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June 2011

CIRRELT-2011-36

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A Decision Support System for Distribution Network Design for Disaster Response

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Abstract. This paper proposes a Decision Support System (DSS) for designing a distribution network for humanitarian relief in disasters. Based on our observations and discussions with experts in crisis management, we identify and model the decision-making steps for designing this type of network. We identify the objectives and constraints for each of these decision steps, and then we propose the mathematical formulations appropriate for each step and implement them in a DSS prototype embedded with a 3-step algorithm. Finally, we report the results of many numerical experiments that illustrate how the prototype should be used by crisis managers. These results allow us to assess the prototype's relevance to decision support in disasters.

Keywords. Emergency logistics, network design, decision support system, mathematical modeling.

Acknowledgements. This research was partially financed by grants [OPG 0371655, OPG 0293307 and OPG 0172633] from the Natural Sciences and Engineering Research Council of Canada (NSERC), by Fujitsu Consulting (Canada) Inc. and by Partnerships for Research on Microelectronics, Photonics and Telecommunicstion (PROMPT). This financial support is gratefully acknowledged. We would also like to thank Mr. Sébastien Paquet (Ph. D.), R&D Manager at Fujitsu Consulting (Canada) Inc., for providing us with relevant data and useful comments.

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Dépôt légal – Bibliothèque et Archives nationales du Québec
Bibliothèque et Archives Canada, 2011

1. Introduction

Humanitarian aid can be of different natures depending on the type of disaster. Humanitarian aid can require evacuating injured people to hospitals or health care centers, supplying isolated areas of water and food or restoring power lines, for example. The main goals of the authorities faced with a humanitarian aid situation are to insure the safety of the people concerned and to support the major infrastructures. The relief of disaster victims is a vast problem that involves a huge number of activities, organizations and decisions. This paper focuses on the logistics aspect of the problem, more precisely on the physical deployment of the logistics network. This physical deployment is a central element that determines the responsiveness, ability and speed of the network to cope with people needs in the affected region.

As pointed out by Sheu (2007b), emergency logistics is different from business logistics in terms of operational purposes, demand features and information accuracy, for example. Balcik et al. (2010) reported that while logistics is well established in commercial operations, it is still in its infancy in humanitarian relief. Although there is still no generally accepted definition for emergency logistics, we retain the one proposed by Sheu (2007b): "A process of planning, managing and controlling the efficient flow of relief, information and services from the point of origin to the point of destination to meet the urgent needs of the affected people under emergency conditions".

Altay and Green (2006) report that, although emergency management problems fit perfectly into the discipline of management science and operations research (MS/OR), the research conducted by the MS/OR community on the subject is still limited. Too few studies have addressed the problem of logistics management in crisis situations. In addition, the models and solution approaches proposed are often incomprehensible to the decision-makers and offer little interaction between these decision-makers and the crisis management tools.

In this context, we propose a decision support system (DSS) to help crisis managers with the process of designing a network for distributing humanitarian aid. This DSS makes a series of decisions that mimic the decision process observed in real-life emergency situations. Our system relies on frequent close interactions with experienced decision-makers who have valuable field knowledge. To this end, we propose a distributed approach based on decomposing the problem into several interconnected sub-problems according to the hierarchy of decisions observed in real-life. We consider three main questions: (1) how many humanitarian aid distribution centers will be needed, (2) where to locate them and which humanitarian aid functions will be offered by each open center, and (3) what quantities of each aid function will be allocated to each center according to its mission and responsibilities. Needless to say, these decisions all seek to minimize the deployment time and service time.

Our decomposition approach offers two main advantages of capital importance. First, the sub-problems obtained by our decomposition approach are relatively small and thus are easier to handle and solve. Second, decomposing the global problem into several sub-problems allows managers a great deal of flexibility, for example, to select the desired level of detail at each step or to question any decisions at any level.

The paper is structured as follows. The next section provides a brief literature review on emergency logistics problems as dealt with in the MS/OR discipline over the last decade. Section 3 presents the particularities of emergency situations. Section 4 describes the decision process that addresses the questions encountered while designing humanitarian aid distribution networks and introduces the mathematical formulations used in the different steps of network design. In Section 5, we report the results of our computational experiments that we used to evaluate the potential of our system in real-life situations. In Section 6, we draw our conclusions.

2. Literature review

Given the growing number of natural disasters in recent years and the enormous amount of damage that these disasters have caused, the interest of the scientific community in emergency logistics problems has considerably increased over the last ten years. For example, Özdamar et al. (2004) addressed the problem of planning vehicle routes to collect and deliver products in disaster areas. To handle the dynamic aspect of supply and demand, these authors proposed to divide the planning horizon into a finite number of intervals and solve the problem for each time interval, taking into account the system state. Vehicles are not required to return to their starting point (depot) at the end of the trip, but they can move between depots from one planning period to another. The distribution problem associated with each time interval is modeled with two multi-commodity network flow problems and solved by Lagrangian relaxation.

More recently, Chang et al. (2007) proposed a decision support system for logistics planning in case of flooding, which takes uncertainty into account. They presented two stochastic programming models to determine the locations of distribution centers and the required quantities of emergency equipment, as well as the distribution of this equipment, to establish robust deployment plans using the Sample Average Approximation (SAA) method.

Tzeng et al. (2007) proposed a humanitarian aid distribution model that used multi-objective programming. Three objectives were considered: minimizing costs, minimizing travel time and maximizing the satisfaction of demand points. They handled the dynamic data by considering a multi-period model in which most of parameters and variables are time-related. The goal of the model is to determine the transfer (i.e., distribution) centers to be opened and the quantities of products to be transported from collection points to transfer points and from transfer points to the final demand points.

Minciardi et al. (2007) pointed out that accurate information about transport infrastructures is fundamental to emergency intervention. They developed a DSS to model and evaluate the efficiency of the elements of an infrastructure network for a given emergency situation. Thompson et al. (2006) highlighted the enormous potential benefits of DSS; they also discussed the necessary conditions for decision support technology to effectively support emergency managers when making their decisions. Sheu (2007a, 2010) proposed an approach to plan aid distribution that included 3 phases: 1) forecasting the demand of the affected regions, 2) grouping the affected areas based on the estimated severity of the damage, and 3) determining the priorities for aid distribution to affected areas.

