Decision making in humanitarian logistics – A multi-objective optimization model for relocating relief goods during disaster recovery operations

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ABSTRACT

Disaster recovery operations rarely proceed smoothly and disruptions often require the redistribution of relief items. Such a redistribution has to be carried out taking into account both the current disruption and the uncertainty regarding possible future incidents in the respective area. As decisions have to be made fast in humanitarian operations, extensive optimization runs cannot be conducted in such a situation. Nevertheless, sensible decisions should be made to ensure an efficient redistribution, considering not only satisfaction of needs but also operational costs, as the budget is usually scarce in the recovery phase of a disaster.

In this work, different scenarios are generated and then solved with a multiobjective optimization model to explore possible developments. By evaluating the results of these scenarios, decision rules are identified which can support the decision maker in the actual disaster situation in making fast, but nevertheless well-founded, decisions.

Keywords

Decision making support, multiobjective decision making, constraint method, scenario planning

INTRODUCTION

In disaster situations, aid workers need to make decisions regarding relief item distribution and evacuation planning in a very time-critical setting. Hence, no extensive data evaluation can be carried out to support these decisions, as the collection and evaluation of all available data would take far too long in the tight timeframe. Therefore, only the information which is of high relevance for the decisions to be made should be collected and analyzed. Moreover, data change dynamically over time in disaster situations; hence, data evaluation would have to be revised multiple times. (Comes, Wijngaards and Schultmann, 2012) Reporting to authorities to obtain decision support would slow down the process as well. Therefore, the respective decisions are often made without even having an overview over the entire affected area and all available resources (Long, 1997). As the decisions made are crucial for the well-being of the disaster-affected people, rules for decision making are helpful which are easy to apply in emergency situations where only incomplete information is available (Van Wassenhove, 2006). While such decision rules cannot substitute the experience of the aid worker - who in humanitarian operations is often also the decision maker, i.e. the person in charge -, they can give him/her support in making sensible decisions.

Although the situation is relaxed partly when a relief operation has already been established, changes in information regarding the infrastructure, the needs for relief items or resource availability lead to new situations requiring new decisions. During ongoing relief operations, very often disruptions occur, and the aid workers have to react to them while in the meantime, the ongoing relief operation has to proceed. These situations are termed “overlapping disasters”. (Rottkemper, Fischer, Blecken and Danne, 2011)

As an example for this class of problems, the outbreak of a malaria epidemic in Central Africa is considered in this work. While a fast reaction to the epidemic is important to prevent its further spread, also regularly emerging malaria infections in neighboring regions have to be dealt with and furthermore, the risk of future epidemical spreads in these regions has to be considered. As budget is scarce in long-term aid programs, e.g. as in Burundi where Non-governmental Organizations still support the recovery from the long lasting civil war

(Protopopoff, Van Herp, Maes, Reid, Baza, D'Alessandro, Van Bortel and Coosemans, 2007), a cost efficient solution is required. Hence, the decision maker faces multiple objectives and the goal is to find a tradeoff between:

1. The minimization of unmet needs,

2. The minimization of the risk of future shortages, and

3. The minimization of operational costs.

The approach presented in this work uses scenario planning to intensify the understanding of overlapping disaster settings and in particular to explore possible future developments of the current situation (Wright, Cairns and Goodwin, 2009). These insights can be deployed to obtain decision rules for relocating available relief items and for making replenishment decisions when new information becomes available.

In the next section, the research question and the problem description are stated. Subsequently, some theoretical background of scenario planning is given and specific scenarios for the problem at hand are generated. In the following section, a multiobjective optimization approach to solve these scenarios is presented and finally, the results of the optimization runs and the consequences of these results for decision making in overlapping disaster situations are discussed.

RESEARCH QUESTION AND PROBLEM DESCRIPTION

Research question

The objective of this work is to analyze whether general strategies can be defined for coping with overlapping disaster situations without carrying out extensive optimization runs in the emergency situation. In particular, it is important to know which amounts of the relief items should be replenished at which point in time, and where the relief items should be stocked. Therefore, a multiobjective optimization model for replenishment and relocation of relief goods is developed and solved for different scenarios. Similarities as well as differences regarding the best distribution strategy are identified. Finally, the aim is to develop decision making rules which are easy to apply and which help the aid worker to shift from a reactive to a proactive strategy in overlapping disaster situations.

