \sqrt{Var_{customer}} = \sqrt{1.72 \cdot 10 \cdot Var_{person}} \\ &= \sqrt{1.72 \cdot 10} \cdot sd_{person} \approx 1.564 \frac{kg}{d} \end{aligned} \qquad [6\text{-}17]$$

The density function of the gamma distribution is defined as (Bol 2003):

$$f(x) = \begin{cases} \dfrac{\beta^{\alpha}}{\Gamma(\alpha)} x^{\alpha-1} e^{-\beta x} & \text{for } x > 0 \\ 0 & \text{for } x \leq 0 \end{cases} \qquad [6\text{-}18]$$

where, in the depicted decision situation, $\alpha = (\mu_{customer})^2 / (sd_{customer})^2$, $\beta = \mu_{customer} / (sd_{customer})^2$, and $\Gamma(\alpha)$ is the function value of the gamma function. A customer food demand b_j of each $j \in \{1, \ldots, 21{,}630\}$ is randomly generated by using this gamma distribution.

The constructed prognostic scenarios differ in the specifications of the obtained 21,630 values of customer food demands. A set of 100 prognostic scenarios $S^{prog} = \{s_1^{prog}, \ldots, s_{100}^{prog}\}$ is constructed by randomly generating 100 food demands per customer and using the constant specifications of the planning variables. Figure 6-5 exemplarily shows the histogram of the obtained customer food demands which primarily defines s_1^{prog}.

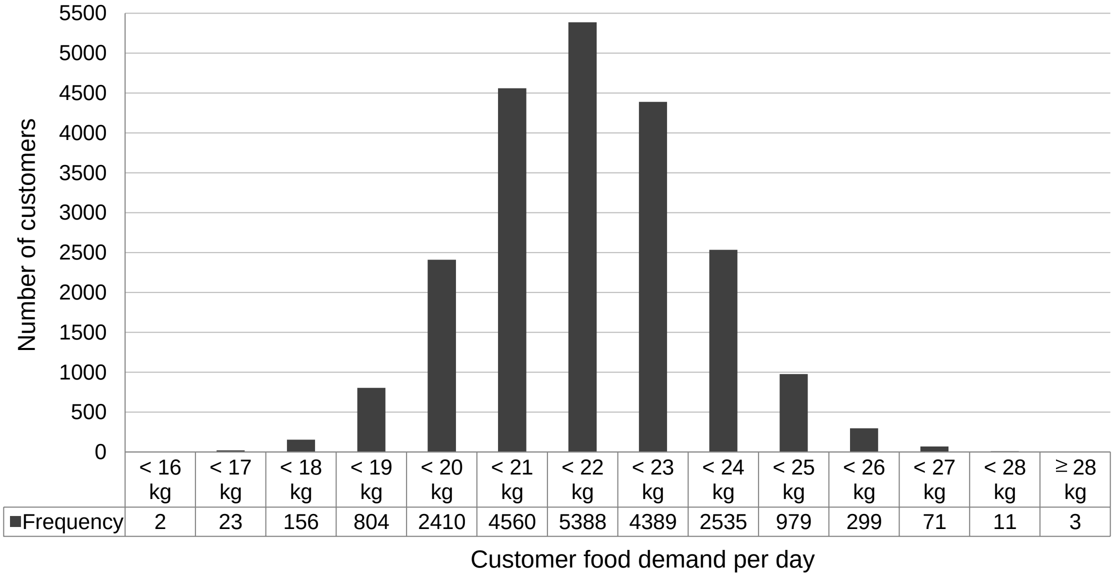


Figure 6-5: Histogram of customer food demands in a prognostic scenario

6.3.2 Alternatives

With respect to the constant specifications of the planning variables, the food retail company is able to satisfy an overall customer food demand $B^{sat} = m \cdot \gamma = 702 \cdot 266.1 \approx 187{,}000$ kg on one day. The optimization calculus prescribes opening stores and allocating available staff members to these stores that increase the chance that this food demand is met by the served customers as they require a minimum sum of purchasing distances to the serving stores (see section 6.2.1).

The optimal alternative is computed per prognostic scenario-specific optimization sub-model (*ReDRiSS part B*, *processing step 4*). An alternative is defined by the binary values of decision variable $x_i, \forall i \in I$, which indicates whether a store is opened ($x_i = 1$) or not ($x_i = 0$), and $t_i, \forall i \in I$ which is the allocated number of staff members to the opened stores. The binary values of decision variable $y_{ij}, \forall i \in I, \forall j \in J$ highlight whether b_j is served by store i ($y_{ij} = 1$) or not ($y_{ij} = 0$). As opposed to the other decision variables, $y_{ij}, \forall i \in I, \forall j \in J$ is adaptable to the scenario-specific characteristics when testing an alternative in another scenario than it has been generated for. An alternative is, thus, defined by the binary values of $x_i, \forall i \in I$ and $t_i, \forall i \in I$.

In total, 100 optimization sub-models are formulated and solved. Branch-and-bound algorithms, cutting plane algorithms, and their combination in terms of branch-and-cut algorithms can be applied to solve integer linear programming problems in general (Rader 2010). In the case study, a branch-and-cut algorithm is applied.[27]

The result of solving each of the 100 optimization sub-models is a set of 45 heterogeneous alternatives which is summarized by the set $A = \{a_1, \dots, a_{45}\}$. It becomes obvious that several alternatives have been identified as the optimal solution in just one optimization sub-model while further alternatives characterize the optimal solution in various optimization sub-models and, thus, of different prognostic scenarios. Detailed information about the alternatives in terms of their underlying opened and closed stores as well as the number of allocated staff members to the opened stores have been attached to appendix B.2.

For example, a_1 has been generated as the optimal solution in s_1^{prog}. The alternative prescribes opening 19 of the 29 stores. The histogram of the resultant purchasing distances between the served customers and the serving stores compared to the shortest purchasing distances of all 21,630 customers (see section 6.3.1.2) is shown in Figure 6-6. One can see that the purchasing distances according to a_1 are significantly below the shortest purchasing distances of all customers. This can be explained by the optimization calculus. Those stores are opened that are able to meet the food demands of the customers that can reach the store within a short purchasing distance. This is additionally motivated by the finding that about 98% of the served customer food demands are served by their nearest opened store. The food retail company then increases the chance to actually meet B^{sat}.

[27] For information regarding the functioning of branch-and-cut algorithms, see Rader (2010).

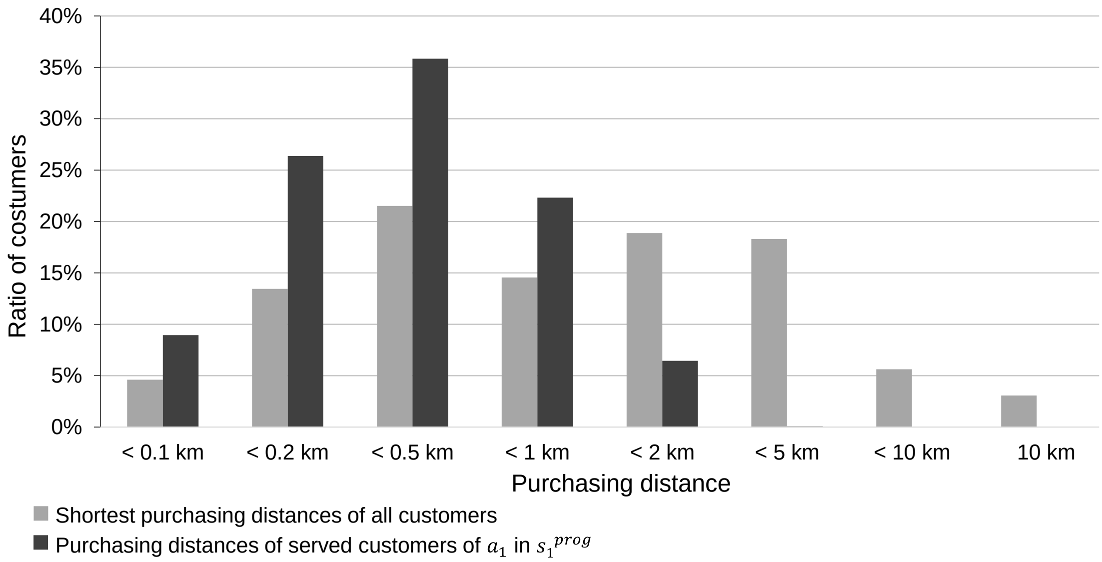


Figure 6-6: Exemplary purchasing distances

Across all alternatives of A, 19 of the 29 stores are always opened while 9 of 29 stores are always closed. Seven alternatives suggest additionally opening store 9 (district XI). This store is closed in the remaining 38 alternatives. Hence, alternatives can be classified into two groups, *group 1* (38 alternatives) and *group 2* (seven alternatives). The alternatives within each group differ in the allocation of staff members to the opened stores. Moreover, 17 of 18 consumer markets are always opened across all alternatives. Just the consumer market of store 7 which is located in the sparsely populated district XII is always closed. In turn, only the self-service warehouses of store 2 (district I) and store 11 (district VI) and, in alternatives of group 2, store 9 are opened. The remaining eight self-service warehouses are always closed. Alternatives within each group just vary slightly in the allocation of the staff members to the stores. Thus, the main question that has to be answered by the food retail company is to choose between an alternative of group 1 or group 2. Alternatives are discussed in-depth when assessing their robustness in section 6.4.

6.3.3 Hypothetical scenarios

The reason for constructing prognostic scenarios is to explore consequences of an allocation planning of available staff members under realistic and expected specifications of customer food demands. They provide the basis to generate a breadth of alternatives which the food retail company can select from. The objective of hypothetical scenarios is to explore the performance of these alternatives when the flu pandemic causes extreme developments of customer food demands that are actually not expected but that are, however, plausible to characterize the decision environment. As computational effort is sufficient and with respect to the ReDRiSS process, the special feature arises in the case study that all generated alternatives of A and prognostic scenarios of S^{prog} are respected when constructing hypothetical scenarios (see section 4.2.2). Therefore, stress test 1 (*ReDRiSS part C*, *processing step 5*) is omitted (all alternatives of A are seen as "promising" and all prognostic scenarios of S^{prog} as "significant"). The following paragraphs describe the process and results of the construction of hypothetical scenarios (*ReDRiSS part B*, *processing step 6*).

In the case study, hypothetical scenarios are constructed by simulating *generic dynamic developments* of customer food demands (see section 4.3.5). Thus, the constructed set of hypothetical scenarios is the same for each $a_b \in A$. Their construction is based on a re-specification process[28] to develop modified specifications of $b_j, \forall j \in J$. The re-specification process prescribes varying the input data of the gamma distribution (see section 6.3.1.3) in terms of simulating (i) increased fluctuations of customer food demands and (ii) decreased and increased average food demands of a customer per day. Based on (i) and (ii), each 100 hypothetical scenarios are constructed. The overall set of hypothetical scenarios is $S^{hyp} = \left\{S_{(i)}^{hyp}, S_{(ii)}^{hyp}\right\} = \left\{s_1^{hyp}, \dots, s_{200}^{hyp}\right\}$.

The subset $S_{(i)}^{hyp} = \left\{s_1^{hyp}, \dots, s_{100}^{hyp}\right\}$ explores increased fluctuations of customer food demands which can be directly or indirectly caused by the flu pandemic. In the first sense, it might be possible that an amplification of the flu pandemic triggers an increased number of customers that stay at home for several days. They use their private stocks of

[28] The development of this re-specification is actually the task of ReDRiSS part A, processing step 2. For the sake of clarity, the re-specification process is presented in this section.

foodstuff during this time. In turn, customers that have already overcome their diseases might make bulk purchases to substitute their already used stocks of foodstuff. Moreover, increased fluctuations of customer food demands can be indirectly caused when customers respond to developments such as closed stores or longer queues at the checkout (purchasing) area within the stores in terms of reducing their bulk purchases. The possibility of decreased fluctuations in customer food demands is not assumed in the case study. This would imply a more homogenous and uniform behavior of the customers.

To translate the increased fluctuations into the specifications of $b_j, \forall j \in J$, the coefficient of variation c_v of the gamma distribution (see [6-18], section 6.3.1.3) is modified. In fact, c_v is defined as (Kohn & Öztürk 2013):

$$c_v = \frac{sd_{customer}}{\mu_{customer}} \qquad [6\text{-}19]$$

The coefficient of variation (regarding the customer food demands) is $c_v = 7.23\%$ in any prognostic scenario. To construct $S_{(i)}^{hyp}$, c_v is increased by 100% (factor 2), 200% (3), 300% (4), 400% (5), and 900% (10). Each 20 hypothetical scenarios are constructed per modification factor. Table 6-4 provides an overview of the characteristic values of the gamma distribution as well as the resultant minimum and maximum customer food demand [kg] per modification factor.

Table 6-4: Characteristic values of hypothetical scenarios (i)

	$\left\{S_{1-20}^{hyp}\right\}$	$\left\{S_{21-40}^{hyp}\right\}$	$\left\{S_{41-60}^{hyp}\right\}$	$\left\{S_{61-80}^{hyp}\right\}$	$\left\{S_{81-100}^{hyp}\right\}$
Factor	2	3	4	5	10
c_v [%]	14.47	21.7	28.93	36.17	72.34
$\mu_{customer}$ [kg]	21.62	21.62	21.62	21.62	21.62
$sd_{customer}$ [kg]	3.13	4.69	6.26	7.82	15.63
Minimum demand [kg]	8.7	6.3	4	2.1	0.1
Maximum demand [kg]	39.3	49.2	61.6	81.5	170.9

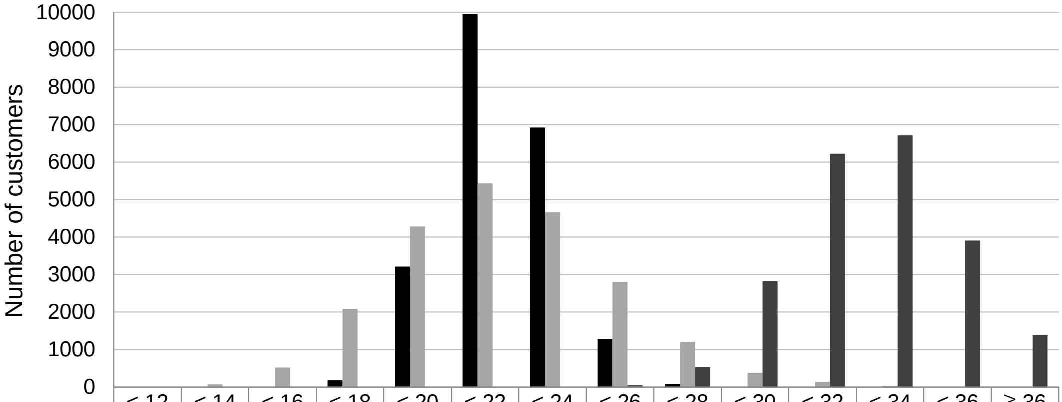
The subset $S_{(ii)}^{hyp} = \{s_{101}^{hyp}, \dots, s_{200}^{hyp}\}$ explores decreased and increased average food demands of customers per day. An increase can be motivated by the possibility of “panic purchases” of customers when an amplification of the flu pandemic occurs. In turn, customer food demands might decrease when the flu pandemic triggers more people to stay at home sick as they are not able to make their purchases for several days.

To simulate such developments, the expected customer food demand $\mu_{customer} = 21.62$ kg/d, which has been assumed within the prognostic scenarios, is modified. In fact, each 20 hypothetical scenarios are constructed by defining a decrease of $\mu_{customer}$ by 50% (factor 0.5) and an increase of $\mu_{customer}$ by 50% (1.5), 100% (2), 200% (3), and 400% (5). Table 6-5 provides an overview of the characteristic values of the gamma distribution as well as the resultant minimum and maximum demand [kg] per modification factor.

Table 6-5: Characteristic values of hypothetical scenarios (ii)

	$\{s_{101-120}^{hyp}\}$	$\{s_{121-140}^{hyp}\}$	$\{s_{141-160}^{hyp}\}$	$\{s_{161-180}^{hyp}\}$	$\{s_{181-200}^{hyp}\}$
Factor	0.5	1.5	2	3	5
$\mu_{customer}$ [kg]	10.81	32.43	43.24	64.68	108.1
$sd_{customer}$ [kg]	0.78	2.34	3.13	4.69	7.82
c_v [%]	7.23	7.23	7.23	7.23	7.23
Minimum demand [kg]	7.5	22.1	29.9	45.7	72.6
Maximum demand [kg]	14.9	43.8	60.9	92.5	147.3

Figure 6-7 exemplarily shows the histograms of the customer food demands of $s_1^{hyp} \in S_{(i)}^{hyp}$ and $s_{121}^{hyp} \in S_{(ii)}^{hyp}$ in comparison to $s_1^{prog} \in S^{prog}$ (see Figure 6-5, section 6.3.1.3).



	< 12 kg	< 14 kg	< 16 kg	< 18 kg	< 20 kg	< 22 kg	< 24 kg	< 26 kg	< 28 kg	< 30 kg	< 32 kg	< 34 kg	< 36 kg	≥ 36 kg
$s_1{}^{prog}$	0	0	2	179	3214	9948	6924	1278	82	3	0	0	0	0
$s_1{}^{hyp}$	2	73	521	2084	4287	5434	4661	2810	1205	377	138	34	2	2
$s_{121}{}^{hyp}$	0	0	0	0	0	0	0	46	533	2821	6227	6715	3909	1379

Customer food demand per day

Figure 6-7: Histograms of customer food demands

6.4 Results

ReDRiSS is applied to develop a robust decision recommendation for the food retail company in terms of a robust allocation of staff members to the stores that withstands fluctuating demands. Therefore, the alternatives are tested across the prognostic and hypothetical scenarios and the risk preferences are adjusted by the food retail company to assess the obtained results. The following sections outline the results of the case study.

6.4.1 Robustness measurement

With respect to section 6.3.2, the generated set of alternatives A can be split into group 1 and group 2. Both groups are characterized by the following equal allocations of staff members which can, thus, be described as *totally robust*:

- 26 staff members (minimum number of staff members) are allocated to consumer markets at the stores 6, 13, 19, 20, 22, 23, and 26
- 55 staff members (minimum number of staff members) are allocated to the self-service warehouse at store 11

- 42 staff members (maximum number of staff members) are allocated to the consumer markets at the stores 8 and 29
- No staff member is allocated to the consumer market at store 7 which is closed
- No staff member is allocated to the self-service warehouses at the stores 3, 4, 10, 12, 16, 21, 27, and 28 which are closed

Hence, the alternatives of group 1 and group 2 differ in the allocation of staff members to the stores 1, 2, 5, 14, 15, 17, 18, 24, and 25 and in the allocation of staff members to the self-service warehouse at store 9 which is closed in group 1 and opened in group 2 (by the minimum number of 55 staff members). Figure 6-8 visualizes the findings regarding totally robust and variable allocations of staff members.

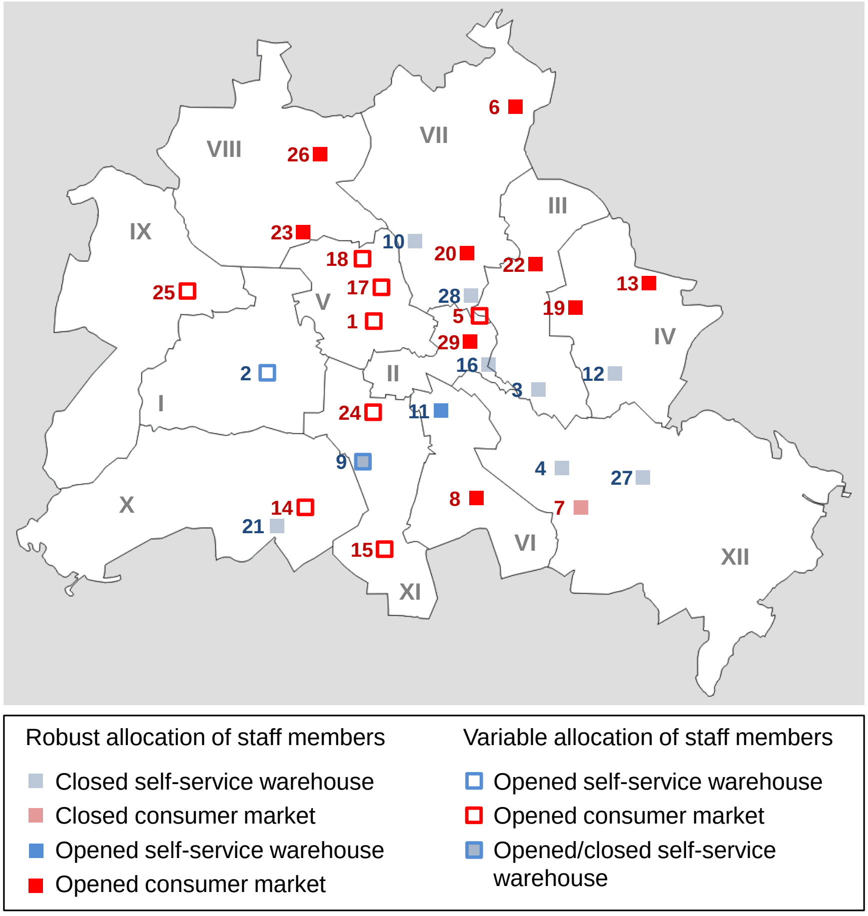


Figure 6-8: Robust and variable allocation of staff members

The findings can be explained as follows. Consumer markets are characterized by a smaller capacity (of staff members) than self-service warehouses. Opening consumer markets increases the chance of better geographically covering the customer food demands. When more customer food demands are served that are located closely distanced to the opened stores, the chance increases of turning over B^{sat} and, thus, of maximizing revenue and profit (see section 6.2.1). Due to its larger capacity and, therefore, the high possible throughput of foodstuff to be achieved in a self-service warehouse, opening such a store is just valuable if it is located in a district that is characterized by a high density of population and/or a lack of available consumer markets (e.g. store 2 and 11).