In another context, Yi and Özdamar (2007) proposed an integrated location-distribution model (i.e., location-routing model) over a given planning period, in which the products need to be delivered to demand points from distribution points or depots. Injured people must be evacuated from certain points to emergency centers. These authors proposed a two-step procedure. The first step determines the amount of products and injured flowing through each arc of the network at each period of the planning horizon to minimize a weighted sum of unsatisfied demand for all products and all the requests for transporting the injured over the planning horizon. This problem is modeled using a MIP formulation. The second step seeks to construct explicit vehicle routes. A routing algorithm is used to develop a series of pick-up and delivery activities for each vehicle without considering the vehicle capacity. After the routing algorithm is executed, the quantities that are loaded and unloaded for each vehicle on each route are determined by solving a system of linear equations.

Since the travel time is a very important decision parameter in logistics management in emergency situations, Yuan and Wang (2009) proposed a multi-objective path selection model that takes into account the effects of real disasters on both the travel time and the path complexity. Their model is solved using an ant colony algorithm.

Recently, Velasquez et al. (2010) implemented a computer-based, collaborative training prototype for emergency response in order to improve organizational communication to lessen emergency situations. This training system stores information about the emergency situations and the organizational aspects, such as the different types of emergency situations a manager may encounter. They showed that the training system has the ability to improve the communication within the organization.

Only a few studies have proposed models and solution approaches that can be easily understood by decision-makers and offer the decision-makers a high level of interaction with the decision tools. Most studies propose monolithic models that do not map the decision-making process actually observed in the field. This paper proposes a comprehensive, interactive decision support system (DSS) to help crisis managers to design a humanitarian aid distribution network. We adopt a sequential approach rather than a monolithic approach, which decomposes the problem into sub-problems. Inspired by the steps commonly observed in the emergency management process during the first hours after a disaster, this decomposition process mimics the hierarchy of decisions observed in real life. However, our DSS offers managers choices that have been optimized by our mathematical formulations.

3. The particular context of a humanitarian crisis

Humanitarian crisis are vast, extremely complex situations. This study is inspired by the particular situation observed in Quebec (Canada). In order to improve the preparedness, response and management of potential humanitarian crisis, the Civil Protection Act was adopted by the Quebec government and went into effect on December 20, 2001. Now, each municipality must develop and update its own emergency plan, which includes a list of topics related to emergency logistics. As these requirements are relatively new, there are almost no tools or software to help and train municipality emergency managers. This led us to develop a decision support system (DSS) for distribution network design.

This paper describes a DSS to support decision-making with a number of alternatives regarding the number, location and staffing of distribution centers for distributing humanitarian aid. This network design problem is considered in a rather static manner since the decisions to be made are made immediately following the disaster (i.e., a few hours later). We assume that requests for products and services are estimated by homeland security organizations or their experts based on their experience and their evaluation of the disaster's seriousness. Demand is therefore assumed deterministic throughout the planning horizon.

In the following sub-sections, we first present a detailed discussion of the characteristics, nature, location and quantification of the population requirements (i.e., the demand) (3.1). Then, we describe the network facilities (3.2).

3.1 Relief demand

In disaster situations, it makes sense thinking that each particular house or building within the affected region could require relief or humanitarian aid, thus becoming a potential demand point. The humanitarian aid may consist of tangible products (e.g., food, health products, medicines, water, beds) or services (e.g., securing a bridge, restoring a power line). In a severe crisis that affects a large area, the number of demand points and the number of types of products and services required may be very large. The amount of information to be managed is huge, and it would be impractical (if not impossible) to consider the fine details in designing humanitarian aid distribution networks.

To cope with these difficulties, our modeling approach applies two kinds of aggregation operations. The first operation, geographical aggregation, groups the individual demand points into demand zones according to certain rules. The second operation, functional aggregation, groups the various products or services required in the affected region into generic humanitarian functions.

3.1.1 Geographical aggregation

Demand points may be aggregated into demand zones in a straightforward manner by using the zip code or postal code. The aggregated zone is represented by an aggregated demand computed as the sum of the individual demands sharing the same three characters in the zip code (North America) and a location corresponding to the centroid (i.e., gravity center) of the corresponding covered area. Other criteria for grouping could also be appropriated. In emergency situations, given the multitude of needs, public organizations (e.g., Army, National Guard, and Police) and private companies (e.g., power companies, communications suppliers, grocery stores supplying food and water) will have to act jointly. Each organization/company involved may have its own geographic districting plan; however, without loss of generality, we assume that they will divide the disaster area into meaningful demand zones, and this division will be adopted by all the organizations/companies involved. These demand zones can be prioritized in terms of damage severity, criticality of the affected strategic points, or other aspects specified by the crisis managers.

3.1.2 Functional aggregation

The aggregation of products and services required in the affected areas may be supervised by the humanitarian aid coordinator who, based on his/her experience and data from the affected areas, suggests a classification system. For example, a rough classification could yield the following four generic humanitarian functions[1]: (1) a

[1] Clearly, other aggregations are possible. For example, the Pan American Health Organization (PAHO) and the US Government use a standard operational classification for donated relief supplies composed of 10 broad classes (i.e., medicines, health supplies/equipment, water and environmental health, food/beverages, shelter/housing/electrical/construction, logistics/administration,

survival function, including food and lodging (e.g., meals, water, beds); (2) a *safety* function, encompassing all the needs for population security in cases of social disorder, terrorist threats or contamination dangers; (3) a *medical* function, including medical consumables (e.g., drugs, bandages) and medical professionals (e.g., physicians, nurses); and (4) a *technical* function, including technical services for infrastructure repairs. These humanitarian functions can also be prioritized according to the nature of the disaster or other specific objectives. Both kinds of aggregation rely on the experience of managers and decision-makers, and their accuracy and meaningfulness have an impact on the performance of the decision support system design.

