Chapter 1
A Decision Support System for Humanitarian Network Design and Distribution Operations

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1.1 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 and Green 2006). But, on the other hand, response phase planning is still an emerging subject in the literature. In practice, only a few tools are presently 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. These observations have motivated the increasing amount of work devoted to emergency management, and by now several seminal references are available (Rubin 2007; Lindell et al. 2007; Canton 2007; Haddow et al. 2008; Bumgarner 2008). These works are completed by many recent academic literature reviews presenting the current trends of the research (Altay and Green 2006; Kavács and Spens 2007; Balcik et al. 2010; Overstreet et al. 2011; Caunhye et al. 2012; de la Torre et al. 2012).

In this chapter, 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.
aid from these depots towards the affected people. As we address the very short-term problem, we consider the available data and solve the problem as deterministic. 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 1.2 details the problem studied. Sections 1.3 and 1.4 describe, respectively, the models proposed for network design and the distribution problems. The DSS structure and the multi-criteria analysis module are presented in Sect. 1.5. Section 1.6 reports the results of our numerical experiments, and Sect. 1.7 presents our conclusions.

1.2 Problem Description

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 \( \theta_z \), whose value is comprised within the \([0, 1]\) interval. The larger the value of \( \theta_z \) 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 known and 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 and Wang 2009) and the infrastructures.
condition (Minciardi et al. 2007). 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 $\tau$. This time is determined by the decision-maker, according to the nature of the disaster and the needs of the population. In other situations, the access time may correspond to distance between help centers and population residences (Dekle et al. 2005; Naji-Azimi et al. 2012).

In addition, we define, for each distribution point $z$, a subset $L_z$ of depots that are within the maximum access time $\tau$ (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, $h = 1 \ldots e_l$, 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 $\pi_{hl}$ 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\(^1\) such as survival (e.g., meals, water, beds), safety, medical (e.g., drugs, bandages), technical, etc. In the following, without loss of generality, we assume that we are delivering only humanitarian functions, which correspond to goods, and that they are handled in pallets. We denote the set of functions to be delivered with $F = \{1, \ldots, p\}$. In addition, we prioritize humanitarian functions using a weighting coefficient $\omega_f$ defined in the [0, 1] interval. The higher the function’s value of $\omega_f$, 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 $\alpha_{fh}$, where $\alpha_{fh} = \infty$ if function $f$ cannot be loaded into a type-$h$ vehicle.

The capacity, in pallets, of HAD $l$ for function $f$ is denoted $c_{lf}$. Capacity can be shared between functions but HAD $l$ cannot hold more than $c_l$ pallets. The amount of function $f$ needed at distribution point $z$ is denoted as $d_{fz}$. Each HAD $l$ has the ability $\beta_{lf}$ for handling function $z$. The values of $\beta_{lf}$ are in the interval [0, 1]. A value close to 1 indicates a strong aptitude for deploying the function in question (e.g., a warehouse for storing and handling pallets of food). A value near 0 indicates a weak aptitude; for example, a school is not normally equipped for storing and transferring pallets efficiently.

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 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.

\(^1\) Clearly, other classes/functions are possible. For example, the Pan American Health Organization (PAHO 2001) 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.
The deterministic *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, 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.

As defined, the NDHADP is a mix of network design and distribution problems with several objectives. In the past years, many researchers have addressed related but different versions of this problem. Haghani and Oh (1996) studied a particular version of disaster relief operations as a multi-commodity, multi-modal network flow model with time windows. They considered that a shipment can change from one mode to another at some given nodes, that earliest delivery times are given for commodities and that arc capacity may be time-dependent. Özdamar et al. (2004) addressed the problem of planning vehicle routes to collect and deliver products in disaster areas. To handle the dynamic aspects 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. 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. Balcik and Beamon (2008) developed a multi-scenario facility location and stock pre-positioning model. Balcik et al. (2008) studied delivery of relief supplies from local distribution centers to beneficiaries affected by disasters, which they called the *last mile distribution*. They minimized the sum of transportation costs and penalty costs for unsatisfied and late-satisfied demands for two types of relief supplies. Therefore, the model of Özdamar et al. (2004) addresses the distribution centers supply problem, while Balcik et al. (2008) performs the *last mile distribution*. Conceptually, the Balcik et al. (2008) paper is most similar to what we propose in Sect. 1.4 since they considered a heterogeneous limited fleet, multiple vehicle routes, and two product types. They solved a single depot problem having four demand nodes using two identical vehicles.

