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A Decision Support System for Network Design and Humanitarian Aid Distribution in Emergency Response Operations

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Abstract. In this paper, we model the situation faced by decision-makers in the first hours following a disaster when they have to deploy a humanitarian aid distribution network. This is done by first determining the number and the choice of depots to be opened and then by planning the distribution of humanitarian aid from these depots towards the affected people. We propose a decision support system (DSS) to help decision-makers in these tasks. The DSS is built around mathematical models that provide answers to the network design and distribution problems, and is completed by a multi-criteria analysis module. The DSS also provides a complete interface to display the problem's geographic structure, including distribution routes and the location of network nodes.

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

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1. Introduction

A growing research area for both practitioners and operations research researchers, emergency logistics is faced with numerous challenges. Often supported by government legislation, both mitigation and preparedness phases are rather well documented and are implemented both in practice and in the research literature [Altay & Green, 2006]. On the other hand, response phase planning is still an emerging subject in the literature. In practice, only a few tools are available to help decision-makers in the first hours following a disaster. However, the rapid deployment of an appropriate distribution network, as well as the efficient distribution of humanitarian aid, is crucial to save human lives and to alleviate suffering.

In this paper, we model the situation faced by decision-makers in the first hours following a disaster when they have to deploy a *humanitarian aid distribution network* by opening a number of depots and planning the distribution of humanitarian aid from these depots towards the affected people. We introduce several concepts that appear to us to be of capital importance to model adequately the associated decision problems subtleties. Then, we propose a *Decision Support System* (DSS) based on our observations and our discussions with experts in crisis management. This DSS reproduces the different steps of the natural decision-making process observed in the field, each step being solved by appropriate operations research techniques.

Two main problems are addressed: (1) a location-allocation problem that tries to determine the number, the location and the mission of *Humanitarian Aid Depots* (HAD) that need to be opened; and (2) a distribution problem to determine appropriate ways for distributing the humanitarian aid from the open HAD to different demand or *Distribution Points* (DP). Both the location and the distribution solvers are embedded into an interactive DSS, which incorporates geographical maps. Finally, as a way to help the decision-makers to choose the network configuration that best corresponds to their objectives, a multi-criteria analysis module is added to the DSS.

This chapter is organized as follows. Section 2 details the problem studied. Sections 3 and 4 describe, respectively, the models proposed for network design and the distribution problems. The DSS structure and the multi-criteria analysis module are presented in section 5. Section 6 reports the results of our numerical experiments, and section 7 presents our conclusions.

2. Problem modeling

In this section, we present the concepts and notations needed to adequately model what we call the *Network Design and Humanitarian Aid Distribution Problem* (NDHADP). Help request locations are denoted $Z = \{1, \ldots, n\}$, and they correspond to demand or distribution points (DP). A DP can be viewed as an aggregation of individual demands over a given zone, assuming that people can travel to the DP to get their help. The damage level of a distribution point (or the zone it represents) is modeled using a severity degree parameter θ_z, whose value is comprised within the [0, 1] interval. The larger the value of θ_z for a DP, the more urgent it is to satisfy this DP's demand.

Potential *Humanitarian Aid Depots* (HAD) are identified by $L = \{1, \ldots, m\}$. These sites are identified in the emergency plans of a given city or municipality. For example, in the province of Quebec (eastern Canada), the Civil Protection Act, which was adopted in 2001 by the Quebec government, requires that each municipality develops and updates its own emergency plan, which includes a list of topics related to emergency logistics. These potential HAD correspond to infrastructures, such as the city hall, schools, arenas, and hospitals, as well as the distribution centers of the industrial partners identified in the emergency plan. We use t_{lz} to denote the time needed to travel from HAD l to DP z, which takes into account routing access difficulty of the region [Yuan & Wang, 2009]. Generally, emergency decision-makers require that each DP can be reached from at least one HAD 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.

In addition, we define, for each distribution point z, a subset L_z of depots that are within the maximum access time τ (i.e., $L_z = \{l \in L : t_{lz} \leq \tau\}$). At each depot l, it is assumed that there are e_l vehicle types, h=1 … e_l, and u_{hl} vehicles of each type h. Since all depots may not be equally equipped for receiving a particular vehicle type, different docking times π_{hl} are considered, one for each vehicle type h and the corresponding HAD l .

Each HAD can hold some or all of the products to be delivered. In emergency logistics, products are generally grouped into generic humanitarian functions, such as the following four functions[1]: (1) a *survival* function, including food and lodging (e.g., meals, water, beds); (2) a *safety* function, encompassing all the needs for the security of the population in cases of social disorder, terrorist threats or danger of contamination; (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. We denote the set of functions to be delivered with $F = \{1, \ldots, p\}$. In addition, we prioritize humanitarian functions using a weighting coefficient ω_f defined in the [0, 1] interval. The higher the function's value of ω_f, the more critical it is to satisfy the demand for this function. Some vehicles may have certain equipment that makes them more efficient with some functions. The time needed for loading and unloading one unit (i.e., a pallet) of function f into a vehicle of type h is defined as α_{fh}, where $\alpha_{fh} = \infty$ if function f cannot be loaded into a type-h vehicle.

