Building robust supply networks for effective and efficient disaster response

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ABSTRACT

The effective and efficient distribution of relief goods is a key challenge in disaster management. Typically, ad-hoc supply networks (SNs) need to be built, in which various actors with different interests collaborate. Although information is sparse and highly uncertain, time for SN design is short, and important strategic decisions (e.g., location of facilities), whose revision requires investing substantial time, effort and resources, must be made promptly. This paper presents an iterative approach for the design of robust SNs that combines (i) an optimisation model to identify promising alternatives to be analysed in detail, (ii) a scenario-based approach to analyse the weaknesses of these alternatives and generate alternative solutions for comparison and benchmarking, and (iii) a decision support module for detailed comparisons and consensus building. By following the iterative approach, successively robust SNs are created to enable effective and efficient disaster response. We illustrate our approach by an example from the Haiti 2010 earthquake.

Keywords

Robust supply network, effectiveness, efficiency, humanitarian relief logistics, scenario-based decision support, optimisation, Multi-Criteria Decision Analysis (MCDA)

INTRODUCTION

Disasters triggered by natural hazards are typically characterised by sudden disruptions that involve a high toll in human well-being and a substantial degradation of the environment, which together exceed the ability of the affected community to cope and recover by using its own resources (UN/ISDR, 2004). The management of humanitarian relief supply networks (SNs) aims at distributing relief goods from different sources to the destinations where they are needed (Afshar and Haghani, 2012). Natural hazards typically involve the disruption of critical infrastructures (CIs). As CIs constitute the backbone of any society (Kroeger, 2008) and comprise, e.g., food and water supply, power, transportation and ICT networks or healthcare, their disruption causes severe consequences. Humanitarian relief logistics needs to respond to such CI failures (providing food, water or medical supply), while managing the disruption of further CIs (particularly physical CIs such as roads) and the unforeseeable cascading effects that propagate through interlaced CI networks (Boin and McConnell, 2007).

SN design is of strategic importance in humanitarian relief logistics: it sets the frame for all further operations (on a tactical or operational level). To avoid that the typically large number of actors, the competition and lack of trust between them (Shen and Shaw, 2004) cause further problems, the goals of all SN partners should be aligned such that the right aids are supplied to the right places in the right quality and at the right time (Hendricks and Singhal, 2005). This is more difficult than in business environments, as in disasters information about the needs of the population, the CI system and the available resources is typically uncertain, conflicting or lacking (Ozel, 2001). Confronted with a large number of victims, decision-makers need to make fast decisions even if they are strategic, i.e., they have a long term impact and are irreversible on the short term. An example of such a decision is the choice of locations for camps of dislocated people or field hospitals (Altay and Green, 2006). In summary, the need arises for decision support for consensus building by making the strengths and drawbacks of different SN designs transparent while taking into account uncertainty.

This paper presents an iterative approach to provide decision support for the construction of SNs that enable robust disaster response. Given the large number of possible developments and the time pressure, decision-makers need to focus on what is most important for their decision. As stakes are high, we propose to focus on the most critical parts of a SN. By assessing the consequences of their disruption, the most difficult or harmful conditions for maintaining operations can be elicited, and effective SNs that allow supplies to be distributed to all people in need, even under very adverse environmental conditions, can be designed. Although effectiveness has been considered as the dominant criterion in humanitarian aid, longer term operations, such as in Haiti or the Fukushima region, illustrate the need for efficient SNs that avoid wasting scarce resources and enable fast recovery (Beamon and Balcik, 2008).

The remainder of this paper is organised as follows. In the next section, we briefly review the design of robust SNs for disaster response. In Section 3, we describe our approach to iterative decision support by combining dynamic scenario construction with simulation models and MCDA. To illustrate this approach, we analyse a facility location problem for the Haiti earthquake. The results and their robustness are presented in Section 4. We conclude with a discussion and an outlook of future research.

DESIGNING ROBUST SUPPLY NETWORKS

How good is good enough? Robustness versus optimality

Unlike optimisation models that strive to identify the best solution given a set of constraints and an objective function (Wagner and Neshat, 2010), robust SN design pursues a twofold aim (Tang, 2006): achieving a good performance in expected circumstances and being able to maintain operations if fundamental changes occur. Robustness itself can be understood in two ways, referring to the stability or quality of results. In the first case, it is means to address the question how flawed or defective the models and data can be without jeopardising the analyses' quality (Ben-Haim, 2000). In the second sense, it is required that a robust alternative reaches a minimum required performance under all eventualities (Vincke, 1999). We follow an approach that combines both aspects: a robust decision aims at identifying an alternative that performs relatively well when compared to further alternatives across a wide range of scenarios (Comes et al., 2010; Hites et al., 2006).