3.2 Potential network sites

An emergency response network is often articulated around two main types of facilities: Emergency Operations Center (EOC) and Humanitarian Aid Distribution Centers (HADCs). The EOC is usually located outside the affected area (the "cold" zone) since it must rely on communication infrastructure and efficient transportation systems. The affected area is generally delimited by a police perimeter so that access can be controlled. Adjacent to the disaster area, a "warm" zone is mainly used to optimize the deployment logistics between the affected zone, called the "hot" zone, and the cold zone. Several HADCs are mobilized to receive and distribute the products and the equipment necessary to support relief distribution operations. Thus, the HADCs' primary mission is to provide first-line relief. They are expected to be located as close as possible to the disaster victims in order to deliver aid in the shortest time. Depending on the situation, HADCs may need to be located in both the warm and hot zones.

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human resources, personal needs, agriculture, unsorted). Pan American Health Organization, Humanitarian supply management in logistics in the health sector, Washington, D.C.: PAHO, 2001, ISBN 92 75 12375 6.

3.2.1 Site geographical location

The notion of proximity is of paramount importance in emergency logistics. However, physical distance does not adequately measure how easy or fast the access to a given site is, mostly because road conditions after the disaster can be affected or because public transportation is not operating. Therefore, access time becomes more relevant than physical distance, and site location is translated in terms of time required to access the different affected areas. The access time explicitly takes into account the state of roads (e.g., broken, damaged, intact) through an access difficulty criterion associated with each zone. This parameter is set by the decision-maker and may change over time.

3.2.2 Site profile

Each HADC receives, stores, and delivers relief products using a fleet of vehicles. In addition, it manages materials, staff and support vehicles for delivering services. Its *profile* tells if a particular HADC is more or less effective to perform a given humanitarian task (e.g., distribution of food, shelter, medical services).

Depending on the needs of the affected areas, the humanitarian functions to be accomplished and the various logistical needs, the options for an HADC location may be more or less advantageous. In addition to distributing aid, HADCs must play certain roles, such as communications services, accommodation, and food provision for rescue teams as well as for the people affected by the disaster. Thus, government buildings or schools can be attractive locations from which to perform supporting roles that require intensive communication infrastructure (e.g., telephone, Internet) and a large workspace to plan logistics operations. On the other hand, these places will be an unattractive option for receiving and storing humanitarian aid. For this purpose, a commercial store, a distribution center or a municipal arena will provide facilities for handling and storage that are much more advantageous.

The next section presents the three-step decision-making process observed when managers have to deploy a distribution network.

4. A comprehensible decisional hierarchy for deploying disaster relief

Deploying a logistics network to support humanitarian aid distribution is a complex, difficult task. In this paper, we focus on the very first response that takes place a few hours after the disaster. In this context, a good response that is delivered quickly is often preferred to a better response that is delivered later. In the hours following a disaster, the operations manager must answer three main questions: (1) How many humanitarian aid distribution centers (HADCs) should be opened?; (2) Where to locate these HADCs and which humanitarian aid functions will be offered by each open center?; and (3) What quantities of each aid function will be allocated to each HADC opened?

The modeling approach proposed in this paper decomposes the global problem into three decision-making steps, which are embedded into a decisional algorithm that interacts with the users. This interaction allows adjustments to be made to the present solution according to their preferences and experience. If the performance of the solution proposed by the system does not satisfy the user's requirements, these adjustments may be made after each step or after the whole decisional process has been executed. A global system loop has been added to the algorithm in order to allow it to iterate until it finds solution that satisfies specific user objectives. The structure of this algorithm is shown in Figure 1.

