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A new focus on risk reduction: an ad hoc decision support system for humanitarian relief logistics

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Abstract. Particularly in the early phases of a disaster, logistical decisions are needed to be made quickly and under high pressure for the decision-makers, knowing that their decisions may have direct consequences on the affected society and all future decisions. Proactive risk reduction may be helpful in providing decision-makers with optimal strategies in advance. However, disasters are characterized by severe uncertainty and complexity, limited knowledge about the causes of the disaster, and continuous change of the situation in unpredicted ways. Following these assumptions, we believe that adequate proactive risk reduction measures are not practical. We propose strengthening the focus on ad hoc decision support to capture information in almost real time and to process information efficiently to reveal uncertainties that had not been previously predicted. Therefore, we present an ad hoc decision support system that uses scenario techniques to capture uncertainty by future developments of a situation and an optimization model to compute promising decision options. By combining these aspects in a dynamic manner and integrating new information continuously, it can be ensured that a decision is always based on the best currently available and processed information. And finally, to identify a robust decision option that is provided as a decision recommendation to the decision-makers, methods of multi-attribute decision making (MADM) are applied. Our approach is illustrated for a facility location decision problem arising in humanitarian relief logistics where the objective is to identify robust locations for tent hospitals to serve injured people in the immediate aftermath of the Haiti Earthquake 2010.

Key words: *ad hoc decision support; humanitarian relief logistics; information and communication technology; multi-criteria decision analysis; public safety-critical supply chains; robustness; scenario techniques.*

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Introduction

Definitions of critical infrastructure (CI) have been primarily proposed by national governments and international institutions (Abou El Kalam et al. 2009, Schätter et al. 2014). 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). According to Kröger (2008), CIs are the backbone of our society. The European Commission distinguishes between the CI sectors of energy, information and communication technology, finance, health care, food, water, transportation, production, storage and transport of dangerous goods, and government (European Commission 2004). Although any CI sector is denoted as a critical "infrastructure," several sectors are not "infrastructures" in the proper meaning of the word; rather, they are supply chains (SCs) that are responsible for the delivery of "essential products or services" (European Commission 2004). These SCs are denoted in the following as public-safety-critical SCs (P-SCs), as they threaten, when disrupted or destroyed, the vital welfare of people in the affected society (Braubach 2011, Lin et al. 2011, Herlin and Pazirandeh 2012). P-SCs mainly arise within the CI sectors food, water, health care, and energy. Parts of a P-SC may be highly interconnected to

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parts of further CI sectors such as built assets (i.e., roads referring to the CI sector transportation are required for distribution logistics of a food P-SC) and social infrastructure (i.e., personnel to operate medical facilities). This paper is concerned with all parts of a P-SC and interrelated CI sectors that ensure the functioning of distribution logistics in a P-SC.

Disturbances of CI sectors in terms of P-SCs have become an important topic in the domain of humanitarian relief logistics that focus on the provision of food, water, medicine, shelter, and supplies to areas affected by large-scale emergencies (Comes et al. 2015). Developed approaches to support decision-makers in establishing humanitarian relief SCs mostly concentrate on the early phase (response phase) of the emergency, which usually comprises the first 72 hours. Humanitarian relief SCs are required to supply relief goods and services as quickly as possible in order to minimize human suffering and death (Balcik and Beamon 2008). The management of humanitarian relief SCs is crucial, as the distribution of relief goods from different sources to the destination where they are most urgently needed (Afshar and Haghani 2012) is typically restricted by a highly uncertain and even complex environment. Uncertainty basically refers to the unknown or even dynamically evolving state of CIs. To respond to uncertainty and complexity, humanitarian relief SCs need to be designed in a manner that allows being somehow "immune" to uncertain CI states. Coupling effects are crucial in this regard: humanitarian relief SCs as a CI itself (in terms of P-SCs) need to respond to the direct CI disturbance (i.e., food shortages) while managing the disruption of further CIs (i.e., road networks; Boin and McConnell 2007). This overwhelming uncertainty and complexity are the reasons why computational models from operations research have become increasingly important in the context of disaster management to analyze large amounts of information (Comes et al. 2015). To handle uncertainty, approaches with a focus on distribution logistics as essential elements of humanitarian relief supply chain management have been developed that process uncertainty by stochastic elements. This comprises, inter alia, facility location problems (i.e., Balcik and Beamon 2008), network flow problems (i.e., Barbarosoğlu and Arda 2004), and vehicle-routing problems (i.e., Van Hentenryck et al. 2010). An extensive review of approaches from operations research with a focus on distribution logistics in disaster management is provided by Rennemo et al. (2014). Although these approaches have been tested successfully in many decision-analytic settings with a focus on disaster management, it is frequently hard for decision-makers to understand their rationales. This is a crucial aspect, as decision support (provided by the optimization models) must assist decision-makers under extreme circumstances in terms of stress, time pressure, and personal biases. We believe that there is a need for a decision support methodology regarding the management of humanitarian relief SCs that is (indeed based on methods from operations research) transparent and easily to understand by the decision-makers.