All stores within district XII in the south-eastern part of Berlin are closed (stores 4, 7, and 27). This can be directly explained by the density of population of the district that is 1,481 residents/km^2 which is significantly below the average density of population of Berlin of 3,891 residents/km^2. The high number of opened stores in the central part of Berlin can be explained in the same way. Various stores are opened within district V (9,032 residents/km^2), district II (13,554 dents/km^2), and district VI (7,249 residents/km^2). For example, the consumer market at store 29 (district II) is opened in any alternative with the maximum number of 42 staff members. The self-service warehouse at store 2 is opened because of the above average density of population of district I (5,043 residents/km^2) and the fact that the food retail company doesn't possess any further store in the vicinity. Furthermore, all consumer markets of the north-eastern part of Berlin are opened by the minimum number of 26 staff members. Those districts are characterized by an average density of population and the objective is to achieve a good geographical coverage of customer food demands within this part of Berlin.

Hence, robustness measurement of alternatives (*ReDRiSS part C*) must respond to the following questions:

1. Should the self-service warehouse at store 9 be opened (group 2) or closed (group 1)?

2. What is the most robust allocation of staff members to the stores 1, 2, 5, (9), 14, 15, 17, 18, 24, and 25?

To answer to these questions, each alternative $a_b \in A$ is tested in each prognostic scenario $s_l^{prog} \in S^{prog}$ and in each hypothetical scenario $s_k^{hyp} \in S^{hyp}$ (*ReDRiSS part C, processing step 7*). As the underlying optimization model refers to a single-objective minimization problem, the *normalized regre*t of a_b in a scenario $s \in S^{prog}, S^{hyp}$ is calculated by (when using a linear value function):

$$r(a_b, s) = \frac{z(a_b, s) - z^{min}(A, s)}{z^{max}(A, s) - z^{min}(A, s)} \qquad [6\text{-}20]$$

where $z(a_b, s)$ is the objective function value when a_b is tested in the s-specific optimization sub-model, and $z^{min}(A, s)$ and $z^{max}(A, s)$ are the minimal (best) and maximal (worst) objective function values that can be achieved by any other alternative of A in this sub-model. The result is a $45 \times (100 + 200)$ matrix of normalized regret values.

Based on this matrix, the *expected normalized regret* of a_b per scenario category S^{prog} and S^{hyp} is determined:

$$RE(a_b, S^{prog}) = \frac{1}{100} \sum_{l=1}^{100} r(\, a_b, s_l^{prog}) \qquad [6\text{-}21]$$

$$RE(a_b, S^{hyp}) = \frac{1}{200} \sum_{k=1}^{200} r(\, a_b, s_k^{hyp}) \qquad [6\text{-}22]$$

The *maximal aggregated regret* of a_b per scenario category is:

$$RM(a_b, S^{prog}) = \max_{l=1,\dots,100} \left(r\left(a_b, s_l^{prog}\right)\right) \qquad [6\text{-}23]$$

$$RM(a_b, S^{hyp}) = \max_{k=1,\dots,200} \left(r\left(a_b, s_k^{hyp}\right)\right) \qquad [6\text{-}24]$$

The obtained matrix of expected and maximal normalized regret values has been attached to appendix B.3. This matrix provides the basis for measuring the robustness of alternatives in a risk preference dependent manner by integrating the *inter-* and *intra-scenario degrees of pessimism* of the decision-makers (*ReDRiSS part D*, *processing step 8*). According to preference-related information provided by the food retail company, the following degrees of pessimism are assumed:

- Inter-scenario degree of pessimism: $we^{prog} = 0.3, we^{hyp} = 0.7$
- Intra-scenario degree of pessimism: $\lambda^{prog} = 0.7, \lambda^{hyp} = 0.3$

The reason for selecting these values is that alternatives of set A, that have been generated based on prognostic scenario-specific optimization sub-models, are very stable. In fact, group 1 and group 2 just differ in one additionally opened store and the differences of the alternatives of each group are slight. Thus, the food retail company aims at primarily measuring robustness of alternatives based on the hypothetical scenarios to explore their robustness to large-scale shifts within the customer food demand. This is reflected by the inter-scenario degree of pessimism of $we^{prog} = 0.3$ and $we^{hyp} = 0.7$. Moreover, the food retail company aims at measuring robustness of alternatives within prognostic scenarios by rather using the expected normalized regret ($\lambda^{prog} = 0.7$) and within hypothetical scenarios based on the maximal normalized regret ($\lambda^{hyp} = 0.3$). Hence, the decision-makers operate rather *pessimistically* in their principle risk aversion. The *robustness value* $RV(a_b)$ is calculated by:

$$RV(a_b) = 0.3 \cdot \left(0.7 \cdot RE(a_b, S^{prog}) + 0.3 \cdot RM(a_b, S^{prog})\right) + 0.7 \cdot \left(0.3 \cdot RE(a_b, S^{hyp}) + 0.7 \cdot RM(a_b, S^{hyp})\right) \quad [6\text{-}25]$$

Table 6-6 shows the five best ranked alternatives of the obtained robustness ranking. The robustness values of all alternatives have been attached to appendix B.3. It becomes obvious that differences in the robustness values of alternatives are small, particularly between alternatives of the same group. This is because they just differ in the allocation of several staff members. However, differences between group 1 and group 2 are significant: the three best ranked alternatives refer to group 2 and, thus, suggest opening the self-service warehouse at store 9. This is confirmed by exploring the average robustness value of all alternatives of group 1 (0.659) and group 2 (0.607). As alternatives of group 2 prescribe allocating the minimum number of 55 staff members within the self-service warehouse at store 9, this number must be reduced in its further opened stores. This causes a decrease in the achievable throughputs of these stores. The most significant decrease of allocated staff members (compared to alternatives of group 1) refers to the self-service warehouse at store 2 (decrease of up to 12 staff members) and to the consumer market at store 24 (decrease of up to 14 staff members). While store 2 is located within a district that is characterized by a medium density of population (district I: 5,043 residents/km^2), store 24 is, as store 9, located within district XI.

Table 6-6: Robustness ranking (case study 2)

Number	Alternative (group)	Allocation of staff members	Robustness value
1	a_4 (group 2)	1(store)-38(staff); 2-78; 5-26; 6-26; 8-42; 9-55; 11-55; 13-26; 14-26; 15-27; 17-34; 18-35; 19-26; 20-26; 22-26; 23-26; 24-26; 25-36; 26-26; 29-42	0.558
2	a_{31} (group 2)	1-37; 2-78; 5-26; 6-26; 8-42; 9-55; 11-55; 13-26; 14-26; 15-28; 17-34; 18-35; 19-26; 20-26; 22-26; 23-26; 24-26; 25-36; 26-26; 29-42	0.569
3	a_{12} (group 2)	1-37; 2-79; 5-26; 6-26; 8-42; 9-55; 11-55; 13-26; 14-26; 15-27; 17-33; 18-35; 19-26; 20-26; 22-26; 23-26; 24-26; 25-36; 26-26; 29-42	0.572
4	a_{20} (group 1)	1-42; 2-90; 5-31; 6-26; 8-42; 11-55; 13-26; 14-27; 15-32; 17-39; 18-40; 19-26; 20-26; 22-26; 23-26; 24-39; 25-41; 26-26; 29-42	0.577
5	a_{33} (group 1)	1-42; 2-89; 5-32; 6-26; 8-42; 11-55; 13-26; 14-27; 15-32; 17-39; 18-40; 19-26; 20-26; 22-26; 23-26; 24-40; 25-40; 26-26; 29-42	0.581

Hence, ReDRiSS recommends implementing an alternative of group 2 (question 1, see above) and, thus, also opening store 9. Although, according to the alternatives of group 2, the exact allocation of staff members to the stores just varies slightly, a decision must be finally made. Therefore, ReDRiSS suggests the allocation as specified by a_4 as it achieves the best robustness value (question 2, see above).

6.4.2 Sensitivity analyses

ReDRiSS prescribes the conduction of sensitivity analyses to explore the stability of the robust decision recommendation a_4 when preference-related information of the decision-makers changes (*ReDRiSS part D*, *processing step 9*). Sensitivity analyses concentrate on varying adjustments of the inter- and intra-scenario degrees of pessimism. The following investigates sensitivities in the robustness values of the ten most robust alternatives within the initial robustness ranking. Data of the sensitivity analyses have been attached to appendix B.4.

To explore the effects of a changing inter-scenario degree of pessimism, a robustness value per alternative is calculated based on the discrete value pairs $(we^{prog}, we^{hyp}), we^{prog} = 0.1 \cdot n, we^{hyp} = 1 - we^{prog}, n = 1, \dots, 10$. The intra-scenario degree of pessimism is assumed to be the same as used to develop the initial robustness ranking $(\lambda^{prog} = 0.7, \lambda^{hyp} = 0.3)$. As the expected and maximal normalized regret per alternative doesn't depend on (we^{prog}, we^{hyp}), obtained robustness values in the range of values $we^{prog} \in [0,1], we^{hyp} = 1 - we^{prog}$ are located on a linear straight line. The results of the sensitivity analysis are shown in Figure 6-9. For the sake of clarity, just the robustness values of the two most robust alternatives per group, according to the initial robustness ranking, are visualized (group 1: a_{20}, a_{33}; group 2: a_4, a_{31}).

Results confirm the stability of alternatives of group 2 to be more robust than alternatives of group 1 (see blue lines in Figure 6-9). In fact, a_4 is always the most robust alternative when $we^{hyp} \leq 0.9$. Just in the case that robustness is exclusively measured based on hypothetical scenarios ($we^{hyp} = 1$), an alternative of group 1, a_{20}, achieves a better robustness value. Nevertheless, differences between a_4 and a_{20} are slight in this case which is reflected by a delta of their robustness values of 0.0018.

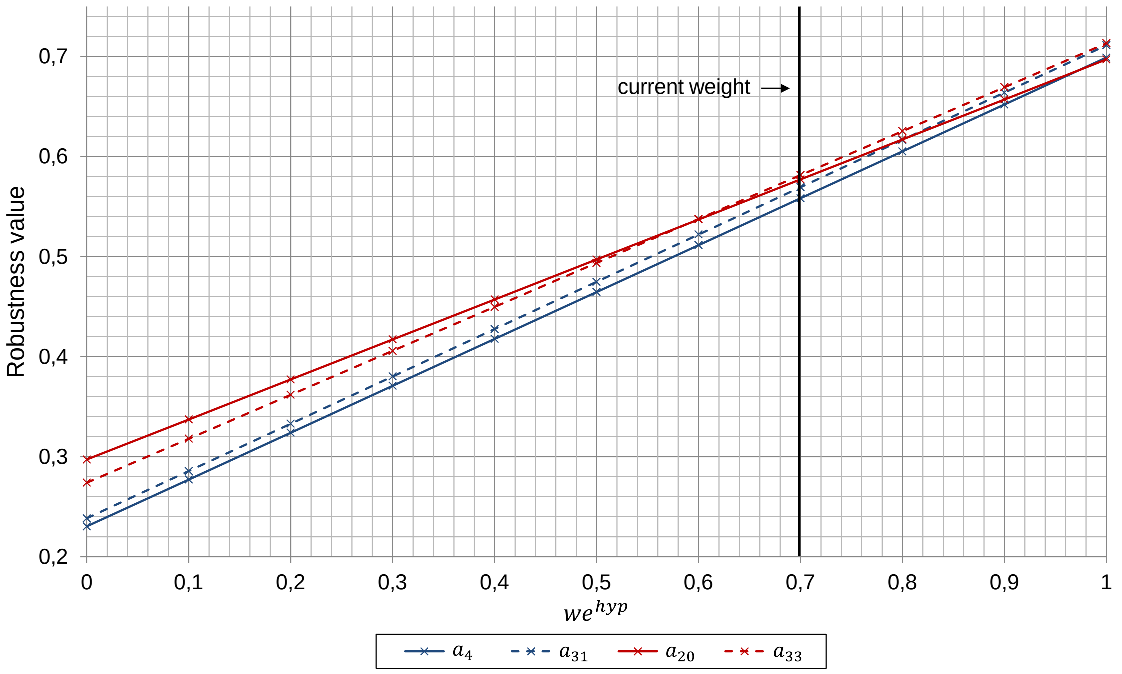


Figure 6-9: Sensitivity of the inter-scenario degree of pessimism (case study 2)

The sensitivity analysis of the intra-scenario degree of pessimism requires calculating a robustness value per alternative based on the discrete value pair $(\lambda^{prog}, \lambda^{hyp}), \lambda^{prog} = 0.1 \cdot n, \lambda^{hyp} = 0.1 \cdot m, n = 1, \dots, 10, m = 1, \dots, 10$. It is assumed that the inter-scenario degree of pessimism is the same as used to develop the initial robustness ranking ($we^{prog} = 0.3, we^{hyp} = 0.7$). As the expected and maximal normalized regret per alternative does not depend on $(\lambda^{prog}, \lambda^{hyp})$, obtained robustness values in the range of values $\lambda^{prog} \in [0,1], \lambda^{hyp} \in [0,1]$ are located on a linear plane surface.

The results of the sensitivity analysis are shown in Figure 6-10. For the sake of clarity, just the surfaces of alternatives achieving a best robustness value in any value pair $(\lambda^{prog}, \lambda^{hyp})$ are colored. This second sensitivity analysis confirms the findings of the first sensitivity analysis. The initial decision recommendation a_4 is the most robust alternative when $\lambda^{hyp} > 0.1$ (for any given value of λ^{prog}). When $\lambda^{hyp} \leq 0.1$ and, thus, robustness is rather measured based on the maximal regret which is achieved by an alternative in the hypothetical scenarios, alternatives of group 1 (a_{20}, a_{29}) are the most robust. Nevertheless, differences in the robustness value of alternatives of group 1 and group 2 are slight.

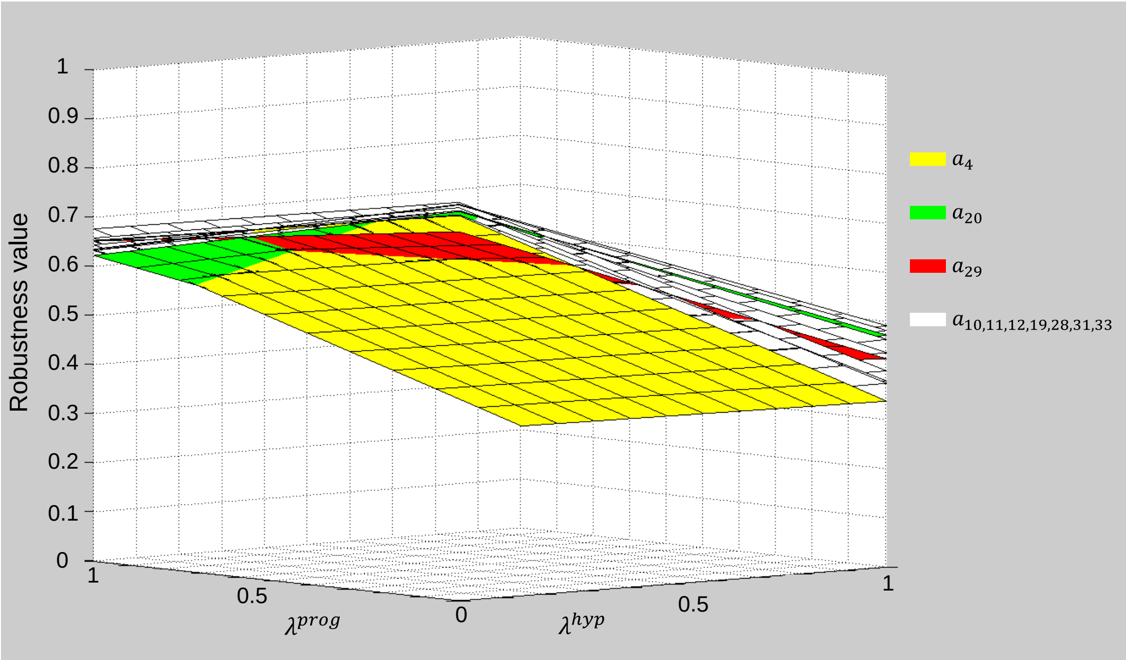


Figure 6-10: Sensitivity of the intra-scenario degree of pessimism (case study 2)

6.4.3 Interpretation of results

Both sensitivity analyses indicate that the robustness of the alternatives of group 1 improves, compared to the alternatives of group 2, when decision-makers operate rather *pessimistically* in their principle risk aversion. To understand this effect, implications of the set S^{hyp} and its two subsets $S^{hyp}_{(i)}$ and $S^{hyp}_{(ii)}$ are analyzed in the following.

The subset $S^{hyp}_{(i)}$ specifies increased fluctuations in customer food demands. Alternatives of group 2 suggest opening an additional self-service warehouse (store 9) located in district XI. This district is characterized by a medium density of population. Because of the increased fluctuations, it might be possible that the customer food demand within the catchment area of store 9 decreases. In such a case, it is the disadvantage of the medium density of population in the district that many customers must be served to meet the achieved throughput of foodstuff in store 9. As an effect, the sum of purchasing distances between the served customers and serving store 9 increases. In turn, the alternatives of group 1 suggest closing store 9. Instead, they prescribe increasing the achievable throughput of foodstuff within the stores in the districts that are characterized by high densities of population (e.g. district II and V). This is done by allocating more staff members to these stores. Although customer food demands might also decrease within the catchment areas of these stores, the high number of customers within these districts (as the number of customers in a district depends on the density of population, see section 6.3.1.2) limits an increase in the sum of purchasing distance between the served customers and the serving stores.

Subset $S_{(ii)}^{hyp}$ specifies changes in the average customer food demands in comparison to the one that has been assumed within the prognostic scenarios ($\mu = 21.62$ kg). Most of the hypothetical scenarios in this subset describe an increase in this average customer food demand. With respect to such developments of the customer food demands, the alternatives of group 2 perform more robustly. This is because the high-capacity (regarding the number of staff members) self-service warehouse at store 9 is now able to turn over its large throughput of foodstuff to just a few customers. As a result, the sum of purchasing distances between the served customers and serving store 9 decreases.

These findings can be verified by the average robustness values of alternatives of group 1 and group 2 when just hypothetical scenarios are used for robustness measurement ($we^{hyp} = 1$). When measuring robustness of alternatives exclusively when they are applied to $S_{(i)}^{hyp}$, just one alternative of group 2 is ranked within the ten most robust alternatives (a_4, ranked 3rd). The average robustness values of alternatives of group 1 and group 2 are 0.738 and 0.753. When just measuring robustness based on $S_{(ii)}^{hyp}$, six alternatives of group 2 are ranked within the ten most robust alternatives. The best alternative of group 1 is a_{23} which is ranked 6th; the average robustness values of alternatives of group 1 and group 2 are 0.782 and 0.714.

As the final result of the senility analyses and the interpretation of their findings, the robustness of a_4 (group 2) is confirmed which is, thus, provided as the decision recommendation for the food retail company.

6.5 Summary and discussion

In this chapter, ReDRiSS has been used as a measure of BCM of a food retail company that is located in Berlin, Germany. Section 6.2 outlined the BCM lifecycle which refers to a framework that operationalizes the establishment of BCM within an organization. This lifecycle prescribes developing a BCM strategy and a BCP in order to protect the critical business processes of the organization from the negative consequences of disruptive events. In the case study, the food retail company has developed a BCM strategy that suggests preparing for the risk of a disease-caused staff absence. Therefore, ReDRiSS has been implemented to support the food retail company in reactively developing a BCP that assists SCCM in the, in this regard, occurring logistical decision problem of robustly allocating available (healthy) staff members to its stores. Such a robust allocation of staff members must thereby withstand shifts in the customer food demands caused by the disease. In section 6.3, the application of ReDRiSS has been illustrated for a decision situation where the middle-eastern part of Europe, including Berlin, is hit by a pandemic. This pandemic impacts the food retail company with a 60% staff absence. The results of the application have been presented in section 6.4. Therefore, the process of measuring robustness of alternatives has been outlined and the generated robust decision recommendation has been verified via sensitivity analyses.

The application of ReDRiSS reveals two groups of alternatives (group 1 and group 2) where each alternative specifies the optimal solution of at least one prognostic scenario-specific optimization sub-model. Alternatives of each group equate in the prescribed opened and closed stores but slightly differ in the actual number of allocated staff members to the opened stores. The robustness measurement indicates that the alternatives of group 2 perform more robustly than the alternatives of group 1. In fact, they lead to more stable results when they are applied to all prognostic and hypothetical scenarios (and when robustness measurement follows the adjusted risk preferences of the food retail company). Thus, the alternatives of group 2 are characterized by the pronounced ability to deal with the constructed states of the customer food demands.

Whether an actually implemented alternative (as a decision) is, however, successful or not can just be assessed in retrospect. Nevertheless, the application of ReDRiSS ensures that decision-makers obtain the information that prognostic scenarios exist where the optimal alternatives differ across two groups. It is, thus, at least beneficial for the decision-makers to think about the existence of alternatives that suggest opening or closing store 9 (group 2, group 1). In summary, ReDRiSS allows decision-makers to analytically generate and evaluate alternatives that might handle varying patterns of customer food demands. Its application increases both transparency within the decision-making process and knowledge about advantages and drawbacks of alternatives.

ReDRiSS has been developed to support reactive SCCM in the post-disaster period. Nevertheless, a preventive application of ReDRiSS is possible in the depicted case study. This is because just one environmental variable is considered (customer food demands) and no exogenous information arises ad-hoc that allows the deterministic specification of (parts) of this variable. Therefore, the preventive application of the underlying specification and re-specification processes steering the constructing of prognostic and hypothetical scenarios is possible. The only variable that depends on exogenous information arising ad-hoc is the planning variable m which specifies the available number of staff members. To preventively apply ReDRiSS in the depicted decision situation, varying severity levels of staff absence - which are reflected by the specifications of m - must be simulated. In this way, the food retail company receives a BCP for each considered severity level of staff absence. The preventive application of ReDRiSS is additionally required to steadily validate the system as it is prescribed by the final professional practice of the BCM lifecycle (professional practice 6: validation). This is firstly important to ensure that responsible persons of reactive SCCM obtain a certain routine in applying ReDRiSS. Secondly, the validation might reveal drawbacks of the system that must be adjusted and advancements to be implemented (e.g. modifications of the optimization model). General requirements that must be fulfilled to preventively use ReDRiSS are discussed in chapter 7.