The capacity of HAD l for function f is denoted c_{lf}, and each HAD l has a global capacity c_l such that $\sum_{f=1}^{p} c_{lf} \geq c_l$. The amount of function f needed at distribution point z is denoted as d_{fz}. Each HAD l has the ability β_{lf} for handling function z. The values of β_{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 storing and transferring construction equipment.

Each unit or pallet of function f weighs w_f and requires s_f volume units. Thus, a vehicle of type h must not load more than $\bar{q}_h$ weight units nor have a volume over $\bar{v}_h$ volume units. A maximum daily work time $\bar{t}_h$ for each vehicle type h is imposed. As requested

[1] Clearly, other classes/functions 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: medicines, health supplies/equipment, water and environmental health, food, shelter/electrical/construction, logistics/administration, human resources, personal needs/education, agriculture/livestock and unclassified.

quantities are generally large in terms of vehicle capacity (in weight and/or volume), each vehicle trip is assumed to visit only one distribution point at a time. In other words, only back and forth trips are considered. Obviously, a DP may be visited many times. A given vehicle can perform as many trips as needed during a day as long as the corresponding work time limit is respected.

The *Network Design and Humanitarian Aid Distribution Problem* (NDHADP) can now be stated as follows:

Given a set of humanitarian aid depots where a certain number of vehicles of different types are located and a given quantity of each humanitarian aid is stored, determine (1) which depots to open and (2) the vehicle trips that minimize the total transportation duration, so that (3) each distribution point receives the required quantity of each function, (4) all vehicle constraints are satisfied, and (5) the depot product availability is respected.

3. Network design

In the hours following a disaster, decision-makers must determine the distribution network structure for delivering aid the most efficiently. Even if many infrastructures are available, the decision-makers may want to limit the number of operating depots depending on the available resources and to minimize the number of rescuers entering the affected zone. We decompose this network design problem into a sequence of three decisions reflecting the way in which crises decision-makers handle the problem. These decisions are: (1) what is the minimum number of depots to be opened, (2) the locations of these depots, and (3) how to best allocate resources to depots. We propose a mathematical formulation to model each of these decisions.

3.1 M1: Determining the minimum number of humanitarian aid depots (HAD)

The goal of this first decision is to determine the minimum number of HAD needed to insure that every distribution point (DP) is covered. We consider that a distribution point is *covered* if it is accessible from at least one open HAD within the access time τ. We used a classic 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 HAD is opened at site l, and 0 otherwise. Model M1 produces $\underline{p}$, the minimal number of HAD to be opened to insure that every DP is covered.

$$Min\ \underline{p} = \sum_{l=1}^{m} x_l \tag{1.1}$$

subject to

$$\sum_{l \in L_z} x_l \geq 1 \qquad z = 1, \ldots, n \tag{1.2}$$

$$x_l \in \{0,1\} \qquad l = 1, \ldots, m \tag{1.3}$$

The objective function (1.1) minimizes the number of HAD to be opened. Constraints (1.2) insure that every DP z has an access time lower or equal to the maximum access time from an open HAD. Constraints (1.3) require variables x_l to be binary.

3.2 M2: Locating the depots

Among the set of candidates sites, the second decision chooses exactly $\underline{p}$ sites to be opened (determined by M1) in such a way that the total demand covered is maximized. While M1 focuses exclusively on time access or geographic criteria, model M2 selects the sites by taking into account the nature of the demand of each zone, its priority, and the particular profile of the candidate sites. To formulate this second decision, three sets of decision variables are used. The first set includes the same binary variables $x_l, l \in L$ used in model M1. The second set includes binary variables y_{zf}, defined for each DP z and each humanitarian function 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 depot l, when open, provides humanitarian function of type f, and 0 otherwise. Model M2 is formulated as follows:

$$Max \sum_{z=1}^{n}\sum_{f=1}^{p}\theta_z w_f\left(\frac{d_{zf}}{\sum_{z=1}^{n} d_{zf}}\right) y_{zf} + \sum_{l=1}^{m}\sum_{f=1}^{p}\omega_f \beta_{lf} o_{lf} \qquad (2.1)$$

subject to

$$y_{zf} \leq \sum_{l\in L_z} o_{lf} \qquad z = 1, \ldots, n \quad f = 1, \ldots, p \qquad (2.2)$$

$$o_{lf} \leq x_l \qquad l = 1, \ldots, m \quad f = 1, \ldots, p \qquad (2.3)$$

$$\sum_{l=1}^{m} x_l = \underline{p} \qquad (2.4)$$

$$x_l, y_{zf}, o_{lf} \in \{0,1\} \qquad l = 1, \ldots, m \quad z = 1, \ldots, n \quad f = 1, \ldots, p \qquad (2.5)$$

The objective function (2.1) contains two parts. The first part accounts for the total covered demand for all DP and all humanitarian functions, taking into account both the relative importance of humanitarian functions (coefficients w_f) and DP priorities (coefficients θ_z). The objective here is to give priority to coverage of the demand of the DP with the highest damage level, considering the relative importance of the humanitarian functions. The second part maximizes the total ability of open depots by taking into account the humanitarian function's priorities and the depot profiles.

