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Humanitarian and Relief Logistics

Research Issues, Case Studies and Future Trends

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Humanitarian Logistics: An Opportunity for Research in Operations to Save Lives and Limit the Effects of Devastation

In the past few years, the world has witnessed an increasing trend in natural and manmade disaster numbers. The alarming and devastating impacts of these disasters on human lives and the global economy motivated the increased interest in the field of emergency management. According to the U.S. Center for Research on the Epidemiology of Disasters (CRED), the number of disasters resulting in 100,000 to 999,999 victims around the globe doubled during 1987–2006 (CRED 2006). In 2010, 385 natural disasters were reported worldwide with more than 297,000 fatalities, affecting over 217.0 million people and causing US$ 123.9 billion in economic damages (Guha-Sapir et al. 2011). Despite the importance of disasters' economic effects, mitigating their impacts on human lives remains the major concern. When a major disaster strikes, a timely response is critical to saving lives and mitigating affected population sufferings. In fact, the first 72 h of a disaster relief effort are critical as the chance for survival beyond that time window without water or food decreases drastically. The challenge is to deliver the appropriate emergency supplies in sufficient quantities exactly when and where they are needed. Thus humanitarian logistics is one of the most crucial functions of an effective disaster response. In fact, logistics operations accounts for 80 % of the work of humanitarian organizations (Van Wassenhove 2006). In the event of large-scale disasters, such as Japan Tsunami in 2011, and most recently, Hurricane Sandy in 2012, the logistical function becomes more challenging as vital decisions must be made in a highly dynamic disruption-prone environment where urgent demand is high and resources are scarce. Oftentimes though, the performance of relief logistics operations after a major disaster onset similar to hurricane Katrina in 2005, or the Haiti earthquake in 2010, is sluggish and may be improved. Areas of improvement may be found in both pre-disaster preparedness and post-disaster responsiveness. Haiti's earthquake left more than 2 million people homeless with no access to basic needs such as water and urgent care. While emergency supplies were reportedly stacking up at Port-au-Prince airport, the Haitian government and its partners including the non-governmental organizations and foreign governments, have been struggling to distribute these available supplies to populations in need (Ichoua 2010). The slowness of aid distribution apparently resulted in some violent incidents marked by looting out of desperation and frustration. As it is typically the case in large-scale disasters, failure to provide adequate relief was mainly caused by the lack of coordination among multiple parties involved in relief logistics operations.

In distribution networks operated by humanitarian relief organizations, different types of emergency supplies must be delivered quickly to disaster-affected populations in order to mitigate suffering. Emergency supplies may generally be classified into two categories: Consumable items, such as clothing and food; and non-consumable items such as shelters and electricity devices. Each demand type is characterized by its degree of urgency and its targeted response time. Moreover disasters are generally low probability high impact events. Hence, demand arrival, size and location are random factors that are hard to forecast. Consequently, emergency managers are forced to make quick vital decisions in a highly dynamic and uncertain environment where time pressure is high and resources are scarce due to strict budget limitations. Compared to their commercial counterparts, humanitarian logistics are more complex and more challenging because of their particularities and characteristics. Thus, a better understanding of the distinctive processes that govern the scene of a real-world disaster is the first step towards the planning and operations delivery of effective relief humanitarian logistics. For example, system performance is typically assessed through service-based performance matrix (or objective functions) that often prioritize demand satisfaction and/or risk reduction rather than cost minimization. Other issues that have to be addressed with caution include modelling uncertainly, modelling demand coverage, elaborating adequate storage and replenishment strategies and coordination in collaborative relief responses.

This edited volume is aimed at highlighting recent advances in the development of effective modeling and solution approaches to enhance the performance of humanitarian relief logistics. The contributed Chapters span the spectrum of key issues and activities from preparedness to mitigation operations (response) planning and execution. The volume also presents the implementation of state-of-the-art methods and systems in current case studies.