Relief item relocation

In the situation which is considered here, a global depot is located, e.g. in Europe, for replenishment of the relevant relief item. (Note that only one type of relief item, e.g. a specific medicine, is considered in this work.) Deliveries are made to a central depot which is located near an airport in the affected area. A third echelon is represented by the regional depots which are located in the affected regions to directly serve the beneficiaries. A certain amount of the relief item is already in stock at these depots because a relief operation has already been established in the respective area. Now, a disruption – i.e. a shortage in supply or a sudden increase in needs – occurs in one or more of the regions which triggers a relocation of relief items. On the one hand, the short distances between the regional depots could be exploited to enable a quick response to the disruption. On the other hand, the risk of future shortages in the respective regions has to be taken into account. Furthermore, it has to be decided how many items should be transported from the central depot to the regional depots and how many should be replenished from the global depot, if any. Due to the aforementioned scarcity of resources, especially of time but also of IT infrastructure, the application of a mathematical model is usually not possible when a disaster has already occurred. Hence, the model developed in this work is applied in advance to enhance the understanding of possible overlapping disaster situations. Therefore, scenarios which represent different future developments are generated, and they are solved to analyze possible overlapping disaster settings and to develop decision rules which support fast and sensible decisions in those situations.

The situation considered in this work is the outbreak of a malaria epidemic in Kayanza, a province in northern Burundi. As malaria is endemic in this area, the infrastructure for relief item distribution already exists (Médecins Sans Frontières, 2010). The relief item under consideration is artemisinin based combination therapy (ACT) which has been introduced to treat malaria, after the resistance for chloroquine increased considerably in the malaria endemic regions in Africa (Médecins Sans Frontières, 2002). The planning horizon is nine days (i.e., one day equals one period, see model description below); after that the outbreak of the epidemic, which causes the replanning process, is assumed to be mitigated, as during this time span regular replenishment orders can arrive in the affected area. There are four regional depots in the respective area and a central depot in

Bujumbura, the capital of Burundi, where an airport is located. Some ACT is already stocked in the depots. In addition, replenishment from a global depot in Europe is possible and the stock at the global depot is considered to be unlimited; however, transportation is expensive, as it is done by plane and on rather short notice. The epidemic has broken out in one region in Kayanza leading to an ACT shortage at the respective regional depot. This shortage can be (at least partly) compensated by transshipments from regional depots nearby. Nevertheless, the risk of future epidemical spreads in these regions also has to be considered. Hence, decisions are to be made on how much of the ACT should be relocated and replenished in reaction to the current situation, taking into account the risk of epidemical spreads to the nearby regions and the possibility of resulting future shortages.

In the planning problem considered below, the following assumptions regarding the relevant cost parameters are made: Replenishment costs 400 MU (money units) per order (fixed costs) and 16 MU per unit ACT (variable costs), transportation between the central and the regional depots incurs fixed transportation costs of 200 MU per vehicle and 2 MU per unit ACT, and handling and transshipment between the regional depots also costs 200 MU per vehicle and 1 MU per unit ACT.

SCENARIO PLANNING

Scenario planning is an emerging technique in humanitarian logistics. Scenarios are used to examine possible future developments and hence to enable reasonable decision making (Bañuls, Turoff and Hiltz, 2012). Due to the high level of uncertainty in emergency settings, scenarios with considerably shorter time horizons than in business applications are used (Schnaars, 1987). Several authors apply scenarios in humanitarian logistics problems without explicitly explaining the scenario generation process or the evaluation techniques which are deployed, e.g., Balçik and Beamon (2008), Barbarosoğlu and Arda (2004), Mete and Zabinsky (2010), or Salmerón and Apte (2010). However, the importance of a more detailed investigation of scenario techniques in the context of emergency management has lately been recognized by, e.g., Bañuls et al. (2012) and Comes et al. (2012). This work summarizes important steps of scenario generation for humanitarian logistics settings in general and for the situation under consideration in particular.

In humanitarian logistics, usually low probability - high impact scenarios are considered (Lodree and Taskin, 2008). Nevertheless, it is crucial also to define a more likely “baseline scenario”, presuming that no disaster occurs (Schnaars, 1987). The scenarios in humanitarian logistics are usually of an explorative nature, examining several future developments from one starting point (Bunn and Salo, 1993). To generate applicable scenarios, it is important to thoroughly separate domains which can be influenced by the decision maker from those which cannot be influenced. Domains are aspects of the decision situation, defined by a set of characteristics, relevant for the decisions to be made. These relevant characteristics are called risk factors. (Huss, 1988) Usually, at least some of the domains cannot be influenced by the decision maker. For example, the amount of relief items in stock depends on the decision of the aid worker while the occurrence of an earthquake cannot be influenced. In the next step, factors influencing these domains are to be identified. For example, a flood is influenced by the rainfall in the respective region or by the presence of dikes. These factors are grouped by impact (increased or decreased risk of a flood) or by source (natural, man-made) (Protopopoff, Van Bortel, Speybroeck, Van Geertruyden, Baza, D`Alessandro and Coosemans, 2009). The recognized groups are used to identify key-factors, which are those particularly important for the future development of the respective situation (Schnaars, 1987). Finally, dependencies between the factors themselves are to be examined. For example, the age structure of a population has an influence on the immunity against a certain disease, because children are less immune than adults. Hence, the age structure also influences the risk of an epidemical spread (Protopopoff et al., 2009).
Subsequently, variables influencing the emergence of the risk factors are identified. The density of mosquitoes, for example, increases with the temperature and the humidity, leading to a higher risk of a malaria epidemic. The characteristics of the key-factors define possible future developments. These developments can be similar for several key-factors leading to an aggregation into different risk states (for example, a low, a high, or a medium risk of an epidemical spread) which can be used to define the main scenarios. Most authors tend to define 3 or 4 main scenarios (Linnemann and Kennell, 1977; Schnaars, 1987). Based on these main scenarios, individual sub-scenarios can be defined by varying values of the characteristics of the main scenarios: E.g., the regions affected by an epidemic can vary, as can the number of affected people or the epidemic's severity.