Constraints (2.1) insure that the demand of a given DP for a given humanitarian function is covered only if at least one HAD within its maximum access time offers this humanitarian function. Constraints (2.2) link the o_{lf} and x_l variables, insuring that a HAD may provide a humanitarian function only if it is open. Equality constraint (2.4) sets the number of open facilities to $\underline{p}$, as determined in M1 or as decided by the decision-maker, and constraints (2.5) express the binary nature of the decision variables.

At this point, the HAD are still assumed to have unlimited capacity. Hence, if a HAD is opened at a given location, and this HAD is selected to provide humanitarian function *f*, then this HAD is able to satisfy the demand for function *f* of all the DP that are within its maximum access time. The o_{lf} variables, although redundant in some aspects, add greater flexibility for the decision-makers during their interaction with the algorithm by allowing, for example, the deployment of a humanitarian function on a particular site to be prevented or encouraged.

3.3 *M3: Allocating resources to depots*

This third decision specifies the amount of each humanitarian aid that will be allocated to each HAD opened at the end of model M2, which is done by assigning the distribution points to open HAD. However, since M2 did not take into account capacity when choosing the HAD to be opened, there is no guarantee that the solution produced in M2 is feasible with respect to satisfying the demands. Therefore, since depot capacities are now considered, M3 determines the quantity of each humanitarian aid that will be stored in each open HAD in order to maximize the demand covered or, in other words, minimize the uncovered demand.

Let $\hat{L}$ denote the set of open depots, and let $\hat{F}_l$ denote the set of humanitarian functions offered by open depot l, as determined in M2. We introduce the decision variables v_{lzf}, which represent the percentage of the demand of DP z of humanitarian function f that is satisfied by a depot l. We also define a continuous variable u_{zf}, $z \in Z, f \in F$, which represents the percentage of uncovered demand for DP z for humanitarian function f. Model M3 is formulated as follows:

$$Min \sum_{z=1}^{n} \sum_{f=1}^{p} \theta_z w_f \left(\frac{d_{zf}}{\sum_{z=1}^{n} d_{zf}} \right) u_{zf} \tag{3.1}$$

subject to

$$\sum_{l \in \hat{L} \cap L_z} v_{lzf} + u_{zf} = 1 \qquad z = 1, \ldots, n \quad f = 1, \ldots, p \tag{3.2}$$

$$\sum_{z: l \in L_z} \sum_{f \in \overline{F}_l} d_{zf} v_{lzf} \leq c_l \qquad \forall l \in \hat{L} \tag{3.3}$$

$$\sum_{z: l \in L_z} d_{zf} v_{lzf} \leq c_{lf} \qquad \forall l \in \hat{L} \quad f \in \hat{F}_l \tag{3.4}$$

$$v_{lzf} \geq 0 \qquad \forall l \in \hat{L} \quad f \in \hat{F}_l \quad z = 1, \ldots, n \tag{3.5}$$

$$u_{zf} \geq 0 \qquad f = 1, \ldots, p \quad z = 1, \ldots, n \tag{3.6}$$

The objective function (3.1) minimizes the total uncovered demand, weighted by the DP priority and the relative importance of the humanitarian functions. Constraints (3.2) describe the balance between portions of covered and uncovered demand. Constraints (3.3) and (3.4) insure that the capacity of each open HAD is respected, in terms of the global demand (3.3) and each humanitarian function (3.4). Finally, constraints (3.5) and (3.6) are non-negative constraints on the decision variables.

4. Distribution planning

Once the decision-makers have selected a set of depots to be opened that satisfy their objectives, the distribution planning of the DSS is called. The set of open depots $\hat{L} = \{1, \dots, \hat{m}\}$ and the quantity of function *f* available at each depot *l*, $p_{fl} = \sum_{z=1}^{n} d_{zf} v_{lzf}$ (see equation 3.3) are known. At this point, if model M3 results in uncovered demand, it is possible that some of the quantities requested by some of the distribution points cannot be delivered. In this situation, the initial DP's demand d_{fz} must be updated to $d_{fz} = d_{fz}(1 - u_{zf})$, and the following additional decision variables are introduced:

- x_{zlhkv}, equal to 1 if DP z is visited from depot l with the k^{th} vehicle of type h on its v^{th} trip to z; and
- q_{zflhkv}, the quantity of product f delivered to DP z from depot l with the k^{th} vehicle of type h on its v^{th} trip to z.