Causes of disturbances in the distribution logistics of a P-SC are frequently located outside a P-SC and can be a naturally, technologically, or intentionally triggered hazardous event (Kolves et al. 2013). Disturbances may affect any flow (physical and nonphysical) in a P-SC and lead to a mismatch between supply and demand that potentially hinders the functioning of the whole P-SC (Jüttner et al. 2003, Merz 2011). Consequences of climate change in combination with social trends (i.e., urbanization, population growth) increase the vulnerability of societies to hazardous events steadily (Comes et al. 2015). Natural hazards refer to forces of nature, technological hazards are produced by man-made technology or unplanned and non-malicious actions, and intentional hazards are created by intentionally executed actions (ICDRM 2010). To protect a society from the negative consequences of P-SC disturbances concerning distribution logistics, adequate disaster management measures need to be implemented in both periods of the occurring hazardous event: its origin and aftermath. Proactive disaster management is targeted at developing and implementing risk mitigation measures in advance and refers to the reduction of the vulnerability of a society and/or of occurrence probabilities of hazardous events (cf. Merz 2011). Ad hoc disaster management focusses on the immediate aftermath of the event to protect society from or reduce already triggered negative consequences.

This paper presents the rationale of a decision support system (DSS) that is tailored to the ad hoc disaster management of distribution logistics in a hazard-affected P-SC. Indeed, proactive efforts of risk reduction are essential, e.g., to provide decision-makers with optimal risk mitigation strategies in advance of a hazardous event to establish redundant systems or plans in the energy sector or in the case of disturbances of food SCs. However, disaster situations are typically faced with severe uncertainty and a continuous change of the situation over time, and unpredictable behaviors of the sociocultural environment and consequences on interrelated CI sectors. In particular, dynamic developments are difficult to forecast by decision-makers, as they make the decision situation complex or even chaotic. Anticipating such developments from scratch and without any real information as a "clue" is simply not feasible. Proactively developed strategies are tailored for hypothetical situations without any guarantee that just parts of the assumption will occur in reality. It is thus likely that these strategies will rarely meet the requirements in the actual disaster (and decision) situation. Instead, we suggest strengthening the focus on the real-time processing of already available data to reveal information and uncertainty in the immediate aftermath of a hazardous event. Therefore, decision-analytic tools are required to make use of the, no doubt short, but nevertheless available, period of time until decisions need to be implemented. We believe that an ad hoc-generated decision recommendation will be more beneficial than proactive strategies that have been probably developed under wrong, or at least inadequate (as not anticipatable), assumptions of information.

The remainder of this paper is organized as follows. In the *Ad hoc disaster management for P-SC protection* section, the scope of ad hoc disaster management for the protection of P-SCs, and in particular, of its distribution logistics, are highlighted. The section *An ad hoc decision support system* presents the rationale of the DSS. Uncertainty is revealed based on already available data and further processed by a new forecasting methodology (iterative–dynamic scenario construction). Based on scenarios that process available information, feasible alternatives are determined by an optimization model. By answering the question "What could happen to these alternatives?" vulnerable parts in the decision environment are individually identified for each alternative to reveal weaknesses of the alternatives. The objective of the DSS is to provide decision-makers with a robust decision recommendation that responds adequately to uncertain conditions and flexible to dynamic developments in the environment when the identified alternative-specific vulnerable parts are disturbed. In the section *Illustrative example: compensation strategies in humanitarian relief logistics*, the DSS is briefly illustrated for a decision situation arising in humanitarian relief logistics where preexisting P-SCs completely collapse. The paper closes with a conclusion and future research recommendations in the section *Conclusion and future research*.

Ad Hoc Disaster Management for P-SC Protection

To protect P-SCs or to reduce the consequences of already triggered P-SC disturbances, various decisions need to be made depending on the specific disaster and decision situation. Possible decisions in ad hoc disaster management can be deviated from the planning tasks of commercial supply chain management (SCM). Decision problems in distribution logistics (and thus for the management of a P-SC) are in general classified dependent upon the planning horizon and the addressed management level (Günther and Tempelmeier 2012). Strategic decisions deal with the strategic design of SCs (i.e., facility locations, physical distribution structures), tactical decisions refer to the planning of SC networks (i.e., capacity planning, distribution planning), and operational decisions focus on the execution of certain logistical operations (i.e., transport planning) (Hertel et al. 2011). Various models from operations research have been developed and applied in SCM, such as inter alia, facility location models, vehicle-routing models, and network flow models (Schwindt and Trautmann 2003). There are various solution algorithms (exact algorithms, heuristics) associated with these models to determine optimal solutions. Optimization problems differ in their specification, i.e., single-objective or multi-objective optimization problems that are solved for fixed data (deterministic optimization problems) or under uncertainty (stochastic optimization problems, robust optimization problems). The following assumes that ad hoc disaster management is able to process any of the highlighted decision problems. Furthermore, an appropriate optimization model and solution algorithm is available to solve the problem and to generate optimal respectively Pareto optimal solutions.

Adaptation and compensation strategies

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 weather 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 situation where a hazardous event 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 extraordinary 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 hazardous event, is disrupted or delayed because interrelated CI sectors and P-SCs fail and consequences cascade through the network.