Most optimisation models assume that uncertainties can be represented by probability. They prioritise SN designs that ensure minimal cost by referring implicitly to standard operations and assuming that no fundamental changes occur (Melo et al., 2009). Crises are, however, typically complex and uncertain, i.e., they are prone to fundamental changes, and the situation may evolve in unpredicted ways. Therefore, flexibility and agility (i.e., the ability to quickly adapt to a dynamically changing environment) are key aspects in the design of robust humanitarian relief SNs (Beamon and Balcik, 2008).

What is a good supply network? Making trade-offs between effectiveness and efficiency

This paper focusses on the design of SNs that consider both efficiency and effectiveness aims (Goerner et al., 2009). By efficiency, we understand the SN's capacity to perform in a sufficiently organized manner as to minimise duration or cost, whereas effectiveness aims at creating flexible SNs that allow meeting the exigencies of unforeseen disturbances. Effectiveness ensures that the needs are met: relief goods and services are supplied to those in need Efficiency avoids wasting of scarce resources and ensures that aid can be supplied to a higher number (Tomasini and Van Wassenhove, 2009). Typically, these aims conflict and need to be balanced in the design of robust SNs (Kotabe, 1998).

To resolve trade-offs MCDA has often been chosen as the basis for decision support (French, 1996). MCDA's popularity is due to the transparent evaluation it offers by refining abstract goals in terms of concrete criteria, on which preference relations can be expressed (Stewart, 1992). We chose Multi-Attribute Value Theory (MAVT) from the multitude of MCDA approaches, for it has frequently been applied successfully in strategic emergency management (Bertsch et al., 2006). MAVT provides support in selecting one out of a (finite) list of alternatives. In the context of this paper, these alternatives are different facility locations. To develop a list of feasible and promising alternatives – a problem that is usually not addressed in MAVT –, we use a simulation model that determines optimal locations based on a set of assumptions about the situation that is described below.

We aim at designing SNs that achieve a set of goals in an environment of continuous changes that are at least partly unpredictable. In our use case, the aims are supplying health care to all people in need in minimum time. Therefore, SN performance is measured in terms of the criteria *duration* (how long does it take until the demand is fulfilled for varying scenarios?) and *service level* (to what extent can the needs of the population be fulfilled?). While the first criterion represents *efficiency* concerns, the latter addresses *effectiveness.*

AN ITERATIVE DYNAMIC APPROACH TO DECISION SUPPORT IN HUMANITARIAN RELIEF SCM

To assess the effectiveness and efficiency of SNs, we use an iterative approach that acknowledges complexity and uncertainty by using scenarios. In a nutshell, scenarios support decision-makers in thinking about the implications of uncertainties before they actually occur (Wright and Goodwin, 2009). Scenarios have been used in different settings and contexts; as diverse as their fields of application are their definitions (Bradfield et al., 2005). We define scenarios as dynamic descriptions of the disaster's development including the disruptions of CIs, the need for supplies, the resources available and the decisions made. Our iterative approach for the construction of robust ad-hoc SNs follows the procedure shown in Figure 1.

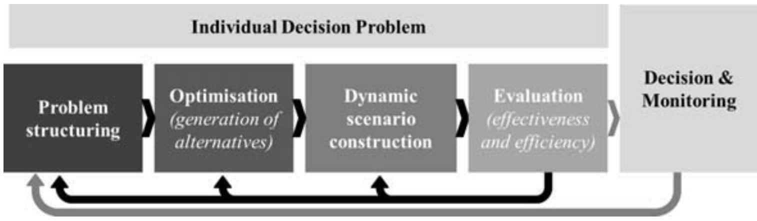

Figure 1: An iterative approach to decision support under complexity and uncertainty