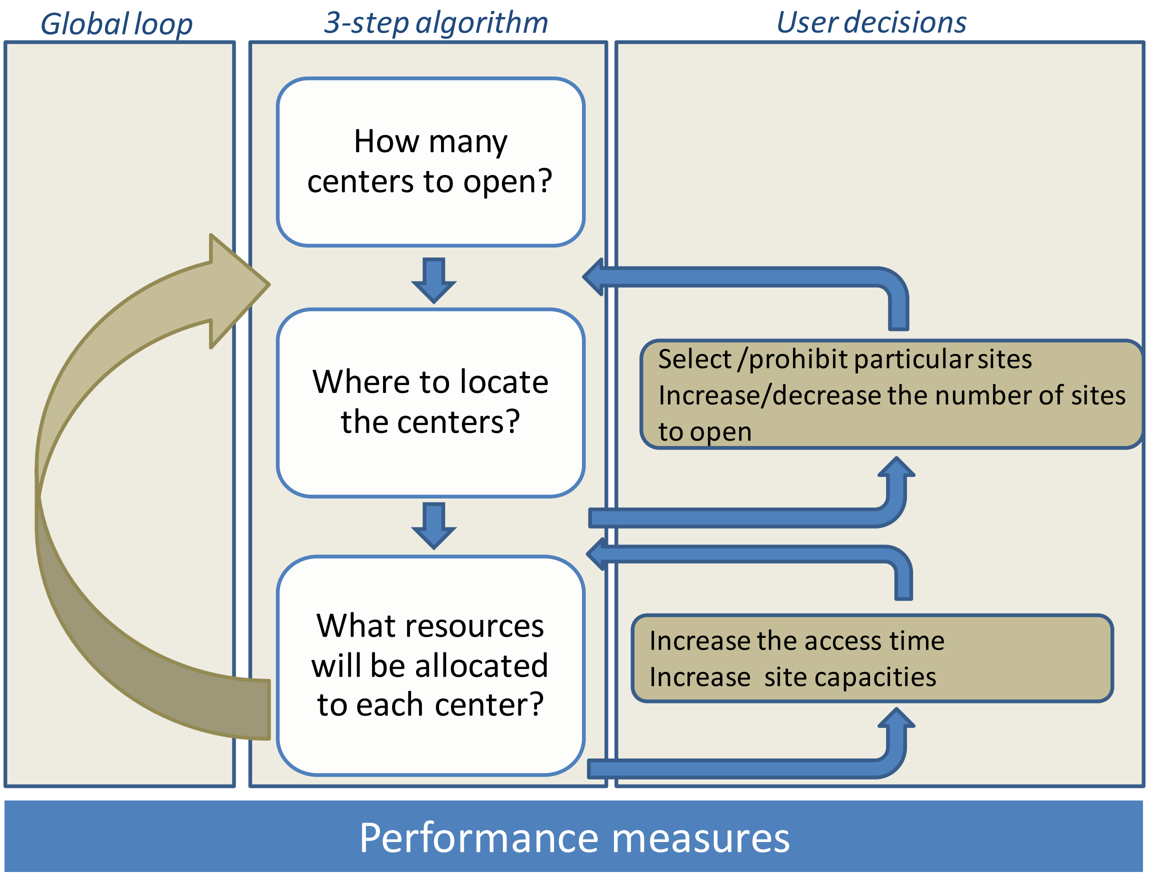

Figure 1: The structure of our 3-step algorithm

Minimizing deployment time could be achieved by locating a large number of humanitarian aid distribution centers in the affected region. However, opening many HADCs would require considerable human and material resources to operate them, which would be unfeasible. In fact, nobody wants to bring more people (e.g., drivers, policemen, technicians) into the disaster zone than necessary because more people would require more food and water and increase the need for coordination, as well as the potential risk to these people's lives.

In the next three sub-sections, we present mathematical models for the decisions in steps 1 to 3. These decisions need to be addressed in the hierarchical decisional process. Data, parameters and decisional variables will be introduced as needed throughout the sub-sections. In the following, the set of aggregated geographical zones and aggregated humanitarian functions are denoted, respectively, Z and F. The aggregated demand for each zone for each humanitarian function is denoted by d_{zf}. The set of candidate sites is denoted by L.

4.1 Step 1: Determine the number of HADCs needed

The goal of this first step is to determine the minimum number of HADCs needed to insure that every demand zone is accessible from at least one HADC in a time less than or equal to a *maximum access time*, denoted τ. This time is determined by the decision-maker according to the nature of the disaster and the needs of the population. This step takes only the geographical location of potential sites into account, regardless of their profile or capacity.

We used a traditional set covering formulation to model the problem, in which a binary variable x_l is defined for each candidate site $l \in L$. Variable x_l equals 1 if a HADC is opened at site l, and 0 otherwise. We also use t_{lz} to denote the time needed to travel from site $l \in L$ to demand zone $z \in Z$, which takes into account the access difficulty of the zone. Finally, we define for each zone $z \in Z$, a subset L_z of potential sites that are within the maximum access time τ, i.e., $L_z = \{l \in L : t_{lz} \leq \tau\}$.

Let p be the minimal number of HADCs to be opened. p is determined by solving the following mathematical model (M1):

$$\text{(M1): } Min \quad p = \sum_{l \in L} x_l \qquad (1)$$

$$\text{s.t} \qquad \sum_{l \in L_z} x_l \geq 1 \quad \forall z \in Z \qquad (2)$$

$$x_l \in \{0,1\} \quad \forall l \in L \qquad (3)$$

The objective function (1) minimizes the number of HADCs to be opened. Constraints (2) insure that every demand zone z has an access time lower or equal to the maximum access time from the HADCs that have been opened. Constraints (3) require variables x_l to be binary.

4.2 Step 2: Determine the location of HADCs

Among the set of candidates sites, the second step chooses the exact number of p sites (determined in step 1) to be opened in such a way that the total demand covered – within the maximum access time – is maximized. While step 1 produces a list of sites exclusively based on time access or geographic criteria, step 2 selects the sites by taking into account the nature of each demand zone, the priority or urgency accorded by the user to each demand zone, and the particular profile of the candidate sites. Therefore, it is not surprising to find that steps 1 and 2 select different sites to open, giving the user different perspectives on potential deployments.

The profile of a candidate site l is modeled by a set of parameters h_{lf}, one for each humanitarian function . The parameters h_{lf} reflect the aptitude of the candidate site l to provide humanitarian function f. The values of h_{lf} are in the interval [0 , 1]. A value of 1 indicates a strong aptitude for deploying the function in question (e.g., a hospital for providing health care services). A value near 0 indicates a weak aptitude; for example, a hospital is not normally suitable for transferring and storing construction equipment.

As already mentioned, humanitarian functions are prioritized using a weighting coefficient w_f. The higher the value of w_f for a function, the more critical it is to satisfy the demand for this function. Aggregated zones are also classified in terms of damage severity using a severity degree parameter θ_z. The larger the value of θ_z for a demand zone, the more urgent it is to satisfy the demand for this zone.

To model this second step's decision problem, three sets of decision variables are used. The first set includes binary variables $x_l, l \in L$ defined as in model M1. The second set includes binary variables y_{zf}, defined for each zone $z \in Z$ and each humanitarian function $f \in F$ so that $y_{zf} = 1$ if the demand of zone z for humanitarian function f is satisfied; otherwise, $y_{zf} = 0$. The third set includes binary variables O_{lf} that equal 1 if the site l, when open, provides humanitarian aid of type f, and 0 otherwise.