The objective of the distribution model is to minimize the total transportation time (i.e., the sum of all vehicles trip times). The duration of the v^{th} trip of the k^{th} vehicle of type h, from depot l to distribution point z, is given by:

$$\left(2t_{zl}x_{zlhkv} + \pi_{hl}x_{zlhkv} + \sum_{f=1}^{p} \alpha_{fh}q_{zflhkv}\right)$$

where the first part ($2t_{zl}$) represents the back and forth travel times, the second part (π_{hl}) is the docking time, and the last part ($\sum_{f=1}^{p} \alpha_{fh} q_{zflhkv}$) is the loading and unloading time of all the products delivered from DC l to DP z. If t'_{zlh} is defined as $t'_{zlh} = 2t_{zl} + \pi_{lh}$, then the trip time becomes $\left(2t'_{zlh} x_{zlhkv} + \sum_{f=1}^{p} \alpha_{fh} q_{zflhkv}\right)$. The distribution model M4 is formulated as follows:

$$Min \sum_{z=1}^{n} \sum_{l=1}^{\widehat{m}} \sum_{h=1}^{e_l} \sum_{k=1}^{u_{hl}} \sum_{v=1}^{r} \left(t'_{zlh} x_{zlhkv} + \sum_{f=1}^{p} \alpha_{fh} q_{zflhkv} \right) \tag{4.1}$$

subject to

$$\sum_{l=1}^{\widehat{m}} \sum_{h=1}^{e_l} \sum_{k=1}^{u_{hl}} \sum_{v=1}^{r} q_{zflhkv} \geq d_{zf} \qquad z = 1, \dots, n \quad f = 1, \dots, p \tag{4.2}$$

$$\sum_{z=1}^{n} \sum_{h=1}^{e_l} \sum_{k=1}^{u_{hl}} \sum_{v=1}^{r} q_{zflhkv} \leq p_{fl} \qquad f = 1, \dots, p \quad l = 1, \dots, \widehat{m} \tag{4.3}$$

$$\sum_{z=1}^{n} \sum_{v=1}^{r} \left(t'_{zlh} x_{zlhkv} + \sum_{f=1}^{p} \alpha_{fh} q_{zfjlhkv} \right) \leq \bar{t}_h \qquad l=1, \dots, \widehat{m} \quad h=1, \dots, e_l \quad k=1, \dots, u_{hl} \tag{4.4}$$

$$\sum_{f=1}^{p} w_f q_{zflhkv} \leq \bar{q}_h x_{zlhkv} \qquad z = 1, \dots, n \quad l=1, \dots \widehat{m}, \quad h=1, \dots, e_l \quad k=1, \dots, u_{hl} \quad v=1, \dots, r \tag{4.5}$$

$$\sum_{f=1}^{p} s_f q_{zflhkv} \leq \underline{v}_h x_{zlhkv} \qquad z = 1, \dots, n \quad l=1, \dots, \widehat{m} \quad h=1, \dots, e_l \quad k=1, \dots, u_{hl} \tag{4.6}$$

$$v=1,\ldots,r$$

$$q_{zflhkv} \in \mathbb{R}^+ \quad z=1,\ldots,n;\ f=1,\ldots,p;\ l=1,\ldots,\widehat{m};\ h=1,\ldots,e_l;\ k=1,\ldots,u_{hl};\ v=1,\ldots,r \tag{4.7}$$

$$x_{zlhkv} \in \{0,1\} \quad z=1,\ldots,n;\ l=1,\ldots,\widehat{m};\ h=1,\ldots,e_l;\ k=1,\ldots,u_{hl};\ v=1,\ldots,r \tag{4.8}$$

The objective function (4.1) minimizes the total distribution time. Constraints (4.2) insure that each DP z receives the requested quantity of each product f. Constraints (4.3) guarantee that the total quantity of a given product f delivered from an open depot l does not exceed its capacity. Constraints (4.4) are the maximum daily work time restrictions associated to each vehicle k of type h located at depot l. Constraints (4.5) and (4.6) impose the vehicle capacity constraints for each trip, in terms of weight (4.5) and volume (4.6). Finally, constraints (4.7) and (4.8) are, respectively, the non-negativity and binary constraints on the quantity and routing variables.

5. Multi-criteria decision support system

The models M1 to M4 were integrated in a DSS that incorporates geographical maps to support decision-makers in their decision process. This section describes the system structure and the way in which the user interacts with models M1 to M4 to obtain good solutions. Then, it presents a multi-criteria approach in order to compare several solutions.