1. The **structuring of the decision problem** and its context makes precise what the decisions and questions to be addressed are: which actors are involved in different roles? What are their respective goals? Which information is required to determine how good an alternative performs? Additionally, a set of initial assumptions about the status quo and its possible developments is assembled (initial scenarios).
2. **Generation of alternatives** to be (further) investigated. Typically, there is an overwhelming number of feasible alternatives, particularly, when sequences of interdependent decisions or strategies need to be devised (Kerstholt and Raaijmakers, 1997). The difficulties to oversee the options may lead to simplifications that result in unfavourable consequences, particularly in situations of time pressure (Maule and Edland, 1997). We use a simulation model to identify and a finite set of promising alternatives *A*.
3. **Dynamic scenario construction.** As in disasters, information are mostly heterogeneous and uncertain, the implications of the respective uncertainties should be explored. Due to time pressure and limited resources, it is only possible to analyse a small set of scenarios. Owing to the high stakes and the risk averseness of decision-makers, we construct the scenarios dynamically to address the question what could go wrong for each alternative a_i in *A*. In this manner, per a_i a set of scenarios SS_i is generated.
4. **Evaluation and robustness.** The sets SS_i are evaluated and compared to analyse the robustness of an alternative. These results can be used as a basis for decision-making process. As the scenarios are targeted at unveiling weaknesses, severe losses in some scenarios may occur, and ways to increase the alternatives' performance for these specific scenarios may be investigated leading to a new set of alternatives.

This approach is of iterative nature to take into account interdependencies and potentially necessary adaptations to changes in information or preferences. In this manner, it can be ensured that the decision is based on the best currently available information and reflects the preferences and goals of all actors involved. Using heuristics for the rapid simulation and efficient scenario updating procedures enables the assessment of changing problem structures or an adaptation of the evaluation

THE FACILITY LOCATION PROBLEM IN HUMANITARION RELIEF

In the following, we show how the iterative procedure described above can be used to determine robust locations of health care centres for the 2010 Haiti earthquake. In SCM, this type of problem is referred to as facility location problem (FLP) and includes different aspects, e.g., geographical location, number and capacity of facilities (Kovacs and Paganelli, 2003). FLPs are strategic problems for they determine the flows of goods, services and information and are irreversible on the short term. As FLPs are NP-hard, one of the main challenges is balancing computation time (requiring simple models) and the precision and granularity of model results. In the following, we will discuss this challenge for each step of our iterative decision support approach.

Problem structuring

After the earthquake, health care demand increases, and additional health care centres (facilities) such as tent hospitals need to be set up. Thus, decisions have to be made where to best locate the centres to reduce travelling and transportation times and ensure that health care services and medication can be distributed to all in need. Therefore, the criteria *effort, duration* and *service levels* are determined for varying scenarios. As budget and available resources are constrained, the number of facilities is limited to a number significantly below the number of potential locations.

In a first step, the geographical representation and the level of detail need to be determined. Figure 2 shows that Haiti is divided into 42 arrondissements (called sections in the following) with a population of 9.8 million in 2009 (Institut Haitien de Statistique et d'Informatique, 2009). The sections that were most severely affected by the earthquake are highlighted in grey. To choose an adequate abstraction level, the required granularity on the one hand and the time required to elicit information and compute results on the other hand must be balanced. Information about adequate locations within each section typically needs to be elicited from local experts, which may be time-consuming and requires considerable effort. Therefore, we focus on the identification of the sections, in which the health care centres should be located. These locations may be refined later on within each of the determined sections. To model transportation durations or travelling times between sections, we consider air and road traffic. The modelling of the road network is limited to larger tarred roads, as only those are sufficiently reliable for truck transportation. Travelling times were determined by analysing navigation data for the intact transportation networks using GPS data.

Information needs and initial scenario construction

The information needs cover those pieces of information that may affect the evaluation of facility locations. In essence, the robustness of a location depends on the dynamic development of health care needs over time and the question in what time and to what extent each demand can be met. These questions depend on the disaster impact, the population movements, and the longer-term health impact. Additionally, uncertainties in the transportation infrastructure need to be modelled, e.g. disruptions of main routes, or further environmental developments such as potential aftershocks that may affect both infrastructure and health care demand. These impact factors are called scenarios variables (SVs) in the following.

To structure the scenarios, make interdependencies transparent and facilitate scenario construction, we use three classes of SVs to develop the initial scenarios and determine the variations in the dynamic scenario construction process. We distinguish context variables, strategies and specifying variables. The context variables describe the background for the decision and include information about the triggering event as well as the actors and their goals and preferences. In our example, the context variables include the epicentre, the disaster phase (from first response to recovery) and constraints for facility locations (e.g., coastal sections are preferred to facilitate transportation by sea). While the context variables' values remain constant across all scenarios, the strategies and specifying variables vary. Strategies describe combinations of alternatives, i.e., they comprise variables that can be controlled by the decision makers. In our example, these are the transportation mode (air or road) and the maximum number of facilities to be set up (3, 5 or 7). The specifying variables are prone to uncertainty and can have multiple values to describe events or developments that affect the effectiveness and efficiency of any SN. As a start, we used the actual values and some extreme values that had maximum variation from these. We used the initial demand levels (3 distributions across sections), the population's behaviour and migration (3 patterns), and environmental developments such as possible aftershocks (reflected by 4 demand developments and 2 CI disruption levels). Note that scenarios are consistent combinations of the context variables, the strategies and the specifying variables. We combine the values of these uncertain variables to $3^2*4*2=72$ initial scenarios, which are basis for a first assessment of candidate options via optimisation.