At this point, HADCs are still assumed to have unlimited capacity. Hence, if a HADC is opened at a given location, such as l (i.e., x_l=1), and this HADC is selected to provide humanitarian function f, then this HADC is able to satisfy the demand for function f of all the zones that are within its maximum access time. The problem is formulated using model M2:

$$\text{(M2): } Max \sum_{z \in Z} \sum_{f \in F} \theta_z w_f \frac{d_{zf}}{\sum_{z} d_{zf}} y_{zf} + \sum_{l \in L} \sum_{f \in F} w_f h_{lf} O_{lf} \tag{4}$$

s.t

$$y_{zf} \le \sum_{l \in L_z} O_{lf} \quad \forall z \in Z, f \in F \tag{5}$$

$$O_{lf} \le x_l \quad \forall l \in L, f \in F \tag{6}$$

$$\sum_{l \in L} x_l = p \tag{7}$$

$$x_l, y_{zf}, O_{lf} \in \{0,1\} \quad \forall l \in L, f \in F, z \in Z \tag{8}$$

The objective function (4) contains two parts. The first part accounts for the total covered demand for all zones and all humanitarian functions, taking into account both the relative importance of humanitarian functions (coefficients w_f) and zones' priorities (coefficients θ_z). The objective here is to cover, first, the demand of the zones with the greatest severity and the greatest needs for the most important humanitarian functions. The second part of (4) maximizes the total ability of open sites by taking into account the humanitarian function's priorities and the site profiles. The objective is to open HADCs in candidate sites that are the most appropriate for the most important humanitarian functions. Constraints (5) insure that the demand of a given zone for a given humanitarian function is covered only if at least one HADC within its maximum access time offers this humanitarian function. Constraints (6) link the O_{lf} and x_l variables, which insure that a HADC may provide a humanitarian function only if it is open. Equality constraint (7) fixes the number of open facilities to p, as determined in the first step or as decided by the decision-maker. Finally, constraints (8) express the binary nature of the decision variables.

The O_{lf} variables, although redundant in some respects, add greater flexibility for the decision-makers during their interaction with the algorithm by allowing, for example, to prevent, or promote, the deployment of a humanitarian function on a particular site. Note that site capacities are not considered at this step. However, looking at the site profiles anticipates somewhat its suitability for satisfying each of the needed humanitarian functions. While working with unlimited capacity may seem unreasonable, in practice, there would be ways to increase the capacity of sites (e.g., installing tents, using other adjacent areas not initially available), assuming a given but difficult-to-estimate cost.

4.3 Step 3: Allocate the quantities of humanitarian aid functions

This third step specifies the quantities of each humanitarian aid function that will be allocated to each HADC that was opened at the end of step 2, which is done implicitly through the decision to assign the demand zones to open HADCs. A feasible solution assigns each zone to a HADC within the maximum access time and satisfies the demands of all zones for all the humanitarian functions. However, remember that step 2 did not take into account capacity when choosing the HADCs to be opened, so there is no guarantee that the solution produced in step 2 is feasible with respect to satisfying the demands, both in terms of quantity and access time. Therefore, at this final step, site capacities are taken into account to decide what resources need to be allocated to each open HADC in order to maximize the covered demand (i.e., minimize the uncovered demand).

Formally, let $\hat{L}$ denote the set of open facilities, and $\hat{F}_l$ the set of humanitarian functions offered by any open facility l as determined in the second step. Each HADC open at a site l is associated to a capacity for each humanitarian function f, denoted S_{lf} , and a global capacity S_l. Obviously, it is assumed that $\sum_{f \in F} S_{lf} \geq S_l$. For example, a HADC opened as a warehouse has storage space dedicated to food, to building materials and to accommodations. Some of these spaces can be exclusively used for storing some specific humanitarian aids, whereas others can be shared and used for storing one or more humanitarian aids.

A decision must be made on what quantity of each humanitarian aid will be stored in each open HADC in order to minimize the uncovered demand. To model this resource allocation problem, we introduce the decision variables v_{lzf}, which represent the percentage of the demand of zone z of humanitarian function f that is satisfied by a HADC open at site. We also define a continuous variable u_{zf}, $z \in Z, f \in F$, which represents the percentage of uncovered demand for zone z for humanitarian function f.

The problem is formulated using model M3, as follows:

$$\text{(M3): } Min\sum_{z\in Z}\sum_{f\in F}\theta_z w_f \frac{d_{zf}}{\sum_z d_{zf}} u_{zf} \tag{9}$$

$$\text{s.t} \quad \sum_{l\in \hat{L}\cap L_z} v_{lzf} + u_{zf} = 1 \quad \forall z\in Z, f\in F \tag{10}$$

$$\sum_{z:l\in L_z}\sum_{f\in \hat{F}_l} d_{zf} v_{lzf} \le S_l \quad \forall l\in \hat{L} \tag{11}$$

$$\sum_{z:l\in L_z} d_{zf} v_{lzf} \le S_{lf} \quad \forall l\in \hat{L}, f\in \hat{F}_l \tag{12}$$

$$v_{lzf} \ge 0 \quad \forall l\in \hat{L}, f\in \hat{F}_l, z\in Z \tag{13}$$

$$u_{zf} \ge 0 \quad \forall z\in Z, f\in F \tag{14}$$

The objective function (9) minimizes the total uncovered demand, weighted by the zones' priority and the relative importance of the humanitarian functions. Constraints (10) describe the balance between portions of covered and uncovered demand; their sum must be equal to the total demand. Constraints (11) and (12), respectively, insure that the capacity of each HADC is satisfied, in terms of the global demand and each humanitarian function. Finally, constraints (13) and (14) are non-negative constraints on the decision variables.

As shown in Figure 1, some performance indicators are offered to the decision-maker. By looking at these indicators, the decision-maker may decide to modify partially the present solution or to adjust the problem parameters (e.g., the maximum access time). Next section presents a number of performance indicators that are used to evaluate the quality of the solutions produced by the system.

4.4 Performance indicators

In order to evaluate the quality of the solutions produced by our DSS, we consider three types of performance indicators: the number of open HADCs indicator (I^n), the global demand shortage indicator (I^u), and the HADC aptitude indicator (I^h). These indicators are explained in more detail below.

The *number of open HADCs indicator* (I^n) is an important element that must be taken into account while evaluating a solution. In fact, opening a large number of HADCs requires a considerable amount of human and material resources to operate them. Depending on the type of disaster, the number of persons that have access to the warm or hot zones would preferably be limited for security reasons. In addition, a large number of HADCs complicates the coordination and management operations.