It has been assumed that the food retail company owns planning information about its customers' locations. As this information is not communicated by the food retail company considered for the purpose of this case study, a procedure has been developed that allows the realistic estimation of customer location data. Actions of companies that can be observed at their stores, however, corroborate the belief that customer location data is principly available. In fact, customer surveys, queries of the zip code of the customers over the counter, or customer loyalty schemes where the customers must provide their addresses to participate are systematic approaches of companies to collect customer data. They, thus, receive an in-depth picture of their catchment area.

The developed optimization model prescribes minimizing the aggregated purchasing distances between all serving (opened) stores and the served customers. Then, the chance increases that the possible revenue and, as the costs are neglected, the profit that is achievable by the available number of staff members (by their achieved throughputs in all opened stores) is actually met by the customers. Hence, the optimization model follows a calculus that is people-oriented. This can be motivated by the so-called "availability competition" of companies. Besides its objective of maximizing profit, the food retail company takes over the responsibility to be available for its customers in times of crises and to support them in their (personal) critical situations. Such goodwill of the food retail company in times of crises might increase customer loyalty under normal conditions. This might even acquire new customer potentials in the long term.

Various extensions of the case study are possible. The food retail company considered owns stores in any district of Berlin. However, the results (alternatives) show that all stores of district XII, which is characterized by a low density of population, are closed (store 4, 7, and 27). Although the objective of profit maximization is processed in a people-oriented manner (by minimizing aggregated purchasing distances), the focus is not on a comprehensive supply of foodstuff. To strengthen the objective of protecting public safety by applying ReDRiSS where a comprehensive supply of foodstuff is strived for, further constraints must be added. For example, a modification of the optimization model might be in this regard to prescribe that at least one store is opened per district or to restrict the maximally allowed purchasing distance between any customer and the opened stores. A further future research direction is to additionally respect local vulnerabilities of inhabitants of the districts by analyzing the customer structure of each district in-depth (e.g. their demographic distributions). Therefore, the set of hypothetical scenarios should be extended to explore local effects of the flu pandemic on the customer food demands.

7 Conclusions and outlook

The focus of this research contribution has been on post-disaster DSSs that aid decision-makers of reactive SCCM in managing disaster-caused P-SC disturbances. Therefore, ReDRiSS has been developed to reactively solve logistical decision problems that might arise and which either adapt a disrupted P-SC or compensate a destructed P-SC (as the two severity levels of a P-SC disturbance). To ensure that ReDRiSS can be applied in the post-disaster phase, efforts of preventive SCRM are required in the pre-disaster phase. Rather than predicting disasters to proactively reduce disaster risks, its objective is thereby to implement and customize ReDRiSS. This can be understood as an innovative measure of disaster risk reduction. In fact, the threat of mismanaging the consequences of a disaster in its aftermath is mitigated as a tool is available that aids decision-makers of reactive SCCM in solving a logistical decision problem analytically.

The following sections conclude the findings of this research. Therefore, the remainder of this chapter is organized into three sections. Section 7.1 provides a critical appraisal to evaluate the achievement of the research objectives which have been presented in section 3.4. In section 7.2, the implementation and application of ReDRiSS is discussed from a superior perspective. Finally, possible fields of future research are outlined in section 7.3.

7.1 Critical appraisal

Research objective RO1 prescribed to develop a DSS that takes the analytical advantage of OR/MS models by using them within an applicable decision support tool.

ReDRiSS includes an analytical methodology that combines a two-stage scenario technique, an optimization model, and a decision-analytic evaluation procedure (using MAVT and the decision rule of Hodge-

Lehmann) for robustness measurement. The task of the optimization model is to solve an addressed logistical decision problem. Scenario-specific optimization sub-models are formulated where each sub-model specifies one state of the disaster-affected decision environment which is represented by the optimization model's parameters. Rather than applying the optimization model stochastically or following the rationale of robust optimization, each optimization sub-model is solved deterministically. Thus, a breadth of alternatives is generated that can be further analyzed. Each generated alternative has been thereby proven as advantageous in at least one of the constructed scenarios. The procedure of evaluating the alternatives derives from the Hodge-Lehmann decision rule. To provide the required data base therefore, each alternative is stress tested in each constructed scenario by using the respective optimization sub-models. The result is one outcome per alternative and scenario (which is represented by the indicator of regret). This outcome reflects the appropriacy of the alternative to be used as the decision in the scenario. The outcomes are evaluated by taking into account the personal degree of pessimism of the decision-makers (inter- and intra- scenario degrees of pessimism). Thereby, the opportunity is provided for the decision-makers, according to the basic idea of the Hodge-Lehmann decision rule, to either perform neutrally or pessimistically in their principle risk aversion (which is generically assumed because decision-makers operate at the interface of DOM and SCM).

The analytical methodology of ReDRiSS combines methods of OR/MS that refer to mathematical programming, decision theory, and scenario techniques to handle non-quantifiable uncertainty. Thus, ReDRiSS provides, to a certain degree, an analytical security for the decision-makers as they can make their decision based on a sound analysis. This is an important requirement when considering the major obstacles facing the management of a disaster-caused P-SC disturbance in disaster response: lacking information, dynamic developments within the decision environment, time pressure, and cognitive overload that cause biases to occur. Analytical security is additionally important from the legal perspective. As the persons responsible, decision-makers might be personally liable for a finally made decision ex post and be probably forced to justify this decision. In this regard, transparency of the identification process of an implemented decision increases when an analytically accurate methodology has been used.

The objective of a DSS in general is never the replacement of the decision-makers who are still the persons responsible that must make and implement a decision (Er 1988). It is ensured within the analytical methodology of ReDRiSS that the decision-makers are recurrently involved in the decision-making process. In fact, they obtain the opportunity to directly steer adjustment screws which influence the development of the decision recommendation. Such adjustment screws mainly refer to the integration of their preferences concerning objectives when developing the optimization model and solving the scenario-specific sub-models, their participation when setting up the specification processes (of environmental variables) steering scenario construction, and the integration of their degree of pessimism when measuring the robustness of alternatives. In this way, ReDRiSS guarantees that the decision recommendation achieves a high analytical accuracy without excluding the decision-makers from its development process. This, in turn, strengthens the applicability of ReDRiSS as both the transparency of its functioning increases and trust of the decision-makers can be built into the analytical methodology.

The quality of a decision that has been recommended by a DSS should be higher than without. Nevertheless, the quality of a made decision can just be assessed in retrospect. This is especially true in the context of disaster management where the sum of all disaster-caused consequences characterizing the decision environment do not typically become obvious before the situation has recovered. ReDRiSS has been prototypically implemented and applied within two case studies to validate its applicability. Although these case studies have illustrated the functioning of the analytical methodology and plausible results have been obtained, further validations are essentially required. This is mainly important to reveal and eradicate drawbacks of the analytical methodology. Further validations refer to both additional case studies and practical field tests. Thereby, experts and potential end users should participate. Case studies should re-simulate real world decision situations ex post to compare the decision made (and its consequences) and the decision that would have been recommended by ReDRiSS.

Research objective RO2 prescribed the development of a reactive DSS that aids decision-makers in the disaster response phase by providing a robust decision recommendation.

It is the requirement of decision-making in general to implement a decision that leads to an appropriate result under varying circumstances facing the decision environment. Thus, robustness must be the crucial feature of decision-making. Following the assumed conditions of a disaster-affected decision environment, it must therefore be the particular ability of ReDRiSS to recommend a robust decision. Robustness measurement within ReDRiSS is based on the idea of stress testing each generated alternative within each constructed scenario. Thereby, the outcome of an alternative in a scenario refers to the indicator of regret. The regret constitutes the difference between the objective function value(s) of the tested alternative in a scenario-specific optimization sub-model and the best objective function value(s) that can be achieved in this sub-model by any other of the generated alternatives. Hence, an alternative that is provided as the robust decision recommendation by ReDRiSS is characterized by the ability to lead to more stable outcomes across all scenarios compared to all further alternatives. In this regard, robustness measurement also respects the steered degree of pessimism of the decision-makers within their principle risk aversion (inter-and intra-scenario degree of pessimism).

The degree of robustness of an alternative measured within ReDRiSS explicitly reflects its ability to achieve a better outcome than the further generated alternatives. Thus, robustness measurement does not allow any statement concerning the achieved “absolute” robustness of an alternative. It explicitly highlights the “relative” robustness of the alternatives. Furthermore, robustness measurement just focusses on the constructed sets of scenarios. It is, however, not ensured that these sets include the state of the disaster-affected decision environment that meets its real conditions. The analytical methodology exclusively guarantees that the scenarios are constructed by a sound procedure to identify states that might be relevant or critical for decision-making (two-stage scenario technique). Hence, it can be neither excluded by ReDRiSS that the robust decision recommendation actually hedges against states of the decision environment that do not characterize the real state nor that further alternatives exist that would have been more appropriate to handle the decision situation in retrospect.

Preventive SCRM must implement ReDRiSS to prepare its application by reactive SCCM in disaster response (this reference case of using ReDRiSS is discussed in-depth in section 7.2). The preventive implementation ensures that basic components of ReDRiSS are set up such as the optimization model, the solution algorithm to solve this model, and specification processes to construct scenarios. Although this ensures that the available time in disaster response can be, thus, exclusively used to apply ReDRiSS, time pressure remains a crucial factor within this application. In fact, exogenous information arising in disaster response and that provides insights about the conditions of the decision environment might be, if it is available, vague or cryptic in its format. Therefore, it might be necessary to translate this information into an appropriate format to be useable by the specification processes steering scenario constructions. This, however, might be highly time-consuming. Furthermore, the research contribution has assumed that the reliability of all arising information is guaranteed. This is a strong assumption in a real world application and requires that upstream processes of information gathering are functional (e.g. ICT systems). Finally, computational effort is also required to solve the scenario-specific optimization sub-models and to test the generated alternatives. Although ReDRiSS reduces computational effort by filtering promising alternatives and significant scenarios to relieve at least the time-consuming construction of hypothetical scenarios, computational effort is still a crucial factor when applying ReDRiSS.

Research objective RO3 prescribed the development of an innovative scenario-based approach that allows the processing of uncertainty and complexity in a disaster-caused decision situation.

ReDRiSS includes a two-stage scenario technique. Prognostic scenarios are constructed in the first stage. They are targeted at overcoming uncertainty in terms of ignorance caused by lacking information about the state of the disaster-affected decision environment. Their constructions require activating the preventively developed specification processes of the environmental variables which refer to those parameters of the optimization model that are prone to be affected by the disaster. Prognostic scenarios aim at describing probable and expected states of the decision environment. They are integrated into the analytical methodology of ReDRiSS as they provide the basis for formulating optimization sub-models in order to generate alternatives. The second stage of the two-stage scenario technique refers to the construction of hypothetical scenarios. Their objective is to explore relevant effects of complexity facing the disaster-affected environment. In fact, dynamic developments that are caused by critical events are simulated by using the preventively developed re-specification processes of the environmental variables. Hypothetical scenarios describe critical and unexpected states of the decision environment and are exclusively needed within the analytical methodology to stress test alternatives.

The construction of hypothetical scenarios assumes that a critical event causes a dynamic development which is simulated by re-specifying one or more environmental variables. ReDRiSS provides the opportunity to simulate either alternative-specific, scenario-specific, or generic dynamic developments, and combinations of these possibilities. To simulate an alternative-specific dynamic development, the re-specification of an affected environmental variable respects the effects of a hypothetically implemented alternative within the decision environment. A scenario-specific dynamic development depends on the specification of an environmental variable as it has been assumed within a prognostic scenario (significant scenario). When simulating a generic dynamic development, the re-specification of an environmental variable is directly defined without respecting its specification in a prognostic scenario or the characteristics of a generated alternative. The construction of hypothetical scenarios in case study 1 referred to a combination of alternative- and scenario-specific dynamic developments to simulate earthquake aftershocks. In case study 2, generic dynamic developments have been simulated by modifying customer food demands in Berlin from scratch.

The objective of the two-stage scenario technique is to systematically scan the scenario space to construct relevant scenarios. Relevance refers to the ability of the scenarios to increase the knowledge about the decision environment. This relevance is, however, exclusively verified by the expertise of end users or external experts. In fact, the relevance of the constructed prognostic and hypothetical scenarios depends on the appropriacy of the specification- and re-specification processes which are developed in contribution of end users and external experts.

The construction of hypothetical scenarios provides the opportunity to construct a customized set of hypothetical scenarios per generated alternative. Each alternative is stress tested in its customized set (each alternative is still tested in any prognostic scenario). Hence, regret data as the result of the stress test to be used by robustness measurement have been generated based on different sets of hypothetical scenarios in this case. Comparability is guaranteed as the customized sets of hypothetical scenarios have been constructed based on the same re-specification processes. However, in-depth analyses might be valuable to exclude inaccurate results of robustness measurement in this regard.

The two-stage scenario technique and, in particular, its second stage provides a novel approach to systematically explore the effects of complexity facing the decision environment. This ability of ReDRiSS just refers to the simulation of dynamic developments that are caused by critical events and that are associated with the main disaster (secondary disasters, socioeconomic changes). Thus, further dynamic developments as well as the great majority of the further properties that might characterize a complex system (see chapter 3) are not addressed. Nevertheless, the aforementioned specifications of dynamic developments in particular have been emphasized as the main source of complexity restricting disaster management.

Robustness measurement respects the degree of pessimism of the decision-makers. A distinction is made between the inter- and intra-scenario degrees of pessimism. The first determines to what degree robustness is measured based on prognostic scenarios and on hypothetical scenarios. Pessimistic decision-makers rather respect hypothetical scenarios for robustness measurement. The latter defines whether each obtained set of regret data (across all prognostic scenarios and hypothetical scenarios) should be evaluated based on the expected regret (neutral decision-makers) or on the worst regret (pessimistic decision-makers) of this set. ReDRiSS assumes that the end users have the skills to select plausible values of the two degrees of pessimism. For example, values that have been used within the case studies reflect rather pessimistic decision-makers. Nevertheless, so far ReDRiSS does not exclude the possibility of selecting implausible values. Such implausibility might be caused by an extreme mixture of the values selected for the inter- and intra-scenario degrees of pessimism describing both pessimistic and neutral decision-makers at once. Hence, extensions of the analytical methodology are required such as assuming plausible value combinations from which the end users can choose.

Research objective RO4 prescribed the development of a DSS that is generic in nature, is able to adapt to varying logistical decision problems, and supports either internal or external decision-makers.

Two severity levels of a disaster-caused P-SC disturbance have been distinguished: disruptions and destructions. ReDRiSS has not been developed to provide a highly specific application that supports decision-makers in solving one pre-defined logistical decision problem. It rather focusses on the similarities in the challenges that confront the decision-makers when solving any logistical decision problem. These challenges in particular refer to the properties of the disaster-affected decision environment to be faced by uncertainty and complexity. Whether a disaster has caused a destruction of a P-SC or whether the consequences on the P-SC have been less severe in terms of a disruption does not influence the disaster-caused consequences within the decision environment. Hence, reactive SCCM and, in this regard, both internal and external decision-makers in principle operate under the same environmental conditions. Most research that focuses at the interface of DOM and SCM can be found in the field of humanitarian logistics and, thus, addresses external decision-makers. However, the similarities of disaster-caused consequences and the primarily focus of ReDRiSS to analytically consider these consequences allows it to be used to aid internal decision-makers. Thus, this research contributes in bridging the gap between SCM, DOM, and BCM.

Relevant elements of the decision environment whose states depend on the disaster-caused consequences refer to the environmental variables of the optimization model. Their specifications are, thus, prone to uncertainty and complexity. In turn, it has been assumed that the specifications of planning variables are deterministically available and constant across all constructed scenarios. However, real world decision situations in the past have shown that discrepancies in the specifications of planning variables in particular have led to inappropriate decisions or issues in the decision-making process (e.g. Haiti earthquake 2010). This is because varying norms, goals, and value judgements of different stakeholders must be typically respected when planning which is especially the case in the field of humanitarian logistics (Eßig & Tandler 2010). ReDRiSS does not respect such problems of coordination and collaboration.

The case studies have illustrated the applicability of ReDRiSS when addressing different types of disasters (earthquakes, pandemics), logistical decision problems (facility location planning, resource allocation planning), decision-makers (association of NGOs, food retail company), and dynamic developments (secondary disasters in terms of earthquake aftershocks, socioeconomic changes in terms of fluctuating demands). Nevertheless, to mark out the system boundaries and, thus, the possible cases of application of ReDRiSS, a classification scheme of disasters and caused logistical decision problems is required. Such a classification scheme should provide information about the optimization model to solve the disaster-caused logistical decision problem, its parameters in terms of environmental and planning variables, the properties of the decision variables characterizing the alternatives (e.g. whether they possess the flexible properties to adapt to different environmental conditions by modifying their specifications), and the type of the dynamic developments to be simulated via hypothetical scenarios.

7.2 Preventive application and reactive implementation

This research contribution has presented the reference case of using ReDRiSS where its implementation is the task of preventive SCRM in the pre-disaster phase and its application supports reactive SCCM in the post-disaster phase. The need for preventively setting up the basic components of ReDRiSS (e.g. optimization model, specification processes) is motivated by the lack of time in disaster response. Therefore, it must be the task of preventive SCRM to identify both disaster risks concerning disturbances of P-SCs and logistical decision problems that might arise and require analytical support.

For example, the NGO association which is the (external) decision-maker in case study 1 identified, based on its experiences of the Haiti earthquake in 2010, the threat of mismanaging the identification of locations for quick rotation warehouses. These warehouses are part of a humanitarian health care SC and are needed to store medicine or medical equipment. Thus, the NGO association decided to invest in an implementation of ReDRiSS that provides analytical support in the post-disaster phase to solve the facility location problem. In this way, the NGO association is prepared for another earthquake disaster affecting Haiti in future.

The example reveals that it is, following the reference case, possible that the NGO association invests in an implementation of ReDRiSS which will, however, possibly never be applied. This would be the case if Haiti is not hit by an earthquake in the future. With respect to this controversy, the question arises whether the possibility exists to implement ReDRiSS not before a disaster is concretely impending or when a disaster has already occurred in the post-disaster phase. Such a reactive implementation of ReDRiSS would be the task of SCCM. In turn, the contrary question is whether it could provide an added value for the decision-makers to apply ReDRiSS ex ante. Such an application would be the task of preventive SCRM to proactively develop robust decision recommendations to be prepared for a disaster occurring in the future.

Referring to the first question, a *reactive implementation* of ReDRiSS is mainly restricted by the time exposure of its underlying processing steps. Those must be conducted in the timeframe that has actually been reserved for the application-related processing steps which are time-consuming on their own (see section 7.1). The additional implementation-related processing steps refer to the formulation of the optimization model according to the objectives of the decision-makers and the implementation of an appropriate solution algorithm. Moreover, specification and re-specification processes must be developed to prepare scenario construction. Initial information might be needed to set up these processes (e.g. the road network) and information sources to activate the processes must be acquired. Those tasks altogether are likely to exceed the time which is available to make a decision. For example, this time has been defined in literature as typically 72 hours after the occurrence of a disaster in the field of humanitarian logistics (Balcik & Beamon 2008).

Nevertheless, there are decision situations imaginable where a reactive implementation of ReDRiSS might be valuable. Taking again the decision situation of case study 1 as an example, it is expected that the NGO association does not exclusively intervene to establish humanitarian health care SCs in Haiti. Rather, its objective is the establishment of such SCs wherever a disaster causes destructions of the preexisting health care P-SCs. Following the example, the facility location problem might, thus, also become relevant in further earthquake-affected countries. Hence, it might be useful to transfer the components of an already implemented "version" of ReDRiSS (optimization model, solution algorithm, specification and re-specification processes) to another setting. Such a transfer might be possible to start in the post-disaster phase. This is because the implementation time can then be significantly decreased and the most time-consuming tasks refer to the gathering of initial information and the acquiring of information sources.

According to the second question, a *preventive application* of ReDRiSS in the pre-disaster phase provides the possibility of proactively developing robust decision recommendations (for a logistical decision problem) by simulating different specifications of the occurring disaster in advance. As it has been highlighted in this research contribution, however, there are a practically unlimited number of possible consequences of a disaster. With respect to the decision situation assumed in case study 1, for instance, the epicenter of an earthquake might arise in any arrondissement with varying intensities. Thus, to preventively develop a robust decision recommendation for any possible specification of the earthquake (epicenter location and intensity), the analytical methodology of ReDRiSS must be repeated a large number of times. Nevertheless, even when this has been done it might be possible that an actually occurring disaster provides exogenous information that indicates disaster-caused consequences which have not been respected preventively.

As well, there are decision situations imaginable where a preventive application of ReDRiSS could still provide an added value for the decision-makers. Taking the decision situation of case study 2, the decision environment is characterized by just one environmental variable that is prone to uncertainty (customer food demands). As it is expected that it might rarely be the case that parts of this environmental variable can be specified deterministically due to exogenous information arising in the post-disaster phase, a preventive application is useful. The food retail company then simulates different severity levels of the staff absence (planning variable) to obtain, for each severity level, the robust decision recommendation. In this way, the food retail company owns preventive plans assuming different escalation levels of the staff absence that can be activated in the case of necessity.

The preventive application of ReDRiSS is always useful for training reasons to ensure its appropriate application by the end users when a disaster actually occurs. In this regard, it is important that end users practice the steering of their controlled adjustment screws. Those refer to the usage of the specification and re-specification processes to construct scenarios, the provision of preferences to trade-off the objectives considered by the optimization model, the prioritization of promising alternatives and significant scenarios required for the construction of hypothetical scenarios, and the definition of values regarding the inter- and intra-scenario degrees of pessimism. Furthermore, training refers to the activation of the acquired information sources that provide the input for the scenario construction. Finally, weaknesses of the analytical methodology and of its applicability might become obvious and can be preventively eradicated.