Optimisation to generate alternatives and create benchmarks

As the information about the current situation is uncertain and future developments can hardly be foreseen, we propose to construct a large number of scenarios to support decision-makers in exploring the potential consequences of an alternative instead of predicting likely outcomes. As FLPs are NP-hard, we use heuristics that allow a (relatively) rapid calculation of results rather than using more precise or realistic models.

The optimisation consists of three steps. First, we use the Dijkstra algorithm to compute the shortest paths (in terms of duration) from each section to all other sections. Second, we compute, based on these distances, the optimal facility locations, by solving an uncapacitated facility location problem (UFLP). Third, the optimal allocation of sections is determined to make explicit, which section receives supplies from which facility. In this manner, we compute the duration and the service levels for each alternative.

As the UFLP requires most computational effort, we describe the choice of algorithm for this second step of the optimisation. In business environments, the UFLP is used to minimise the sum of transportation and fixed costs of facilities (Cura, 2010). In our context, the "costs" associated to a facility are the durations to reach further sections. Although the UFLP simplifies the problem by making several (unrealistic) assumptions (e.g., homogeneity of facilities, unlimited capacity), it is still NP-hard (Krarup and Pruzan, 1983). Numerous exact algorithms and heuristic approaches have been developed to solve it (ReVelle and Eiselt, 2005). To choose an approach adequately reflecting the problem's characteristics, again trade-offs need to be made between the precision and the number of simulations that can be run. As uncertainties are fundamental, a large number of scenarios should be constructed. Additionally, the precision of the solution is flawed anyways by the uncertainty in the data so that investing a lot of time for having a more precise model will still not lead to accurate and reliable results. Moreover, the use of a rapid heuristic enables integrating new information and updates, which is very important in highly dynamic situations (Comes et al., 2012). Therefore, we chose the ADD-heuristic (implemented in Matlab), a greedy algorithm that adds or removes facilities with maximal reduction of overall duration and enables a (relatively) rapid calculation of results (order of magnitude $O(m^2n)$ where m is the number of locations and n the number of neighbours per location; Jacobsen, 1983).

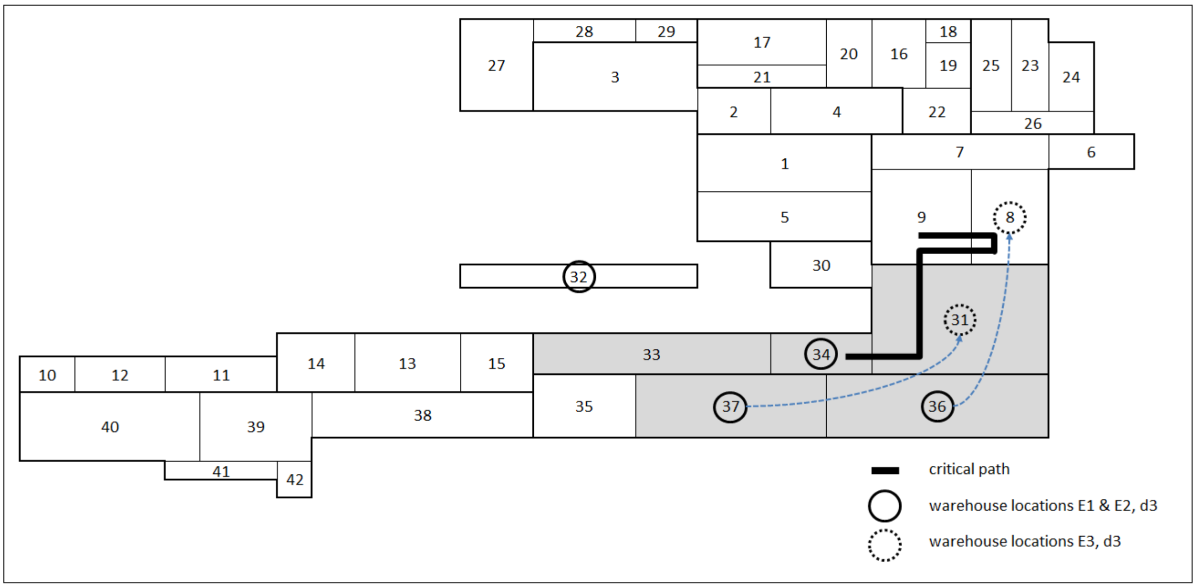

Figure 2: Representation of possible locations and optimal results for changing environments