The *global demand shortage indicator* (I^u) gives the weighted average percentage of uncovered demand for all zones and all humanitarian functions. It is computed as:

$$I^u = \frac{\sum_{z \in Z} \sum_{f \in F} \theta_z w_f u^*_{zf}}{\sum_{z \in Z} \sum_{f \in F} \theta_z w_f}$$

Where $\left(u^*_{zf}\right)_{z \in Z, f \in F}$ is an optimal solution for the allocation problem solved in the third step. Obviously, the lower the value of I^u, the better the solution in terms of covered demand.

The *HADC aptitude indicator* (I^h) evaluates how appropriate the site choice (see step 2) is in terms of their aptitude for offering the humanitarian functions needed. A good solution would select the candidates with high aptitudes for the humanitarian functions that have the highest priorities. Hence, given the number p of open HADCs (i.e., the output of model $M1$ or as decided by the decision-makers), the set of the p most suitable sites, denoted L_f^*, is determined for each humanitarian function . That is, $\left|L_f^*\right| = p$ and $\forall l \in L_f^*, \forall l' \in \left(L - L_f^*\right), h_{lf} \geq h_{l'f}$. Then, for each humanitarian function $f \in F$ we consider the percentage deviation of the aptitudes of the open sites offering f (i.e., $\hat{L}_f$), in terms of this "ideal" aptitude. This is formally done by calculating:

$$E_f = \frac{\sum_{l \in L_f^*} h_{lf} - \sum_{l \in \hat{L}_f} h_{lf}}{\sum_{l \in L_f^*} h_{lf}}$$

Taking humanitarian functions' priorities into account, the HADC aptitude indicator is given by:

$$I^h = \frac{\sum_{f \in F} w_f E_f}{\sum_{f \in F} w_f}$$

The lower the value of I^h, the closer the open sites are to the "ideal" choice in terms of aptitude. A low value of this indicator would give incentive to keep these HADCs open at the same locations and overcome the lack of demand coverage by, for example, extending sites capacities, enlarging access times for certain humanitarian function, or in

5. Computational experiments and results

The goal of this section is twofold. First, we want to assess the usefulness of the proposed system when facing a real-life situation. To this end, we need to evaluate the computation times required to solve the models present in the 3-step algorithm. Then, we need to evaluate the quality of the solutions, using the performance indicators defined in the previous section. Second, we want to show how the models and the solutions can be used to support the manager decision process in a humanitarian crisis. To this end, we generated sets of instances with specific features. These features are controlled by a number of parameters, including the problem size (e.g., number of zones, number of potential HADCs) and the demand (e.g., number of humanitarian functions, quantities).

All the models were coded in Java, and the branch-and-bound algorithm of CPLEX 12.0 (with its default parameters) was used to solve the instances on a 3.00 GHz Intel Core 2 Duo PC with a 4.00 Go RAM. All the computation times reported in the rest of this paper are in seconds.

5.1 Problem instances

The problem instances model three emergency situations that essentially differ on the geographical extent of the disaster. An emergency situation is defined by the size of the affected area (given by square of [X × X] surface units) and the number of demand zones in the area $|Z|$. The first and second situations consider a surface of [500 x 500] and 80 and 100 demand zones, respectively. The third situation considers a bigger surface ([1000 x 1000]) with 200 demand zones.

For each situation ($|Z|$, X), we generated eight sets of instances by varying the number of potential sites ($|L|=|Z|$ and $|L|=2|Z|$) and the number of humanitarian functions ($|F|$=4, 6, 8, and 10). For each combination ($|L|$, $|F|$) associated to each situation ($|Z|$, X), we considered two values for the maximum access time $-\ \tau = \left\lfloor \frac{X}{3} \right\rfloor$ and $\tau = \frac{X}{2}\ -$ in order to evaluate the sensitivity of the decisional process with respect to this parameter. For each combination of the values of (|*Z*|, *X*), |*L*|, |*F*| and, we generated 60 instances randomly. In each instance, demand zone is modeled by a single point representing the centroid or barycenter of the zone and by an array containing demand quantities for each humanitarian function *f*. A total of 2880 instances were thus generated.

5.2 Performance of the 3-step algorithm

This section analyses the quality of the solutions produced by our 3-step algorithm in terms of computation times and the global demand shortage indicator. This analysis evaluates the quality of the solutions found by the algorithm without any user interaction and to see whether or not the execution of the models in the decomposition process is fast enough to allow its implementation in a commercial decision support system.

Table 1 reports the average results for the instances for every combination of parameters (|Z|, X), |L|, |F| and for the two values for the maximum access time headers ($\tau = \left\lfloor \frac{X}{3} \right\rfloor$ and $\tau = \frac{X}{2}$, respectively). Three results are reported in Table 1: the average computation time in seconds (Time), the average number of open HADCs (I^n), and the average percentage of the uncovered demand (I^u). Each line in Table 1 corresponds to the average over 60 instances.

Our first observation concerns the computation time. On average, the total time needed to solve the three steps ranges from a fraction of a second to a few seconds (5.77) for the largest problem size. The computation time increases with the size of the problem (given by parameters (|Z|, X), |L| and |F|).