7.3 Directions for future research

Following the reference case of using ReDRiSS as has been discussed in the previous sections, there is one essential upstream task required before ReDRiSS can be implemented by preventive SCRM. This upstream task addresses both the identification of disaster risks that might threaten the functioning of a P-SC and of logistical decision problems that must be solved to manage a caused P-SC disturbance in this regard. Based on the results of this upstream task, disaster-caused logistical decision problems can be filtered whose solutions should be analytically supported by ReDRiSS.

It has been outlined in this research contribution that disaster risks in general refer to the category of low probability high impact risks. Although these risks are characterized by a particular criticality as they are likely to trigger severe consequences when they occur, risk management typically provides instruments/tools to process (recurring) high probability low impact risks (Chopra & Sodhi 2004).

It should therefore be the scope of future research to develop an innovative approach of risk management that is tailored to deal with disaster risks. With respect to the standard (cyclically-ordered) risk management approach as has been outlined in chapter 3 (Hölscher 1999; Rosenkranz & Missler-Behr 2005; Zsidisin & Ritchie 2008; DHS 2010; ICDRM/GWU 2010) the identification of disaster risks should be triggered by the critical consequences within a P-SC that impact its functioning. Rather than predicting possible disaster events from scratch and subsequently analyzing their consequences, these critical consequences as well as the logistical decision problems that must be solved for their eradication should be analyzed first. By backtracking from these critical consequences, relevant disaster risks that might cause the critical consequence can then be identified to concretize the decision environment to be handled by ReDRiSS.

The research contribution has been part of the research program "civil security research" and the announcement of "securing food SCs" which was funded by the BMBF.[29] From a superior perspective, the well-functioning of SCs in general is essential to ensure the provision of supplies for the population in a community or society. This is in particular crucial when SCs steer the provision of public safety critical supplies (e.g. water, foodstuff). These SCs have been denoted P-SCs in this research contribution and they are part of the CI network in a commu-

[29] The research project SEAK has been funded within this announcement (see chapter 6).

nity or society. ReDRiSS has been developed to aid decision-makers when the sound provision of public safety critical supplies is threatened as a disaster disturbs the smooth functioning of a P-SC. In the case of a disaster-caused P-SC disturbance, the dilemma might be that, due to the disaster, public safety critical supplies are in short supply while the demands of the population increase.

It should be the scope of future research to analyze possibilities of adapting ReDRiSS to support decision-makers of SCs of further branches in the management of disaster-caused disturbances. As opposed to P-SC disturbances, internal decision-makers bear responsibility in this regard. This is because these SCs steer the provision of supplies that might not necessarily impact public safety. External decision-makers might therefore rather not intervene. The dilemma that has been mentioned above in terms of a simultaneous increase in demand and decrease in the offer of supplies in the aftermath of a disaster does not typically arise in such a case. Despite these differences, decision-making in reactive SCCM is basically challenged to handle the same conditions within the disaster-affected decision environment. It has been one objective of this research contribution to strengthen the relevance of BCM to deal with P-SC disturbances. The next step of research must be the adaptation of ReDRiSS to be used not just within the BCM of P-SCs but also within the BCM of SCs of other branches.

Beside these two major directions for future research, further, mostly technical aspects of ReDRiSS should be addressed as it has already been outlined in the critical appraisal in section 7.1. Those aspects mainly refer to validations of ReDRiSS via case studies and field tests and to the reduction of computational effort when applying its analytical methodology in disaster response. Further extensions refer to the consideration of uncertain planning variables in order to simulate issues of coordination and collaboration of the involved stakeholders and to the in-depth analysis of the degree of pessimism of the decision-makers.

ReDRiSS has been prototypically implemented within two case studies. These prototypes have been implemented within the programming platforms MATLAB[30] (case study 1 and 2) and Python[31] (case study 2). Particularly modules of robustness measurement and sensitivity analyses have been thereby standardized (by MATLAB) to be used within both cases. The reason therefore is that robustness measurement is the same in its process in each application. In contrast, further parts of ReDRiSS (two-stage scenario technique, stress test) depend on the implemented optimization model and the steered specification and re-specification processes and, thus, vary across the applications. Hence, future research should intensify efforts in standardizing these parts to provide the basis for an efficient customization/implementation of ReDRiSS across various decision situations.

[30] For further information, see: http://de.mathworks.com/products/matlab/
[31] For further information, see: https://www.python.org/

8 Summary

In recent years research efforts in the field of disaster management have been intensified. This is motivated by a significant increase in both natural and man-made disasters in the past decades (Cookson 2011). Apart from direct impacts (e.g. deaths, injuries), a disaster might affect the functioning of supply chains (SCs). Such a disaster-caused SC disturbance might trigger an unavailability of supplies to be provided for the population. This is crucial, in particular when supplies are products or services that must meet the basic needs of the population (e.g. foodstuff, water, health care). The terms public safety critical supplies and public safety critical supply chains (P-SCs) are used in this research contribution to express the relevance of such supplies and their underlying SCs for public safety. P-SCs are part of the critical infrastructure (CI) network in a community or society. Basically, it must be the scope of the two subdivisions of supply chain management (SCM), preventive supply chain risk management (SCRM) and reactive supply chain crisis management (SCCM), to protect the functioning of P-SCs in times of disasters.

Preventive SCRM is targeted at proactively handling disaster risks in the pre-disaster phase. Two stereotypical risk categories can be distinguished: high probability low impact risks and low probability high impact risks. Disaster risks refer to the latter category (Chopra & Sodhi 2004; Kleindorfer & Saad 2005; Oke & Gopalakrishnan 2009). As there is a practically unlimited number of possible specifications of disasters (e.g. types, sources, consequences), they have been described as almost unpredictable and uncontrollable (Charles et al. 2010; Johnson 2013). Instruments/tools of standard risk management are appropriate to handle high probability low impact risks as they are the ones that typically recur (Chopra & Sodhi 2004). Their ability to manage disaster risks (e.g. by statistical analysis) is, however, futile if they continue to predict something that cannot be predicted (Taleb et al. 2009).

The estimation of the consequences of a disaster by reactive SCCM in the immediate post-disaster phase (disaster response) is challenged by the characteristics of the disaster-affected environment. Information about the sources of an occurring disaster and its resulting consequences is typically sparse or lacking. Even the information available might be heterogeneous in terms of format, quality, and uncertainty (Wybo & Lonka 2003; Comes et al. 2011). Moreover, the state of a disaster-affected environment is described as evolving continuously. Decision-makers are under pressure to make their decision quickly. This may cause cognitive overload to occur and biases to be reinforced (Maule et al. 2000; Ariely & Zakay 2001; Comes et al. 2012). Despite these challenges, decision-makers are forced to operate quickly in disaster response to maintain or recover the availability of public safety critical supplies.

There are different possible severity levels of a disaster-caused P-SC disturbance. This research contribution focusses on an either disrupted or destructed P-SC. The relevant criterion of this distinction is the time required to restore the functioning of the disturbed P-SC. In the case of a disruption, the provision of public safety critical supplies by the affected P-SC itself can be typically recovered or maintained within the timeframe of disaster response. Nevertheless, efforts of reactive SCCM are needed to strengthen its functioning (e.g. by conducting business continuity plans). The management of a P-SC disruption is usually the task of internal decision-makers. They are located in the companies of the disturbed P-SC. In the case of destruction, the provision of public safety critical supplies by the affected P-SC itself cannot be typically recovered within the short timeframe of disaster response. Thus, the need arises for reactive SCCM to compensate the destruction by establishing logistical replacement structures from scratch. These structures must temporarily take over the provision of public safety critical supplies (e.g. humanitarian relief SCs). External decision-makers bear responsibility in this regard. They are located outside the disturbed P-SC and refer to companies of further P-SCs, companies of SCs of other branches, or (independent) public authorities. External decision-makers must intervene when a P-SC disturbance cannot be handled by the internal decision-makers.

The reactive management of both disaster-caused P-SC disruptions and destructions in disaster response goes together with the need for solving logistical decision problems (e.g. planning of resource allocation, transportation, or facility location). To aid both internal and external decision-makers of reactive SCCM, this research contribution suggests strengthening the focus on post-disaster DSSs. Basically, DSSs are software-based tools that assist the decision-making process (Pearson & Shim 1995; Mattiussi 2012). The establishment of a DSS requires efforts of preventive SCRM. Rather than predicting disasters to proactively reduce disaster risks, the task of preventive SCRM must be the implementation/customization of the DSS to a specific decision situation in order to estimate and manage consequences of the disaster ex post. This can be understood as an innovative measure of disaster risk reduction. In fact, the availability of a DSS mitigates the threat of mismanagement in disaster response.

This research contribution develops a DSS that is denoted ReDRiSS (Reactive Disaster and supply chain Risk decision Support System). The crucial requirement of ReDRiSS is to analytically process a logistical decision problem while taking into account the characteristics of a disaster-affected decision environment (which comprises all elements of the environment whose state might influence decision-making). A lack of information about the disaster and its consequences triggers, from a decision theoretic perspective, a state of uncertainty in terms of ignorance. Moreover, the state of the decision environment might change dynamically over time. Such dynamic developments have been described as a property of a complex system in literature (Snowden & Boone 2007; Flach 2012).

ReDRiSS includes an analytical methodology that combines methods of operations research (OR) and management sciences (MS) referring to mathematical programming, decision theory, and scenario techniques. This analytical methodology is integrated into a framework that comprises four parts (A to D) and nine processing steps (1 to 9). Part A describes the process of implementing and customizing ReDRiSS to be prepared for a specific post-disaster decision situation. The conduction of part A is, thus, the task of preventive SCRM in the pre-disaster phase. Part B (two-stage scenario technique), part C (stress test), and part D (robustness measurement) comprise processing steps that must be applied by reactive SCCM in disaster response.

The main objective of ReDRiSS is to provide a robust decision recommendation for the decision-makers. Thereby, robustness refers to the feature of the decision recommendation to perform stably under different states of the uncertain and complex decision environment. These states are specified by scenarios. Scenario techniques have been proven as appropriate to handle decision situations under ignorance. ReDRiSS includes a two-stage scenario technique to additionally construct scenarios that explore dynamic developments in the decision environment (in terms of complexity). Widespread possibilities of such dynamic developments exist which can never be completely explored by scenario construction. Therefore, the focus of ReDRiSS is on the simulation of dynamic developments that are directly related to the main disaster. Those have been described as most crucial in disaster management and refer to both secondary disasters in the aftermath of the main disaster (e.g. earthquake aftershocks) and socioeconomic changes (e.g. demand fluctuations due to population movements) (Prelipcean & Boscoianu 2011; Hoyos et al. 2015).

Each constructed scenario describes a state of the disaster-affected decision environment. An optimization model is formulated to solve the underlying logistical decision problem. The decision environment and, thus, the structure of scenarios are directly defined by the optimization model's parameters. Thereby, a distinction is made between parameters whose specifications can be deterministically defined by processing information that is provided by the decision-makers (planning variables) and parameters whose specifications depend on the disaster-caused consequences (environmental variables). Each scenario includes the deterministic specifications of the planning variables and one developed specification per environmental variable. Hence, the exploration of effects of uncertainty and complexity by ReDRiSS is always associated with the specifications of the environmental variables.

The two-stage scenario technique prescribes the construction of two scenario categories. Prognostic scenarios (stage 1) are constructed to process ignorance caused by sparse and lacking information in disaster response. They are targeted at highlighting probable and expected states of the decision environment. Based on the constructed prognostic scenarios, a set of optimization sub-models is formulated and each of them is solved deterministically by applying an appropriate exact algorithm or heuristic. Thus, a breadth of alternatives is generated that can be further analyzed. Each generated alternative has been thereby proven as advantageous to solve the logistical decision problem in at least one of the prognostic scenarios.

Hypothetical scenarios (stage 2) are constructed to explore the effects of complexity facing the decision environment. In fact, a hypothetical scenario simulates a dynamic development within the decision environment that is caused by a critical event. ReDRiSS provides the opportunity to simulate either alternative-specific, scenario-specific, or generic dynamic developments, and combinations of these possibilities. An alternative-specific dynamic development assumes that one of the generated alternatives is hypothetically implemented to the decision environment; a scenario-specific dynamic development simulates changes within a prognostic scenario; a generic dynamic development provides a new state of the decision environment from scratch. In this way, ReDRiSS can be used to capture dynamic developments by a customized set of hypothetical scenarios per alternative. Each set, thus, includes alternative specific critical and unexpected states of the decision environment.

Each alternative is stress tested in each prognostic and (customized) hypothetical scenario by using the respective optimization sub-models.

The result of the stress test is one outcome per alternative and scenario. This outcome refers to the indicator of regret. Basically, the regret constitutes in ReDRiSS the difference between the objective function value(s) of the tested alternative in a scenario-specific optimization sub-model and the best objective function value(s) that can be achieved in this sub-model by any other of the generated alternatives. The regret is used to determine the stability of an alternative across the scenarios compared to all further alternatives. The obtained data set of regret values provides the basis for robustness measurement.

The procedure of measuring robustness of alternatives via the obtained regret data derives from the Hodge-Lehmann decision rule. According to the basic idea of this decision rule, decision-makers either perform neutrally or pessimistically in their principle risk aversion which is generically assumed because decision-makers operate at the interface of disaster operations management (DOM) and SCM. Robustness measurement integrates the inter- and intra-scenario degrees of pessimism whose values are directly steered by the decision-makers. The first determines to what degree robustness is measured based on prognostic scenarios (neutral decision-makers) and on hypothetical scenarios (pessimistic decision-makers). The latter defines whether each obtained set of regret data (across all prognostic scenarios and hypothetical scenarios) should be evaluated based on the expected regret (neutral decision-makers) or on the worst regret (pessimistic decision-makers) of this set. Transparency and trust of the decision-makers increases as they obtain the opportunity to influence the decision-making process by adjusting their degree of pessimism.

The applicability of ReDRiSS is illustrated by two case studies. Those consider different types of disasters (earthquake, pandemic), logistical decision problems (facility location planning, resource allocation planning), decision-makers (association of NGOs, food retail company), and dynamic developments in the decision environment (secondary disasters in terms of earthquake aftershocks, socioeconomic changes in terms of fluctuating demands).

Case study 1 refers to a decision situation arising in the field of humanitarian logistics where an earthquake causes a destruction of preexisting health care P-SCs in Haiti. An association of non-governmental organizations (NGOs) (external decision-maker) intervenes by establishing a humanitarian health care SC from scratch to temporarily compensate the destructed P-SCs. Within this establishment, the logistical decision problem arises of building quick rotation warehouses. These warehouses are required to store medicine or medical equipment. The scope of ReDRiSS is to support the decision-makers in identifying five robust locations of these warehouses. ReDRiSS processes ignorance in terms of an unknown intensity of the earthquake affecting the states of the road network and the distribution of health-care demands of the population. Furthermore, the decision environment is prone to secondary disasters in terms of earthquake aftershocks that might restrict the appropriacy of the identified locations. The bi-objective unconstrained facility location problem (BOUFLP) (optimization model) is adapted to the decision situation to identify the locations by trading-off the required costs to serve people (objective of efficiency) and the possible coverage of people needing health care (objective of effectiveness). In total, 256 prognostic scenarios, 31 alternatives, and 26 hypothetical scenarios per alternative (in total 806 hypothetical scenarios) are constructed and generated in the course of the ReDRiSS application. The results highlight three totally robust warehouse locations and two locations whose robustness depends on the degree of pessimism adjusted by the decision-makers.

In case study 2, ReDRiSS supports the business continuity management (BCM) of a food retail company (internal decision-makers) that owns stores (consumer markets and self-service warehouses) in Berlin, Germany. A flu pandemic that spreads in the middle-eastern part of Europe causes a large-scale staff absence within the food retail company. ReDRiSS is applied to develop a robust allocation of the available staff members to the stores for the scope of one day. As a store must employ a minimum number of staff members to be operated smoothly, several stores must be closed. The resource allocation problem is restricted by fluctuating customer food demands due to the flu pandemic. Those are hard to predict because of diseased people changing their purchasing behavior. An optimization model is developed to allocate staff members by ensuring low purchasing distances of customers. By following this optimization calculus, the chance increases that the customers make their purchases despite being diseased which, in turn, reduces the losses of profit of the food retail company. 100 prognostic scenarios and 200 hypothetical scenarios are constructed to highlight various patterns of customer food demand fluctuations. The robust decision recommendation shows that in particular the smaller consumer markets are opened by the minimum required number of staff members in districts of Berlin with a high density of population. In turn, the larger self-service warehouses are mainly closed. They are just then opened when the underlying district is characterized by a low density of stores of competing food retail companies.

The research contribution reveals two major directions of future research. Firstly, innovative approaches of risk management are required that are tailored to deal with disaster risks (low probability high impact risks). They must operationalize the preliminary step of implementing/ customizing ReDRiSS by preventive SCRM. In fact, decision situations must be identified that might arise in the course of a P-SC disturbance and that should receive analytical support by ReDRiSS. The research contribution focusses on P-SCs to provide public safety critical supplies for the population. Therefore, it should secondly be the scope of future research to analyze possibilities of adapting ReDRiSS to be used by reactive SCCM of companies of SCs of further branches. Beside these two future research directions, further validations of ReDRiSS via case studies and field tests are required and technical aspects should be improved to reduce computational effort when applying its analytical methodology within the short timeframe of disaster response.

Appendix

A. Additional data of case study 1

A.1 Country-specific information of Haiti

Table A-1: Haiti in 2012 (IHSI 2012) (1/2)

	Arrondissement	Largest city	Département	IATA code	Population 2012 (absolute)	Population 2012 (relative)
1	Jérémie	Jérémie	Grand Anse	JEE	227,333	2.18%
2	Les Cayes	Les Cayes	Sud	CYA	330,454	3.17%
3	Port-Salut	Arniquet	Sud	PST	70,471	0.68%
4	Jacmel	Jacmel	Sud-Est	JAK	323,252	3.10%
5	Port-au-Prince	Port-au-Prince	Ouest	PAP	2,633,874	25.29%
6	Gonâve	Anse-à-Galets	Ouest	LGN	83,099	0.80%
7	Lascahboas	Belladère	Centre	BEL	160,977	1.55%
8	Hinche	Hinche	Centre	HIN	252,837	2.43%
9	Saint-Raphaël	Pignon	Nord	PGN	162,104	1.56%
10	Cap Haïtien	Cap Haïtien	Nord	CAP	340,598	3.27%
11	Fort-Liberté	Fort-Liberté	Nord-Est	FLT	57,862	0.56%
12	Ouanaminthe	Ouanaminthe	Nord-Est	OAN	139,791	1.34%
13	Môle-Saint-Nicolas	Jean-Rabel	Nord-Ouest	MSN	234,368	2.25%
14	Port-de-Paix	Port-de-Paix	Nord-Ouest	PAX	321,265	3.09%
15	Gros-Morne	Gros-Morne	Artibonite	ANR	219,813	2.11%
16	Anse-d´Hainault	Dame-Marie	Grand Anse	-	94,020	0.90%
17	Chardonnières	Les Anglais	Sud	-	74,828	0.72%
18	Côteaux	Côteaux	Sud	-	55,940	0.54%
19	Corail	Pestel	Grand Anse	-	125,548	1.21%
20	Baradères	Baradères	Nippes	-	44,911	0.43%
21	Aquin	Aquin	Sud	-	207,873	2.00%

Table A-2: Haiti in 2012 (IHSI 2012) (2/2)

	Arrondissement	Largest city	Département	IATA code	Population 2012 (absolute)	Population 2012 (relative)
22	Anse-à-Veau	L'Asile	Nippes	-	146,617	1.41%
23	Miragoâne	Miragoâne	Nippes	-	135,346	1.30%
24	Bainet	Bainet	Sud-Est	-	129,588	1.24%
25	Léogâne	Léogâne	Ouest	-	486,007	4.67%
26	Belle-Anse	Belle-Anse	Sud-Est	-	150,858	1.45%
27	Croix-des-Bouquets	Croix-des-Bouquets	Ouest	-	453,111	4.35%
28	Arcahaie	Arcahaie	Ouest	-	189,479	1.82%
29	Mirebalais	Mirebalais	Centre	-	184,040	1.77%
30	Saint-Marc	Saint-Marc	Artibonite	-	422,765	4.06%
31	Dessalines	Dessalines	Artibonite	-	394,038	3.78%
32	Cerca-la-Source	Thomassique	Centre	-	114,284	1.10%
33	Gonaïves	Gonaïves	Artibonite	-	432,018	4.15%
34	Marmelade	Marmelade	Artibonite	-	179,952	1.73%
35	Saint-Louis-du-Nord	Saint-Louis-du-Nord	Nord-Ouest	-	139,869	1.34%
36	Borgne	Borgne	Nord	-	111,464	1.07%
37	Plaisance	Plaisance	Nord	-	117,983	1.13%
38	Limbé	Limbé	Nord	-	101,348	0.97%
39	Acul-du-Nord	Acul-du-Nord	Nord	-	123,253	1.18%
40	Trou-du-Nord	Trou-du-Nord	Nord-Est	-	109,745	1.05%
41	Grande-Rivière-du-Nord	Grande-Rivière-du-Nord	Nord	-	61,661	0.59%
42	Vallières	Mombin-Crochu	Nord-Est	-	68,568	0.66%
				Total	**10,413,212**	**100%**