We distinguish between two severity levels in the consequences to P-SCs: disruptions and destructions of P-SCs. In the case of the first severity level, the scope of ad hoc disaster management is to develop *adaptation strategies* (ASs) whose implementation strengthens the functioning of disrupted P-SCs. In this case, public safety has not been directly affected; the objective thus is rather to prevent society from being affected by belated consequences. In the case of the second severity level, ad hoc disaster management needs to reestablish P-SCs rapidly. *Compensation strategies* (CSs) are required to temporarily bypass unavailable P-SCs with replacement

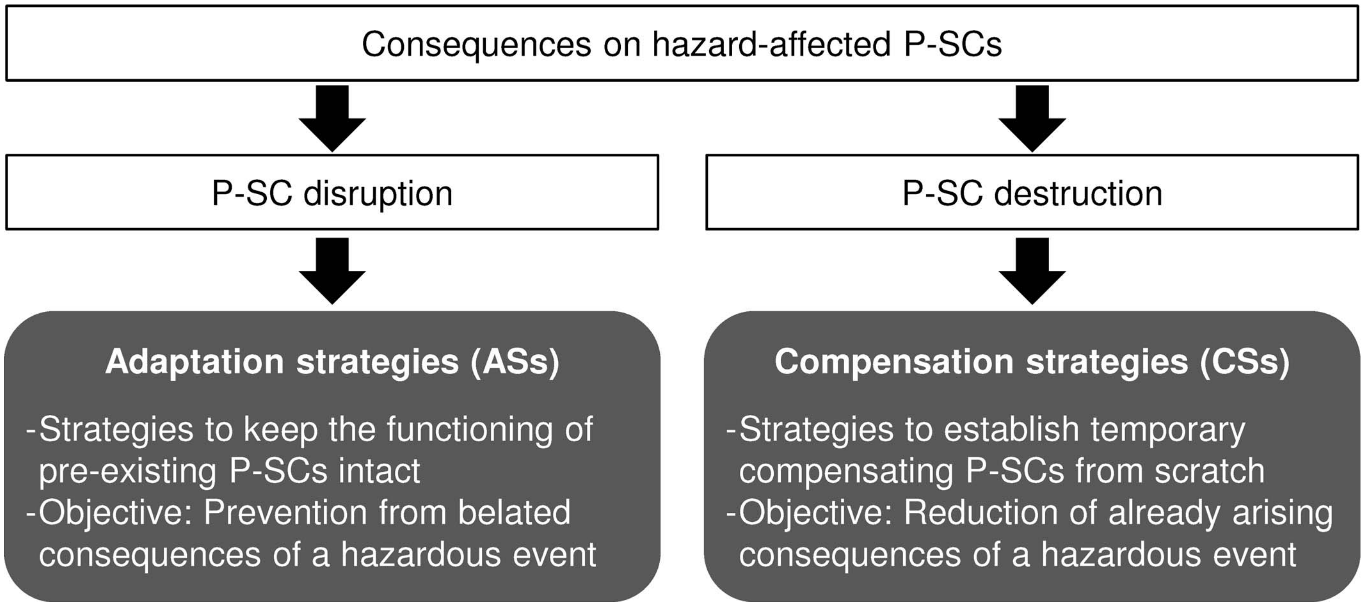

Fig. 1. Adaptation and compensation strategies.

structures (compensating P-SCs) that take over the functions of preexisting P-SCs. As the hazardous event has, in this case, already triggered severe consequences, the objective of CSs is to reduce further deterioration of the situation. In several situations, both ASs and CSs are required; for example, when several nonredundant P-SCs fail and need to be replaced, while further P-SCs can be kept functioning with adequate ASs.

Specifications of ASs depend on the situational context and the underlying decision problem. ASs can principally be any decision problem already highlighted. CSs theoretically refer to any decision problem as well; as opposed to ASs, however, the strategic network design of compensating P-SCs arises from a higher priority than network planning (tactical decision problems) and network operation strategies (operational decision problems). This is because time is a crucial restriction for ad hoc disaster management, 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. Fig. 1 summarizes the scope and objectives of ASs and CSs.

Uncertainty in ad hoc disaster management

The Oxford dictionary defines uncertainty as "the state of being uncertain," where uncertain means "not able to be relied on; not known or definite" (Oxford English Dictionary 2010, Liberatore et al. 2013). In decision-making, uncertainty is strongly related to having no knowledge about a situation. A state of knowledge and finally, certainty, in turn, is reached when relevant information about this situation becomes available. Consequently, uncertainty is caused by a lack of knowledge due to a lack of information. The relevant source of uncertainty in ad hoc disaster management is exogenously and is, opposed to inherent uncertainty within any SC, triggered by a hazardous event. As highlighted by Sowinski (2003), hazardous events are "the embodiment of randomness. You don't know when they're going to happen, where it's going to happen, and who's going to be affected. [...] Every other supply chain is based on predictability." This statement points to the major features of exogenous uncertainty: unpredictability and randomness. It has to be noted that this unpredictability and randomness mainly refers to unknown consequences caused by a hazardous event. The occurrence likelihood of a hazardous event is, to a certain degree, measurable and thus, predictable. For example, seismological measurements create a relatively accurate forecast of the time and intensity of a volcanic eruption.