5.1 System structure

Interactive DSS can provide enormous benefits to decision-makers since they can be used to suggest and simulate different logistics deployments [Thompson et al., 2006]. The DSS proposed in this paper was developed and programmed in VB.Net 2010, using CPLEX 12.1 to solve the mathematical models. Data was loaded with a XML format file, which contained all of the problem data including, among others, the latitude and longitude of HAD and DP. After loading the data, the system used the Google Maps API to perform all the necessary distance calculations. The GMap.NET is an open-source interface that is contained within the application to display the geographic structure of the problem, including routes and HAD and DP locations. The system solved the models M1 to M4 and displayed the solution obtained, as well as the percentage of uncovered demand. The DSS is illustrated in Figure 1.

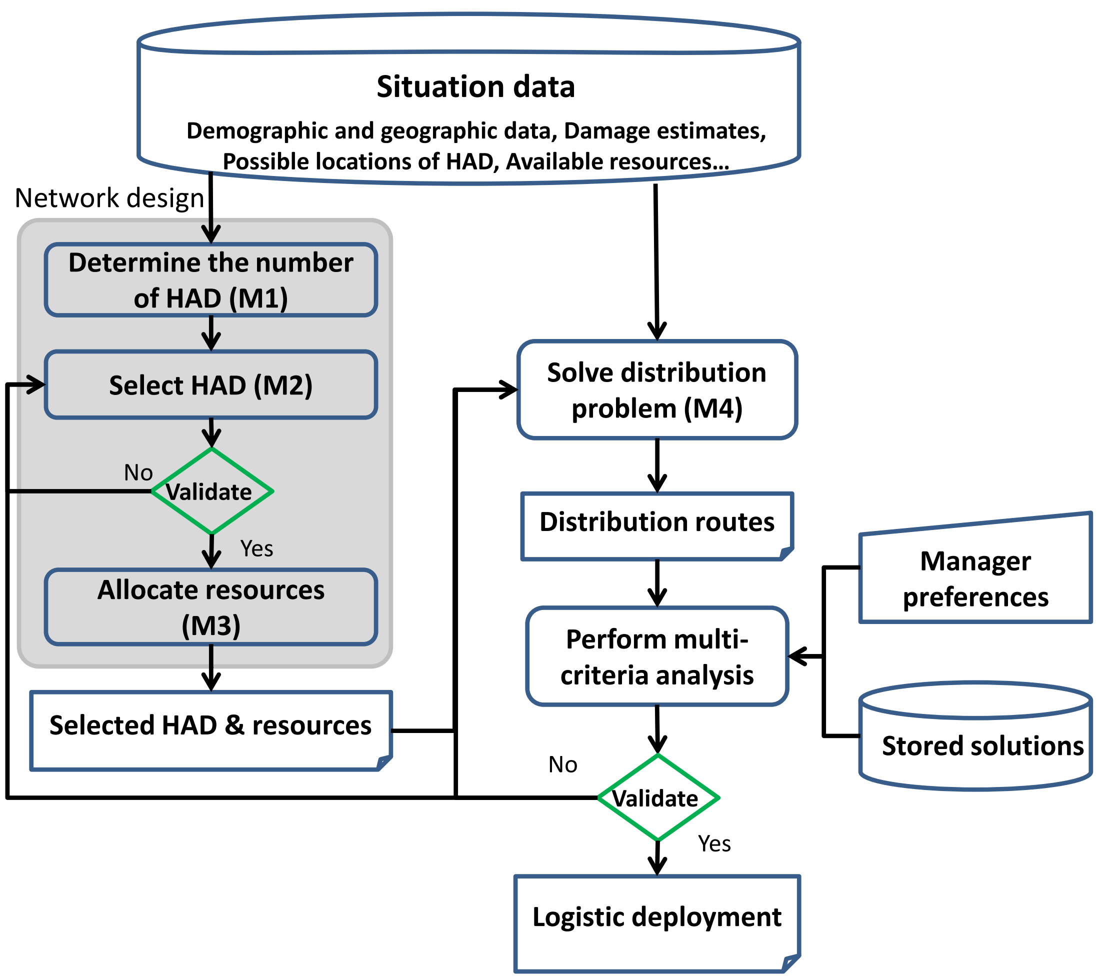

Figure 1: System diagram of our Decision Support System

Decision-makers can modify a part of the solution or the problem parameters at any time. For example, the status of a HAD maybe shifted by clicking on it. Then, the models are updated and solved again. With each new resolution, solutions and performance indicators are recorded so that they can be subsequently displayed and then analyzed by the multi-criteria analysis module.

5.2 Multi-criteria Decision Support

Decision-making in the context of humanitarian aid distribution requires careful trade-offs between the objectives in conflict. For example, increasing the number of open HAD would increase the proximity of relief for the people in the affected area, thus reducing the access time. However, such a solution could have an extremely high "cost" because it would require considerable human and material resources to operate the network. Also, bringing more rescuers into the disaster zone increases the need for coordination, as well as the potential risk to lives of these people. The *Multi-Criteria Analysis* (MCA) module tries to help the decision-maker to analyze these trade-offs.