The optimal solutions for the UFLP in the Haiti use-case provide the first set of "promising" alternatives A that are evaluated in detail and refined iteratively. To understand the relations between the alternatives, we start with an analysis of location triples created for the 3-facilities problem (*3-FLP*): which of the combinations of locations $a_i^3=[a_{1i}, a_{2i}, a_{3i}]$ are optimal for more than one scenario? Which of them are part of the solutions for the 5- or 7-FLP? In this manner, favourable patterns can be identified.

Solving the optimisation problem results in 17 different solutions for the 3-FLP, each of which is optimal for at least one scenario. In 24 out of 72 scenarios, the alternative [20, 32, 34] describes the best facility locations, in nine scenarios [32, 34, 37]. In more than 50 % of all scenarios (43 out of 72), the combination 32 and 34 is part of the optimal solution. Furthermore, some individual locations are especially favourable, e.g., the Port-au-Prince section 34, where the initial demand is highest, is among the selected locations in 69 out of 72 scenarios. 32 is also frequently among the optimal locations, mainly because there are no road infrastructures connecting it to the main island. Figure 2 illustrates the location of two optimal solutions [32, 34, 37] and [32, 34, 36] and illustrates the impact of changing environments on the optimal solutions that will be detailed in the next section.

Before considering the scenario-construction, we would like to emphasize the usefulness of the iterative approach. An analysis of the 5- and 7-FLPs shows that all optimums a_i^3 for the 3-FLP are parts of the solutions for the extended problems, i.e., each solution a_j^5 and a_l^7 can be represented as an extension of at least one a_i^3. Therefore, the a_i^3 solutions provide a sound initial basis for starting the SN design. Particularly if resources are (initially) scarce and budgets are constrained, it can be useful to start with the implementation of an a_i^3-solution and to extend it later. As shifting locations is very difficult (Beamon and Kotleba, 2006), particularly if the revision of locations is needed because of infrastructure disruptions, waiting until more information is available can be beneficial in terms of gains in efficiency and even effectiveness. As mere waiting is impossible because of the urgent need for help, starting with an initial small number of locations is a way to maintain flexibility and adaptability without compromising effectiveness.

Dynamic criticality-based scenario construction

The aim of the scenario construction is the identification of scenarios that reveal the drawbacks of any chosen location. Although scenarios ideally explore *all* eventualities, the limitations in time and resources require selecting some significant scenarios SS_i* for the decision at hand. Each alternative that was optimal for an initial scenario *Si* is now assessed for further scenarios in SS_i*. Significance is measured in terms of deviations from the initial results. By following the iterative procedure described previously, this enables alternatives to be improved successively through recombination of locations (within the 3-, 5 or 7-FLP) or complementing (adding further locations and moving from 3- to 5- or 7-FLP).

To create such significant scenarios we construct environments that are targeted at disturbing the functions of most critical parts of the SNs. Environments are parts of a scenario (such as episodes in an overall story). The use of environments enables that only the values of few SVs can be changed without having to re-construct the scenarios from scratch. Figure illustrates how the dynamic scenario construction is embedded in our overall approach. Starting from the optimal locations determined for the initial scenarios, we dynamically construct scenarios from harmful environments for each optimum (Step 3) and assess the performance of the SN under the changed conditions (Step 4). As it is impossible to consider all scenarios for all alternatives, we select the most significant ones (with respect to their impact on the evaluation). In Figure 3, Step 4, this is illustrated by selecting one out of three possible scenarios. Our use-case will later illustrate that typically more scenarios will arise and that the number of scenarios per alternative may vary. By analysing the results for these disruptive scenarios a better understanding can be gained about the drawbacks of an alternative, and we exploit these insights results for revision of alternatives. For these revised alternatives, new disturbing environments and scenarios are created (branching of scenarios in Step 5) to test their performance and to compare it. By continuing this process, robust locations are identified that are effective and efficient.