### 1.3 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.
1.3.1 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 \( \tau \). 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 \( p \), the minimal number of HAD to be opened to insure that every DP is covered.

\[
\text{Min } p = \sum_{l=1}^{m} x_l \quad (1.1)
\]

subject to

\[
\sum_{l \in L_z} x_l \geq 1 \quad z = 1, \ldots, n \quad (1.2)
\]

\[
x_l \in \{0,1\} \quad l = 1, \ldots, m \quad (1.3)
\]

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.

1.3.2 M2: Locating the Depots

Among the set of candidates sites, the second decision chooses exactly \( p \) 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 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:

\[
\text{Max } \sum_{z=1}^{n} \sum_{f=1}^{p} \theta_{zw} \left( \frac{d_{zf}}{\sum_{z=1}^{n} d_{zf}} \right) y_{zf} + \sum_{l=1}^{m} \sum_{f=1}^{p} \omega_{f} \beta_{lf} o_{lf} \quad (1.4)
\]

subject to

\[
y_{zf} \leq \sum_{l \in L_z} o_{lf} \quad z = 1, \ldots, n; \quad f = 1, \ldots, p \quad (1.5)
\]
The objective function (1.4) 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 $\theta_z$). The objective here is to encourage the 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 (1.5) 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 (1.6) link the $o_{lf}$ and $x_l$ variables, insuring that a HAD may provide a humanitarian function only if it is open. Equality constraint (1.7) sets the number of open facilities to $p$, determined in M1 or as decided by the decision-maker, and constraints (1.8) 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.

### 1.3.3 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:

$$\text{Min} \sum_{z=1}^{n} \sum_{f=1}^{p} \theta_{zf} \left( \frac{d_{zf}}{\sum_{z=1}^{n} d_{zf}} \right) u_{zf}$$

(1.9)

subject to

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

(1.10)

$$\sum_{z \in L_z} \sum_{f \in \hat{F}_f} d_{zf} v_{lzf} \leq c_l \quad \forall l \in \hat{L}$$

(1.11)

$$\sum_{z \in L_z} d_{zf} v_{lzf} \leq c_{zf} \quad \forall l \in \hat{L}; \quad f \in \hat{F}_f$$

(1.12)

$$v_{lzf} \geq 0 \quad \forall l \in \hat{L}; \quad f \in \hat{F}_f; \quad z = 1, \ldots, n$$

(1.13)

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

(1.14)

The objective function (1.9) minimizes the total uncovered demand, weighted by the DP priority and the relative importance of the humanitarian functions. Constraints (1.10) describe the balance between portions of covered and uncovered demand. Constraints (1.11) and (1.12) insure that the capacity of each open HAD is respected, in terms of the global demand (1.11) and each humanitarian function (1.12). Finally, constraints (1.13) and (1.14) are non-negative constraints on the decision variables.

### 1.4 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 $\hat{L} = \{1, \ldots, \hat{m}\}$ and the quantity of function $f$ available at each depot $l$, $p_{fl} = \sum_{z=1}^{n} d_{zf} v_{lzf}$ (see Eq. 1.12) 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:

- $x_{zfkhv}$, 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
- $q_{zfkhv}$, 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 $z$. 

In order to limit the number of variables, the number of trips performed to a delivery point \( z \) by a specific vehicle will be bounded by a maximum value \( r \). In our experimental study, we first set \( r = 2 \) and solved each instance to optimality. Then we set \( r = 3 \) and \( r = 4 \) and resolved again each instance to see if some improvement can be achieved. We found that for all instances, \( r = 2 \) is the smallest value leading to the optimal solution.