A multi-criteria decision problem can be defined by the process of determining the best option among a set of options. Several analytical techniques, such as hierarchical AHP and ELECTRE [Shih et al., 2007], are available in the literature. However, the multi-criteria analysis method we decided to implement in the DSS described in this paper takes a TOPSIS approach [Hwang and Yoon, 1981; Jahanshahloo et al., 2006]. TOPSIS, the acronym for "*Technique for Order Performance by Similarity to Ideal Solution*", is a tool designed to help decision-makers by ordering the alternatives. TOPSIS is based on the principle that the best alternative should be the one that comes closest to the ideal action and the furthest from the non-ideal action.

The MCA module works as follows. The decision-maker defines the set of criteria that will be analyzed. Then, according to a precise protocol, the decision-maker proposes the relative weight of each criterion, provided that the sum of the weights equals 1.

TOPSIS has several advantages. First, the representation makes sense and somehow reproduces the human way of classifying. Second, it uses scalar values that simultaneously take the best and the worst options into account. Finally, the simplicity of the calculation method makes it very easy to program. On the other hand, the main disadvantage of this technique lies in the fact that it does not offer tools to assess the allocation of weighs to the various criteria. In addition, TOPSIS does not to offer a tool to assess the consistency of the decision-maker's judgments. Other tools for decision support, such as MACBETH (*Measuring Attractiveness by a Categorical Based Evaluation Technique*), propose a way to aggregate the decision-maker preferences and could be easily integrated into our DSS [Bana e Costa et al., 2005]. Moreover, our DSS's modularity and flexibility allow almost any other method to be incorporated.

6. Numerical experiments

This section details the problem generation procedure. Then, it analyzes the results produced by solving the models M1 to M4. Finally, it illustrates the usefulness of the MCA module and its impact on the decision-making process.

6.1 Problem generation

The instances are based on Quebec City's specific configurations. First, we identified sites that could act as potential HAD. Secondly, we identified the 650 city locations that may be used as gathering places or aid distribution points. Each city location is geolocated with its latitude and longitude coordinates. The considered area is nearly 1 250 km^2, and all distances are calculated using Google Maps API.

The instances are generated by randomly selecting *n* delivery points from the set of city locations and *m* potential HAD from the corresponding sites set. The number of humanitarian aid functions is set to 4, and the demand unit used is one pallet. The demand for each of the humanitarian functions for each delivery point or client is randomly drawn from a uniform distribution whose parameters are given in Table 1, along with other physical characteristics of these functions.

Table 1: Humanitarian aid function characteristics

Function	Demand (pallets)		Weight (pounds)	Volume (ft^3)	Loading time per vehicle type (min/pallet)	
	Minimum	Maximum			T1	T2
F1	20	60	200	30	0.1	0.1
F2	20	40	250	30	0.2	0.2
F3	30	50	200	25	0.3	0.1
F4	30	50	250	25	0.3	0.3

When the demand generation is completed, the capacity for each HAD with respect to each function is randomly generated to cover between 25 % and 35 % of the total demand. Doing so leads to feasible instances (in terms of capacity) that require three or four HAD, which is representative of real logistics deployments. We assume that two types of vehicles may be used to distribute aid. The vehicle characteristics are provided in Table 2.

Table 2: Vehicle characteristics

Vehicle type	Capacity		Maximum length (min)	Docking time at depot (min)
	Weight (pounds)	Volume (ft^3)		
T1	32,000	10,000	600	10
T2	34,000	12,000	600	5

We generated three sets of 10 instances, named *A*, *B* and *C*. *A* instances have 15 potential HAD and 40 DP; *B* instances have 20 potential HAD and 60 DP; and *C* instances have 20 potential HAD and 80 DP. The tests were performed on a IBM x3550 with an Intel Xeon E5420 running at 2.5Ghz with 4 Gig RAM. Cplex 12.1 was used to solve the mathematical models.

6.2 Numerical analysis

This section reports the results produced by solving the models M1 to M4, which are embedded into a decisional algorithm that interacts with the decision-makers (Figure 1). This interaction allows adjustments to be made to the current solution according to their preferences and experience. If the performance of the solution proposed by the system does not satisfy the decision-makers' requirements, these adjustments may be made after solving each model or after the whole decisional process has been executed.

To illustrate the potential use of our system, let us assume that the decision-maker sets an upper bound on the global uncovered demand. Then, as long as the global uncovered demand of the current solution is greater than the bound, the number of open HAD is incremented and a new distribution network is produced by solving models M2 and M3. We arbitrarily chose to set this bound at 0%, meaning that the system will iterate until a solution satisfying all the demand requirements and opening the lowest number of HAD p is found. For the purpose of this experiment, we recorded the solution with $p - 1$ HAD and also solved models M1 to M4 for $p+1$ HAD. The results are reported in Table 1.