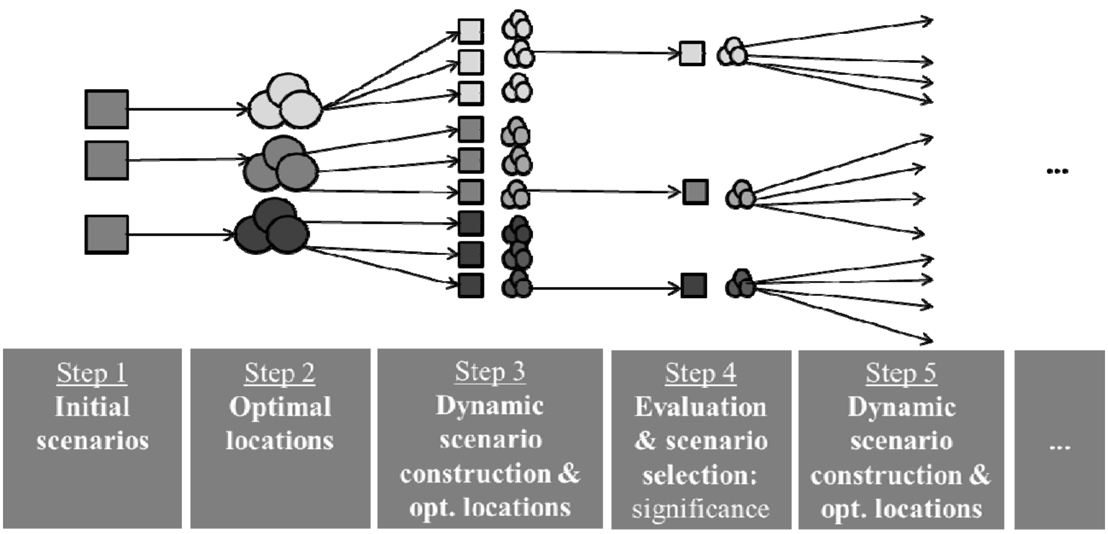

Figure 3: Dynamic scenario construction

For their fundamental importance, the disturbances focus on the uncertainties about the CIs' capacity and state. In our use-case we apply the therefore create environments that imply harmful disruptions of the road network. (Air transport by helicopter is assumed to be robust against CI disruptions.) Per initial scenario S_i, we create two disruptive environments E_2 and E_3. While all initial scenarios (and the CI environment E_1) include the assumption that the main transit routes are intact, in E_2 the routes to and from the sections where the facilities are located are disrupted (doubled durations to all neighbouring sections). In E_3, the most *critical* path is assumed to fail, i.e., the path whose failure leads to the maximum increase of duration. Note that E_2 and E_3 are tailored to test the robustness of any given alternative a_i and create the most important disturbances that hamper

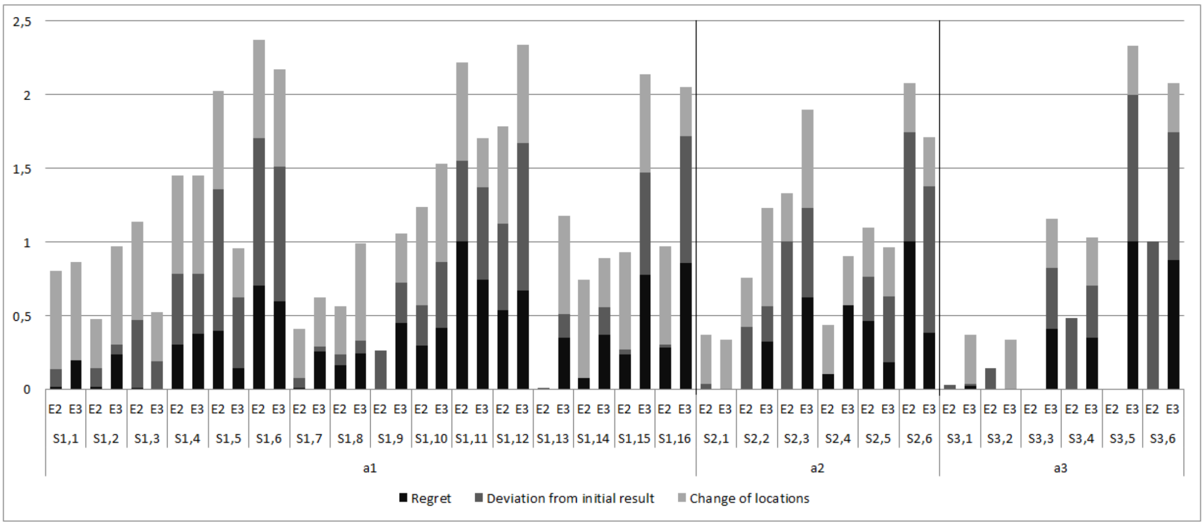

Figure 4: Significance measures for alternatives a_1 to a_3

efficiency and effectiveness of a_i. In other words, $E_2(a_i)$ is not necessarily equal to $E_2(a_j)$ ($i \neq j$). These assumptions about the new environments are then combined with the further uncertainties that were already represented by the initial scenarios. That means per alternative a_i, the n_i scenarios *Sij* for which is was optimal is identified, and in these scenarios the assumptions about the environments are changed, leading to 2^*n_i new scenarios $Sij(E_{2,3})$ per alternative.