Significant issues in planning and execution of humanitarian relief logistics that are discussed include the following:

- Approaches that tackle realistic relief distribution networks. In addition to large-scale computing issues, heuristics may handle the complexity and particularities of humanitarian supply chains accurately. A key element to the success of these efforts is to account for uncertainty while integrating long-term and tactical decisions
- Solution approaches that integrate real-time information while effectively coping with time pressure and uncertainty which are inherent to a disaster scene
- Judicious recourse strategies that allow a quick and effective restoration of pre-planned solutions whenever an unpredictable event occurs. Examples of these events include sudden changes in travel times due to severe damages in the transportation network, etc.
- Coordination of multiple parties that are often involved in managing a disaster. These parties typically include NGOs, local, state and federal agencies. In this multiparty setting, a successful disaster response depends on the judicious

management of the flow of real-time information that unfolds. Issues related to effectively communicating and sharing information as well as rapidly integrating and processing the shared information need to be addressed carefully.

In the area of **preparedness** there are four contributions focusing on the design of supply networks, relief centers, and vehicle fleet systems, as well as on the assessment of the level of preparedness.

Specifically, Chapter 1 introduces and addresses the Network Design and Humanitarian Aid Distribution Problem (NDHADP). This problem seeks to determine the most appropriate structure of a distribution network to deliver various types of supplies to demand points. The network activates a suitable number of humanitarian aid depots at suitable locations, and defines effective ways of distributing the humanitarian aid from the depots to the demand points. The Chapter proposes mathematical formulations to model the above problems, and describes a Decision Support System (DSS) that may be used by decision makers in the hours following a disaster to determine the distribution network for delivering aid efficiently (i.e. with the minimum total transportation time). The underlying problems are solved by CPLEX, and the selection of the most appropriate solution from multiple alternatives is performed by balancing certain trade-offs. The selection is based on a multi-criteria analysis that leverages the TOPSIS approach. The proposed methods and DSS are assessed through simulated problems inspired by Quebec City setting. The results demonstrate that the proposed models can lead to optimal solutions in very short computing times. The major contributions of this Chapter include the decomposition of the network design problem in a natural way that aligns with the decision makers' approach, the modeling of the related problems, and the synthesis of the DSS that interactively balances several tradeoffs to reach an appropriate design.

Chapter 2 focuses on aspects of relief centers layouts and their effects on waiting times experienced by affected individuals. These temporary facilities are set up in open spaces immediately after a disaster and play an important role in minimizing disaster effects on human lives. However, improving their efficiency is challenging due to the congestion caused by the rush of affected individuals. This work examines the effect of layout decisions on the performance of such a center. The latter is modeled by state dependent M/G/C/C queues that are able to account for the congestion delays along walkways. Furthermore, closer to the distribution point, the queuing effects are modeled by M/M/1/K queues. These queuing models are used as building blocks to construct open queuing network models of relief centers in order to evaluate alternative layouts and estimate the average waiting time experienced by served individuals. The resulting analytical expressions are used to examine relief operations. Experimental analysis shows that by choosing appropriate layouts of the relief center, queuing delays can be reduced significantly. Finally the work indicates that simple strategies may be used by relief agencies to reduce waiting times and improve service at disaster relief centers. The contributions of this research may be used by relief agencies to develop guidelines for setting up and operating efficient disaster relief centers.

Chapter 3 focuses on the design and planning of fleet systems that support development programs of humanitarian organizations, as well as disaster relief operations. In such environments, uncertainty stems from the intrinsic nature of the disaster, as well as from limitations in coordination and planning between programs. In order to account for these uncertainties, the authors propose stochastic models to describe the last mile distribution problem. In the instance of development programs, the proposed model seeks to locate vehicle hubs, assign demand areas, determine the fleet size, and perform vehicle scheduling seeking to minimize travel time under several constraints, such as budget, and fleet capacity. This model is adapted to the case of simultaneous disaster response operations and development programs where the amount of supplies and/or services delivered to beneficiaries is maximized. The major contribution of this chapter is the development of the above comprehensive models, which can be utilized as generic decision making tools by humanitarian organizations, provided that they are populated with the appropriate data, the latter being a critical issue in such environments.