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:

\[
2t_{zl}x_{zlhkv} + \pi_{hl}x_{zlhkv} + \sum_{f=1}^{p} \alpha_{fh}q_{zfhkv}
\]

where the first part \( (2t_{zl}) \) represents the back and forth travel times, the second part \( (\pi_{hl}) \) is the docking time, and the last part \( \left( \sum_{f=1}^{p} \alpha_{fh}q_{zfhkv} \right) \) 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

\[
t'_{zlh}x_{zlhkv} + \sum_{f=1}^{p} \alpha_{fh}q_{zfhkv}
\]

The distribution model \( M4 \) is formulated as follows:

\[
\text{Min} \quad \sum_{z=1}^{n} \sum_{l=1}^{\hat{m}} \sum_{h=1}^{e_l} \sum_{u_l}^{u_{hl}} \sum_{k=1}^{r} \sum_{v=1}^{\bar{r}} \left( t'_{zlh}x_{zlhkv} + \sum_{f=1}^{p} \alpha_{fh}q_{zfhkv} \right)
\]

subject to

\[
\sum_{l=1}^{\hat{m}} \sum_{h=1}^{e_l} \sum_{u_l}^{u_{hl}} \sum_{k=1}^{r} \sum_{v=1}^{\bar{r}} (q_{zfhkv} \geq d_{zf}) \quad z = 1, \ldots, n; \quad f = 1, \ldots, p
\]

\( (1.16) \)

\[
\sum_{z=1}^{n} \sum_{l=1}^{\hat{m}} \sum_{h=1}^{e_l} \sum_{u_l}^{u_{hl}} \sum_{k=1}^{r} \sum_{v=1}^{\bar{r}} q_{zfhkv} \leq p_{fl} \quad f = 1, \ldots, p; \quad l = 1, \ldots, \hat{m}
\]

\( (1.17) \)

\[
\sum_{z=1}^{n} \sum_{l=1}^{\hat{m}} \sum_{h=1}^{e_l} \sum_{u_l}^{u_{hl}} \sum_{k=1}^{r} \sum_{v=1}^{\bar{r}} \left( t'_{zlh}x_{zlhkv} + \sum_{f=1}^{p} \alpha_{fh}q_{zfhkv} \right) \leq \bar{t}_h \quad l = 1, \ldots, \hat{m};
\]

\[
h = 1, \ldots, e_l; \quad k = 1, \ldots, u_{hl}
\]

\( (1.18) \)

\[
\sum_{f=1}^{p} w_{f} q_{zfhkv} \leq \bar{q}_{h} x_{zlhkv} \quad z = 1, \ldots, n; \quad l = 1, \ldots, \hat{m}; \quad h = 1, \ldots, e_l;
\]

\[
k = 1, \ldots, u_{hl}; \quad v = 1, \ldots, r
\]

\( (1.19) \)

\[
\sum_{f=1}^{p} s_{f} q_{zfhkv} \leq \bar{s}_{h} x_{zlhkv} \quad z = 1, \ldots, n; \quad l = 1, \ldots, \hat{m}; \quad h = 1, \ldots, e_l;
\]

\[
k = 1, \ldots, u_{hl}; \quad v = 1, \ldots, r
\]

\( (1.20) \)
The objective function (1.15) minimizes the total distribution time. Constraints (1.16) ensure that each DP \( z \) receives the requested quantity of each product \( f \). Constraints (1.17) guarantee that the total quantity of a given product \( f \) delivered from an open depot \( l \) does not exceed its capacity. As \( p_{fl} = \sum_{z=1}^{n} d_{zf} v_{lf} \) the capacity constraint \( c_{fl} \) is satisfied by (1.12). Constraints (1.18) are the maximum daily work time restrictions associated to each vehicle \( k \) of type \( h \) located at depot \( l \). Constraints (1.19) and (1.20) impose the vehicle capacity constraints for each trip, in terms of weight (1.19) and volume (1.20). Finally, constraints (1.21) and (1.22) are, respectively, the non-negativity and binary constraints on the quantity and distribution variables. It is worth to mention that operating and transportation costs were considered in the models. The considered objectives were to minimize uncovered demand and total distribution time. Considering costs may therefore lead to different results.