Malaria epidemic in Central Africa

The situation outlined in the problem description above is now considered in more detail and different scenarios which capture possible future developments are generated. In this work, the possibility of an epidemical spread is considered as a domain influenced by external factors. Therefore, different scenarios are generated considering different developments of the external factors influencing an epidemical spread. An overview of these factors, identified by Protopopoff et al. (2009), is presented in Figure 1. They can be differentiated into the factors influencing the number of mosquitoes which can transmit malaria (i.e. the density of Anopheles) and the factors influencing a malaria infection (these are the two dependent variables, see Figure 1). Of course, not all of these factors are external, some of them, e.g. the health access, the use of insecticide treated nets, and the indoor residual spraying can, at least in the long run, be influenced by the aid workers. However, in this work a short time horizon is considered and therefore it is assumed that no considerable improvement in the other factors can be obtained in this timeframe and only decisions on the ACT distribution can be made. Moreover, the distribution of ACT influences the spread of a malaria epidemic (a better treatment will decrease the risk of an epidemical spread). However, these repercussions are not considered in this work.

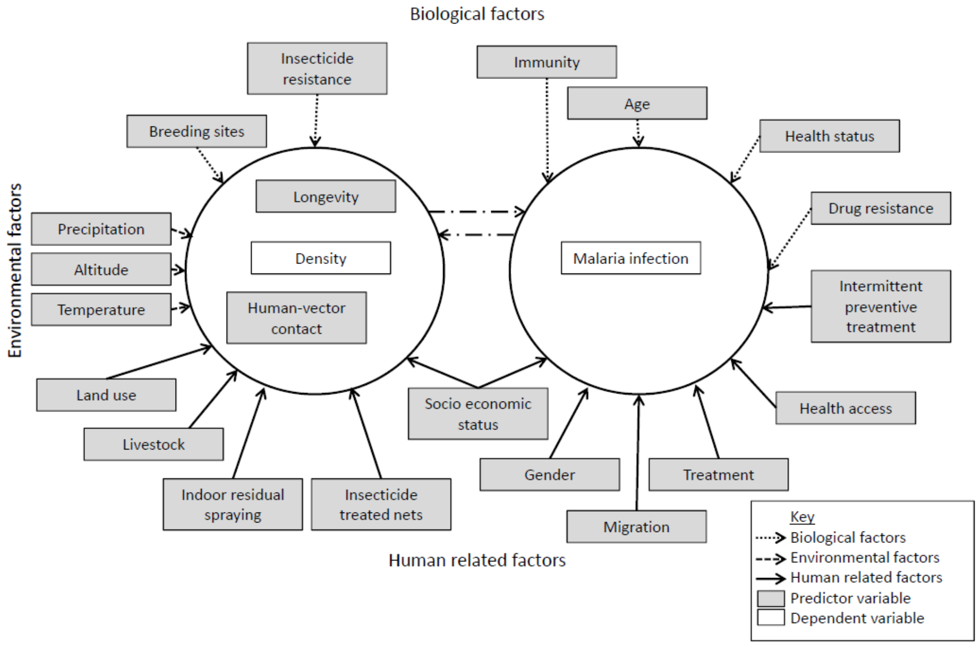

Figure 1. Malaria risk factors in the African highlands (Protopopoff et al., 2009)

In Figure 1, the factors are already grouped by source (biological, environmental and human related factors). Moreover, a ranking of the factors has been conducted by Protopopoff et al. (2009). The key-factors identified for malaria infection are: Anopheles density, housing conditions, age, and past malaria treatment. Anopheles density is influenced mainly by rainfall, spraying, usage of insecticide nets, temperature, distance from march, altitude, and type of crop in the marsh, in descending order. Depending on the values of the variables, two possible future states are defined according to Protopopoff et al. (2009): A high and a low risk state which can be present in the different regions. The (sub-)scenarios used in this work are derived from these basic risk states, and a variation of the scenario characteristics.