Chapter 4 focuses on the assessment of preparedness in view of disaster relief operations or emergency management. Specifically, this Chapter discusses the development of quantitative measures to evaluate plans and preparations, and compare related areas and organizations. Note that the challenge in constructing such measures stems from the complex relations between the event, the response, the vulnerability, and the consequences. The author proposes a general methodology to develop appropriate measures comprising four steps: Select event and perspective, select indicators, combine the indicators, and validate the measure. The proposed methodology is applied to two case studies. In the first study, a hurricane disaster risk index is developed to benchmark the preparedness for managing the effects of hurricanes in different counties. The second case study develops and validates a preparedness measure related to emergency medical services. The proposed measure is validated using three different methods: Comparison to coverage measures, simulation, and dispatcher's evaluation. The validation indicates that this measure may be used to support decisions concerning ambulance dispatch and relocation. This Chapter's main contributions revolve around the concept of measuring preparedness and the discussion of the associated difficulties. The proposed method and the case studies provide significant insights into the way of constructing such measures.

Chapters 5 to 9 focus on the area of **mitigation operations planning and execution**. They present systems, models and algorithmic approaches of significant applicability in the coordination of disaster relief operations. The latter include procurement auctions, routing and scheduling methods, as well as resource allocation models.

Chapter 5 discusses certain emerging challenges that military forces face in Humanitarian and Relief Operations (HROs) and proposes logistics optimization models for planning HROs. Initially, a review on relief distribution scheduling models is conducted followed by a description of the proposed optimization method, which is based on Column Generation (CG). The proposed method extends the classical Capacitated Vehicle Routing Problem with Time Windows (CVRPTW) by allowing trans-shipments and change in transportation mode at intermediate nodes during transportation. The performance of the proposed CG algorithm is assessed and the results obtained show its effectiveness in obtaining optimal continuous solutions and good integer ones. The proposed optimization method is further evaluated via simulation in an HR environment. The results show a significant improvement in distribution efficiency. Chapter 5 concludes with suggestions of future research in the field of military HRO. This Chapter's main contribution is the development and testing of the CG algorithm for solving the CVRPTW problem in HR environment.

Chapter 6 proposes an auction-based procurement framework for single coordinating platforms in humanitarian logistics. This framework is developed to be used during response and recovery operations after the first rush (i.e., 12–72 h) of the disaster onset. The auction model handles unique characteristics and restrictions of disaster relief environments using a single round sealed-bid auction. The framework consists of three phases: a) announcement construction, b) bid construction and submission, and c) bid evaluation. The proposed framework with its formulations is tested using various data sets and the system behaviour under different conditions is also studied using simulation techniques. The results indicate that the proposed announcement options (i.e. substitution and partial fulfilment) increase the fill rate, allow for better utilization of the inventory on hand, and provide a richer set of suppliers. The main contribution of this chapter is the development of an innovative auction-based framework that tackles various restrictions that are faced in an HR environment.

Chapter 7 presents a multi-criteria model (SINRGAR) that is used for implementing fuzzy distributed Emergency Management Systems (EMS). The model allows dynamic management of priorities based on situational parameters and selection of the most appropriate resources in emergency situations. The SINGRAR model a) provides a common platform for the compilation of the incident status, b) includes decision support system features that provide support for managing priorities of alternative courses of action based on the current operational context, c) supports the command and control process, d) acts as an expert system advising lines of actions, and e) integrates different databases, which are used in conjunction with the knowledge base. The applicability of SINGRAR in man-made and natural disasters is illustrated through a case study in which the proposed model assesses the priorities in incident response for a complex inter-agency emergency management scenario. Chapter 7's contribution revolves around the management of emergency situations via a systemic approach.

Chapter 8 proposes various polynomial scheduling heuristics to solve the complex problem of gate assignment to trucks in a transshipment facility. Limited resources for cargo handling in disaster areas, various weights and sizes of relief goods, time-sensitive shipments, erratic truck arrival times and different departure times are taken into consideration. Alternative strategies to schedule incoming trucks, buffer areas and handling equipment are applied and compared based on real data. Moreover, six different scheduling heuristics are developed to solve the problem of planning the utilization of unloading gates, the buffer area related to each unloading zone, and a fleet of forklift trucks. The proposed scheduling heuristics are evaluated based on the total distance traveled, total discharge end, total waiting time of tours and average discharge duration. The results are encouraging showing that the proposed *distance-time-optimized with priority* strategy outperforms the current practice and improves significantly the handling of relief goods in terminals of urgent shipments. The contribution of this chapter is the use of optimization methods and techniques to tackle the handling of trucks in warehouse and storage areas.