### 1.5 Multi-Criteria Decision Support System

The models M1–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–M4 to obtain good solutions. Then, it presents a multi-criteria approach in order to compare several solutions. This DSS is to be used as training tool (Velasquez et al. 2010) for government managers as well as for our industrial consulting partner for their defense and public safety operations. Appendix A presents two screens of the developed DSS called ELDS for Emergency Logistics Decision Support.

#### 1.5.1 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–M4 and displayed the solution obtained, as well as the percentage of uncovered demand. The DSS is illustrated in Fig. 1.1.

As the models are not related, the final solution cannot be said optimal. However, the advantage of such a decision decomposition approach is that the decision-makers can modify a part of the solution or the problem parameters at any time. For example, the status of a HAD provided by model M2 can be changed manually by selecting the HAD in a graphical interface. 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.

1.5.2 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. Finally, as
delivery tours are exposed to the risk of being interrupted (Nolz et al. 2011), the risk associated to a distribution plan should be evaluated by the decision-makers. 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. 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. An alternative is a specific solution to the problem. By using the DSS proposed, the decision-makers can generate and store many different alternatives (solutions) to the same problem. These alternatives may use different numbers of HADs or, for the same number of HADs, choose different locations.

Each of these alternatives is characterized and evaluated over a number of criteria (number of HAD to be opened, percentage of uncovered demand, total distribution time, maximum covering distance, . . . ). These criteria are normalized and weighted by the decision-makers preferences. Then, for each criterion, TOPSIS identifies the ideal action (the alternative which performs best for this criterion) and the non-ideal action (the alternative which performs worst for this criterion). A distance is then calculated for each alternative by comparing its value on each criterion with respect to the ideal and non-ideal actions. At the end of the TOPSIS procedure, a ranking is obtained, the first alternative being the one that comes closest to the ideal action and the furthest from the non-ideal action. Implementation details on the TOPSIS method can be found in (Hwang and Yoon 1981; Jahanshahloo et al. 2006). Note that other techniques, as goal programming can also be used when dealing with multiple criteria such as time of response, equity of the distribution or reliability and security of the operations routes (Vitoriano et al. 2011).

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 weights to the various criteria. In addition, TOPSIS does not 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.
Table 1.1 Humanitarian aid function characteristics

<table>
<thead>
<tr>
<th>Function</th>
<th>Demand (pallets)</th>
<th>Weight (pounds)</th>
<th>Volume (ft³)</th>
<th>Loading time per vehicle type—$\alpha_{fb}$ (min/pallet)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Minimum</td>
<td>Maximum</td>
<td></td>
<td>T1</td>
</tr>
<tr>
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<td>20</td>
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<td>50</td>
<td>250</td>
<td>25</td>
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Table 1.2 Vehicle characteristics

<table>
<thead>
<tr>
<th>Vehicle type</th>
<th>Capacity</th>
<th>Maximum length ($\bar{t}_b$)</th>
<th>Docking time at depot (min)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weight (pounds)</td>
<td>Volume (ft³)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>T1</td>
<td>32,000</td>
<td>10,000</td>
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<tr>
<td>T2</td>
<td>34,000</td>
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</tbody>
</table>

1.6 Numerical Experiments

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

1.6.1 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 km², 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 1.1, along with other physical characteristics of these functions.

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 1.2. Two vehicles of each type are available at each opened
HADs. Values of $\omega_f$, $\beta_f$ and $\theta_z$ are drawn randomly generated in the [0, 1] interval and the maximum access time $\tau$ is set to 75 min. All data are available on request.

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 2.5 Ghz with 4 Gig RAM. Cplex 12.1 was used to solve the mathematical models.

### 1.6.2 Numerical Analysis

This section reports the results produced by solving the models M1–M4, which are embedded into a decisional algorithm that interacts with the decision-makers (Fig. 1.1). 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–M4 for $p + 1$ HAD. The results are reported in Table 1.3.

Table 1.3 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–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 $\Delta$ 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 s, 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.).