Name of scenario	Risk state	Region	Period
0	Low risk	-	-
1.a)	Low risk	3	4
1.b)	Low risk	2	2
1.c)	Low risk	4	3
2.a)	High risk	2, 3	5, 4
2.b)	High risk	2, 4	2, 4
2.c)	High risk	3, 4	3, 2
3.a)	High risk	2, 3, 4	4, 3, 2

Table 1. Individual sub-scenarios

The concrete scenarios are presented in Table 1: Scenario 0 is the baseline scenario, where no further outbreak of the epidemic occurs. Scenarios 1.a), 1.b), and 1.c) are low risk scenarios where one region is affected by an epidemical spread, for example, in scenario 1.a), it is region 3 in period 4. Scenarios 2.a), 2.b), and 2.c) are high risk scenarios where the epidemic spreads in two regions (e.g., in scenario 2.a) first in region 2 in period 5 and then in region 3 in period 4). Scenario 3.a) is a high risk scenario where the epidemic spreads in three regions.

MODELING APPROACH AND SOLUTION METHOD

The question how much ACT should be replenished and where it should be stocked can be answered by solving the respective planning problem using a multiobjective optimization model. However, in an acute disaster situation, solving an optimization model would, of course, be too time consuming. Hence, multiple scenarios as those developed in the previous section are to be solved beforehand and then can be used to develop decision rules which support the aid worker in his/her decision making.

The optimization model is based on a network flow model formulated by Herer, Tzur and Yücesan (2006). This model has been extended by Rottkemper, Fischer and Blecken (2012) to solve relief item redistribution problems. The model consists of stock balance constraints for each period and each depot, one total inventory balance constraint considering all periods and depots, constraints for calculating the number of vehicles required for transportation and transshipments, replenishment constraints, and constraints to calculate the beneficiaries' needs at each depot and for all periods. Adjustments of the model of Herer et al. (2006) were necessary to integrate particular characteristics of humanitarian operations, as the uncertainty regarding future needs and the goal to minimize the overall unmet need. If needs are not met, they are not lost in this model but persist in the subsequent periods. This is due to the fact that usually there are no other organizations that can compensate a lack of relief items in the recovery phase of disaster relief operations.

Depot	Start inventory	Certain needs	Uncertain needs
Central depot	20,000	-	-
Regional depot 1	900	1000	0
Regional depot 2	1000	100	1000
Regional depot 3	800	80	3000
Regional depot 4	1500	150	2000

Table 2. Available inventory and needs (in units of ACT) in the relevant regions

The model developed by Rottkemper et al. (2012) considers two types of needs: Certain and uncertain needs. The certain needs can be forecasted and model the malaria infections which occur on a regular basis. The uncertain needs represent the risk of future epidemical spreads; they might, but do not have to occur. The amount of this need is calculated for each region under the assumption of an epidemical spread: It is given by the doses of ACT required to respond in case of such a spread. The data for the different scenarios considered in this work are presented in Table 2: The amounts of relief items needed in a region are identical for each period with exception of the first period, where no uncertain needs occur. Moreover, due to the first disruption in region 1, the amount of relief items needed here in the first period is 20,000 units (due to the fact that the outbreak was not noticed instantaneously, and hence needs have accumulated), whereas in the subsequent periods it is assumed to be 1000 units of ACT. As the epidemic has already spread there, no further uncertain needs are considered for region 1.

Due to the uncertainty regarding the developments in future periods, the model is solved by a rolling horizon solution approach. I.e., the results of the first solution run are introduced as starting settings for the second solution run (and so on), and the information that has become available in the meantime, e.g. regarding a spread of the epidemic, is used in the calculation for the following period. In the end, the operational costs of each period are added up to the total costs. The model by Rottkemper et al. (2012) combines the three objectives in a weighted sum applying a penalty cost approach. Periodically increasing penalty costs are introduced to ensure that needs which have been unsatisfied for a longer time are satisfied first. Hence, the penalty costs increase with each period the needs remain unmet. Furthermore, the penalty costs differ between the certain and the uncertain needs: As the occurrence of the certain needs is out of the question, they should be satisfied as completely as possible, while the uncertain needs represent the risk of future shortages and do not necessarily occur. Therefore, penalty costs for unmet uncertain needs are considerably lower than those for certain needs.