Chapter 9 addresses a dynamic vehicle routing problem that models the relief distribution operations in a post-disaster environment. As an approximate solution method, a multi-agent system with two hierarchical levels is proposed. Within the proposed framework, the vehicles have the ability to dynamically re-route, bid for new tasks and de-commit to previously undertaken tasks to take advantage of the continuous flow of incoming information. In order to assess the proposed architecture, a discrete-event simulator has been developed and used to compare the proposed architecture to a centralized, on-line routing algorithm in solving randomly generated problem instances. Based on the results obtained, the proposed multi-agent system outperforms the on-line routing algorithm in a statistically significant manner. The contribution of this chapter lies in the area of dynamic vehicle routing in a post-disaster environment.

Two **case studies** illustrate the significance of rigorous methods in designing and operating effective and efficient disaster relief systems.

Chapter 10 reviews and analyzes the relief logistics networks set up in Indonesia, a disaster prone area, by various organizations, such as governmental ministries and agencies, Non-Governmental Organizations (NGOs) and the Indonesia Red Cross. This analysis suggests that although the Indonesian Government has already established a distinct agency for policy making and operations coordination in disaster management, it is still a challenge to coordinate the various organizations involved in relief operations. Each organization tends to operate independently using their own relief logistics facilities, a practice that may lead to inefficiencies or undersupply of relief goods and services at the affected areas. Motivated by these results, and the fact that relief organizations have already set up their permanent facilities, the authors propose two models to design relief logistics networks that comprise temporary forward facilities for the response stage of the disaster management cycle, at the village and district levels, respectively. These models have been applied to analyze the relief logistics network operated in the district of East Jakarta by the Ministry of Social Welfare during the 2007 Jakarta flood. The results show that the locations proposed by the models are consistent with the locations selected during the actual event. This is a significant indication that the proposed models may be used to support each Indonesian organization in designing their relief logistics network during the response phase.

Chapter 11 focuses on the humanitarian logistics systems implemented following the Great Tohoku Disasters and subsequent tsunami on 11th March 2011. It introduces a multi-objective optimization model to describe the distribution of relief supplies to displaced persons when demand cannot be fully satisfied. The objectives include the total shortage of supply, and the fuel consumption. Solutions are provided by the Elitist Non-Dominated Sorting Genetic Algorithms (NSGA-II). The model has been applied to the city of Ishinomaki in relation to the Tohoku disaster. Two cases are analyzed: The first identifies the number and type of distribution trucks, as well as the number of depots. Comparison with the actual operations indicates that the type of trucks was selected appropriately, while the actual number of vehicles used was greater than the optimal number. In addition, multiple depots reduce the distance travelled (and related costs), but do not affect the shortage of supplies substantially. The second case focuses on preplanning for distribution of emergency relief goods, and examines the effectiveness of three tactics in delivery operations, indicating the superiority of one. Both case studies illustrate that the proposed model is valuable in optimizing the delivery system in case demand exceeds supply. More generally rigorous OR-based models may bring considerable benefits in disaster relief operations, in both effectiveness in terms of humanitarian aid, and efficiency in terms of resources and costs.

All Chapters in this volume provide robust evidence that research in humanitarian logistics may lead to substantial improvements in effectiveness and efficiency of disaster relief operations. This, in turn, may reduce the toll in human lives, as well as limit other devastating effects of disasters. We strongly believe that this cause provides considerable incentives to researchers in logistics. In addition, the unique characteristics of disaster scenes provide significant opportunities to investigate novel approaches that can adequately address their challenges.

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Contents

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

Monia Rekik, Angel Ruiz, Jacques Renaud, Djamel Berkoune and Sébastien Paquet

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

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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 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 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 τ. 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 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, $h = 1 \ldots e_l$, 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 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[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 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, in pallets, of HAD l for function f is denoted c_{lf}. Capacity can be share 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 β_{lf} for handling function z. The values of β_{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 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

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

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

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.