A.2 Road and waterway distances of neighbored arrondissements

Table A-3: Road and waterway distances [km] (1/3)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	42	0	0	0	0	0	0	0	0	0	0	0
3	0	42	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	100	0	0	0	0	0	0	0	0	0
5	0	0	0	100	0	66	0	0	0	0	0	0	0	0
6	0	0	0	0	66	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	30	0	0	0	0	0
9	0	0	0	0	0	0	0	30	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	23	0	0
12	0	0	0	0	0	0	0	0	0	0	23	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0	47
14	0	0	0	0	0	0	0	0	0	0	0	0	47	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	49	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0
18	0	0	31	0	0	0	0	0	0	0	0	0	0	0
19	67	98	0	0	0	0	0	0	0	0	0	0	0	0
20	0	56	0	0	0	0	0	0	0	0	0	0	0	0
21	0	56	0	0	0	0	0	0	0	0	0	0	0	0
22	0	0	0	0	0	0	0	0	0	0	0	0	0	0
23	0	0	0	0	0	0	0	0	0	0	0	0	0	0
24	0	0	0	46	0	0	0	0	0	0	0	0	0	0
25	0	0	0	53	36	0	0	0	0	0	0	0	0	0
26	0	0	0	77	77	0	0	0	0	0	0	0	0	0
27	0	0	0	0	19	0	0	0	0	0	0	0	0	0
28	0	0	0	0	0	0	0	0	0	0	0	0	0	0
29	0	0	0	0	0	0	42	57	0	0	0	0	0	0
30	0	0	0	0	0	0	0	0	0	0	0	0	0	0
31	0	0	0	0	0	0	0	102	0	0	0	0	0	0
32	0	0	0	0	0	0	0	27	0	0	0	0	0	0
33	0	0	0	0	0	0	0	0	0	0	0	0	0	0
34	0	0	0	0	0	0	0	0	63	0	0	0	0	0
35	0	0	0	0	0	0	0	0	0	0	0	0	0	15
36	0	0	0	0	0	0	0	0	0	0	0	0	0	0
37	0	0	0	0	0	0	0	0	0	0	0	0	0	0
38	0	0	0	0	0	0	0	0	0	0	0	0	0	0
39	0	0	0	0	0	0	0	0	0	17	0	0	0	0
40	0	0	0	0	0	0	0	0	0	30	28	0	0	0
41	0	0	0	0	0	0	0	0	36	25	0	0	0	0
42	0	0	0	0	0	0	0	42	18	0	0	0	0	0

Table A-4: Road and waterway distances [km] (2/3)

	15	16	17	18	19	20	21	22	23	24	25	26	27	28
1	0	49	0	0	67	0	0	0	0	0	0	0	0	0
2	0	0	0	0	98	56	56	0	0	0	0	0	0	0
3	0	0	0	31	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	46	53	77	0	0
5	0	0	0	0	0	0	0	0	0	0	36	77	19	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	0	0	48	0	0	0	0	0	0	0	0	0	0	0
17	0	48	0	25	0	0	0	0	0	0	0	0	0	0
18	0	0	25	0	0	0	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0
20	0	0	0	0	0	0	70	46	0	0	0	0	0	0
21	0	0	0	0	0	70	0	21	47	85	0	0	0	0
22	0	0	0	0	0	46	21	0	0	0	0	0	0	0
23	0	0	0	0	0	0	47	0	0	86	61	0	0	0
24	0	0	0	0	0	0	85	0	86	0	0	0	0	0
25	0	0	0	0	0	0	0	0	61	0	0	0	0	0
26	0	0	0	0	0	0	0	0	0	0	0	0	0	0
27	0	0	0	0	0	0	0	0	0	0	0	0	0	47
28	0	0	0	0	0	0	0	0	0	0	0	0	47	0
29	0	0	0	0	0	0	0	0	0	0	0	0	43	0
30	0	0	0	0	0	0	0	0	0	0	0	0	0	54
31	0	0	0	0	0	0	0	0	0	0	0	0	0	0
32	0	0	0	0	0	0	0	0	0	0	0	0	0	0
33	31	0	0	0	0	0	0	0	0	0	0	0	0	0
34	0	0	0	0	0	0	0	0	0	0	0	0	0	0
35	0	0	0	0	0	0	0	0	0	0	0	0	0	0
36	0	0	0	0	0	0	0	0	0	0	0	0	0	0
37	52	0	0	0	0	0	0	0	0	0	0	0	0	0
38	0	0	0	0	0	0	0	0	0	0	0	0	0	0
39	0	0	0	0	0	0	0	0	0	0	0	0	0	0
40	0	0	0	0	0	0	0	0	0	0	0	0	0	0
41	0	0	0	0	0	0	0	0	0	0	0	0	0	0
42	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table A-5: Road and waterway distances [km] (3/3)

	29	30	31	32	33	34	35	36	37	38	39	40	41	42
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	42	0	0	0	0	0	0	0	0	0	0	0	0	0
8	57	0	102	27	0	0	0	0	0	0	0	0	0	42
9	0	0	0	0	0	63	0	0	0	0	0	0	36	18
10	0	0	0	0	0	0	0	0	0	0	17	30	25	0
11	0	0	0	0	0	0	0	0	0	0	0	28	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	15	0	0	0	0	0	0	0
15	0	0	0	0	31	0	0	0	52	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0
20	0	0	0	0	0	0	0	0	0	0	0	0	0	0
21	0	0	0	0	0	0	0	0	0	0	0	0	0	0
22	0	0	0	0	0	0	0	0	0	0	0	0	0	0
23	0	0	0	0	0	0	0	0	0	0	0	0	0	0
24	0	0	0	0	0	0	0	0	0	0	0	0	0	0
25	0	0	0	0	0	0	0	0	0	0	0	0	0	0
26	0	0	0	0	0	0	0	0	0	0	0	0	0	0
27	43	0	0	0	0	0	0	0	0	0	0	0	0	0
28	0	54	0	0	0	0	0	0	0	0	0	0	0	0
29	0	86	89	0	0	0	0	0	0	0	0	0	0	0
30	86	0	35	0	0	0	0	0	0	0	0	0	0	0
31	89	35	0	0	34	58	0	0	0	0	0	0	0	0
32	0	0	0	0	0	0	0	0	0	0	0	0	0	0
33	0	0	34	0	0	53	0	0	53	0	0	0	0	0
34	0	0	58	0	53	0	0	0	29	0	0	0	0	0
35	0	0	0	0	0	0	0	37	0	0	0	0	0	0
36	0	0	0	0	0	0	37	0	0	30	0	0	0	0
37	0	0	0	0	53	29	0	0	0	22	0	0	0	0
38	0	0	0	0	0	0	0	30	22	0	14	0	0	0
39	0	0	0	0	0	0	0	0	0	14	0	0	0	0
40	0	0	0	0	0	0	0	0	0	0	0	0	0	0
41	0	0	0	0	0	0	0	0	0	0	0	0	0	0
42	0	0	0	0	0	0	0	0	0	0	0	0	0	0

A.3 Linear distances of arrondissements

Table A-6: Linear distances [km] (1/3)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	0	64	61	174	189	134	244	229	224	235	265	271	166	197
2	64	0	16	129	155	117	217	211	214	236	260	261	194	216
3	61	16	0	144	170	132	232	226	229	250	274	276	204	228
4	174	129	144	0	40	76	103	115	131	171	176	170	194	192
5	189	155	170	40	0	66	65	76	92	135	137	131	173	165
6	134	117	132	76	66	0	111	97	97	123	143	145	119	123
7	244	217	232	103	65	111	0	39	63	107	91	79	183	161
8	229	211	226	115	76	97	39	0	24	70	62	55	147	124
9	224	214	229	131	92	97	63	24	0	46	48	48	127	101
10	235	236	250	171	135	123	107	70	46	0	40	55	105	69
11	265	260	274	176	137	143	91	62	48	40	0	18	144	108
12	271	261	276	170	131	145	79	55	48	55	18	0	158	124
13	166	194	204	194	173	119	183	147	127	105	144	158	0	39
14	197	216	228	192	165	123	161	124	101	69	108	124	39	0
15	190	199	212	161	132	96	129	92	70	50	88	101	58	34
16	34	82	73	203	221	167	277	262	258	267	298	305	194	227
17	40	52	40	179	201	155	261	251	250	266	293	298	204	233
18	50	31	18	160	184	143	246	238	239	258	284	287	204	231
19	37	39	45	138	155	104	212	200	198	214	241	245	160	186
20	54	34	46	121	138	91	197	187	187	206	231	234	160	183
21	87	39	54	92	116	84	179	175	179	205	226	226	177	194
22	80	40	55	96	117	78	178	172	175	199	221	222	167	185
23	112	76	91	63	81	50	142	138	143	172	190	190	158	169
24	153	106	120	25	60	74	124	133	145	183	192	187	192	195
25	158	123	138	33	32	44	95	96	107	144	154	151	161	160
26	222	178	193	50	44	108	74	101	123	168	161	151	216	206
27	200	167	182	51	13	74	53	67	85	130	128	121	175	165
28	170	146	161	60	33	38	74	67	76	113	123	121	141	135
29	214	188	204	81	42	81	30	36	56	102	97	90	162	145
30	158	151	165	100	76	37	98	73	66	87	110	114	97	93
31	182	176	190	115	83	60	87	55	43	63	85	90	98	83
32	246	225	240	121	81	113	26	21	41	83	66	54	167	142
33	176	179	193	137	109	72	113	79	61	60	92	102	70	57
34	209	207	221	144	110	93	94	56	33	30	58	68	95	68
35	206	222	234	191	161	124	153	115	92	58	97	113	51	12
36	214	225	237	180	148	119	133	95	72	36	75	90	71	34
37	203	206	220	153	120	95	108	71	48	32	67	79	81	54
38	215	220	233	165	131	109	113	75	52	22	60	74	85	52
39	222	224	238	163	128	111	107	69	45	14	51	64	94	61
40	245	241	255	163	125	124	88	53	33	24	21	33	126	92
41	230	227	241	155	118	111	89	52	28	18	36	47	112	80
42	239	228	242	139	100	111	60	26	15	48	37	35	138	110

Table A-7: Linear distances [km] (2/3)

	15	16	17	18	19	20	21	22	23	24	25	26	27	28
1	190	34	40	50	37	54	87	80	112	153	158	222	200	170
2	199	82	52	31	39	34	39	40	76	106	123	178	167	146
3	212	73	40	18	45	46	54	55	91	120	138	193	182	161
4	161	203	179	160	138	121	92	96	63	25	33	50	51	60
5	132	221	201	184	155	138	116	117	81	60	32	44	13	33
6	96	167	155	143	104	91	84	78	50	74	44	108	74	38
7	129	277	261	246	212	197	179	178	142	124	95	74	53	74
8	92	262	251	238	200	187	175	172	138	133	96	101	67	67
9	70	258	250	239	198	187	179	175	143	145	107	123	85	76
10	50	267	266	258	214	206	205	199	172	183	144	168	130	113
11	88	298	293	284	241	231	226	221	190	192	154	161	128	123
12	101	305	298	287	245	234	226	222	190	187	151	151	121	121
13	58	194	204	204	160	160	177	167	158	192	161	216	175	141
14	34	227	233	231	186	183	194	185	169	195	160	206	165	135
15	0	221	223	218	173	167	173	165	144	166	130	172	131	102
16	221	0	36	57	66	83	113	108	142	181	189	251	232	203
17	223	36	0	22	52	65	88	85	121	156	170	228	213	188
18	218	57	22	0	46	53	69	68	105	136	153	209	197	173
19	173	66	52	46	0	18	52	44	76	117	123	186	166	138
20	167	83	65	53	18	0	35	26	59	99	107	169	150	123
21	173	113	88	69	52	35	0	11	38	69	85	141	129	108
22	165	108	85	68	44	26	11	0	37	74	85	145	129	106
23	144	142	121	105	76	59	38	37	0	45	49	110	93	71
24	166	181	156	136	117	99	69	74	45	0	39	73	72	70
25	130	189	170	153	123	107	85	85	49	39	0	67	44	32
26	172	251	228	209	186	169	141	145	110	73	67	0	42	76
27	131	232	213	197	166	150	129	129	93	72	44	42	0	38
28	102	203	188	173	138	123	108	106	71	70	32	76	38	0
29	112	247	232	217	182	167	151	149	113	100	67	67	32	45
30	62	192	184	174	132	122	119	113	86	104	68	119	79	44
31	49	215	209	199	157	147	143	138	110	122	85	123	82	55
32	111	279	267	253	216	202	188	186	151	140	106	98	70	80
33	25	208	206	199	155	148	151	143	121	141	105	150	109	78
34	38	242	238	230	186	177	176	170	143	154	116	146	106	85
35	30	236	241	238	192	189	198	189	171	195	159	201	160	132
36	26	246	248	243	198	192	197	190	168	187	149	186	145	120
37	24	236	234	227	183	175	177	170	145	161	123	158	117	93
38	29	248	247	240	196	188	190	183	158	173	135	167	127	105
39	38	254	252	245	201	193	193	187	161	173	135	163	124	104
40	69	278	273	264	221	212	207	202	172	177	139	154	118	107
41	55	263	259	250	207	198	194	189	160	168	129	150	112	98
42	81	272	264	253	212	201	192	188	156	155	118	126	92	87

Table A-8: Linear distances [km] (3/3)

	29	30	31	32	33	34	35	36	37	38	39	40	41	42
1	214	158	182	246	176	209	206	214	203	215	222	245	230	239
2	188	151	176	225	179	207	222	225	206	220	224	241	227	228
3	204	165	190	240	193	221	234	237	220	233	238	255	241	242
4	81	100	115	121	137	144	191	180	153	165	163	163	155	139
5	42	76	83	81	109	110	161	148	120	131	128	125	118	100
6	81	37	60	113	72	93	124	119	95	109	111	124	111	111
7	30	98	87	26	113	94	153	133	108	113	107	88	89	60
8	36	73	55	21	79	56	115	95	71	75	69	53	52	26
9	56	66	43	41	61	33	92	72	48	52	45	33	28	15
10	102	87	63	83	60	30	58	36	32	22	14	24	18	48
11	97	110	85	66	92	58	97	75	67	60	51	21	36	37
12	90	114	90	54	102	68	113	90	79	74	64	33	47	35
13	162	97	98	167	70	95	51	71	81	85	94	126	112	138
14	145	93	83	142	57	68	12	34	54	52	61	92	80	110
15	112	62	49	111	25	38	30	26	24	29	38	69	55	81
16	247	192	215	279	208	242	236	246	236	248	254	278	263	272
17	232	184	209	267	206	238	241	248	234	247	252	273	259	264
18	217	174	199	253	199	230	238	243	227	240	245	264	250	253
19	182	132	157	216	155	186	192	198	183	196	201	221	207	212
20	167	122	147	202	148	177	189	192	175	188	193	212	198	201
21	151	119	143	188	151	176	198	197	177	190	193	207	194	192
22	149	113	138	186	143	170	189	190	170	183	187	202	189	188
23	113	86	110	151	121	143	171	168	145	158	161	172	160	156
24	100	104	122	140	141	154	195	187	161	173	173	177	168	155
25	67	68	85	106	105	116	159	149	123	135	135	139	129	118
26	67	119	123	98	150	146	201	186	158	167	163	154	150	126
27	32	79	82	70	109	106	160	145	117	127	124	118	112	92
28	45	44	55	80	78	85	132	120	93	105	104	107	98	87
29	0	71	65	40	93	81	139	121	94	102	98	88	84	61
30	71	0	25	92	38	57	91	84	59	73	75	90	76	81
31	65	25	0	75	28	34	79	66	39	51	52	65	52	58
32	40	92	75	0	99	74	133	112	89	92	84	63	66	36
33	93	38	28	99	0	35	54	48	28	41	47	72	56	75
34	81	57	34	74	35	0	60	41	15	22	19	37	22	44
35	139	91	79	133	54	60	0	23	46	42	51	81	70	100
36	121	84	66	112	48	41	23	0	28	21	29	59	48	78
37	94	59	39	89	28	15	46	28	0	14	19	47	32	58
38	102	73	51	92	41	22	42	21	14	0	10	41	29	58
39	98	75	52	84	47	19	51	29	19	10	0	32	20	50
40	88	90	65	63	72	37	81	59	47	41	32	0	16	28
41	84	76	52	66	56	22	70	48	32	29	20	16	0	31
42	61	81	58	36	75	44	100	78	58	58	50	28	31	0

A.4 Stress test 1 results

Table A-9: Promising alternatives

Promising alternative	Health care facility locations	Maximal aggregated regret across prognostic scenarios
$\tilde{a}_1 = a_{321}$	[5, 8, 9, 10, 12]	0.373
$\tilde{a}_2 = a_{307}$	[5, 8, 10, 11, 12]	0.41
$\tilde{a}_3 = a_{287}$	[5, 9, 10, 11, 12]	0.436
$\tilde{a}_4 = a_{175}$	[6, 8, 10, 12, 15]	0.458
$\tilde{a}_5 = a_{301}$	[5, 8, 10, 12, 15]	0.458
$\tilde{a}_6 = a_{302}$	[5, 8, 10, 12, 14]	0.459
$\tilde{a}_7 = a_{303}$	[5, 8, 10, 12, 13]	0.459
$\tilde{a}_8 = a_{371}$	[5, 7, 8, 10, 12]	0.459
$\tilde{a}_9 = a_{427}$	[5, 6, 8, 10, 12]	0.459
$\tilde{a}_{10} = a_{721}$	[4, 5, 8, 10, 12]	0.459
$\tilde{a}_{11} = a_{1051}$	[3, 5, 8, 10, 12]	0.459
$\tilde{a}_{12} = a_{1546}$	[2, 5, 8, 10, 12]	0.459
$\tilde{a}_{13} = a_{2261}$	[1, 5, 8, 10, 12]	0.459
$\tilde{a}_{14} = a_{176}$	[6, 8, 10, 12, 14]	0.47
$\tilde{a}_{15} = a_{637}$	[4, 6, 8, 10, 12]	0.479
$\tilde{a}_{16} = a_{155}$	[6, 9, 10, 12, 15]	0.484
$\tilde{a}_{17} = a_{281}$	[5, 9, 10, 12, 15]	0.484
$\tilde{a}_{18} = a_{156}$	[6, 9, 10, 12, 14]	0.485
$\tilde{a}_{19} = a_{157}$	[6, 9, 10, 12, 13]	0.485
$\tilde{a}_{20} = a_{282}$	[5, 9, 10, 12, 14]	0.485
$\tilde{a}_{21} = a_{283}$	[5, 9, 10, 12, 13]	0.485
$\tilde{a}_{22} = a_{356}$	[5, 7, 9, 10, 12]	0.485
$\tilde{a}_{23} = a_{412}$	[5, 6, 9, 10, 12]	0.485
$\tilde{a}_{24} = a_{706}$	[4, 5, 9, 10, 12]	0.485
$\tilde{a}_{25} = a_{1036}$	[3, 5, 9, 10, 12]	0.485
$\tilde{a}_{26} = a_{1531}$	[2, 5, 9, 10, 12]	0.485
$\tilde{a}_{27} = a_{2246}$	[1, 5, 9, 10, 12]	0.485
$\tilde{a}_{28} = a_{622}$	[4, 6, 9, 10, 12]	0.491
$\tilde{a}_{29} = a_{177}$	[6, 8, 10, 12, 13]	0.491
$\tilde{a}_{30} = a_{1447}$	[2, 6, 9, 10, 12]	0.493
$\tilde{a}_{31} = a_{511}$	[4, 8, 10, 12, 15]	0.504