The model developed in this work applies similar constraints and is also solved by a rolling horizon solution approach, but the approach taken here deals with the multiple objectives in a different way: The objectives are balanced using a constraint method. This method prioritizes the minimization of unmet needs over the minimization of operational costs, as the former is the main objective in a humanitarian operation. Hence, operational costs are formulated as a constraint and limited by different values, varying between the minimum and maximum possible value. To calculate these extreme values, a payoff-table is generated, minimizing the unmet needs without considering costs to determine the maximal costs, and minimizing the operational costs without considering the unmet needs to determine the minimal possible costs (and the maximal unmet needs). Based on these extreme solutions, the whole range of possible compromise solutions can be evaluated by calculating solutions, in equal distances, between the extreme values. In contrast to this, with the weighted sum method some parts of the efficient frontier might be ignored completely (Chankong and Haimes, 1983), even if the weights are varied by constant amounts. Furthermore, the determination of reasonable weights which lead to good results, requires an extensive sensitivity analysis for each new data setting (Rottkemper et al., 2012).

In the approach presented in this work, the objective function of the network flow model, which is given in Formula (1), is a weighted sum of all unmet certain needs (UD^1_{itk}) and of all potential future shortages, i.e. the unmet uncertain needs (UD^2_{itk}) which is to be minimized. Both types of variables exist for each depot (i ϵ {1,…, N}) and each period (k, t ϵ {1,…, T}), and differentiate the unmet needs according to the time span for which they have been unsatisfied. The weighting coefficients differ in order to prioritize the certainly unmet needs (g^1_{ik-t}) over the risk of future shortages (g^2_{ik-t}).

$$\min \sum_{i=1}^{N}\sum_{t=1}^{T}\sum_{k=t}^{T}(g^1_{ik-t}\cdot UD^1_{itk} + g^2_{ik-t}\cdot UD^2_{itk}) \tag{1}$$

The operational costs, containing variable and fixed transshipment costs ($c_{ij}, cFix_{ij}$) for transports between regional depots *i* and *j* (transshipment takes one period: Variables $F_{S_{it}S_{jt+1}}$), variable and fixed transportation costs ($c_{0i}, cFix_{0i}$) between the central depot and depot *i* (transportation takes two periods: Variables $F_{S_t^{CD}S_{it+2}}$), inventory holding costs (h with the variables $F_{S_{it}S_{it+1}}$), and variable and fixed replenishment costs (r, $rFix$) from the global to the central depot (replenishment takes three periods: Variables $F_{S_t^{GD}S_{t+3}^{CD}}$), are formulated as a constraint (see Formula (2)). In this constraint, the right-hand side is varied between the maximum and minimum possible operational costs. The respective values are denoted as grid points (gP) and are chosen equidistantly. The other constraints remain similar to the ones in Rottkemper et al. (2012).

$$\sum_{t=1}^{T}(\sum_{i=1}^{N}(\sum_{j=1,j\neq i}^{N}(c_{ij}\cdot F_{S_{it}S_{jt+1}} + cFix_{ij}\cdot Y_{F_{ijt}}) + c_{0i}\cdot F_{S_t^{CD}S_{it+2}} + cFix_{0i}\cdot Y_{F_{it}^{CD}}) \tag{2}$$

$$+ r\cdot F_{S_t^{GD}S_{t+3}^{CD}} + rFix\cdot Y_{F_t^{GDCD}} + h\cdot F_{S_t^{CD}S_{t+1}^{CD}} + \sum_{i=1}^{N} h\cdot F_{S_{it}S_{it+1}}) \leq gP$$

As the model is solved for different right-hand sides of constraint (2), one of the resulting solutions has to be selected to proceed with in the rolling horizon solution approach. This selection process cannot be carried out by the decision maker as he /she is not involved in the development of the decision rules. Hence, a procedure has to be defined which enables a deterministic and sensible selection process. Therefore, the problem is solved for each grid point in turn, beginning with the lowest costs - i.e. the smallest grid point - and every solution is compared with its predecessor in terms of operational costs and unmet needs. As long as the quotient of the difference of unmet needs and the difference of total costs is above a critical value (which has to be set beforehand), the solution process proceeds with the next grid point, but as soon as this quotient decreases below the critical value, the process is interrupted and the last solution with a quotient above the critical value is chosen as the one to proceed with in the rolling horizon solution approach (see Figure 2). In this way, it is ensured that especially the region promising a sound compromise between costs and risk minimization is examined and those regions of the efficient frontier where the costs increase considerably without much of a change in unmet needs and risk are skipped. In the multiobjective optimization literature, these regions of particular interest are often called the “knees” of the efficient frontier (Das, 1999). Note that higher critical values lead to solutions with lower operational costs and higher unmet needs than smaller critical values. In order to find a good critical value, a limited sensitivity analysis has to be carried out. In this work, results are shown for two different critical values (1 and 0.7) to enable a comparison of the results.