Table 1 reports the solutions produced for each instance in sets A, B and C, using $p - 1$, p, and $p+1$ HAD. (Please note that only the computation time allotted to M4 is reported because optimal solutions to M1 to M3 are obtained in a few of seconds, as reported by Rekik et al. (2011) after extensive computational experiments.) The first column reports the instance type. The column under header % reports the percentage of uncovered demand for solutions with $p - 1$ HADs. For each instance, columns T and Δ report the total distribution time and the optimality gap produced by M4 when CPLEX was allotted computing time limits of up to 60 and 120 seconds, respectively. The bottom lines show the average over the 30 instances for the percentage of uncovered demand, total distribution times, as well as the optimality gaps (line *Avg.*); and the number of times out of 30 that CPLEX gave proof of optimality for M4 within the allotted computation time (line *Opt.*). If larger instances have to be solved in a short time, the distribution planning model M4 can easily be replaced by an heuristic module [Berkoune et al. 2011].

Table 3: Results for solutions with $p-1$, p, and $p+1$ HAD

Instance	p – 1					p					p + 1			
		60 sec		120 sec.			60 sec		120 sec.		60 sec		120 sec.	
	%	T	Δ	T	Δ	p	T	Δ	T	Δ	T	Δ	T	Δ
A1	17.0	2040	0.66	2040	0.4	3	2247	0.00	2247	0.00	2046	0.00	2046	0.00
A2	3.4	2091	0.00	2090	0.00	4	2136	0.15	2136	0.00	2116	0.00	2116	0.00
A3	0.3	2526	0.02	2526	0.00	4	2246	0.00	2246	0.00	2165	0.00	2165	0.00
A4	0.2	2413	1.00	2413	0.9	4	2257	0.2	2257	0.00	2070	1.1	2070	0.9
A5	3.3	2947	1.3	2937	0.9	4	2764	0.00	2764	0.00	2344	2.1	2342	1.9
A6	23.1	1660	0.00	1660	0.00	3	2263	0.5	2263	0.4	2167	0.00	2167	0.00
A7	0.3	2984	0.3	2984	0.3	4	2378	0.4	2378	0.1	2287	0.00	2287	0.00
A8	3.3	2385	0.6	2385	0.4	4	2162	0.3	2162	0.3	2088	0.00	2088	0.00
A9	3.6	2206	0.00	2206	0.00	4	2194	0.00	2194	0.00	2174	0.00	2174	0.00
A10	0.5	1888	0.00	1888	0.00	4	1910	0.00	1910	0.00	1852	0.00	1852	0.00
B1	14.7	2785	0.4	2780	0.1	3	3195	0.00	3195	0.00	3139	0.00	3139	0.00
B2	4.5	3308	1.9	3292	1.3	4	3016	0.6	3010	0.3	2985	0.00	2985	0.00
B3	1.9	2645	0.5	2645	0.5	5	2601	0.00	2601	0.00	2701	0.00	2701	0.00
B4	1.2	3318	0.4	3314	0.2	4	3151	0.4	3147	0.2	2831	0.1	2831	0.00
B5	16.8	3056	1.00	3056	1.00	3	3033	0.9	3025	0.6	2807	0.00	2807	0.00
B6	17.0	2772	2.2	2772	2.2	3	3317	0.4	3317	0.4	2979	0.00	2979	0.00
B7	18.6	2475	1.1	2475	1.00	3	2935	1.5	2928	1.3	2869	0.00	2869	0.00
B8	1.0	3250	2.5	3233	1.9	4	2955	0.1	2955	0.00	2821	0.00	2821	0.00
B9	15.0	3983	1.5	3980	1.3	4	3741	2.3	3717	1.7	3220	0.4	3216	0.2
B10	15.0	2816	2.2	2800	1.5	3	3092	0.3	3088	0.2	2996	0.2	2996	0.2
C1	1.3	3590	0.00	3590	0.00	7	3561	0.00	3561	0.00	3535	0.00	3535	0.00
C2	15.0	4223	4.52	4223	4.5	3	5015	3.52	4937	2.00	4524	0.5	4522	0.5
C3	1.4	3769	0.00	3769	0.00	8	3819	0.00	3819	0.00	3733	0.00	3733	0.00
C4	17.7	3654	3.04	3641	2.6	3	4203	1.93	4148	0.6	3861	0.2	3861	0.2
C5	0.4	4755	0.16	4755	0.16	5	4342	0.95	4342	0.9	4154	0.11	4152	0.11
C6	17.1	3720	2.3	3718	2.2	3	4310	0.2	4310	0.2	4066	0.00	4066	0.00
C7	20.6	3800	0.8	3785	0.4	3	4667	2.1	4603	0.6	4300	1.2	4298	1.1
C8	0.07	4286	3.5	4258	2.4	4	3906	0.00	3906	0.00	3756	0.00	3756	0.00
C9	19.5	3507	0.85	3503	0.7	3	4175	2.7	4168	2.5	3786	0.00	3786	0.00
C10	17.4	4673	4.7	4657	1.4	3	4646	3.2	4624	2.3	4415	0.1	4415	0.1
Avg.	9.04	3117.5	1.25	3112.5	0.94		3207,9	0.76	3198,6	0.49	3026,2	0.20	3025,8	0.17
Opt.			6		7			10		13		20		21