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 1.3 confirm that M4 is also solved efficiently by CPLEX. In fact, the number of distribution problems solved to optimality over
Table 1.3 Results for solutions with \( p - 1 \), \( p \), and \( p + 1 \) HAD

<table>
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<th>( p )</th>
<th>( p + 1 )</th>
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<td></td>
<td></td>
<td>60 s</td>
<td>120 s</td>
<td>60 s</td>
</tr>
<tr>
<td></td>
<td>T</td>
<td>Δ</td>
<td>T</td>
<td>Δ</td>
</tr>
<tr>
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<td>2,040</td>
<td>0.66</td>
<td>2,040</td>
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<tr>
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<td>$T$</td>
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<tr>
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<td>3</td>
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<td>5</td>
<td>5</td>
<td></td>
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<tr>
<td>Avg.</td>
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</tbody>
</table>
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 s were allotted for computing. It is worth mentioning that distribution problems with networks with less HAD seem harder to solve. The average gap decreases from \( p - 1 \) to \( p + 1 \) in Table 1.3 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 1.3, 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 1.3 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.

If larger instances have to be solved in a short time, the distribution planning model M4 can easily be replaced by a genetic algorithm (Berkoune et al. 2012) which is able to solve instances in set B (60 distribution points and three or four depots) within 24 s with an optimality gap below 1\%. If compared to model M4, the genetic algorithm is more than 100 times faster, producing gaps 0.5\% higher than M4.

### 1.6.3 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). 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 two 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; 0.1; 0.6] to criteria \( c_1 \), \( c_2 \) and \( c_3 \), respectively, meaning that the distribution time is of great importance. The second choices is \( W_2 = [0.8; 0.1; 0.1] \), this configuration
corresponds to a situation in which minimizing the uncovered demand is the most important criteria.

For each instance in Table 1.3, we applied TOPSIS to the solution obtained after 120 s of computing time with \( p - 1 \), \( p \), and \( p + 1 \) HAD. For each weight choice \((W_1, W_2)\), Table 1.4 reports the number of times over 30 instances that solutions with \( p - 1 \), \( p \) or \( p + 1 \) HAD was preferred by TOPSIS.

The results in Table 1.4 confirm the impact of the decision-maker’s preferences on the evaluation of alternative solutions. When applying preference weight \( W_1 \), (more emphasis on minimizing distribution time) solutions with \( p \) HAD were preferred 18 times and solutions with \( p + 1 \) were preferred 12 times. Solution with \( p + 1 \) HAD were not always preferred because sometimes the reduction in distribution times is too small and thus it is not worth adding another HAD (going from four to five depots represent an increase of 20% in the number of depots). An example of solution where \( p + 1 \) HAD was preferred is on instance B9 where adding one HAD reduced the total distribution time from 3,717 to 3,216. For preference weight \( W_2 \) (minimizing the uncovered demand) the best solution is always to open \( p \) HAD as it is the lowest number of depot which guarantees to cover all the demand. In this case, a weight of 0.10 associated with the minimization of total distribution time is not enough to worth opening another depot.

More generally, the multi-criteria decision support system can be applied to sort any set of alternative solutions based on numerical criteria. In the previous example, we used the percentage of uncovered demand, number of HAD to be open, and the total distribution time as decision criteria. However, any other criterion computed by the system can be used as the uncovered demand of a zone weighted by its severity degree parameter, the priority of functions (products) delivered, the ability of selected distribution centers, the longest time to deliver a zone, the number of used vehicles, etc.

### 1.7 Conclusion

In this paper, we consider 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 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.

The strength of the proposed problem decomposition into four models is a natural way of reproducing the decision-makers behavior. It also offers a high level of interaction with each step of the decision tool. However, this decomposition may lead to suboptimal solutions. Future research is needed to unify all these models and solve them over a planning horizon taking into account the dynamics of demand, opening times and operating costs of humanitarian aid centers.

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**Appendix A: Screen Shots of the Decision Support System**

After running the location module (models M1–M3), the system displays the open depots, the demand points as well as their level of demand satisfaction. Aggregated performance indicators are also displayed.
The system displays the solution provided by the distribution module, and we can select any route to retrieve its relevant information.

References