The criticality of exogenous uncertainty in disaster management has been addressed by various authors (de la Torre et al. 2012, Liberatore et al. 2013, Rennemo et al. 2014). In terms of P-SCs, exogenous uncertainty can affect the demand and supply sides of P-SCs. Demands, which are volatile even under "normal" conditions, are difficult to forecast when exogenous uncertainty increases. Uncertainty affecting the demand side refers to either or both unknown spatial distributions (i.e., demand locations in remote areas) or demand mixes and volumes (i.e., product specifications and quantities; de la Torre et al. 2012, Rennemo et al. 2014). Dynamic developments in the hazard-affected environment (i.e., movements of people to less affected areas) causing demand fluctuations and hamper demand estimations even amplify uncertainty (de la Torre et al. 2012, Rennemo et al. 2014). On the supply side, exogenous uncertainty hinders logistical operations in procurement and distribution. Procurement operations are faced by delays of supplies or increased product prices due to product scarcities or unavailable suppliers (de la Torre et al. 2012, Liberatore et al. 2013). As a result, affected entities are hindered in their own distribution operations, which probably results in negative consequences for downstream entities.

The predictability of consequences on any CI sector decreases when exogenous uncertainty increases (Liberatore et al. 2013, Comes et al. 2015). In particular, the CI sector transportation is crucial for the functioning of P-SCs (de la Torre et al. 2012, Liberatore et al. 2013, Rennemo et al. 2014). Transportation infrastructure comprises all edges and nodes in the transportation network (i.e., roads, railroads, airports, ports) and all transportation modes that facilitate 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 intact transportation infrastructure, states and conditions determine (to a certain degree) how robust, flexible, or resilient P-SCs can be (Madhusudan and Ganapathy 2011). Moreover, information and communication technology (ICT) systems play a major role in reducing exogenous uncertainty, as providing the right information in the right format at the right time to the right people (Fletcher 2002, Comes et al. 2015). From the IT perspective, ICT systems gather, synthesize, and interpret information; from the communication perspective, ICT systems transmit this information to persons responsible (i.e., decision-makers; Leidner et al. 2009). When exogenous uncertainty is gross, information (if available) is expected to be heterogeneous in terms of format and quality (Schätter et al. 2014, Comes et al. 2015). ICT systems therefore need to be stable and reliable in the handling of information arising from multiple sources, in filtering valid information for logistical purposes, and in communicating this information to decision-makers (Comes et al. 2015).

An Ad Hoc Decision Support System

Decision processes that operate under uncertainty typically comprise (1) the definition of the decision problem, (2) uncertainty handling, and (3) identification and evaluation of alternatives (Scholl 2001, Domschke and Scholl 2003, Fleischmann et al. 2004).

1) Decision problem definition: Initially gathered information highlights the considered decision problem. Based on this information, the problem is defined by determining objectives, assumptions, and restrictions. If the decision situation is highly complex, the decision problem can be optionally subdivided into various subproblems. Additionally, preferences of the involved decision-makers concerning the objectives may be already specified in this step (cf. Scholl 2001, Domschke and Scholl 2003).

2) Uncertainty handling: Capturing and managing uncertainty is the essential task of an uncertainty model that is integrated into the decision process. As exogenous uncertainty is seen as the relevant type of uncertainty, this model needs to be coupled with an information-processing tool in order to reveal uncertainty from insufficient input information flows (Zimmermann 2000). Captured uncertainty needs to be processed by forecasting models (i.e., simulation models) to determine current uncertain situation states and possible future developments (cf. Zimmermann 2000, Domschke and Scholl 2003).

3) Identification and evaluation of alternatives: This part comprises the search for alternatives to solve the decision problem, their evaluation, and finally, the selection of an alternative that is provided as a decision recommendation to the decision-makers (Domschke and Scholl 2003, Fleischmann et al. 2004). Alternatives can have a qualitative (i.e., linguistic descriptions) or quantitative character (i.e., numerical amounts of optimal network flows). Qualitative alternatives are typically generated in a systematic and “creative” process by taking into account one or more objectives. This process can be supported by collaborative approaches (i.e., by expert panels; Schätter et al. 2014). As a result, a discrete and finite set of feasible alternatives is identified. Evaluations of these alternatives need to take revealed uncertainty and the possible conflicting preferences of the decision-makers into account. In contrast, quantitative alternatives can be generated by using models from operations research (cf. Scholl 2001, Domschke and Scholl 2003). The formulation of this optimization model (objective function[s], set of constraints) implicitly specifies a continuous set of feasible alternatives. A solution algorithm is applied to filter solutions out of the continuous set of feasible alternatives. Either heuristics or exact algorithms are useable. While the first produces a compromise solution based on the preferences of the decision-makers prior to the optimization, the latter provides Pareto optimal solutions. If the latter case occurs, additional preferential information from the decision-makers is required ex post to select the appropriate alternative (Shin and Ravindran 1991).

The next sections present the rationale of a DSS for ad hoc disaster management that is oriented toward this decision process. Already available data is processed by an uncertainty model that includes an iterative–dynamic scenario construction methodology. The DSS is explicitly designed for generating quantitative alternatives (robust ASs and CSs) by using an optimization model. Due to the complex or even chaotic features of disaster