1.3.2 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 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:

$$Max \sum_{z=1}^{n} \sum_{f=1}^{p} \theta_z w_f \left(\frac{d_{zf}}{\sum_{z=1}^{n} d_{zf}} \right) y_{zf} + \sum_{l=1}^{m} \sum_{f=1}^{p} \omega_f \beta_{lf} o_{lf} \tag{1.4}$$

subject to

$$y_{zf} \leq \sum_{l \in L_z} o_{lf} \quad z = 1, \ldots, n; \quad f = 1, \ldots, p \tag{1.5}$$

$$o_{lf} \leq x_l \qquad l = 1, \ldots, m; \quad f = 1, \ldots, p \tag{1.6}$$

$$\sum_{l=1}^{m} x_l = \underline{p} \tag{1.7}$$

$$x_l, y_{zf}, o_{lf} \in \{0,1\} \quad l = 1, \ldots, m; z = 1, \ldots, n; f = 1, \ldots, p \tag{1.8}$$

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 θ_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 $\underline{p}$, 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:

$$Min \sum_{z=1}^{n} \sum_{f=1}^{p} \theta_z w_f \left(\frac{d_{zf}}{\sum_{z=1}^{n} d_{zf}} \right) u_{zf} \tag{1.9}$$

subject to

$$\sum_{l \in \hat{L} \cap L_z} v_{lzf} + u_{zf} = 1 \quad z = 1, \ldots, n; \quad f = 1, \ldots, p \tag{1.10}$$

$$\sum_{z:l \in L_z} \sum_{f \in \overline{F}_l} d_{zf} v_{lzf} \leq c_l \quad \forall l \in \hat{L} \tag{1.11}$$

$$\sum_{z:l \in L_z} d_{zf} v_{lzf} \leq c_{lf} \qquad \forall l \in \hat{L}; \quad f \in \hat{F}_l \tag{1.12}$$

$$v_{lzf} \geq 0 \qquad \forall l \in \hat{L}; \quad f \in \hat{F}_l; \quad z = 1, \ldots, n \tag{1.13}$$

$$u_{zf} \geq 0 \qquad f = 1, \ldots, p; \quad z = 1, \ldots, n \tag{1.14}$$

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_{zlhkv}, equal to 1 if DP z is visited from depot l with the kth vehicle of type h on its vth trip to z; and
- q_{zflhkv}, the quantity of product f delivered to DP z from depot l with the kth vehicle of type h on its vth 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 vth trip of the kth 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 $\left(\sum_{f=1}^{p} \alpha_{fh}q_{zflhkv}\right)$ 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 $\left(t'_{zlh}x_{zlhkv} + \sum_{f=1}^{p} \alpha_{fh}q_{zflhkv}\right)$. The distribution model M4 is formulated as follows:

$$Min \sum_{z=1}^{n} \sum_{l=1}^{\widehat{m}} \sum_{h=1}^{e_l} \sum_{k=1}^{u_{hl}} \sum_{v=1}^{r} \left(t'_{zlh}x_{zlhkv} + \sum_{f=1}^{p} \alpha_{fh}q_{zflhkv} \right) \tag{1.15}$$

subject to

$$\sum_{l=1}^{\hat{m}} \sum_{h=1}^{e_l} \sum_{k=1}^{u_{hl}} \sum_{v=1}^{r} (q_{zflhkv} \geq d_{zf}) \quad z = 1, \ldots, n; \quad f = 1, \ldots, p \tag{1.16}$$

$$\sum_{z=1}^{n} \sum_{h=1}^{e_l} \sum_{k=1}^{u_{hl}} \sum_{v=1}^{r} q_{zflhkv} \leq p_{fl} \quad f = 1, \ldots, p; \quad l = 1, \ldots, \hat{m} \tag{1.17}$$

$$\sum_{z=1}^{n} \sum_{v=1}^{r} \left(t'_{zlh}x_{zlhkv} + \sum_{f=1}^{p} \alpha_{fh}q_{zfjlhkv} \right) \leq \bar{t}_h \quad l = 1, \ldots, \hat{m}; \quad h = 1, \ldots, e_l; \quad k = 1, \ldots, u_{hl} \tag{1.18}$$

$$\sum_{f=1}^{p} w_f q_{zflhkv} \leq \bar{q}_h x_{zlhkv} \quad z = 1, \ldots, n; \quad l = 1, \ldots \hat{m}; \quad h = 1, \ldots, e_l; \quad k = 1, \ldots, u_{hl;} \quad v = 1, \ldots, r \tag{1.19}$$