Figure 2 shows the most critical path common for alternatives [32, 34, 36] and [32, 34, 37]. A failure of this path results in new optimal solutions: 36 should ideally be replaced by 8 and 37 by 31 respectively. The next section will discuss how this change can be interpreted in terms of the solutions' robustness.

Evaluation: Selecting scenarios and choosing facility locations

Although ideally all developments should be considered, this is impossible in crisis situations and the need for scenario prioritisation arises (Comes et al., 2012): to reduce the information (over-)load, only the most significant scenarios should be further processed (cf. step 4 in Figure 3). As we focus on testing an alternative's robustness, the significance of a scenario S_{ij} is measured by indicators for the stability and the quality of a_i in the new scenario as compared to the initial performance of a_i in S_i. Stability is modelled in terms of the required number of locations changes to achieve the optimum $a_{ij}^*(E_{2,3})$ for the new scenario $S_{ij}(E_{2,3})$, and the relative loss, measured by deviation of the performance of a_i in $S_{ij}(E_{2,3})$ from the initial performance of a_i in S_{ij} in the initial scenario. Quality is measured by the regret, i.e., the loss of performance due to the implementation of a_i instead of a_i^*. The losses comprise the increase in duration and the decrease in service levels. The most significant scenarios are selected as a basis for the evaluation.

Figure 4 shows the significance assessments for the scenarios, for which one of the three alternatives a_1=[20, 32, 34], a_2=[32, 34, 37] and a_3=[32, 34, 42] was optimal: 2*16 scenarios ($S_{1,1\text{-}16}$) for a_1, and 2*6 scenarios ($S_{2,1\text{-}6}$; $S_{3,1\text{-}6}$) for a_2 and a_3 respectively arise. Additionally, Figure 4 is – as remarked by several reviewers – not very easy to read due to the amount of information that it represents. Knowing that actually even more scenarios need to be assessed, the complexity of even this simplified graph illustrates the need for prioritisation of scenarios; it is simply not possible to intuitively understand and interpret this large amount of information. By using techniques from MAVT the individual contributions to the significance can be normalised and aggregated. In our use-case, we used equal weights, but of course, it is possible to elicit and take into account decision makers' actual preferences. (The overall significance is measured on a scale from 0 to 3, because we normalised the individual contributions.) In this manner, per alternative the scenario with the highest significance can be selected for further evaluation of alternatives. Figure 4 shows that $S_{1,6}$ is chosen for a_1, $S_{2,6}$ for a_2 and $S_{3,6}$ for a_3.

All selected scenarios include the assumption that the initial demand increases dramatically. In $S_{1,6}$ (a_1) the demand increases most in the epicentre's neighbouring sections, and is on the longer term influenced by migration to northern sections. In $S_{2,6}(a_2)$ a more widespread demand increase is assumed, but no signification migration. In $S_{3,6}$ (a_3) demand increases in the very extreme sections (west and north of Haiti), and population migrates to the western sections (the demand increase could, for instance, be caused by epidemics in now more densely populated areas). In summary, the chosen scenarios characterize a wide spectrum of possible situation developments while starting from similar assumptions about the initial phase. This highlights the importance of migration patterns, which are the next stepping stone for further scenario construction and the evaluation of facility locations.

To make a robust decision, the impact of changes in migration patterns is investigated. To this end, we again branch the three scenarios selected for each alternative as shown in Figure 3 by using four migration patterns to represent the additional uncertainty. All results are summarised in Table 1, the impact of migration patterns can be found in the columns to the right.

Table 1: Impact of scenario variations on the results of alternatives a_1, a_2 and a_3

	Impact of changing CI conditions						Impact of changing migration patterns			
	change of locations		duration increase		service levels		duration increase			
	E_2	E_3	E_2	E_3	E_2	E_3	Mig_1	Mig_2	Mig_3	Mig_4
a_1	2	2	34.9%	42 %	100 %	99 %	68.1%	0%	-	130.7%
a_2	1	1	33.3%	117.7%	100%	100%	-	35.2%	40.6%	72.8%
a_3	0	1	1.5%	7.5%	100%	99%	0%	7,2%	14,6%	-

As migration patterns are particularly relevant for considering which solutions are very suitable for further complementation (by adding locations), we also address the impact on the 5- and 7-FLP. In both problems, sections 32 and 34 are part of each solution. Therefore, the decision of the 3-FLP can be reduced to the question if [32, 34] should be combined with section 20, 37 or 42. If more time – for another iteration of scenario construction and analysis is available, further promising locations could be investigated that are among the optimal locations for the 5- or 7-FLP case, but not for the 3-FLP. As we assume that time is short, we focus on the evaluation of sections 20, 37 and 42 (or a_1, a_2, a_3).