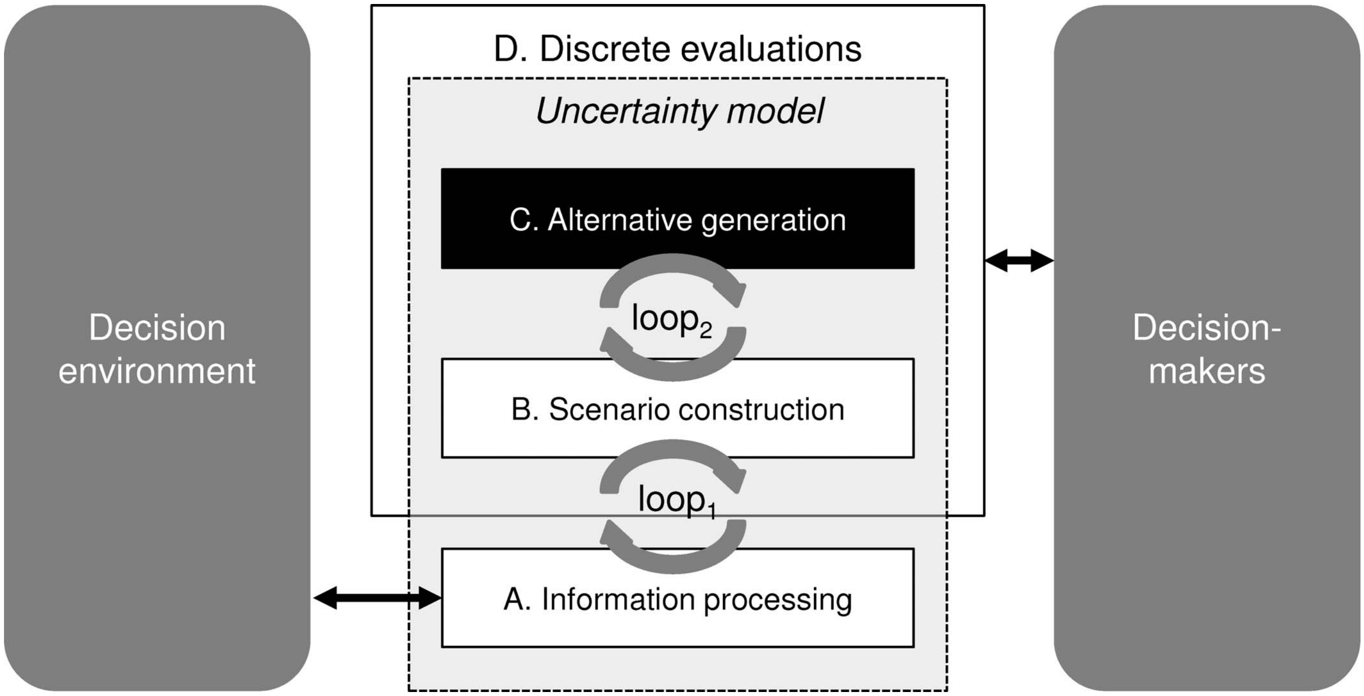

Fig. 2. Rationale of the decision support system.

situations, we believe that standard approaches from operations research handling uncertainty ex post (i.e., sensitivity analysis) or explicitly within the optimization model formulation (i.e., stochastic optimization, robust optimization) are not suitable. For more information concerning this discussion, we refer to previous work presented in Schätter et al. (2013). The DSS includes a methodology that processes the consequences of feasible alternatives into advanced scenarios to anticipate stepwise alternative-specific dynamic developments in the decision environment. The objective is to identify an alternative that fulfils the requirement of robust decisions in literature: performing sufficiently well under all uncertain situation specifications and under (usually) situations that have non-foreseeable changes in the future (Wallenius et al. 2008, Comes 2011, Schätter et al. 2013).

Rationale

The DSS is an interface between the decision environment and the decision-makers. Core element is an uncertainty model that includes the iterative–dynamic scenario construction methodology. The DSS comprises four layers: (A) an information processing layer, (B) a scenario construction layer, (C) an alternative generation layer, and (D) a discrete evaluations layer (see Fig. 2). Layer A ensures the communication between the DSS and the decision environment to gather and process already available information. Based on this information, basis scenarios are constructed in layer B to reveal uncertainty concerning the status quo decision situation. For each scenario, optimal alternatives are determined in layer C using the appropriate optimization model for the underlying decision problem. Layers B and C are embedded in layer D to continuously evaluate obtained alternatives. To explore dynamic developments within the situation, alternative-specific advanced scenarios are iteratively constructed (loop 1). In this way, weaknesses, vulnerabilities, and the flexibility of the determined alternatives are investigated. Loop 1 stops when a (defined) amount of new information arises in the decision environment that is again processed in layer A (loop 2). In this manner, it is guaranteed that scenarios are always based on the best currently available information. The interface between the DSS and the decision-makers ensures that their preferences concerning the objectives are taken into account when generating and/or evaluating the alternatives. The iterations stop when the decision deadline has been reached and a decision recommendation needs to be provided to the decision-makers.

The DSS is designed in a generic manner and is principally suitable for all decision problems highlighted in the previous sections. Instead of integrating uncertainty directly into the optimization model formulation (stochastic optimization models) or determining a robust alternative by a singularly defined set of scenarios (robust optimization models), the DSS is instead targeted at generating a set of feasible alternatives for a set of basis scenarios (by a deterministic optimization model) covering the available data and uncertainty. These feasible alternatives are further analyzed by advanced scenarios to explore dynamic developments in the environment. As the appropriate optimization model depends on the underlying decision problem, layer C can be understood as "black box" of our DSS. Various deterministic single- or multi-objective optimization models can be used in this layer. Feasible alternatives are evaluated in terms of their behavior in any situation specification (basis scenarios) and their flexibility to perform sufficiently well despite alternative-specific dynamic developments in the environment (advanced scenarios). Thus, to measure robustness, the performance of alternatives (regarding all considered objectives) is required when being applied to all constructed scenarios.