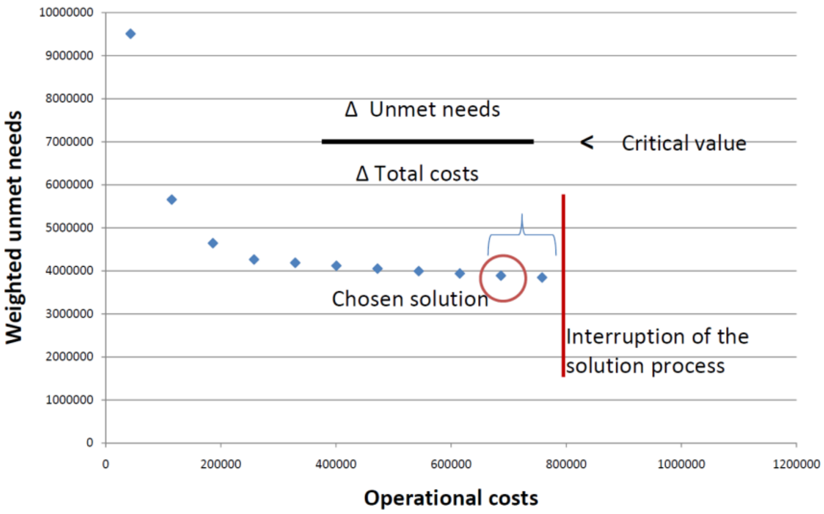

Figure 2. Costs and weighted unmet needs of the grid point model

RESULTS

The scenarios are solved with the constraint method which was presented above. Moreover, a reference model is used in which no uncertainty is considered (i.e. without considering uncertain needs). Except for scenario 0, where no further epidemical spread occurs, unmet needs can always be decreased by solving the model with the constraint method in comparison to the reference model (see Figure 3).

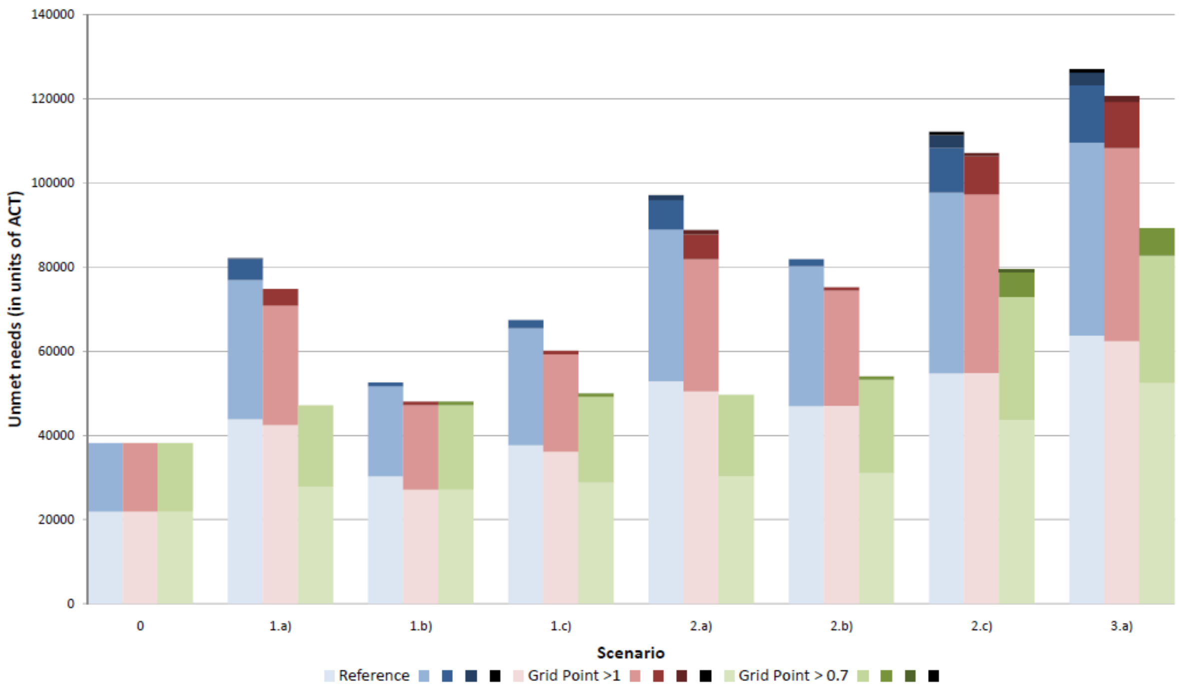

Figure 3. Unmet needs – Distinguished by duration (1 to 5 periods)

That is to be expected, because by this method safety stocks are built up to mitigate future shortages. Especially, the amount of needs remaining unmet for a longer timeframe can be reduced considerably (note that the darker the color in Figure 3, the longer the need has been unmet). On the other hand, in most cases the safety stocks cause an increase in logistics and inventory holding costs (see Figure 4).