$$\sum_{f=1}^{p} s_f q_{zflhkv} \leq \underline{v}_h x_{zlhkv} \quad z = 1, \ldots, n; \quad l = 1, \ldots \hat{m}; \quad h = 1, \ldots, e_l; \quad k = 1, \ldots, u_{hl;} \quad v = 1, \ldots, r \tag{1.20}$$

$$q_{zflhkv} \in \mathbb{R}^{+} \quad z = 1,\ldots,n; \quad f = 1,\ldots,p; \quad l = 1,\ldots,\hat{m}; \quad h = 1,\ldots,e_l; \quad k = 1,\ldots,u_{hl}; \quad v = 1,\ldots,r \tag{1.21}$$

$$x_{zlhkv} \in \{0,1\} \quad z = 1,\ldots,n; \quad l = 1,\ldots,\hat{m}; \quad h = 1,\ldots,e_l; \quad k = 1,\ldots,u_{hl}; \quad v = 1,\ldots,r \tag{1.22}$$

The objective function (1.15) minimizes the total distribution time. Constraints (1.16) insure 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 $p_{fl} = \sum_{z=1}^{n} d_{zf} v_{lzf}$ 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.

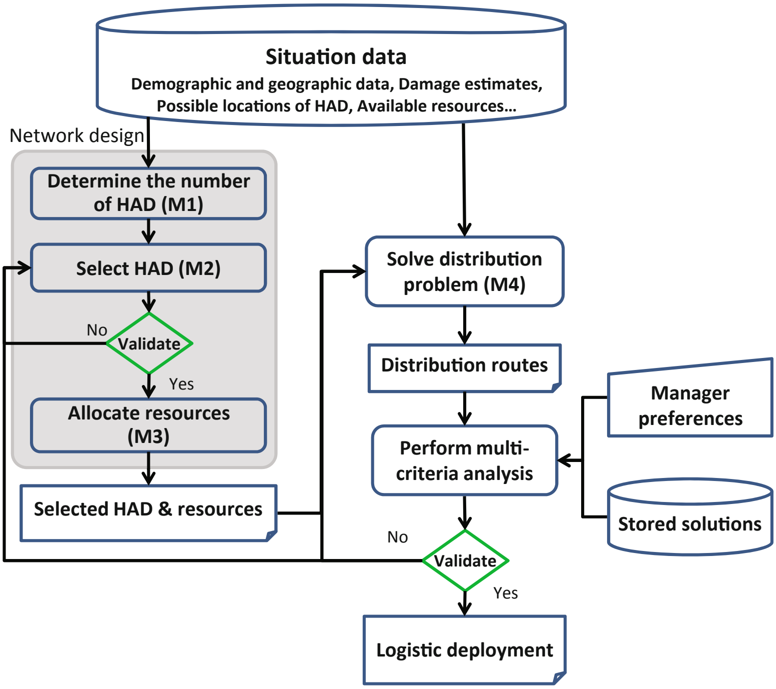

Fig. 1.1 System diagram of our decision support system

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 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.

Table 1.1 Humanitarian aid function characteristics

Function	Demand (pallets)		Weight (pounds)	Volume (ft^3)	Loading time per vehicle type—α_{fh} (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

Table 1.2 Vehicle characteristics

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

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 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 1.1, 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 ω_f, β_{lf} and θ_z are drawn randomly generated in the [0, 1] interval and the maximum access time τ 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 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 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