Iteration loops to construct basis and advanced scenarios

The construction of basis scenarios starts when the first information about the decision situation is available. Due to knowledge gaps concerning the current state of the decision situation, available information is processed and uncertainty is revealed within a set of basis scenarios S. Scenario constructions follow the definition given in Hites et al. (2006), who understand a scenario $\mathbf{s}$ as a vector in $\mathbf{R}^n$, which consists of n uncertain parameters. The ith coordinate of the vector specifies one of the possible values for the ith uncertain parameter. Thus, a scenario $\mathbf{s} \in S$ contains a combination of possible parameter values. In our previous work, Schätter et al. (2014) presented a scenario framework where parameters are specified by scenario variables (SVs) that are classified into scenario variable classes (SVC_{1-3}). The classification of a SV to SVCs depends on its individual state. SVC_1 includes SVs whose specifications are known with certainty as information becomes deterministic. Epistemic uncertain parameters are specified by SVC_2 (uncertainty due to a lack of knowledge) and aleatory uncertain parameters are specified by SVC_3 (uncertainty due to random effects; Schätter et al. 2014, Senge et al. 2014). Loop 1 thus couples layers A and B to ensure that scenarios are plausible depending on available exogenously gathered information.

For each $s \in S$, an optimal alternative is determined by solving the scenario-specific optimization model formulation in layer C, which leads to a set of alternatives A. Due to dynamic developments in the decision environment, we suggest switching the focus from forecasting the future to observing consequences when concrete alternatives are applied to the decision environment. Therefore, alternative-specific vulnerable parts in the environment (i.e., disturbances of interrelated CIs in the environment, behaviors of the sociocultural society) are identified and disturbed within advanced scenarios to investigate the behavior of the underlying alternative. In fact, a set of future scenarios SS^a is constructed for each alternative $a \in A$. As long as no information updates arise in layer A, loop 2 is conducted iteratively to increase the knowledge about the alternatives. By reusing the optimization model in layer C, further alternatives are generated for scenarios in SS^a that can be further investigated by more advanced scenarios. In this way, a large portfolio of feasible alternatives is provided. In the case that information updates are available in layer A, loop 2 stops. Basis scenarios S are updated by processing the new information and again using the scenario variable framework (Schätter et al. 2014). Loop 2 thus couples layers B and C to ensure that scenarios are plausible as depending on available endogenously gathered information.

Discrete evaluations to deviate robust decision recommendations

Layer D continuously evaluates alternatives in order to provide the most robust alternative as decision recommendation to the decision-makers. An alternative, $a_r \in A$, is a robust alternative if it performs sufficiently well across all scenarios S and responds flexibly to alternative-specific disturbances in alternative-specific advanced scenarios SS^{a_r}. Discrete evaluations are conducted sequentially, immediately after finishing loop 2 and before starting loop 1 to process information updates into S. Decision-makers thus receive transparent information such as the rankings of alternatives or key drivers for advantages and weaknesses of alternatives (Schätter et al. 2013). Robustness measurements comprise the two aspects of stability and quality of results (Comes 2011); in our DSS, results are the performance values (concerning each objective) when an alternative is applied to any scenario. Indicators measuring the stability of performance values refer to "relative" objectives. The question is addressed how flawed or defective the situation (scenarios) can be without jeopardizing the performance's quality (Hites et al. 2006, Comes 2011). In $Z = \{z_j\}_{j=1,\dots,n}$, let n be objectives integrated in the optimization model formulation in layer C (if $n = 1$, a single-objective optimization model is used; if $n > 1$, a multi-objective optimization model is used) and B^{z_j} a performance "quality threshold" that needs to be reached by any alternative in any scenario concerning objective z_j (determined by the decision-makers). Moreover, $\mathbf{P}^{\mathbf{Z}}(a_i,S)$ is a $n \times m$ matrix of performance values when an alternative $a_i \in A$ is applied to all basis scenarios $S = \{s_1, \dots, s_m\}$ and $\mathbf{P}^{Z}(a_i,SS^{a_i})$ is an $n \times l$ matrix of performance values when an alternative $a_i \in A$ is applied to all advanced scenarios $SS^{a_i} = \{ss_1^{a_i}, \dots, ss_l^{a_i}\}$.

Three indicators (I_{1-3}) are defined to measure the robustness of $a_i \in A$ by considering the performance value vectors $\mathbf{P}^{z_j}(a_i,S)$ and $\mathbf{P}^{z_j}(a_i,SS^{a_i})$ for each $z_j \in Z$. I_1 is the *maximal deviation* of the worst (minimal or maximal) performance value of a_i in any scenario in S or SS^{a_i} from

Table 1. Results for basis scenarios.

Alternative, a	$\max(\mathbf{P}^{z_1}(a_i, S))$ (h)	$\min(\mathbf{P}^{z_1}(a_i, S))$ (h)	$I_1(a_i, S)$ (h)	$I_2(a_i, S)$ (h)	$I_3(a_i, S)$ (%)
a_1	38 184	30 431	3184 (N:0)	−2589 (N:1)	20 (N:0)
a_2	34 789	30 228	−211 (N:1)	−2402 (N:0)	0 (N:1)

Notes: Abbreviations are: ($\mathbf{P}^{z_1}(a_i,S)$), performance values regarding objective z_i that is achieved by alternative a_i across all scenarios of the set S; and $I_i(a_i, S)$, value of indicator 1, 2, or 3 achieved by alternative a_i across all scenarios of the set S. Values in parentheses show normalized values (1 or 0).