Our first observation concerns the solvability of the proposed models. In fact, the network design problem is easily treated by the commercial solver used (CPLEX 12.1), due to the decomposition of the design decisions into three models M1, M2 and M3. The results reported in Table 3 confirm that M4 is also solved efficiently by CPLEX. In fact, the number of routing problems solved to optimality over 30 instances ranges from 6 to 21. For those instances for which proof of optimality was not provided, the gaps are rather tight, lower than 4.70%, even when only 60 seconds were allotted for computing. It is worth mentioning that routing problems with networks with less HAD seem harder to solve. The average gap decreases from $p - 1$ to $p + 1$ in Table 3 and the number of optimally solved instances increases.

The "added value", in terms of demand satisfaction, of using one additional HAD in the solution can also be observed. As can be seen in Table 3, opening $p - 1$ HAD leads to an average uncovered demand of 9.04%, but, for particular instances, the uncovered demand may be higher, rising to 23.10%. In other instances, opening only $p - 1$ HAD may lead to only a small percentage of the demand being uncovered. Therefore, for these cases, the decision-maker might prefer the $p - 1$ solution.

It can also be observed that, as expected, the total distribution time increases from the $p - 1$ case to the p case due to the higher amount of aid transported, and then decreases when the number of HAD is set to $p + 1$ due to a more efficient HAD locations. Therefore, as the results in Table 3 show, it is not always clear which alternative among $p - 1$, p and $p + 1$ should be preferred. The next section tries to help to clarify this question.

6.3 Multi-criteria analysis of the solutions

In the preceding paragraph, we raised the question about how the decision-maker should choose the best solution for a given humanitarian aid situation. Although the networks opening $p - 1$ HAD lead to some uncovered demand, they require less resources to be operated (one less HAD) and lower distribution times. On the other hand, the networks opening $p + 1$ HAD may be also of great interest to the decision-maker because, although they require opening an additional HAD, they reduce distribution times. A trade-off is thus necessary in order to choose among these three alternatives, and this is where the MCA module facilitates the decision-making process.

Let's assume that the decision-maker evaluates the quality of a solution based on the following three criteria: the percentage of uncovered demand (c_1), the number of HAD to be opened (c_2), and the total distribution time (c_3). For these three criteria, the lowest value corresponds to the preferred solution. Let us also assume three different preference weight choices: the higher the value assigned to a particular criterion, the higher its importance for the decision-maker. The first choice W_1 assigns the weights [0.3;0.2;0.5] to criteria c_1, c_2 and c_3, respectively. The second and third choices are W_2 = [0.3;0.1;0.6] and W_3 = [0.1;0.8;0.1]. The third configuration, W_3, corresponds to a situation in which the number of HAD to be opened is the most important part of a solution, the other two criteria having lower values with respect to c_2.

For each instance, we applied TOPSIS to the solution with $p - 1$, p, and $p + 1$ HAD. Only distribution times produced after 120 seconds were considered. For each weight choice (W_1, W_2 and W_3), Table 4 reports the number of times over 30 instances that solutions with p-1, p or p+1 HAD was preferred by TOPSIS.

Table 4: Results of the multi-criteria analysis

		W_1			W_2			W_3	
	$p - 1$	p	p+1	$p - 1$	p	p+1	p–1	p	p+1
Best	0	30	0	0	18	12	28	2	0

The results in Table 4 confirm the strong impact of the decision-maker's preferences on the evaluation of alternative solutions. When applying preference weight W_1, solutions with p HAD were always preferred. If slight increased importance is granted to distribution time, such as when W_2 was selected, then the solutions with p HAD were preferred in 18 out of 30 cases, while the solutions with p+1 HAD would be preferred in the other 12 cases. Finally, if the most important factor for the decision-maker is the number of HAD to be opened, such as when W_3 was selected, then the solution with $p - 1$ HAD is almost always preferred (28 out of 30 instances).

7. Conclusion

In this paper, we define the network design and humanitarian aid distribution problem and propose a solving approach that breaks it down into two parts: the network design problem and the distribution problem. To solve the network design problem, three models are used to determine the number and the location of humanitarian aid centers and their resource allocation. To handle the distribution problem, a distribution model was used to determine transportation routes. However, since choosing among alternative solutions is difficult, a multi-criteria analysis (MCA) module based on TOPSIS is used. We proposed a complete interactive decision support system, incorporating network design, distribution routing and the MCA module. We showed that these models can lead to optimal solutions in very short computing times. Our DSS system can be a valuable help in emergency situations.

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