The results show that safety stocks are sometimes too high for low-risk scenarios, e.g., for scenario 1.b), leading to high costs and to excess relief items remaining in stock after the last period. This occurs especially for the model with a critical value of 0.7, as in this case potentially unmet needs are reduced more than in the case of a higher critical value. As can be seen from Figures 3 and 4, unmet needs decrease somewhat less when the model is solved with a critical value of 1, but on the other hand in this case no considerable increase in operational costs occurs compared to the reference model. As the budget is usually scarce in disaster recovery situations, the solutions found with this critical value can be useful compromises for the decision maker.

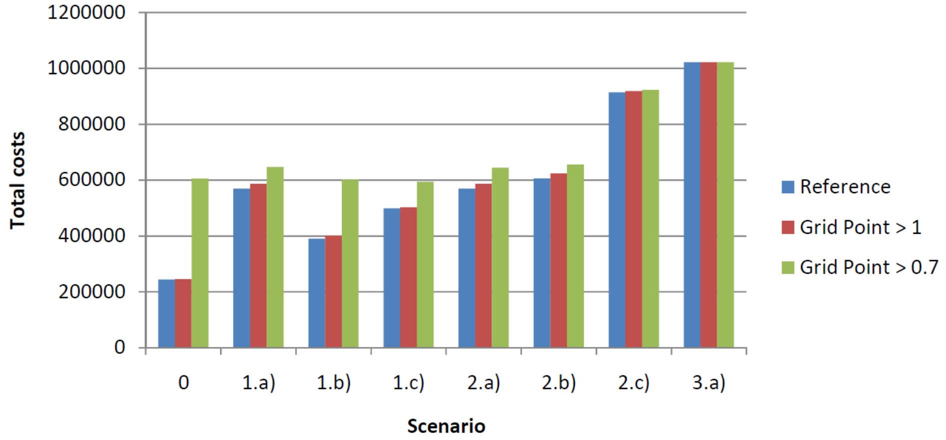

Figure 4. Total operational costs

In high risk scenarios, replenishment and relocation of relief goods lead to a decrease in unmet needs without generating considerably higher costs (e.g., scenario 3.a)). The replenishment amounts show a similar development as the total costs presented in Figure 4, since replenishment is expensive and leads to an increasing relief item density in the entire network. As it is not known if and when a disruption occurs, it seems to be a good strategy to replenish early in order to enable a fast reaction to possible future incidents. This can be concluded from the good results of the grid point model with respect to (especially longer lasting) unmet needs, as replenishment is conducted early when solving the scenarios with these models. The relatively small amount of transshipped relief items in all scenarios and with each of the model configurations (see Figure 5) can be explained by the scarcity of resources in the whole area. As it is usually the case in humanitarian operations, the amounts of relief items in the regional depots do not exceed the amount required to satisfy the expected – i.e. the certain – needs. Nevertheless, in all scenarios transshipments occur in the first period, where as many relief items as possible are transshipped to the affected region in order to mitigate the first occurrence of the epidemic without depleting the other stocks completely. The solutions that are found using the lower critical value show that transshipments increase with increasing budget, i.e. the model tends to store a higher amount of the relief items in the regional depots and to transship them in case of further epidemical spreads. This is a successful strategy with respect to unmet needs, due to shorter transshipment times in comparison to the transportation from the central depot (see, e.g., scenario 2.a)) where unmet needs can be decreased considerably when solving the scenario with a critical value of 0.7).