(|Z|, X)	|L|	|F|	$\tau = \frac{X}{2}$			$\tau = \left\lfloor \frac{X}{3} \right\rfloor$		
			Time	I^n	I^u	Time	I^n	I^u
(80,500)	80	4	0.36	3.00	27.15	0.32	4.33	19.38
		6	0.37	3.00	27.78	0.31	4.17	21.58
		8	0.40	3.00	30.35	0.36	4.17	22.52
		10	0.40	3.00	29.32	0.41	4.17	21.08
	160	4	0.71	3.00	28.38	0.57	4.67	19.65
		6	0.76	3.00	28.85	0.62	4.17	21.27
		8	0.82	3.00	29.97	0.69	4.00	21.45
		10	0.92	3.00	31.35	0.70	4.00	23.27
(100,500)	100	4	0.55	3.00	24.15	0.51	4.50	17.77
		6	0.59	3.00	27.32	0.50	4.17	20.07
		8	0.67	3.00	27.70	0.55	4.33	20.97
		10	0.70	3.00	28.93	0.55	4.33	21.62
	200	4	1.13	3.00	24.87	0.93	4.00	19.40
		6	1.26	3.00	26.38	1.02	4.00	20.75
		8	1.33	3.00	27.92	1.02	4.00	21.75
		10	1.49	3.00	28.08	1.18	4.00	22.42
(200,1000)	200	4	2.42	3.00	23.05	1.99	4.67	15.93
		6	2.57	3.00	24.88	2.04	4.67	17.68
		8	2.86	3.00	25.22	2.22	4.50	17.95
		10	3.02	3.00	26.78	2.34	4.83	19.67
	400	4	4.85	3.00	22.82	4.00	4.17	17.10
		6	5.03	3.00	23.53	3.94	4.00	18.13
		8	5.45	3.00	24.95	4.17	4.00	20.32
		10	5.77	3.00	25.53	4.54	4.00	20.52

Table 1: Results of the 3-step algorithm

Table 1 shows that solving problems with larger access times (columns $\tau = \frac{X}{2}$) takes more time than shorter ones (columns $\tau = \left\lfloor \frac{X}{3} \right\rfloor$). This behaviour may be explained by the fact that, with larger access times, the cardinality of the subset L_z of potential sites in the maximum access time of each zone $z \in Z$ is larger. The results reported in Table 1 confirm that our 3-step algorithm can be efficiently implemented in a decision support system interacting with the decision-maker in real time.

Our second observation concerns the average number of HADCs opened (I^n). As could be expected, the number of HADCs opened is not affected by the number of zones to cover, nor by the number of potential sites. In fact, I^n depends mainly on the access time, with the number of HADCs opened being larger when smaller access times are considered. This behavior is clearly consistent with the choice made in the step 1 by model M1, which chooses the number of sites to be opened based on purely geographical criterion; site capacity and abilities are not considered in this step.

We conclude our analysis of the results presented in Table 1 by looking at the average percentage of the uncovered demand (column I^u). At first glance, better results (i.e., lower average percentages) are reached when smaller access times are used, which is fully coherent with the fact that more HADCs are open. We also observe that, in most cases, shortages increase slightly with the number of humanitarian functions to satisfy.

We wonder if the values reported (between 15.93 and 31.35%) are too high to be acceptable. The first solution provides a good idea of what can be done using the minimum number of HADCs. This first solution is meant to be the basis for further adjustments, to be done in interaction with the decision-makers, who make the right trade-offs (especially the one between the number of HADCs to open and the demand shortage) according to their experience and their goals. This interaction will eventually lead to better solutions.

To emphasize this last point, and illustrate the usefulness of our 3-step algorithm, the next sub-section describes a new set of experiments in which the users can choose the maximum average percentage of the uncovered demand. As stated at the beginning of Section 4, the system loop adjusts the network structure until the preset target is satisfied.

5.3 Performance of the system loop: finding a solution that satisfies the decision-maker

To illustrate the potential use of our 3-step algorithm, let us assume that the decision-maker fixes an upper bound Max^u on the global uncovered demand. Then, as long as the performance indicator I^u is greater than Max^u, the number of open HADCs is incremented and the process is re-iterated. A different approach to help managers in their decision-making task could be to test networks under different values of the maximum access time

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We were therefore interested in seeing how the computation time and the required number of HADCs would evolve as the Max^u requirement changes. We chose to confine ourselves to the case $\tau = \left\lfloor \frac{X}{3} \right\rfloor$. We arbitrarily set five values of parameter Max^u: 0%, 5%, 10%, 20% and 100% (0% means that all the demand of all humanitarian functions of all zones must be covered, and 100% means that no restrictions are imposed on the I^u value and thus the 3-step algorithm is executed only once). We solved the 1440 instances again until the value of Max^u was satisfied.

Table 2 reports the average computation time in seconds (Time) and the average number of HADCs opened (I^n) for the instances for every combination of parameters (|Z|, X), |L| and |F|. Each line in Table 2 corresponds to the average of 60 instances. As expected, for every instance, the computation time – or, in other words, the number of iterations – increases as Max^u decreases. However, the computation time stays fairly low, with a maximum of 16.51 seconds.

(|Z|, X)	|L|	|F|	Max^u=100%		Max^u=20%		Max^u=10%		Max^u=5%		Max^u=0%	
			Time	I^n	Time	I^n	Time	I^n	Time	I^n	Time	I^n
(80,500)	80	4	0.32	4.33	0.26	4.93	0.41	6.17	0.47	7.83	0.99	17.73
		6	0.31	4.17	0.35	5.23	0.49	6.53	0.56	7.97	1.44	19.63
		8	0.36	4.17	0.39	5.33	0.63	6.78	0.67	8.27	2.11	22.33
		10	0.41	4.17	0.44	5.43	0.69	6.93	0.82	8.60	2.40	21.47
	160	4	0.57	4.67	0.72	4.70	0.80	5.68	0.82	6.93	1.48	15.63
		6	0.62	4.17	0.80	4.73	0.96	5.93	0.95	7.10	1.59	13.23
		8	0.69	4.00	0.91	5.05	1.09	6.23	1.14	7.43	2.57	17.17
		10	0.70	4.00	0.96	4.97	1.28	6.28	1.30	7.50	3.48	19.62
(100,500)	100	4	0.51	4.50	0.54	4.97	1.00	6.08	0.58	7.23	1.32	16.88
		6	0.50	4.17	0.60	4.97	0.72	6.15	0.74	7.57	1.68	16.42
		8	0.55	4.33	0.68	5.27	0.80	6.6	0.89	7.93	2.77	21.62
		10	0.55	4.33	0.76	5.42	1.05	6.78	1.05	8.13	3.22	20.95
	200	4	0.93	4.00	1.16	4.62	1.26	5.55	1.16	6.67	1.86	13.00
		6	1.02	4.00	1.28	4.68	1.39	5.93	1.41	7.18	3.07	16.97
		8	1.02	4.00	1.44	4.90	1.67	6.25	1.61	7.38	4.14	19.48
		10	1.18	4.00	1.61	5.05	2.05	6.30	1.94	7.62	4.50	17.92
(200,1000)	200	4	1.99	4.67	1.97	4.83	2.17	5.72	2.19	6.92	3.99	17.53
		6	2.04	4.67	2.16	5.03	2.49	6.05	2.46	7.25	5.13	17.05
		8	2.22	4.50	2.24	5.05	2.72	6.13	2.97	7.50	7.92	20.98
		10	2.34	4.83	2.44	5.28	3.14	6.47	3.40	7.65	10.61	22.70
	400	4	4.00	4.17	3.58	4.67	3.96	5.53	3.89	6.40	6.50	14.72
		6	3.94	4.00	4.46	4.67	4.68	5.75	4.58	6.75	9.20	16.40
		8	4.17	4.00	4.63	4.82	5.24	5.87	5.62	6.98	12.43	17.30
		10	4.54	4.00	5.28	4.88	5.98	6.12	6.59	7.37	16.51	19.38