B^{z_j}; I_2 is the *mean deviation* of all performance values of a_i in each scenario in S or SS^{a_i} from B^{z_j}; I_3 is the percentage *failure rate* of performance values that are worse than B^{z_k}. The indicators fulfill the requirements in literature: being clearly measureable, relevant, analytically and statistically sound, based on available data, and easy to interpret (Birkmann 2006, Merz 2011). As the indicator values are determined for each objective $z_j \in Z$ and probably include different units, methods of multi-attribute decision-making (MADM) are applied to make the obtained indicator values comparable. When, e.g., using the MADM-approach multi-attribute value theory (MAVT), indicator values are normalized to the interval [0, 1]. The exact specification of this normalization depends on the preferences of the decision-makers. Subsequently, the relative importance of the indicators and objectives are weighted (by interacting again with the decision-makers) to finally generate an aggregated robustness measure $R(a_i)$. For more information concerning MAVT, reference is made to Bertsch (2008).

Illustrative Example: Compensation Strategies in Humanitarian Relief Logistics

This section illustrates the importance of splitting scenarios into basis and advanced scenarios for robustness measurements. We consider a decision problem arising in humanitarian relief logistics after the Haiti Earthquake 2010. Most P-SCs were completely destructed and CSs (relief supply chains) were immediately required to provide beneficiaries with relief supplies (relief goods, i.e., food, nonfood, medical supplies, or equipment). In essence, the considered strategic decision problem was a facility location problem (FLP) that was targeted at identifying the three most robust spatial locations (as decision variable of the optimization model formulation) in Haiti to set up temporary tent hospitals. The optimization problem was a minimization problem and optimized the sum of transportation times (objective: efficiency) that was required to transport beneficiaries to the tent hospitals to satisfy their needs of medical support. The constraints included the objective to achieve a complete (100%) service level (objective: effectiveness); as this objective specified within the constraints, the optimization problem was formulated as a single-objective optimization problem ($Z = z_1$). Haiti is divided into 42 sections (corresponding to the arrondissements). It was assumed that demands concentrate in the most populated city in each section; travel times thus were determined by GPS data between these cities and specify a 42×42 matrix.

We took data from the previous draft versions of our case study; there, the objective was to highlight the challenges of humanitarian relief logistics and the possibilities to identify alternative-specific vulnerable parts in a disaster environment (i.e., by investigating possibilities of unpredictable movements of people to less-affected sections and critical damages in transportation infrastructures; Comes et al. 2013, 2015). In the following, we present two exemplary results of an updated version of this case study to demonstrate the relevance of the iterative-dynamic scenario construction methodology for robustness measurements and to show directions of future research. The earthquake's epicenter was located near the capital city Port-au-Prince. By capturing the first available information (affected regions, population, and implied worst-case demands for medical support in each section), a set of 20 basis scenarios $S = (s_1, \ldots, s_{20})$ is constructed. For the fixed data of each $s_k \in S$, the optimization problem is solved, leading to a set of 13 feasible alternatives. We will discuss the results we obtained after one loop 2 iteration for the two alternatives a_1 = {Limbé, Gonâve, Port-au-Prince} and a_2 = {Gonâve, Port-au-Prince, Jacmel}.

When performance values of a_1 and a_2 across all scenarios in S are generated, each performance value vector $\mathbf{P}^{z_1}(a_1,S)$ and $\mathbf{P}^{z_1}(a_i,S)$ contains 20 values. We chose the performance quality threshold $B^{z_1} = 35\,000$ hours. Table 1 summarizes the (absolute) results of indicator values for I_{1-3}. As just one objective and two alternatives are considered, normalizations are trivial: the better value of each indicator is set to 1, the remaining value is set to 0. Furthermore, for simplification we assumed the same weights for each indicator, and obtain the robustness measures

$$R(a_1, S) = \frac{0 + 1 + 0}{3} = 0.33$$

and

$$R(a_2, S) = \frac{1 + 0 + 1}{3} = 0.67.$$

Thus, a_2 is the robust alternative regarding S and is provided as decision recommendation to the decision-

Table 2. Results for advanced scenarios.

Alternative, a	$\max(\mathbf{P}^{z_1}(a_i, SS^{a_i}))$ (h)	$\min(\mathbf{P}^{z_1}(a_i, SS^{a_i}))$ (h)	$I_1(a_i, SS^{a_i})$ (h)	$I_2(a_i, SS^{a_i})$ (h)	$I_3(a_i, SS^{a_i})$ (%)
a_1	50 028	34 421	15 028 (N:1)	7 648 (N:1)	83 (N:1)
a_2	54 633	38 918	19 633 (N:0)	12 617 (N:0)	100 (N:0)

Notes: Abbreviations are: $\mathbf{P}^{z_1}(a_i, SS^{a_i})$, performance values regarding objective z_i that is achieved by alternative a_i across all scenarios of the set SS^{a_i}; and $I_i(a_i,SS^{a_i})$, value of indicator 1, 2, or 3 achieved by alternative a_i across all scenarios of the set SS^{a_i}. Values in parentheses show normalized values (1 or 0).

makers.