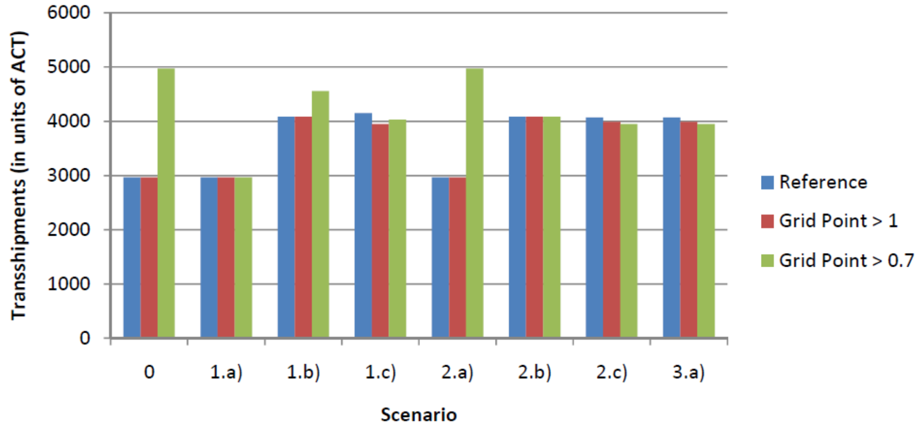

Figure 5. Relief items transshipped between the regional depots

It is also noteworthy that the results are rather similar for all scenarios, which leads to the conclusion that they can be solved by the same strategy. Obviously, it does not make a considerable difference in which region the epidemic spreads, or how many regions are affected. Certainly, the impact with respect to unmet needs and total costs differs, but in comparison the models perform similar in every scenario. This leads to the conclusion that the decision maker can decide based on the available budget and does not have to analyze in detail where an epidemical spread could occur or how many spreads are to be expected. Nevertheless, knowledge about the risk states which the area faces can help in making sensible replenishment decisions. Of course, the risk situation should be monitored anyway by examining the key-factors to prevent the spread of a malaria epidemic as early as possible (Protopopoff et al., 2009). However, a major problem is the reaction time, i.e. the replenishment and transportation time, when the epidemic has already spread. Therefore, the model and the results can help to support replenishment decisions before another epidemical spread occurs, which means that the strategy shifts from reactive to proactive behavior.

	Reference model	**Critical value = 1**	**Critical value = 0.7**
Low risk	20,770	21,220	29,943
High risk	40,539	41,094	42,490

Table 3. Average amount of ACT replenished for the grid point models and the reference model

To generate clear-cut decision rules regarding replenishments for the decision maker, the average replenishment amounts for high and low risk scenarios were evaluated for the three different models; the respective values are stated in Table 3. This evaluation leads to four different alternatives for the decision maker, two when facing a high-risk state and two when facing a low-risk state. As the reference model and the grid point model with a critical value of 1 suggest similar amounts of ACT for replenishment, the first alternative is the mean of these values, e.g., to replenish 20,995 units in a low risk state and 40,816 units in a high risk state. The second possibility is preferable when a higher budget is available: Then it is possible to replenish the amounts of ACT suggested by the grid point model with a critical value of 0.7 (i.e. 29,943 units when facing a low risk state and 42,490 units when facing a high risk state), which leads to a decrease in unmet needs. These replenishments should be conducted early in the planning horizon, as mentioned above, to enable a fast reaction to possible disruptions.

DISCUSSION

Although the evaluation of different possible future developments can help in making sensible decisions, the decision maker has to decide how much he/she wants to replenish without knowledge about future developments, i.e. a decision under uncertainty has to be made. Furthermore, multiple criteria have to be taken into account: The importance of need satisfaction in humanitarian operations is out of the question; nevertheless, cost aspects cannot be ignored as the efficiency of a relief operation has to be justified in front of the donors.

The actual decision on how many relief items are to be replenished can be supported by decision rules: Different alternative strategies can be developed based on the scenario analysis that was carried out above, and a choice should be made by the decision maker based on the available budget. Furthermore, decisions about the transshipment of the relief items have to be made. Here, all models suggested to transship similar amounts in the first period and this would be the recommendation for the decision maker in the respective setting: The regional depots should be able to meet the certain needs in their regions for the current period, and all remaining relief items are to be shipped to depot 1 (located in the affected region) in the first period. Hence, decision making support for relocation problems in overlapping disaster situations is provided which can be easily adapted and is applicable in the emergency situation without an extensive data analysis and long optimization runs.

The decision rules presented in this work were developed for the specific situation of a malaria epidemic in Central Africa and in a certain environmental setting. A broader range of situations has to be analyzed to establish more general decision rules. The adjustments required for solving different settings are easily implemented and first studies of settings with additional regional depots and with longer transshipment times show that those infrastructural characteristics have a relevant impact on the solutions found by the models. Hence, the influence of those characteristics should be analyzed in more detail. It seems likely that these are important factors for the classification of planning situations with respect to the appropriate logistics strategy when facing overlapping disasters.

CONCLUSION AND OUTLOOK

In this work, a model for relocating relief items considering multiple objectives was applied to develop decision support rules for overlapping disaster situations in humanitarian logistics. It could be shown that the distribution decisions suggested by the model lead to decreasing unmet needs in all scenarios that were considered. Furthermore, costs do not increase considerably in scenarios where the impact of the disruptions is high. The similarities of the solutions found for the different scenarios lead to the conclusion that decisions can be made mainly based on the environmental setting and on a monitoring of the relevant risk factors, but without an extensive analysis of all possible future developments. However, an important aspect influencing replenishment decisions is the available budget; hence, it is suggested that the decision maker evaluates different options based on resource availability for the respective project.

As a specific setting is considered in this work, no further conclusions regarding the influence of infrastructural conditions are possible. Future work is aimed at the comparison of different logistics structures in order to identify relevant logistical key-factors. Based on these factors, a decision support system could be developed which provides support in relief item distribution decisions by analyzing the values of the key-factors in the current situation and by suggesting an appropriate strategy. Furthermore, the finite planning horizon could be extended after each disruption to enable an appropriate reaction also to future disruptions.

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