Table2: Results for fixed maximum average demand shortage when $\tau = \left\lfloor \frac{X}{3} \right\rfloor$

Looking at the number of HADCs to be opened, a similar behavior is observed: the number of open HADCs increases smoothly to improve the average percentage of uncovered demand from the initial solution (i.e., the solution from the first iteration) to 20% or less, and from there to 10% or less and to 5% or less. However, reducing the last 5% of uncovered demand is quite expensive in terms of the number of HADCs to be opened.

We believe that our algorithm can be of considerable help to crisis managers in the decision-making process. In fact, decisions need to be made, taking several criteria into account. Among them, the three performance indicators I^n, I^u, and I^h (see Section 4.4) seem to be valuable. To illustrate this point, let us consider 10 instances generated for problem (80, 500, 160, 4, 166) (i.e., instances with 80 demand points for a surface of [500 x 500] with 160 potential sites, 4 humanitarian functions and a maximum access time equal to $\tau = \left\lfloor \frac{X}{3} \right\rfloor$).

For these instances, Table 3 reports the associated values of the three indicators for the set of average demand shortage targets selected previously. A trade-off must be made between the different alternatives; a good alternative is the one in which the three performance indicators have acceptable values. Obviously, the tighter the restriction on the global demand to be covered, the higher the number of HADCs to be opened. However, the number of HADCs to be opened can grow significantly versus a slight improvement in the global percentage of covered demand.

For example, let us consider instance 1. The solution that guarantees a total demand satisfaction of all humanitarian functions and all demand zones requires opening 43

HADCs compared to only 6 HADCs to be opened for a global demand shortage of 5%. With 4 HADCs to be opened, the global demand shortage is equal to 10.10%. If a target of 10% is imposed, 5 HADCs need to be opened. If instance 2 is considered, the number of HADCs needed is not as large as for instance 1 when Max^u =0%. In this case, the decision-maker may hesitate between opening 11 HADCs and have the guarantee that all the demand is satisfied or opening only 5 HADCs and satisfying 95% of the global demand. When considering the overall HADC aptitude, the second alternative with 5 HADCs provides a better performance. Thus, the second alternative is more likely to be preferred.

Inst.	Max^u=100%			Max^u=10%			Max^u=5%			Max^u=0%		
	I^n	I^u	I^h	I^n	I^u	I^h	I^n	I^u	I^h	I^n	I^u	I^h
1	4	10.10	18.20	5	6.20	17.10	6	5.00	17.10	43	0.00	19.50
2	4	7.50	11.60	4	7.50	11.60	5	5.00	10.10	11	0.00	13.10
3	4	11.40	14.10	5	10.00	14.10	8	2.50	16.70	10	0.00	17.30
4	4	15.60	20.70	5	9.10	23.20	6	4.70	23.20	11	0.00	22.60
5	4	5.20	14.60	4	5.20	14.60	5	2.70	13.90	9	0.00	15.10
6	4	11.20	16.60	5	7.40	17.10	7	0.00	17.20	7	0.00	17.20
7	4	8.20	19.50	4	8.20	19.50	7	0.00	18.70	7	0.00	18.70
8	4	16.00	20.80	5	4.60	18.80	5	4.60	18.80	9	0.00	16.50
9	4	6.80	22.00	4	6.80	22.00	6	3.80	18.30	56	0.00	18.50
10	4	15.40	22.60	5	8.90	20.70	11	2.50	20.00	20	0.00	21.30

Table 3: Performance indicators for 10 instances of problem (80, 500, 160, 4, 166) and different average demand shortage targets

6. Conclusion

This article focused on a decision support system for helping crisis managers in the strategic process of designing a humanitarian aid distribution network. The proposed system does not attempt to solve all the aspects related to the logistics of disaster relief, at least not directly. Instead, it makes a series of decisions that mimics the decision process observed in real-life emergency situations. The system relies on frequent, close interactions with experienced decision-makers who have valuable field knowledge.

Decomposing the problem offers several advantages. First, the sub-problems are smaller in size than the global problem and thus are easier to handle and solve. Second, decomposing the global problem into several sub-problems allows managers a great deal of flexibility, for example, to select the desired level of detail at each step or to question any decisions at any level. Extensive numerical experiments were conducted that show how the system should be used by crisis management experts, and the results of these experiments showed its relevance in the context of decision support in crisis situations.

Acknowledgements

This research was partially financed by grants [OPG 0371655, OPG 0293307 and OPG 0172633] from the Canadian Natural Sciences and Engineering Research Council (NSERC), by Fujitsu Consulting (Canada) Inc. and by *Partnerships for Research on Microelectronics, Photonics and Telecommunications* (PROMPT). This financial support is gratefully acknowledged. We would also like to thank Mr. Sébastien Paquet (Ph. D.), R&D Manager at Fujitsu Consulting (Canada) Inc., for providing us with relevant data and useful comments.

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