Instance	%	$p-1$					p				$p+1$			
		60 s		120 s			60 s		120 s		60 s		120 s	
		T	Δ	*T*	Δ	*p*	*T*	Δ	*T*	Δ	*T*	Δ	*T*	Δ
A1	17.0	2,040	0.66	2,040	0.4	3	2,247	0.00	2,247	0.00	2,046	0.00	2,046	0.00
A2	3.4	2,091	0.00	2,090	0.00	4	2,136	0.15	2,136	0.00	2,116	0.00	2,116	0.00
A3	0.3	2,526	0.02	2,526	0.00	4	2,246	0.00	2,246	0.00	2,165	0.00	2,165	0.00
A4	0.2	2,413	1.00	2,413	0.90	4	2,257	0.20	2,257	0.00	2,070	1.10	2,070	0.90
A5	3.3	2,947	1.30	2,937	0.90	4	2,764	0.00	2,764	0.00	2,344	2.10	2,342	1.90
A6	23.1	1,660	0.00	1,660	0.00	3	2,263	0.50	2,263	0.40	2,167	0.00	2,167	0.00
A7	0.3	2,984	0.30	2,984	0.30	4	2,378	0.40	2,378	0.10	2,287	0.00	2,287	0.00
A8	3.3	2,385	0.60	2,385	0.40	4	2,162	0.30	2,162	0.30	2,088	0.00	2,088	0.00
A9	3.6	2,206	0.00	2,206	0.00	4	2,194	0.00	2,194	0.00	2,174	0.00	2,174	0.00
A10	0.5	1,888	0.00	1,888	0.00	4	1,910	0.00	1,910	0.00	1,852	0.00	1,852	0.00
Avg.	5.5	2,314	0.39	2,313	0.29	3.8	2,256	0.16	2,256	0.08	2,131	0.32	2,131	0.28
Opt.			4		5			5		7		8		8
B1	14.7	2,785	0.4	2,780	0.10	3	3,195	0.00	3,195	0.00	3,139	0.00	3,139	0.00
B2	4.5	3,308	1.9	3,292	1.30	4	3,016	0.60	3,010	0.30	2,985	0.00	2,985	0.00
B3	1.9	2,645	0.5	2,645	0.50	5	2,601	0.00	2,601	0.00	2,701	0.00	2,701	0.00
B4	1.2	3,318	0.4	3,314	0.20	4	3,151	0.40	3,147	0.20	2,831	0.10	2,831	0.00
B5	16.8	3,056	1.00	3,056	1.00	3	3,033	0.90	3,025	0.60	2,807	0.00	2,807	0.00
B6	17.0	2,772	2.2	2,772	2.20	3	3,317	0.40	3,317	0.40	2,979	0.00	2,979	0.00
B7	18.6	2,475	1.1	2,475	1.00	3	2,935	1.50	2,928	1.30	2,869	0.00	2,869	0.00
B8	1.0	3,250	2.5	3,233	1.90	4	2,955	0.10	2,955	0.00	2,821	0.00	2,821	0.00
B9	15.0	3,983	1.5	3,980	1.30	4	3,741	2.30	3,717	1.70	3,220	0.40	3,216	0.20
B10	15.0	2,816	2.2	2,800	1.50	3	3,092	0.30	3,088	0.20	2,996	0.20	2,996	0.20
Avg.	10.57	3,041	1.37	3,038	1.10	3.6	3,104	0.65	3,098	0.47	2,935	0.07	2,934	0.04
Opt.			0		0			2		3		7		8

Table 1.3 (continued)

Instance	%	$p-1$					p				$p+1$			
		60 s		120 s			60 s		120 s		60 s		120 s	
		T	Δ	T	Δ	p	T	Δ	T	Δ	T	Δ	T	Δ
C1	1.3	3,590	0.00	3,590	0.00	7	3,561	0.00	3,561	0.00	3,535	0.00	3,535	0.00
C2	15.0	4,223	4.52	4,223	4.5	3	5,015	3.52	4,937	2.00	4,524	0.50	4,522	0.50
C3	1.4	3,769	0.00	3,769	0.00	8	3,819	0.00	3,819	0.00	3,733	0.00	3,733	0.00
C4	17.7	3,654	3.04	3,641	2.6	3	4,203	1.93	4,148	0.60	3,861	0.20	3,861	0.20
C5	0.4	4,755	0.16	4,755	0.16	5	4,342	0.95	4,342	0.90	4,154	0.11	4,152	0.11
C6	17.1	3,720	2.3	3,718	2.2	3	4,310	0.2	4,310	0.20	4,066	0.00	4,066	0.00
C7	20.6	3,800	0.8	3,785	0.4	3	4,667	2.1	4,603	0.60	4,300	1.20	4,298	1.10
C8	0.07	4,286	3.5	4,258	2.4	4	3,906	0.00	3,906	0.00	3,756	0.00	3,756	0.00
C9	19.5	3,507	0.85	3,503	0.7	3	4,175	2.7	4,168	2.50	3,786	0.00	3,786	0.00
C10	17.4	4,673	4.7	4,657	1.4	3	4,646	3.2	4,624	2.30	4,415	0.10	4,415	0.10
Avg.	11.05	3,998	1.99	3,990	1.44	4.2	4,264	1.46	4,241	0.91	4,013	0.21	4,012	0.20
Opt.			2		2			3		3		5		5
Avg.	*9.04*	*3,117.5*	*1.25*	*3,112.5*	*0.94*		*3,207,9*	*0.76*	*3,198,6*	*0.49*	*3,026,2*	*0.20*	*3,025,8*	*0.17*
Opt.			*6*		*7*			*10*		*13*		*20*		*21*