This solution changes when additionally taking into account alternative-specific advanced scenarios SS^{a_1} and SS^{a_2}. In total, six advanced scenarios were determined per alternative ($SS^{a_1} = \{ss_1^{a_1}, \ldots, ss_6^{a_1}\}$ and $SS^{a_2} = \{ss_1^{a_2}, \ldots, ss_6^{a_2}\}$). Advanced scenarios include alternative-specific disturbances of critical roads around the computed facility locations. The results are summarized in Table 2. It becomes obvious that almost all performance values exceed B^{z_1}. After determining indicator values, the robustness measures are $R(a_1,SS^{a_1}) = 1$ and $R(a_2,SS^{a_2}) = 0$. Hence, the new decision recommendation (a_1) is opposite to the former recommendation (a_2) when exclusively considering advanced scenarios. Implications of this result are discussed in the next section and directions of future research are deviated.

Conclusion and Future Research

Our illustrative example highlights the fact that results (robust decision recommendations) can be completely contrary when additionally considering alternative-specific dynamic developments in the environment. The iterative–dynamic scenario construction methodology is an essential step within the ad hoc DSS to systematically explore (formerly) non-anticipatable situation specifications as it is postulated for robust decision-making. However, the possibility of exactly getting results as highlighted shows the crucial challenge for future research: How do we finally assess the results for S compared to SS^{a_i}? When reconsidering the results of the example, intuitively, two possibilities exist. First, as we do not assume any probabilities for the scenarios, the results are weighted by the number of scenarios in S and SS^{a_i}. In this case, the overall robustness measures are

$$R(a_1) = \frac{20}{26}0.33 + \frac{6}{26}1 = 0.48$$

and

$$R(a_2) = \frac{20}{26}0.67 + \frac{6}{26}0 = 0.51$$

and a_2 is recommended to the decision-makers. Second, both categories, basis scenarios and advanced scenarios, are weighted equally regardless the absolute number of scenarios within each category. Then, the overall robustness measures are

$$R(a_1) = \frac{1}{2}0.33 + \frac{1}{2}1 = 0.66$$

and

$$R(a_2) = \frac{1}{2}0.67 + \frac{1}{2}0 = 0.33$$

and a_1 is the decision recommendation.

Future research therefore needs to develop an adequate solution for this issue. In fact, it is important to integrate the risk preferences of the decision-makers who must make decisions about the importance of basis and advanced scenarios. For example, a decision-maker who is highly risk averse would probably follow a decision that hedges against cases specified by advanced scenarios, while a risk-neutral decision-maker instead uses the results from the basis scenarios. Here, it is important to develop measures that can be integrated into the regret value evaluation and that allow the adjustment of individual risk preferences. In this regard, future research should particularly focus on limitations of integrating risk preferences such as the analysis of sensitivities when risk preferences change over time.

In humanitarian relief logistics literature, multiple-use cases have been presented that apply stochastic and robust optimization models to handle uncertain input data. We believe that such optimization models imply two major drawbacks. First, the adequacy of the computed results and the robust decision recommendation can only then be ensured when the underlying uncertain data, and thus, the considered set of scenarios is complete, which is hardly achievable in a decision situation under severe uncertainty and complexity. Secondly, while stochastic optimization models typically neglect "worst case" scenarios in the assessment of different candidate solutions, robust optimization models overstate such "worst case" scenarios, and thus produce "conservative" robust decisions that may perform ineffectively in further scenarios. Concerning these drawbacks, our approach permits a higher degree of flexibility. As the considered set of scenarios can never be complete, the approach allows systematically probing in the decision situation. Candidate alternatives are exclusively computed for basis scenarios, which reduces the risk of producing ineffective (as worst case oriented) alternatives. Potential worst case scenarios are designed in an alternative-specific manner that allows a certain sense of "stress testing" each alternative individually against its possible worst case scenarios. In this regard, it is highly important to compare the results provided by our methodology with results that are generated when "traditional" stochastic or robust optimization models are used to process the problem.

The DSS is designed for ad hoc disaster management. As it is almost impossible to use draft versions of the DSS in reality, further case studies need to be developed specifying decision situations that can be tested under real-time conditions. Thus, the conception and execution of time-pressured experiments will be a further scope of future research. A possible setting for such an experiment is to split test persons into two groups. The first group receives information about the disaster environment without any technical support; the second group uses (parts of) the DSS. Hence, two aspects can be observed: advantages, weaknesses, critical parts, and operating limitations of the DSS, and the comparison of the achieved absolute results by both groups. Finally, a second case study will be developed referring to the development of ASs in terms of business continuity management. Therefore, the DSS will be applied in the German research project Entscheidungsunterstützung zur Bewältigung von Versorgungsengpässen (SEAK), which concentrates on scenario-based decision support for managing disruptions of food supply chains in Germany. In various expert interviews with German food supply companies, the following risks for food shortages in Germany were most often mentioned: heat waves, blackouts in IT-systems, and staff absence. A draft version of a second case study has been designed regarding the category of staff absence. The conception was developed to protect a society from threatening food shortages due to a flu epidemic in Berlin, Germany. An optimization model focuses on the distribution of available staff under the restriction of uncertain demand shifts of the population. Future research will particularly concentrate on the implementation of this case study by following the rationale of the DSS as presented in this paper.

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