Table A-10: Significant scenarios

	$s_1^{si,\tilde{a}_b}$	$s_2^{si,\tilde{a}_b}$	$s_3^{si,\tilde{a}_b}$	$s_4^{si,\tilde{a}_b}$	$s_5^{si,\tilde{a}_b}$	$s_6^{si,\tilde{a}_b}$	$s_7^{si,\tilde{a}_b}$	$s_8^{si,\tilde{a}_b}$	$s_9^{si,\tilde{a}_b}$	$s_{10}^{si,\tilde{a}_b}$	$s_{11}^{si,\tilde{a}_b}$	$s_{12}^{si,\tilde{a}_b}$	$s_{13}^{si,\tilde{a}_b}$
$\tilde{a}_1$	s_{130}^{prog}	s_{131}^{prog}	s_{250}^{prog}	s_{178}^{prog}	s_{80}^{prog}	s_{226}^{prog}	s_{177}^{prog}	s_{11}^{prog}	s_{16}^{prog}	s_{79}^{prog}	s_{248}^{prog}	s_{256}^{prog}	s_{15}^{prog}
$\tilde{a}_2$	s_{225}^{prog}	s_{130}^{prog}	s_{162}^{prog}	s_{226}^{prog}	s_{131}^{prog}	s_{178}^{prog}	s_{80}^{prog}	s_{11}^{prog}	s_{79}^{prog}	s_{250}^{prog}	s_{51}^{prog}	s_{83}^{prog}	s_{16}^{prog}
$\tilde{a}_3$	s_{225}^{prog}	s_{226}^{prog}	s_{130}^{prog}	s_{178}^{prog}	s_{162}^{prog}	s_{233}^{prog}	s_{131}^{prog}	s_{51}^{prog}	s_{250}^{prog}	s_{248}^{prog}	s_{115}^{prog}	s_{83}^{prog}	s_{56}^{prog}
$\tilde{a}_4$	s_{225}^{prog}	s_{40}^{prog}	s_{39}^{prog}	s_{208}^{prog}	s_{80}^{prog}	s_{240}^{prog}	s_{207}^{prog}	s_{177}^{prog}	s_{38}^{prog}	s_{144}^{prog}	s_{239}^{prog}	s_{206}^{prog}	s_{105}^{prog}
$\tilde{a}_5$	s_{225}^{prog}	s_{177}^{prog}	s_{105}^{prog}	s_{233}^{prog}	s_{153}^{prog}	s_{249}^{prog}	s_{226}^{prog}	s_{106}^{prog}	s_{178}^{prog}	s_{161}^{prog}	s_{250}^{prog}	s_{218}^{prog}	s_{17}^{prog}
$\tilde{a}_6$	s_{225}^{prog}	s_{105}^{prog}	s_{226}^{prog}	s_{250}^{prog}	s_{130}^{prog}	s_{233}^{prog}	s_{162}^{prog}	s_{153}^{prog}	s_{178}^{prog}	s_{177}^{prog}	s_{249}^{prog}	s_{146}^{prog}	s_{210}^{prog}
$\tilde{a}_7$	s_{225}^{prog}	s_{105}^{prog}	s_{130}^{prog}	s_{226}^{prog}	s_{162}^{prog}	s_{250}^{prog}	s_{178}^{prog}	s_{233}^{prog}	s_{153}^{prog}	s_{146}^{prog}	s_{177}^{prog}	s_{210}^{prog}	s_{249}^{prog}
$\tilde{a}_8$	s_{225}^{prog}	s_{105}^{prog}	s_{130}^{prog}	s_{162}^{prog}	s_{178}^{prog}	s_{233}^{prog}	s_{226}^{prog}	s_{153}^{prog}	s_{250}^{prog}	s_{131}^{prog}	s_{177}^{prog}	s_{146}^{prog}	s_{249}^{prog}
$\tilde{a}_9$	s_{225}^{prog}	s_{105}^{prog}	s_{130}^{prog}	s_{162}^{prog}	s_{226}^{prog}	s_{250}^{prog}	s_{178}^{prog}	s_{131}^{prog}	s_{233}^{prog}	s_{153}^{prog}	s_{80}^{prog}	s_{146}^{prog}	s_{11}^{prog}
$\tilde{a}_{10}$	s_{225}^{prog}	s_{105}^{prog}	s_{130}^{prog}	s_{162}^{prog}	s_{226}^{prog}	s_{250}^{prog}	s_{178}^{prog}	s_{131}^{prog}	s_{233}^{prog}	s_{153}^{prog}	s_{146}^{prog}	s_{11}^{prog}	s_{177}^{prog}
$\tilde{a}_{11}$	s_{225}^{prog}	s_{105}^{prog}	s_{130}^{prog}	s_{162}^{prog}	s_{226}^{prog}	s_{250}^{prog}	s_{178}^{prog}	s_{131}^{prog}	s_{233}^{prog}	s_{153}^{prog}	s_{146}^{prog}	s_{11}^{prog}	s_{177}^{prog}
$\tilde{a}_{12}$	s_{225}^{prog}	s_{105}^{prog}	s_{130}^{prog}	s_{162}^{prog}	s_{226}^{prog}	s_{250}^{prog}	s_{178}^{prog}	s_{131}^{prog}	s_{233}^{prog}	s_{153}^{prog}	s_{146}^{prog}	s_{11}^{prog}	s_{177}^{prog}
$\tilde{a}_{13}$	s_{225}^{prog}	s_{105}^{prog}	s_{130}^{prog}	s_{162}^{prog}	s_{226}^{prog}	s_{250}^{prog}	s_{178}^{prog}	s_{131}^{prog}	s_{233}^{prog}	s_{153}^{prog}	s_{146}^{prog}	s_{11}^{prog}	s_{177}^{prog}
$\tilde{a}_{14}$	s_{80}^{prog}	s_{225}^{prog}	s_{79}^{prog}	s_{152}^{prog}	s_{151}^{prog}	s_{88}^{prog}	s_{208}^{prog}	s_{40}^{prog}	s_{207}^{prog}	s_{16}^{prog}	s_{78}^{prog}	s_{150}^{prog}	s_{87}^{prog}
$\tilde{a}_{15}$	s_{80}^{prog}	s_{79}^{prog}	s_{225}^{prog}	s_{78}^{prog}	s_{88}^{prog}	s_{179}^{prog}	s_{168}^{prog}	s_{240}^{prog}	s_{167}^{prog}	s_{112}^{prog}	s_{87}^{prog}	s_{208}^{prog}	s_{96}^{prog}
$\tilde{a}_{16}$	s_{225}^{prog}	s_{240}^{prog}	s_{239}^{prog}	s_{238}^{prog}	s_{40}^{prog}	s_{237}^{prog}	s_{233}^{prog}	s_{39}^{prog}	s_{208}^{prog}	s_{48}^{prog}	s_{236}^{prog}	s_{207}^{prog}	s_{80}^{prog}
$\tilde{a}_{17}$	s_{225}^{prog}	s_{233}^{prog}	s_{226}^{prog}	s_{106}^{prog}	s_{178}^{prog}	s_{114}^{prog}	s_{250}^{prog}	s_{249}^{prog}	s_{234}^{prog}	s_{154}^{prog}	s_{33}^{prog}	s_{177}^{prog}	s_{153}^{prog}
$\tilde{a}_{18}$	s_{225}^{prog}	s_{152}^{prog}	s_{240}^{prog}	s_{151}^{prog}	s_{239}^{prog}	s_{80}^{prog}	s_{238}^{prog}	s_{208}^{prog}	s_{150}^{prog}	s_{226}^{prog}	s_{237}^{prog}	s_{88}^{prog}	s_{207}^{prog}
$\tilde{a}_{19}$	s_{225}^{prog}	s_{152}^{prog}	s_{80}^{prog}	s_{240}^{prog}	s_{151}^{prog}	s_{239}^{prog}	s_{179}^{prog}	s_{184}^{prog}	s_{88}^{prog}	s_{208}^{prog}	s_{183}^{prog}	s_{79}^{prog}	s_{238}^{prog}
$\tilde{a}_{20}$	s_{225}^{prog}	s_{226}^{prog}	s_{233}^{prog}	s_{250}^{prog}	s_{178}^{prog}	s_{234}^{prog}	s_{130}^{prog}	s_{162}^{prog}	s_{146}^{prog}	s_{114}^{prog}	s_{106}^{prog}	s_{154}^{prog}	s_{242}^{prog}
$\tilde{a}_{21}$	s_{225}^{prog}	s_{226}^{prog}	s_{233}^{prog}	s_{178}^{prog}	s_{250}^{prog}	s_{130}^{prog}	s_{234}^{prog}	s_{162}^{prog}	s_{154}^{prog}	s_{146}^{prog}	s_{114}^{prog}	s_{179}^{prog}	s_{106}^{prog}
$\tilde{a}_{22}$	s_{225}^{prog}	s_{233}^{prog}	s_{226}^{prog}	s_{178}^{prog}	s_{130}^{prog}	s_{162}^{prog}	s_{250}^{prog}	s_{154}^{prog}	s_{146}^{prog}	s_{234}^{prog}	s_{114}^{prog}	s_{131}^{prog}	s_{179}^{prog}
$\tilde{a}_{23}$	s_{225}^{prog}	s_{226}^{prog}	s_{233}^{prog}	s_{178}^{prog}	s_{130}^{prog}	s_{250}^{prog}	s_{234}^{prog}	s_{162}^{prog}	s_{154}^{prog}	s_{51}^{prog}	s_{131}^{prog}	s_{146}^{prog}	s_{248}^{prog}
$\tilde{a}_{24}$	s_{225}^{prog}	s_{226}^{prog}	s_{233}^{prog}	s_{178}^{prog}	s_{130}^{prog}	s_{250}^{prog}	s_{234}^{prog}	s_{162}^{prog}	s_{154}^{prog}	s_{51}^{prog}	s_{131}^{prog}	s_{146}^{prog}	s_{115}^{prog}
$\tilde{a}_{25}$	s_{225}^{prog}	s_{226}^{prog}	s_{233}^{prog}	s_{178}^{prog}	s_{130}^{prog}	s_{250}^{prog}	s_{234}^{prog}	s_{162}^{prog}	s_{154}^{prog}	s_{51}^{prog}	s_{131}^{prog}	s_{146}^{prog}	s_{179}^{prog}
$\tilde{a}_{26}$	s_{225}^{prog}	s_{226}^{prog}	s_{233}^{prog}	s_{178}^{prog}	s_{130}^{prog}	s_{250}^{prog}	s_{234}^{prog}	s_{162}^{prog}	s_{154}^{prog}	s_{51}^{prog}	s_{131}^{prog}	s_{146}^{prog}	s_{179}^{prog}
$\tilde{a}_{27}$	s_{225}^{prog}	s_{226}^{prog}	s_{233}^{prog}	s_{178}^{prog}	s_{130}^{prog}	s_{250}^{prog}	s_{234}^{prog}	s_{162}^{prog}	s_{154}^{prog}	s_{51}^{prog}	s_{131}^{prog}	s_{146}^{prog}	s_{179}^{prog}
$\tilde{a}_{28}$	s_{240}^{prog}	s_{225}^{prog}	s_{239}^{prog}	s_{238}^{prog}	s_{179}^{prog}	s_{237}^{prog}	s_{112}^{prog}	s_{80}^{prog}	s_{236}^{prog}	s_{168}^{prog}	s_{111}^{prog}	s_{167}^{prog}	s_{235}^{prog}
$\tilde{a}_{29}$	s_{80}^{prog}	s_{79}^{prog}	s_{216}^{prog}	s_{152}^{prog}	s_{88}^{prog}	s_{208}^{prog}	s_{78}^{prog}	s_{151}^{prog}	s_{215}^{prog}	s_{225}^{prog}	s_{207}^{prog}	s_{184}^{prog}	s_{40}^{prog}
$\tilde{a}_{30}$	s_{80}^{prog}	s_{237}^{prog}	s_{240}^{prog}	s_{79}^{prog}	s_{236}^{prog}	s_{238}^{prog}	s_{225}^{prog}	s_{239}^{prog}	s_{88}^{prog}	s_{179}^{prog}	s_{208}^{prog}	s_{207}^{prog}	s_{78}^{prog}
$\tilde{a}_{31}$	s_{48}^{prog}	s_{47}^{prog}	s_{112}^{prog}	s_{240}^{prog}	s_{111}^{prog}	s_{239}^{prog}	s_{238}^{prog}	s_{46}^{prog}	s_{110}^{prog}	s_{237}^{prog}	s_{225}^{prog}	s_{40}^{prog}	s_{184}^{prog}

A.5 Aftershock epicenter locations

Table A-11: Aftershock epicenter arrondissements in hypothetical scenarios (1/2)

	$s_{1,1}^{hyp,\tilde{a}_b}$	$s_{2,1}^{hyp,\tilde{a}_b}$	$s_{3,1}^{hyp,\tilde{a}_b}$	$s_{4,1}^{hyp,\tilde{a}_b}$	$s_{5,1}^{hyp,\tilde{a}_b}$	$s_{6,1}^{hyp,\tilde{a}_b}$	$s_{7,1}^{hyp,\tilde{a}_b}$	$s_{8,1}^{hyp,\tilde{a}_b}$	$s_{9,1}^{hyp,\tilde{a}_b}$	$s_{10,1}^{hyp,\tilde{a}_b}$	$s_{11,1}^{hyp,\tilde{a}_b}$	$s_{12,1}^{hyp,\tilde{a}_b}$	$s_{13,1}^{hyp,\tilde{a}_b}$
$\tilde{a}_1$	1	1	16	24	1	1	24	1	1	1	1	16	1
$\tilde{a}_2$	1	1	1	1	1	24	1	1	1	16	1	1	1
$\tilde{a}_3$	1	1	1	24	1	18	1	1	16	1	1	1	1
$\tilde{a}_4$	1	1	1	1	1	18	1	24	1	1	18	1	28
$\tilde{a}_5$	1	24	28	18	1	16	1	28	24	1	16	1	1
$\tilde{a}_6$	1	28	1	16	1	18	1	1	24	24	16	1	1
$\tilde{a}_7$	1	28	1	1	1	16	24	18	1	1	24	1	16
$\tilde{a}_8$	1	37	1	1	24	18	1	1	16	1	24	1	16
$\tilde{a}_9$	1	28	1	1	1	16	24	1	18	1	1	1	1
$\tilde{a}_{10}$	1	1	1	1	1	16	28	1	18	1	1	1	28
$\tilde{a}_{11}$	28	4	13	42	28	13	24	13	18	28	15	15	24
$\tilde{a}_{12}$	28	28	13	42	28	13	24	13	18	28	15	15	24
$\tilde{a}_{13}$	28	4	13	42	28	13	24	13	20	20	20	20	24
$\tilde{a}_{14}$	1	1	1	1	1	1	1	1	1	1	1	1	1
$\tilde{a}_{15}$	1	1	1	1	1	28	1	18	1	1	1	1	1
$\tilde{a}_{16}$	1	18	18	18	1	18	18	1	1	1	18	1	1
$\tilde{a}_{17}$	1	18	1	7	24	1	16	16	18	1	1	24	1
$\tilde{a}_{18}$	1	1	18	1	18	1	18	1	1	1	18	1	1
$\tilde{a}_{19}$	1	1	1	18	1	18	24	24	1	1	24	1	18
$\tilde{a}_{20}$	1	1	18	16	24	18	1	1	1	1	28	1	1
$\tilde{a}_{21}$	1	1	18	24	16	1	18	1	1	1	1	24	28
$\tilde{a}_{22}$	1	18	1	24	1	1	16	1	1	18	1	1	24
$\tilde{a}_{23}$	1	1	18	24	1	16	18	1	1	1	1	1	1
$\tilde{a}_{24}$	1	1	18	28	1	16	18	1	1	1	1	1	1
$\tilde{a}_{25}$	28	28	18	24	13	13	18	7	28	34	13	8	24
$\tilde{a}_{26}$	28	28	18	24	13	13	18	7	28	34	13	8	24
$\tilde{a}_{27}$	28	28	20	24	13	13	20	7	20	24	13	8	24
$\tilde{a}_{28}$	18	1	18	18	28	18	1	1	18	1	1	1	18
$\tilde{a}_{29}$	1	1	1	1	1	1	1	1	1	1	1	24	1
$\tilde{a}_{30}$	13	18	18	13	18	18	28	18	13	24	13	13	13
$\tilde{a}_{31}$	1	1	1	18	1	18	18	1	1	18	1	1	28

Table A-12: Aftershock epicenter arrondissements in hypothetical scenarios (2/2)

	$s_{1,2}^{hyp,\tilde{a}_b}$	$s_{2,2}^{hyp,\tilde{a}_b}$	$s_{3,2}^{hyp,\tilde{a}_b}$	$s_{4,2}^{hyp,\tilde{a}_b}$	$s_{5,2}^{hyp,\tilde{a}_b}$	$s_{6,2}^{hyp,\tilde{a}_b}$	$s_{7,2}^{hyp,\tilde{a}_b}$	$s_{8,2}^{hyp,\tilde{a}_b}$	$s_{9,2}^{hyp,\tilde{a}_b}$	$s_{10,2}^{hyp,\tilde{a}_b}$	$s_{11,2}^{hyp,\tilde{a}_b}$	$s_{12,2}^{hyp,\tilde{a}_b}$	$s_{13,2}^{hyp,\tilde{a}_b}$
$\tilde{a}_1$	8	5	8	10	5	8	8	10	5	5	5	5	5
$\tilde{a}_2$	11	8	10	8	5	10	5	5	5	10	10	5	5
$\tilde{a}_3$	11	10	9	10	10	9	5	10	10	5	5	5	5
$\tilde{a}_4$	10	10	10	10	10	10	10	10	10	8	10	10	12
$\tilde{a}_5$	10	10	12	8	10	15	10	8	5	10	10	10	10
$\tilde{a}_6$	8	12	8	8	12	8	10	10	10	10	8	10	10
$\tilde{a}_7$	8	12	12	8	10	8	10	8	10	10	10	10	8
$\tilde{a}_8$	8	12	8	10	10	8	8	10	8	5	10	10	8
$\tilde{a}_9$	8	12	8	10	8	8	10	5	8	10	5	10	10
$\tilde{a}_{10}$	8	12	8	10	8	8	10	5	8	10	10	10	10
$\tilde{a}_{11}$	8	12	8	10	8	8	10	5	8	10	10	10	10
$\tilde{a}_{12}$	8	12	8	10	8	8	10	5	8	10	10	10	10
$\tilde{a}_{13}$	8	12	8	10	8	8	10	5	8	10	10	10	10
$\tilde{a}_{14}$	6	8	6	6	10	6	10	10	8	6	6	10	6
$\tilde{a}_{15}$	6	6	8	6	6	10	6	10	6	10	6	10	10
$\tilde{a}_{16}$	12	10	10	10	10	10	9	10	10	10	10	10	10
$\tilde{a}_{17}$	12	9	10	10	10	10	10	15	10	5	10	15	10
$\tilde{a}_{18}$	12	6	10	6	10	6	10	10	10	10	10	6	10
$\tilde{a}_{19}$	12	6	6	10	6	10	10	10	6	10	10	6	10
$\tilde{a}_{20}$	12	10	9	10	10	10	12	10	10	10	10	14	10
$\tilde{a}_{21}$	12	10	9	10	10	12	10	10	5	10	10	5	10
$\tilde{a}_{22}$	12	9	10	10	9	10	10	5	10	10	10	5	5
$\tilde{a}_{23}$	12	10	9	10	9	9	10	10	5	10	5	10	5
$\tilde{a}_{24}$	12	10	9	10	9	9	10	10	5	10	5	10	5
$\tilde{a}_{25}$	12	10	9	10	9	9	10	10	5	10	5	10	5
$\tilde{a}_{26}$	12	10	9	10	9	9	10	10	5	10	5	10	5
$\tilde{a}_{27}$	12	10	9	10	9	9	10	10	5	10	5	10	5
$\tilde{a}_{28}$	6	12	6	10	10	10	10	6	10	6	10	6	10
$\tilde{a}_{29}$	6	6	6	6	6	8	6	6	6	8	8	10	10
$\tilde{a}_{30}$	6	10	10	6	10	10	12	10	6	10	6	6	6
$\tilde{a}_{31}$	10	10	15	10	15	10	10	10	10	10	10	10	15

A.6 Stress test 2 results

Table A-13: Stress test 2 results

Promising alternative	Regret in prognostic scenarios		Regret in hypothetical scenarios		Robustness value
	Expected	Maximum	Expected	Maximum	
$\tilde{a}_1$	0.418	0.731	0.466	0.700	0.515
$\tilde{a}_2$	0.444	0.908	0.557	0.713	0.565
$\tilde{a}_3$	0.450	0.752	0.609	0.736	0.551
$\tilde{a}_4$	0.507	1.000	0.723	1.000	0.673
$\tilde{a}_5$	0.214	1.000	0.501	1.000	0.477
$\tilde{a}_6$	0.370	1.000	0.637	1.000	0.582
$\tilde{a}_7$	0.409	1.000	0.678	1.000	0.609
$\tilde{a}_8$	0.471	1.000	0.662	1.000	0.648
$\tilde{a}_9$	0.517	1.000	0.640	1.000	0.676
$\tilde{a}_{10}$	0.484	1.000	0.656	1.000	0.656
$\tilde{a}_{11}$	0.488	1.000	0.641	1.000	0.658
$\tilde{a}_{12}$	0.471	1.000	0.613	1.000	0.646
$\tilde{a}_{13}$	0.500	1.000	0.656	1.000	0.666
$\tilde{a}_{14}$	0.663	1.000	0.722	0.887	0.755
$\tilde{a}_{15}$	0.688	1.000	0.708	0.913	0.775
$\tilde{a}_{16}$	0.540	1.000	0.753	0.914	0.682
$\tilde{a}_{17}$	0.243	1.000	0.531	0.864	0.475
$\tilde{a}_{18}$	0.673	1.000	0.768	0.863	0.759
$\tilde{a}_{19}$	0.712	1.000	0.716	0.870	0.783
$\tilde{a}_{20}$	0.376	1.000	0.591	0.778	0.549
$\tilde{a}_{21}$	0.415	1.000	0.630	0.804	0.579
$\tilde{a}_{22}$	0.453	1.000	0.597	0.782	0.599
$\tilde{a}_{23}$	0.523	1.000	0.669	0.851	0.658
$\tilde{a}_{24}$	0.490	1.000	0.652	0.813	0.630
$\tilde{a}_{25}$	0.495	1.000	0.594	0.778	0.625
$\tilde{a}_{26}$	0.477	1.000	0.590	0.803	0.618
$\tilde{a}_{27}$	0.507	1.000	0.627	0.803	0.638
$\tilde{a}_{28}$	0.699	1.000	0.765	0.902	0.782
$\tilde{a}_{29}$	0.702	1.000	0.778	0.895	0.783
$\tilde{a}_{30}$	0.774	1.000	0.787	0.945	0.838
$\tilde{a}_{31}$	0.513	1.000	0.742	0.938	0.668

A.7 Sensitivity analyses

Table A-14: Sensitivities of preferences of objectives

we_{z_1}	1	0.9	0.8	0.7	0.6	0.5	0.4	0.3	0.2	0.1	0
we_{z_2}	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
$\tilde{a}_{17}$	0.458	0.464	0.469	0.475	0.481	0.486	0.492	0.502	0.530	0.559	0.588
$\tilde{a}_5$	0.400	0.426	0.451	0.477	0.503	0.528	0.554	0.579	0.605	0.630	0.656
$\tilde{a}_1$	0.692	0.632	0.571	0.515	0.468	0.437	0.415	0.395	0.391	0.387	0.385
$\tilde{a}_{20}$	0.634	0.606	0.577	0.549	0.520	0.493	0.474	0.470	0.470	0.469	0.468
$\tilde{a}_3$	0.728	0.668	0.609	0.551	0.504	0.461	0.426	0.391	0.365	0.346	0.328
$\tilde{a}_2$	0.706	0.659	0.612	0.565	0.523	0.492	0.462	0.438	0.430	0.435	0.440
$\tilde{a}_{21}$	0.669	0.639	0.609	0.579	0.550	0.520	0.497	0.482	0.468	0.453	0.438
$\tilde{a}_6$	0.617	0.605	0.594	0.582	0.571	0.559	0.547	0.536	0.524	0.513	0.501
$\tilde{a}_{22}$	0.716	0.677	0.638	0.599	0.560	0.538	0.519	0.499	0.480	0.460	0.441
$\tilde{a}_7$	0.650	0.636	0.622	0.609	0.595	0.581	0.567	0.553	0.539	0.526	0.512