By using exponential value functions parameterised to reflect risk averseness (particularly for the service levels, which represent effectiveness), the results are normalised and subsequently aggregated by using techniques from MAVT. For more details on the use of MAVT in scenario-based contexts see for instance (Comes et al., 2011). Figure 5 shows an exemplary evaluation for weights (0.4; 0.1; 0.5) for the criteria *Service level, Effort* and (number of required) *Location changes* to achieve the optimum. The weighting was chosen to reflect the importance of supplying goods to all people in need (effectiveness) and the difficulty of relocating a facility (lack of flexibility). Figure 5 shows that for these weights, a_2 is the most robust alternative. Location a_1 is clearly the least robust due to a high number of location changes and considerable effort required. Although fewer changes are required for a_2, the effort associated to changing environments and migration patterns is considerable. a_2 is, however, the only solution to provide a 100% service level and therefore preferred over a_3.

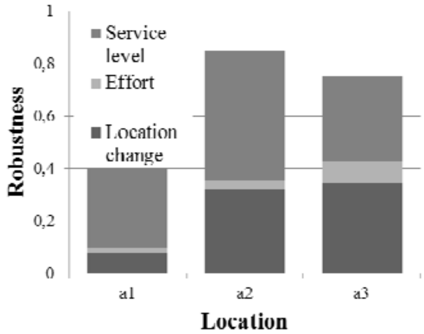

Figure 5: Evaluation of locations a_1 to a_3

DISCUSSION AND CONCLUSION

This paper presented an iterative approach for robust decision support in the design of humanitarian relief supply networks (SNs). In this context, robustness comprises an achievement of absolute and relative aims in terms of effectiveness and efficiency. While effectiveness refers to service levels (ideally guaranteeing that supplies can be provided to all who need them), efficiency ensures that the duration is kept as low as possible.

To support decision makers in the identification of robust options in complex situations, we combine an optimisation model, scenario-based techniques and approaches from Multi-Criteria Decision Analysis (MCDA). The scenarios are the link between (continuous) optimisation and the discrete in-depths evaluations based on Multi-Attribute Value Theory (MAVT). The optimisation model generates promising or benchmark alternatives to be further evaluated and compared to the best solutions so far. The use of rapid heuristics enables the creation of a large number of alternatives although the problem considered may be very (i.e., NP-)hard. Here, trade-offs need to be made between potential gains in precision (whilst taking into account the data uncertainties) and the value of a better exploration of the possible situation developments – the scenarios. Although in principle the automation enables a large number of scenarios to be constructed, not all of them can be considered as time is short and pressure high. Therefore, we use a dynamic approach to scenario construction that is targeted at unveiling the most important weaknesses of the alternatives and selecting the most significant scenarios. The results for these most significant scenarios provide input for further scenario construction (branching).

We illustrated our approach by referring to one of the most well documented disasters: the 2010 Haiti earthquake. To determine, where health care centres should be located, we combined a greedy heuristic to solve an uncapacitated facility location problem with scenarios and MCDA.

Some questions remain for future research. To address the facility location problem in its full complexity, further information from local sources needs to be integrated. For instance, updates of the CIs' status or the available resources could be used for the generation of more reliable scenarios, and, once the sections have been chosen, local information to determine the best location within each section should be elicited and used in a refined sectional model. To address the question of the number of facilities to be chosen an additional iteration step in the scenario-based decision cycle, cf. Figure 1, should be explicitly integrated. Particularly, the question of timing of a decision should be considered, i.e., which locations should be chosen in the early phases to provide a solid basis for further extensions or revisions in later phases? To this end, the (value of) flexibility, the reversibility of locations, and the potential benefits from a higher number of facilities under different scenarios should be analysed. This analysis is also the starting point for considering humanitarian relief SCM strategies: nested series of decisions, covering strategic, tactical and operational planning such scheduling or the last mile problem and their revision and dependence over time. Finally, our approach needs to be further investigated and tested in (moderated) workshops with practitioners and users. To this end, interfaces, visualisations and graphics explaining the results and guiding the users through the process need to be developed.

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