Table A-15: Sensitivities of preferences of objectives

we_{z_1}	1	0.9	0.8	0.7	0.6	0.5	0.4	0.3	0.2	0.1	0
we_{z_2}	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
$\tilde{a}_{17}$	0.394	0.435	0.475	0.515	0.556	0.596	0.636	0.677	0.717	0.757	0.798
$\tilde{a}_5$	0.371	0.424	0.477	0.530	0.583	0.636	0.689	0.741	0.794	0.847	0.900
$\tilde{a}_1$	0.480	0.498	0.515	0.532	0.550	0.567	0.584	0.601	0.619	0.636	0.653
$\tilde{a}_{20}$	0.501	0.525	0.549	0.573	0.597	0.621	0.645	0.669	0.693	0.717	0.741
$\tilde{a}_3$	0.511	0.531	0.551	0.571	0.591	0.611	0.631	0.651	0.671	0.691	0.711
$\tilde{a}_2$	0.536	0.551	0.565	0.580	0.594	0.609	0.623	0.638	0.652	0.667	0.681
$\tilde{a}_{21}$	0.532	0.556	0.579	0.603	0.627	0.651	0.674	0.698	0.722	0.745	0.769
$\tilde{a}_6$	0.496	0.539	0.582	0.625	0.668	0.712	0.755	0.798	0.841	0.884	0.927
$\tilde{a}_{22}$	0.562	0.581	0.599	0.617	0.635	0.654	0.672	0.690	0.709	0.727	0.745
$\tilde{a}_7$	0.527	0.568	0.609	0.649	0.690	0.731	0.772	0.813	0.854	0.895	0.936

Table A-16: Sensitivities of the intra-scenario degree of pessimism (1/4)

$\tilde{a}_{17}$		λ^{hyp}										
		0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
λ^{prog}	0	0.973	0.966	0.960	0.953	0.946	0.940	0.933	0.926	0.920	0.913	0.906
	0.1	0.912	0.906	0.899	0.892	0.886	0.879	0.872	0.866	0.859	0.852	0.846
	0.2	0.852	0.845	0.838	0.832	0.825	0.818	0.812	0.805	0.798	0.792	0.785
	0.3	0.791	0.785	0.778	0.771	0.765	0.758	0.751	0.745	0.738	0.731	0.725
	0.4	0.731	0.724	0.717	0.711	0.704	0.697	0.691	0.684	0.677	0.671	0.664
	0.5	0.670	0.663	0.657	0.650	0.643	0.637	0.630	0.623	0.617	0.610	0.603
	0.6	0.609	0.603	0.596	0.590	0.583	0.576	0.570	0.563	0.556	0.550	0.543
	0.7	0.549	0.542	0.536	0.529	0.522	0.516	0.509	0.502	0.496	0.489	0.482
	0.8	0.488	0.482	0.475	0.468	0.462	0.455	0.448	0.442	0.435	0.428	0.422
	0.9	0.428	0.421	0.414	0.408	0.401	0.395	0.388	0.381	0.375	0.368	0.361
	1	0.367	0.361	0.354	0.347	0.341	0.334	0.327	0.321	0.314	0.307	0.301
$\tilde{a}_{5}$		0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
λ^{prog}	0	1.000	0.990	0.980	0.970	0.960	0.950	0.940	0.930	0.920	0.910	0.900
	0.1	0.937	0.927	0.917	0.907	0.897	0.887	0.877	0.867	0.857	0.847	0.837
	0.2	0.874	0.864	0.854	0.844	0.834	0.824	0.814	0.804	0.794	0.784	0.774
	0.3	0.811	0.801	0.791	0.781	0.771	0.761	0.751	0.741	0.732	0.722	0.712
	0.4	0.748	0.738	0.729	0.719	0.709	0.699	0.689	0.679	0.669	0.659	0.649
	0.5	0.686	0.676	0.666	0.656	0.646	0.636	0.626	0.616	0.606	0.596	0.586
	0.6	0.623	0.613	0.603	0.593	0.583	0.573	0.563	0.553	0.543	0.533	0.523
	0.7	0.560	0.550	0.540	0.530	0.520	0.510	0.500	0.490	0.480	0.470	0.460
	0.8	0.497	0.487	0.477	0.467	0.457	0.447	0.437	0.427	0.417	0.407	0.397
	0.9	0.434	0.424	0.414	0.404	0.394	0.384	0.374	0.364	0.354	0.344	0.334
	1	0.371	0.361	0.351	0.341	0.331	0.321	0.311	0.301	0.291	0.281	0.271
$\tilde{a}_{1}$		0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
λ^{prog}	0	0.725	0.720	0.716	0.711	0.706	0.702	0.697	0.692	0.688	0.683	0.678
	0.1	0.700	0.695	0.691	0.686	0.681	0.677	0.672	0.667	0.663	0.658	0.653
	0.2	0.675	0.670	0.666	0.661	0.656	0.652	0.647	0.642	0.637	0.633	0.628
	0.3	0.650	0.645	0.640	0.636	0.631	0.626	0.622	0.617	0.612	0.608	0.603
	0.4	0.625	0.620	0.615	0.611	0.606	0.601	0.597	0.592	0.587	0.583	0.578
	0.5	0.600	0.595	0.590	0.586	0.581	0.576	0.572	0.567	0.562	0.558	0.553
	0.6	0.575	0.570	0.565	0.561	0.556	0.551	0.546	0.542	0.537	0.532	0.528
	0.7	0.549	0.545	0.540	0.535	0.531	0.526	0.521	0.517	0.512	0.507	0.503
	0.8	0.524	0.520	0.515	0.510	0.506	0.501	0.496	0.492	0.487	0.482	0.478
	0.9	0.499	0.495	0.490	0.485	0.481	0.476	0.471	0.467	0.462	0.457	0.452
	1	0.474	0.470	0.465	0.460	0.455	0.451	0.446	0.441	0.437	0.432	0.427

Table A-17: Sensitivities of the intra-scenario degree of pessimism (2/4)

$\tilde{a}_{20}$		λ^{hyp}										
		0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
λ^{prog}	0	0.956	0.952	0.948	0.944	0.941	0.937	0.933	0.929	0.926	0.922	0.918
	0.1	0.906	0.902	0.898	0.894	0.891	0.887	0.883	0.880	0.876	0.872	0.868
	0.2	0.856	0.852	0.848	0.845	0.841	0.837	0.833	0.830	0.826	0.822	0.818
	0.3	0.806	0.802	0.798	0.795	0.791	0.787	0.783	0.780	0.776	0.772	0.768
	0.4	0.756	0.752	0.748	0.745	0.741	0.737	0.734	0.730	0.726	0.722	0.719
	0.5	0.706	0.702	0.699	0.695	0.691	0.687	0.684	0.680	0.676	0.672	0.669
	0.6	0.656	0.652	0.649	0.645	0.641	0.637	0.634	0.630	0.626	0.622	0.619
	0.7	0.606	0.602	0.599	0.595	0.591	0.588	0.584	0.580	0.576	0.573	0.569
	0.8	0.556	0.553	0.549	0.545	0.541	0.538	0.534	0.530	0.526	0.523	0.519
	0.9	0.506	0.503	0.499	0.495	0.491	0.488	0.484	0.480	0.476	0.473	0.469
	1	0.456	0.453	0.449	0.445	0.442	0.438	0.434	0.430	0.427	0.423	0.419
$\tilde{a}_3$		0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
λ^{prog}	0	0.749	0.746	0.744	0.741	0.739	0.736	0.733	0.731	0.728	0.726	0.723
	0.1	0.725	0.722	0.720	0.717	0.714	0.712	0.709	0.707	0.704	0.702	0.699
	0.2	0.700	0.698	0.695	0.693	0.690	0.688	0.685	0.683	0.680	0.678	0.675
	0.3	0.676	0.674	0.671	0.669	0.666	0.664	0.661	0.659	0.656	0.653	0.651
	0.4	0.652	0.650	0.647	0.645	0.642	0.639	0.637	0.634	0.632	0.629	0.627
	0.5	0.628	0.626	0.623	0.620	0.618	0.615	0.613	0.610	0.608	0.605	0.603
	0.6	0.604	0.601	0.599	0.596	0.594	0.591	0.589	0.586	0.584	0.581	0.578
	0.7	0.580	0.577	0.575	0.572	0.570	0.567	0.565	0.562	0.559	0.557	0.554
	0.8	0.556	0.553	0.551	0.548	0.546	0.543	0.540	0.538	0.535	0.533	0.530
	0.9	0.532	0.529	0.526	0.524	0.521	0.519	0.516	0.514	0.511	0.509	0.506
	1	0.507	0.505	0.502	0.500	0.497	0.495	0.492	0.490	0.487	0.485	0.482
$\tilde{a}_2$		0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
λ^{prog}	0	0.869	0.866	0.863	0.859	0.856	0.853	0.850	0.847	0.844	0.841	0.838
	0.1	0.832	0.829	0.825	0.822	0.819	0.816	0.813	0.810	0.807	0.804	0.800
	0.2	0.795	0.791	0.788	0.785	0.782	0.779	0.776	0.773	0.770	0.766	0.763
	0.3	0.757	0.754	0.751	0.748	0.745	0.742	0.739	0.736	0.732	0.729	0.726
	0.4	0.720	0.717	0.714	0.711	0.708	0.705	0.702	0.698	0.695	0.692	0.689
	0.5	0.683	0.680	0.677	0.674	0.671	0.668	0.664	0.661	0.658	0.655	0.652
	0.6	0.646	0.643	0.640	0.637	0.634	0.630	0.627	0.624	0.621	0.618	0.615
	0.7	0.609	0.606	0.603	0.599	0.596	0.593	0.590	0.587	0.584	0.581	0.578
	0.8	0.572	0.569	0.565	0.562	0.559	0.556	0.553	0.550	0.547	0.544	0.541
	0.9	0.535	0.531	0.528	0.525	0.522	0.519	0.516	0.513	0.510	0.507	0.503
	1	0.497	0.494	0.491	0.488	0.485	0.482	0.479	0.476	0.473	0.469	0.466

Table A-18: Sensitivities of the intra-scenario degree of pessimism (3/4)

$\tilde{a}_{21}$		λ^{hyp}										
		0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
λ^{prog}	0	0.961	0.957	0.954	0.950	0.947	0.943	0.940	0.936	0.933	0.930	0.926
	0.1	0.914	0.910	0.907	0.904	0.900	0.897	0.893	0.890	0.886	0.883	0.879
	0.2	0.867	0.864	0.860	0.857	0.853	0.850	0.846	0.843	0.839	0.836	0.832
	0.3	0.820	0.817	0.813	0.810	0.806	0.803	0.800	0.796	0.793	0.789	0.786
	0.4	0.774	0.770	0.767	0.763	0.760	0.756	0.753	0.749	0.746	0.742	0.739
	0.5	0.727	0.723	0.720	0.716	0.713	0.709	0.706	0.703	0.699	0.696	0.692
	0.6	0.680	0.677	0.673	0.670	0.666	0.663	0.659	0.656	0.652	0.649	0.645
	0.7	0.633	0.630	0.626	0.623	0.619	0.616	0.612	0.609	0.605	0.602	0.599
	0.8	0.586	0.583	0.579	0.576	0.573	0.569	0.566	0.562	0.559	0.555	0.552
	0.9	0.540	0.536	0.533	0.529	0.526	0.522	0.519	0.515	0.512	0.508	0.505
	1	0.493	0.489	0.486	0.482	0.479	0.475	0.472	0.469	0.465	0.462	0.458
$\tilde{a}_{6}$		0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
λ^{prog}	0	1.000	0.993	0.985	0.978	0.971	0.964	0.956	0.949	0.942	0.935	0.927
	0.1	0.950	0.942	0.935	0.928	0.921	0.913	0.906	0.899	0.891	0.884	0.877
	0.2	0.899	0.892	0.885	0.877	0.870	0.863	0.856	0.848	0.841	0.834	0.827
	0.3	0.849	0.841	0.834	0.827	0.820	0.812	0.805	0.798	0.791	0.783	0.776
	0.4	0.798	0.791	0.784	0.776	0.769	0.762	0.755	0.747	0.740	0.733	0.726
	0.5	0.748	0.741	0.733	0.726	0.719	0.712	0.704	0.697	0.690	0.683	0.675
	0.6	0.697	0.690	0.683	0.676	0.668	0.661	0.654	0.647	0.639	0.632	0.625
	0.7	0.647	0.640	0.632	0.625	0.618	0.611	0.603	0.596	0.589	0.582	0.574
	0.8	0.597	0.589	0.582	0.575	0.567	0.560	0.553	0.546	0.538	0.531	0.524
	0.9	0.546	0.539	0.532	0.524	0.517	0.510	0.503	0.495	0.488	0.481	0.474
	1	0.496	0.488	0.481	0.474	0.467	0.459	0.452	0.445	0.438	0.430	0.423
$\tilde{a}_{22}$		0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
λ^{prog}	0	0.956	0.953	0.949	0.945	0.942	0.938	0.934	0.931	0.927	0.923	0.919
	0.1	0.913	0.909	0.905	0.902	0.898	0.894	0.890	0.887	0.883	0.879	0.876
	0.2	0.869	0.865	0.862	0.858	0.854	0.850	0.847	0.843	0.839	0.836	0.832
	0.3	0.825	0.821	0.818	0.814	0.810	0.807	0.803	0.799	0.796	0.792	0.788
	0.4	0.781	0.778	0.774	0.770	0.767	0.763	0.759	0.756	0.752	0.748	0.744
	0.5	0.738	0.734	0.730	0.727	0.723	0.719	0.715	0.712	0.708	0.704	0.701
	0.6	0.694	0.690	0.686	0.683	0.679	0.675	0.672	0.668	0.664	0.661	0.657
	0.7	0.650	0.646	0.643	0.639	0.635	0.632	0.628	0.624	0.621	0.617	0.613
	0.8	0.606	0.603	0.599	0.595	0.592	0.588	0.584	0.580	0.577	0.573	0.569
	0.9	0.563	0.559	0.555	0.551	0.548	0.544	0.540	0.537	0.533	0.529	0.526
	1	0.519	0.515	0.511	0.508	0.504	0.500	0.497	0.493	0.489	0.486	0.482

Table A-19: Sensitivities of the intra-scenario degree of pessimism (4/4)

$\tilde{a}_7$		λ^{hyp}										
		0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
λ^{prog}	0	1.000	0.994	0.987	0.981	0.974	0.968	0.961	0.955	0.948	0.942	0.936
	0.1	0.953	0.946	0.940	0.933	0.927	0.920	0.914	0.908	0.901	0.895	0.888
	0.2	0.905	0.899	0.892	0.886	0.880	0.873	0.867	0.860	0.854	0.847	0.841
	0.3	0.858	0.852	0.845	0.839	0.832	0.826	0.819	0.813	0.807	0.800	0.794
	0.4	0.811	0.804	0.798	0.791	0.785	0.779	0.772	0.766	0.759	0.753	0.746
	0.5	0.763	0.757	0.751	0.744	0.738	0.731	0.725	0.718	0.712	0.705	0.699
	0.6	0.716	0.710	0.703	0.697	0.690	0.684	0.677	0.671	0.665	0.658	0.652
	0.7	0.669	0.662	0.656	0.649	0.643	0.637	0.630	0.624	0.617	0.611	0.604
	0.8	0.621	0.615	0.609	0.602	0.596	0.589	0.583	0.576	0.570	0.564	0.557
	0.9	0.574	0.568	0.561	0.555	0.548	0.542	0.536	0.529	0.523	0.516	0.510
	1	0.527	0.520	0.514	0.508	0.501	0.495	0.488	0.482	0.475	0.469	0.462

B. Additional data of case study 2

B.1 Structure of Berlin

Table B-1: Structure of Berlin in 2012 (provided by the SEAK project; Statistik Berlin Brandenburg 2012; Nielsen 2013)

District		Density of population [1/km^2]	Area [km^2]	Density of stores [1/km^2]
I	Charlottenburg-Wilmersdorf	5,043	64.72	0.7
II	Friedrichshain-Kreuzberg	13,554	20.16	1.4
III	Lichtenberg	5,134	52.29	0.6
IV	Marzahn-Hellersdorf	4,149	61.47	0.6
V	Mitte	9,032	39.47	1
VI	Neukölln	7,249	44.93	1.1
VII	Pankow	3,731	103.1	0.5
VIII	Reinickendorf	2,839	89.46	0.5
IX	Spandau	2,507	91.91	0.3
X	Steglitz-Zehlendorf	2,920	102.5	0.5
XI	Tempelhof-Schöneberg	6,324	53.09	1.1
XII	Treptow-Köpenick	1,481	168.42	0.2

B.2 Alternatives

Table B-2: Alternatives and staff allocations (1/3)

	Store 1	Store 2	Store 3	Store 4	Store 5	Store 6	Store 7	Store 8	Store 9	Store 10
a_1	42	90	0	0	33	26	0	42	0	0
a_2	42	90	0	0	32	26	0	42	0	0
a_3	42	91	0	0	36	26	0	42	0	0
a_4	38	78	0	0	26	26	0	42	55	0
a_5	42	90	0	0	33	26	0	42	0	0
a_6	42	90	0	0	31	26	0	42	0	0
a_7	42	90	0	0	32	26	0	42	0	0
a_8	42	91	0	0	32	26	0	42	0	0
a_9	42	91	0	0	32	26	0	42	0	0
a_{10}	42	90	0	0	32	26	0	42	0	0
a_{11}	42	90	0	0	32	26	0	42	0	0
a_{12}	38	79	0	0	26	26	0	42	55	0
a_{13}	42	90	0	0	32	26	0	42	0	0
a_{14}	42	89	0	0	32	26	0	42	0	0
a_{15}	42	90	0	0	33	26	0	42	0	0
a_{16}	42	90	0	0	33	26	0	42	0	0
a_{17}	42	90	0	0	32	26	0	42	0	0
a_{18}	42	91	0	0	35	26	0	42	0	0
a_{19}	37	78	0	0	26	26	0	42	55	0
a_{20}	42	90	0	0	31	26	0	42	0	0
a_{21}	42	89	0	0	33	26	0	42	0	0
a_{22}	37	79	0	0	26	26	0	42	55	0
a_{23}	42	90	0	0	31	26	0	42	0	0
a_{24}	42	91	0	0	33	26	0	42	0	0
a_{25}	42	91	0	0	33	26	0	42	0	0
a_{26}	42	91	0	0	32	26	0	42	0	0
a_{27}	42	88	0	0	38	26	0	42	0	0
a_{28}	42	89	0	0	32	26	0	42	0	0
a_{29}	42	91	0	0	32	26	0	42	0	0
a_{30}	42	89	0	0	34	26	0	42	0	0
a_{31}	37	78	0	0	26	26	0	42	55	0
a_{32}	42	90	0	0	32	26	0	42	0	0
a_{33}	42	89	0	0	32	26	0	42	0	0
a_{34}	42	89	0	0	33	26	0	42	0	0
a_{35}	42	90	0	0	32	26	0	42	0	0
a_{36}	42	90	0	0	31	26	0	42	0	0
a_{37}	42	90	0	0	31	26	0	42	0	0
a_{38}	42	89	0	0	35	26	0	42	0	0
a_{39}	42	91	0	0	32	26	0	42	0	0
a_{40}	42	90	0	0	32	26	0	42	0	0
a_{41}	37	79	0	0	26	26	0	42	55	0
a_{42}	40	91	0	0	32	26	0	42	0	0
a_{43}	42	89	0	0	37	26	0	42	0	0
a_{44}	42	80	0	0	33	26	0	42	0	0
a_{45}	38	78	0	0	26	26	0	42	55	0

Table B-3: Alternatives and staff allocations (2/3)

	Store 11	Store 12	Store 13	Store 14	Store 15	Store 16	Store 17	Store 18	Store 19	Store 20
a_1	55	0	26	27	33	0	38	40	26	26
a_2	55	0	26	27	32	0	38	40	26	26
a_3	55	0	26	27	31	0	38	40	26	26
a_4	55	0	26	26	27	0	34	35	26	26
a_5	55	0	26	27	32	0	38	40	26	26
a_6	55	0	26	27	32	0	38	40	26	26
a_7	55	0	26	27	32	0	38	41	26	26
a_8	55	0	26	27	32	0	39	40	26	26
a_9	55	0	26	27	32	0	38	40	26	26
a_{10}	55	0	26	27	32	0	39	40	26	26
a_{11}	55	0	26	27	32	0	39	40	26	26
a_{12}	55	0	26	26	27	0	33	35	26	26
a_{13}	55	0	26	27	32	0	38	40	26	26
a_{14}	55	0	26	27	32	0	39	40	26	26
a_{15}	55	0	26	27	32	0	38	40	26	26
a_{16}	55	0	26	27	32	0	39	40	26	26
a_{17}	55	0	26	28	32	0	38	40	26	26
a_{18}	55	0	26	27	30	0	39	39	26	26
a_{19}	55	0	26	26	28	0	33	36	26	26
a_{20}	55	0	26	27	32	0	39	40	26	26
a_{21}	55	0	26	27	32	0	38	40	26	26
a_{22}	55	0	26	26	27	0	34	35	26	26
a_{23}	55	0	26	27	33	0	39	40	26	26
a_{24}	55	0	26	27	32	0	38	40	26	26
a_{25}	55	0	26	27	33	0	39	40	26	26
a_{26}	55	0	26	27	32	0	38	40	26	26
a_{27}	55	0	26	28	34	0	37	39	26	26
a_{28}	55	0	26	27	33	0	39	40	26	26
a_{29}	55	0	26	27	32	0	39	39	26	26
a_{30}	55	0	26	27	32	0	39	40	26	26
a_{31}	55	0	26	26	28	0	34	35	26	26
a_{32}	55	0	26	27	33	0	38	40	26	26
a_{33}	55	0	26	27	32	0	39	40	26	26
a_{34}	55	0	26	28	32	0	38	40	26	26
a_{35}	55	0	26	27	32	0	39	41	26	26
a_{36}	55	0	26	27	32	0	39	40	26	26
a_{37}	55	0	26	27	33	0	38	40	26	26
a_{38}	55	0	26	27	32	0	38	40	26	26
a_{39}	55	0	26	27	33	0	39	40	26	26
a_{40}	55	0	26	27	31	0	38	41	26	26
a_{41}	55	0	26	26	28	0	34	35	26	26
a_{42}	55	0	26	29	34	0	40	41	26	26
a_{43}	55	0	26	28	31	0	40	39	26	26
a_{44}	55	0	26	28	32	0	38	40	26	26
a_{45}	55	0	26	26	28	0	33	35	26	26

Table B-4: Alternatives and staff allocations (3/3)

	Store 21	Store 22	Store 23	Store 24	Store 25	Store 26	Store 27	Store 28	Store 29
a_1	0	26	26	38	40	26	0	0	42
a_2	0	26	26	39	41	26	0	0	42
a_3	0	26	26	37	39	26	0	0	42
a_4	0	26	26	26	36	26	0	0	42
a_5	0	26	26	39	40	26	0	0	42
a_6	0	26	26	40	41	26	0	0	42
a_7	0	26	26	39	40	26	0	0	42
a_8	0	26	26	38	40	26	0	0	42
a_9	0	26	26	39	40	26	0	0	42
a_{10}	0	26	26	38	41	26	0	0	42
a_{11}	0	26	26	39	40	26	0	0	42
a_{12}	0	26	26	26	36	26	0	0	42
a_{13}	0	26	26	40	40	26	0	0	42
a_{14}	0	26	26	39	41	26	0	0	42
a_{15}	0	26	26	38	41	26	0	0	42
a_{16}	0	26	26	38	40	26	0	0	42
a_{17}	0	26	26	39	40	26	0	0	42
a_{18}	0	26	26	39	39	26	0	0	42
a_{19}	0	26	26	26	36	26	0	0	42
a_{20}	0	26	26	39	41	26	0	0	42
a_{21}	0	26	26	39	41	26	0	0	42
a_{22}	0	26	26	26	36	26	0	0	42
a_{23}	0	26	26	39	40	26	0	0	42
a_{24}	0	26	26	38	40	26	0	0	42
a_{25}	0	26	26	35	41	26	0	0	42
a_{26}	0	26	26	38	41	26	0	0	42
a_{27}	0	26	26	36	39	26	0	0	42
a_{28}	0	26	26	38	41	26	0	0	42
a_{29}	0	26	26	39	40	26	0	0	42
a_{30}	0	26	26	37	41	26	0	0	42
a_{31}	0	26	26	26	36	26	0	0	42
a_{32}	0	26	26	39	40	26	0	0	42
a_{33}	0	26	26	40	40	26	0	0	42
a_{34}	0	26	26	38	41	26	0	0	42
a_{35}	0	26	26	38	40	26	0	0	42
a_{36}	0	26	26	40	40	26	0	0	42
a_{37}	0	26	26	39	41	26	0	0	42
a_{38}	0	26	26	38	40	26	0	0	42
a_{39}	0	26	26	37	40	26	0	0	42
a_{40}	0	26	26	40	40	26	0	0	42
a_{41}	0	26	26	26	35	26	0	0	42
a_{42}	0	26	26	35	39	26	0	0	42
a_{43}	0	26	26	36	39	26	0	0	42
a_{44}	0	26	26	38	40	26	0	0	42
a_{45}	0	26	26	26	36	26	0	0	42

B.3 Stress test 2 results

Table B-5: Stress test 2 results (1/2)

Alternative	Regret in prognostic scenarios		Regret in hypothetical scenarios		Robustness value
	Expected	Maximum	Expected	Maximum	
a_1	0.194	0.634	0.409	0.870	0.610
a_2	0.171	0.665	0.388	0.859	0.598
a_3	0.319	0.785	0.494	0.933	0.698
a_4	0.100	0.535	0.253	0.890	0.558
a_5	0.179	0.712	0.430	0.877	0.622
a_6	0.192	0.659	0.403	0.847	0.599
a_7	0.193	0.690	0.430	0.904	0.636
a_8	0.119	0.680	0.407	0.963	0.643
a_9	0.172	0.646	0.426	1.000	0.674
a_{10}	0.120	0.698	0.402	0.853	0.590
a_{11}	0.112	0.650	0.383	0.855	0.582
a_{12}	0.106	0.579	0.286	0.894	0.572
a_{13}	0.174	0.617	0.385	0.868	0.598
a_{14}	0.125	0.671	0.392	1.000	0.659
a_{15}	0.190	0.745	0.416	1.000	0.684
a_{16}	0.117	0.628	0.418	1.000	0.659
a_{17}	0.186	0.647	0.421	0.928	0.640
a_{18}	0.324	0.680	0.436	0.923	0.673
a_{19}	0.120	0.567	0.327	0.915	0.593
a_{20}	0.128	0.692	0.377	0.834	0.577
a_{21}	0.193	0.734	0.508	1.000	0.703
a_{22}	0.099	0.532	0.308	0.969	0.608
a_{23}	0.145	0.687	0.440	1.000	0.675

Table B-6: Stress test 2 results (2/2)

Alternative	Regret in prognostic scenarios		Regret in hypothetical scenarios		Robustness value
	Expected	Maximum	Expected	Maximum	
a_{24}	0.191	0.813	0.441	0.939	0.666
a_{25}	0.220	0.788	0.433	1.000	0.698
a_{26}	0.183	0.695	0.396	1.000	0.674
a_{27}	0.594	1.000	0.543	1.000	0.819
a_{28}	0.144	0.710	0.383	0.846	0.589
a_{29}	0.188	0.517	0.383	0.851	0.583
a_{30}	0.160	0.680	0.473	0.888	0.629
a_{31}	0.104	0.551	0.305	0.885	0.569
a_{32}	0.181	0.655	0.430	0.857	0.607
a_{33}	0.124	0.623	0.356	0.866	0.581
a_{34}	0.212	0.647	0.469	0.987	0.685
a_{35}	0.180	0.705	0.418	0.893	0.627
a_{36}	0.129	0.644	0.662	1.000	0.714
a_{37}	0.200	0.698	0.416	0.933	0.649
a_{38}	0.219	0.628	0.398	0.917	0.635
a_{39}	0.150	0.725	0.541	1.000	0.700
a_{40}	0.227	0.733	0.558	1.000	0.721
a_{41}	0.117	0.928	0.444	1.000	0.691
a_{42}	0.561	1.000	0.563	1.000	0.816
a_{43}	0.474	0.922	0.657	1.000	0.810
a_{44}	0.204	0.626	0.546	1.000	0.704
a_{45}	0.111	0.564	0.432	1.000	0.655

B.4 Sensitivity analyses

Table B-7: Sensitivities of the inter-scenario degree of pessimism

we^{prog}	1	0.9	0.8	0.7	0.6	0.5	0.4	0.3	0.2	0.1	0
we^{hyp}	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
$\tilde{a}_{17}$	0.230	0.277	0.324	0.371	0.418	0.465	0.511	0.558	0.605	0.652	0.699
$\tilde{a}_{5}$	0.238	0.286	0.333	0.380	0.427	0.475	0.522	0.569	0.617	0.664	0.711
$\tilde{a}_{1}$	0.248	0.294	0.341	0.387	0.433	0.480	0.526	0.572	0.619	0.665	0.711
$\tilde{a}_{20}$	0.297	0.337	0.377	0.417	0.457	0.497	0.537	0.577	0.617	0.657	0.697
$\tilde{a}_{3}$	0.274	0.318	0.362	0.406	0.450	0.494	0.538	0.581	0.625	0.669	0.713
$\tilde{a}_{2}$	0.273	0.317	0.361	0.405	0.449	0.493	0.538	0.582	0.626	0.670	0.714
$\tilde{a}_{21}$	0.287	0.329	0.372	0.414	0.456	0.499	0.541	0.583	0.626	0.668	0.710
$\tilde{a}_{6}$	0.314	0.353	0.392	0.432	0.471	0.510	0.550	0.589	0.628	0.668	0.707
$\tilde{a}_{22}$	0.294	0.336	0.379	0.421	0.463	0.506	0.548	0.590	0.633	0.675	0.717
$\tilde{a}_{7}$	0.254	0.303	0.351	0.399	0.448	0.496	0.545	0.593	0.642	0.690	0.738

Table B-8: Sensitivities of the intra-scenario degree of pessimism (1/4)

a_4		λ^{hyp}										
		0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
λ^{prog}	0	0.783	0.739	0.694	0.650	0.605	0.560	0.516	0.471	0.427	0.382	0.338
	0.1	0.770	0.726	0.681	0.637	0.592	0.547	0.503	0.458	0.414	0.369	0.324
	0.2	0.757	0.713	0.668	0.623	0.579	0.534	0.490	0.445	0.401	0.356	0.311
	0.3	0.744	0.700	0.655	0.610	0.566	0.521	0.477	0.432	0.388	0.343	0.298
	0.4	0.731	0.687	0.642	0.597	0.553	0.508	0.464	0.419	0.375	0.330	0.285
	0.5	0.718	0.674	0.629	0.584	0.540	0.495	0.451	0.406	0.361	0.317	0.272
	0.6	0.705	0.660	0.616	0.571	0.527	0.482	0.438	0.393	0.348	0.304	0.259
	0.7	0.692	0.647	0.603	0.558	0.514	0.469	0.425	0.380	0.335	0.291	0.246
	0.8	0.679	0.634	0.590	0.545	0.501	0.456	0.411	0.367	0.322	0.278	0.233
	0.9	0.666	0.621	0.577	0.532	0.488	0.443	0.398	0.354	0.309	0.265	0.220
	1	0.653	0.608	0.564	0.519	0.475	0.430	0.385	0.341	0.296	0.252	0.207

Table B-9: Sensitivities of the intra-scenario degree of pessimism (2/4)

a_{31}		λ^{hyp}										
		0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
	0	0.785	0.744	0.704	0.663	0.622	0.582	0.541	0.501	0.460	0.419	0.379
	0.1	0.772	0.731	0.690	0.650	0.609	0.568	0.528	0.487	0.447	0.406	0.365
	0.2	0.758	0.718	0.677	0.636	0.596	0.555	0.514	0.474	0.433	0.393	0.352
	0.3	0.745	0.704	0.664	0.623	0.582	0.542	0.501	0.460	0.420	0.379	0.339
	0.4	0.731	0.691	0.650	0.609	0.569	0.528	0.488	0.447	0.406	0.366	0.325
λ^{prog}	0.5	0.718	0.677	0.637	0.596	0.555	0.515	0.474	0.434	0.393	0.352	0.312
	0.6	0.705	0.664	0.623	0.583	0.542	0.501	0.461	0.420	0.380	0.339	0.298
	0.7	0.691	0.651	0.610	0.569	0.529	0.488	0.447	0.407	0.366	0.326	0.285
	0.8	0.678	0.637	0.597	0.556	0.515	0.475	0.434	0.393	0.353	0.312	0.272
	0.9	0.664	0.624	0.583	0.543	0.502	0.461	0.421	0.380	0.339	0.299	0.258
	1	0.651	0.610	0.570	0.529	0.489	0.448	0.407	0.367	0.326	0.285	0.245
a_{12}		0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
	0	0.799	0.757	0.714	0.672	0.629	0.587	0.544	0.501	0.459	0.416	0.374
	0.1	0.785	0.743	0.700	0.657	0.615	0.572	0.530	0.487	0.445	0.402	0.360
	0.2	0.771	0.728	0.686	0.643	0.601	0.558	0.516	0.473	0.431	0.388	0.345
	0.3	0.757	0.714	0.672	0.629	0.587	0.544	0.502	0.459	0.416	0.374	0.331
	0.4	0.743	0.700	0.658	0.615	0.572	0.530	0.487	0.445	0.402	0.360	0.317
λ^{prog}	0.5	0.728	0.686	0.643	0.601	0.558	0.516	0.473	0.431	0.388	0.346	0.303
	0.6	0.714	0.672	0.629	0.587	0.544	0.502	0.459	0.416	0.374	0.331	0.289
	0.7	0.700	0.658	0.615	0.572	0.530	0.487	0.445	0.402	0.360	0.317	0.275
	0.8	0.686	0.643	0.601	0.558	0.516	0.473	0.431	0.388	0.346	0.303	0.260
	0.9	0.672	0.629	0.587	0.544	0.502	0.459	0.416	0.374	0.331	0.289	0.246
	1	0.658	0.615	0.572	0.530	0.487	0.445	0.402	0.360	0.317	0.275	0.232
a_{20}		0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
	0	0.791	0.759	0.728	0.696	0.664	0.632	0.600	0.568	0.536	0.504	0.472
	0.1	0.775	0.743	0.711	0.679	0.647	0.615	0.583	0.551	0.519	0.487	0.455
	0.2	0.758	0.726	0.694	0.662	0.630	0.598	0.566	0.534	0.502	0.470	0.438
	0.3	0.741	0.709	0.677	0.645	0.613	0.581	0.549	0.517	0.485	0.453	0.421
	0.4	0.724	0.692	0.660	0.628	0.596	0.564	0.532	0.500	0.468	0.436	0.404
λ^{prog}	0.5	0.707	0.675	0.643	0.611	0.579	0.547	0.515	0.483	0.451	0.419	0.387
	0.6	0.690	0.658	0.626	0.594	0.562	0.530	0.498	0.466	0.434	0.402	0.370
	0.7	0.673	0.641	0.609	0.577	0.545	0.513	0.481	0.449	0.417	0.385	0.353
	0.8	0.656	0.624	0.592	0.560	0.528	0.496	0.464	0.432	0.400	0.368	0.336
	0.9	0.639	0.607	0.575	0.543	0.511	0.479	0.447	0.415	0.383	0.351	0.319
	1	0.622	0.590	0.558	0.526	0.494	0.462	0.430	0.398	0.366	0.335	0.303

Table B-10: Sensitivities of the intra-scenario degree of pessimism (3/4)

a_{33}		λ^{hyp}										
		0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
	0	0.793	0.758	0.722	0.686	0.650	0.615	0.579	0.543	0.508	0.472	0.436
	0.1	0.778	0.743	0.707	0.671	0.635	0.600	0.564	0.528	0.493	0.457	0.421
	0.2	0.763	0.728	0.692	0.656	0.620	0.585	0.549	0.513	0.478	0.442	0.406
	0.3	0.748	0.713	0.677	0.641	0.606	0.570	0.534	0.498	0.463	0.427	0.391
	0.4	0.733	0.698	0.662	0.626	0.591	0.555	0.519	0.483	0.448	0.412	0.376
λ^{prog}	0.5	0.718	0.683	0.647	0.611	0.576	0.540	0.504	0.468	0.433	0.397	0.361
	0.6	0.704	0.668	0.632	0.596	0.561	0.525	0.489	0.454	0.418	0.382	0.346
	0.7	0.689	0.653	0.617	0.581	0.546	0.510	0.474	0.439	0.403	0.367	0.331
	0.8	0.674	0.638	0.602	0.566	0.531	0.495	0.459	0.424	0.388	0.352	0.316
	0.9	0.659	0.623	0.587	0.552	0.516	0.480	0.444	0.409	0.373	0.337	0.302
	1	0.644	0.608	0.572	0.537	0.501	0.465	0.429	0.394	0.358	0.322	0.287
a_{11}		0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
	0	0.794	0.761	0.728	0.694	0.661	0.628	0.595	0.562	0.529	0.496	0.463
	0.1	0.777	0.744	0.711	0.678	0.645	0.612	0.579	0.546	0.513	0.480	0.447
	0.2	0.761	0.728	0.695	0.662	0.629	0.596	0.563	0.530	0.497	0.464	0.431
	0.3	0.745	0.712	0.679	0.646	0.613	0.580	0.547	0.514	0.481	0.448	0.415
	0.4	0.729	0.696	0.663	0.630	0.597	0.564	0.531	0.498	0.465	0.432	0.399
λ^{prog}	0.5	0.713	0.680	0.647	0.614	0.581	0.548	0.515	0.482	0.449	0.416	0.383
	0.6	0.697	0.664	0.631	0.598	0.565	0.532	0.499	0.466	0.433	0.399	0.366
	0.7	0.681	0.648	0.615	0.582	0.549	0.516	0.482	0.449	0.416	0.383	0.350
	0.8	0.665	0.632	0.599	0.565	0.532	0.499	0.466	0.433	0.400	0.367	0.334
	0.9	0.648	0.615	0.582	0.549	0.516	0.483	0.450	0.417	0.384	0.351	0.318
	1	0.632	0.599	0.566	0.533	0.500	0.467	0.434	0.401	0.368	0.335	0.302
a_{29}		0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
	0	0.750	0.718	0.685	0.652	0.620	0.587	0.554	0.522	0.489	0.456	0.424
	0.1	0.741	0.708	0.675	0.642	0.610	0.577	0.544	0.512	0.479	0.446	0.414
	0.2	0.731	0.698	0.665	0.633	0.600	0.567	0.535	0.502	0.469	0.436	0.404
	0.3	0.721	0.688	0.655	0.623	0.590	0.557	0.525	0.492	0.459	0.427	0.394
	0.4	0.711	0.678	0.646	0.613	0.580	0.548	0.515	0.482	0.449	0.417	0.384
λ^{prog}	0.5	0.701	0.668	0.636	0.603	0.570	0.538	0.505	0.472	0.440	0.407	0.374
	0.6	0.691	0.659	0.626	0.593	0.561	0.528	0.495	0.462	0.430	0.397	0.364
	0.7	0.681	0.649	0.616	0.583	0.551	0.518	0.485	0.453	0.420	0.387	0.355
	0.8	0.672	0.639	0.606	0.574	0.541	0.508	0.475	0.443	0.410	0.377	0.345
	0.9	0.662	0.629	0.596	0.564	0.531	0.498	0.466	0.433	0.400	0.367	0.335
	1	0.652	0.619	0.586	0.554	0.521	0.488	0.456	0.423	0.390	0.358	0.325

Table B-11: Sensitivities of the intra-scenario degree of pessimism (4/4)

a_{28}		λ^{hyp}										
		0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
	0	0.805	0.773	0.740	0.708	0.675	0.643	0.611	0.578	0.546	0.514	0.481
	0.1	0.788	0.756	0.723	0.691	0.658	0.626	0.594	0.561	0.529	0.497	0.464
	0.2	0.771	0.739	0.706	0.674	0.641	0.609	0.577	0.544	0.512	0.480	0.447
	0.3	0.754	0.722	0.689	0.657	0.624	0.592	0.560	0.527	0.495	0.463	0.430
	0.4	0.737	0.705	0.672	0.640	0.607	0.575	0.543	0.510	0.478	0.446	0.413
λ^{prog}	0.5	0.720	0.688	0.655	0.623	0.591	0.558	0.526	0.493	0.461	0.429	0.396
	0.6	0.703	0.671	0.638	0.606	0.574	0.541	0.509	0.476	0.444	0.412	0.379
	0.7	0.686	0.654	0.621	0.589	0.557	0.524	0.492	0.459	0.427	0.395	0.362
	0.8	0.669	0.637	0.604	0.572	0.540	0.507	0.475	0.442	0.410	0.378	0.345
	0.9	0.652	0.620	0.587	0.555	0.523	0.490	0.458	0.426	0.393	0.361	0.328
	1	0.635	0.603	0.570	0.538	0.506	0.473	0.441	0.409	0.376	0.344	0.311
a_{10}		0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
	0	0.806	0.775	0.743	0.712	0.680	0.649	0.617	0.586	0.554	0.523	0.491
	0.1	0.789	0.757	0.726	0.694	0.663	0.631	0.600	0.568	0.537	0.505	0.474
	0.2	0.772	0.740	0.709	0.677	0.646	0.614	0.582	0.551	0.519	0.488	0.456
	0.3	0.754	0.723	0.691	0.660	0.628	0.597	0.565	0.534	0.502	0.471	0.439
	0.4	0.737	0.705	0.674	0.642	0.611	0.579	0.548	0.516	0.485	0.453	0.422
λ^{prog}	0.5	0.720	0.688	0.657	0.625	0.594	0.562	0.530	0.499	0.467	0.436	0.404
	0.6	0.702	0.671	0.639	0.608	0.576	0.545	0.513	0.482	0.450	0.419	0.387
	0.7	0.685	0.653	0.622	0.590	0.559	0.527	0.496	0.464	0.433	0.401	0.370
	0.8	0.668	0.636	0.605	0.573	0.541	0.510	0.478	0.447	0.415	0.384	0.352
	0.9	0.650	0.619	0.587	0.556	0.524	0.493	0.461	0.430	0.398	0.367	0.335
	1	0.633	0.601	0.570	0.538	0.507	0.475	0.444	0.412	0.381	0.349	0.318
a_{19}		0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
	0	0.810	0.769	0.728	0.687	0.646	0.605	0.564	0.523	0.481	0.440	0.399
	0.1	0.797	0.756	0.715	0.674	0.632	0.591	0.550	0.509	0.468	0.427	0.386
	0.2	0.783	0.742	0.701	0.660	0.619	0.578	0.537	0.496	0.455	0.413	0.372
	0.3	0.770	0.729	0.688	0.647	0.606	0.565	0.523	0.482	0.441	0.400	0.359
	0.4	0.757	0.716	0.674	0.633	0.592	0.551	0.510	0.469	0.428	0.387	0.346
λ^{prog}	0.5	0.743	0.702	0.661	0.620	0.579	0.538	0.497	0.456	0.414	0.373	0.332
	0.6	0.730	0.689	0.648	0.607	0.565	0.524	0.483	0.442	0.401	0.360	0.319
	0.7	0.717	0.675	0.634	0.593	0.552	0.511	0.470	0.429	0.388	0.347	0.305
	0.8	0.703	0.662	0.621	0.580	0.539	0.498	0.456	0.415	0.374	0.333	0.292
	0.9	0.690	0.649	0.607	0.566	0.525	0.484	0.443	0.402	0.361	0.320	0.279
	1	0.676	0.635	0.594	0.553	0.512	0.471	0.430	0.389	0.347	0.306	0.265

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