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

Table 1.4 Results of the multi-criteria analysis

	W_1			W_2		
	$p-1$	p	$p+1$	$p-1$	p	$p+1$
Best	0	18	12	0	30	0

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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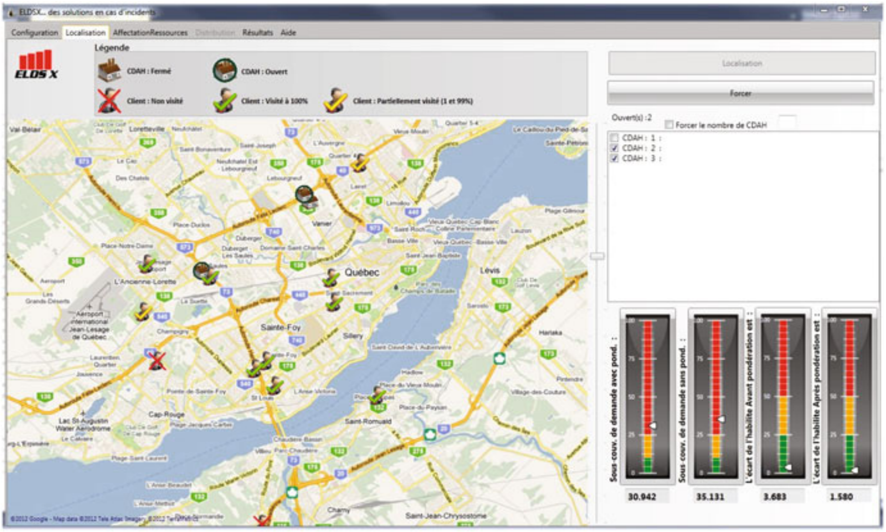
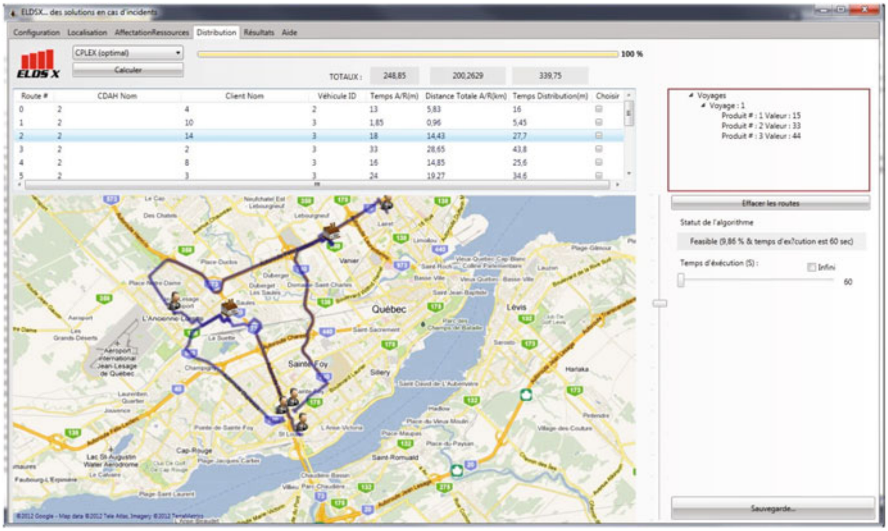
Appendix A: Screen Shots of the Decision Support System



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.

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Chapter 2
Analytical Models for Estimating Waiting Times at a Disaster Relief Center

Ananth Krishnamurthy, Debjit Roy and Sanket Bhat

2.1 Background and Introduction

Every year disasters across the world kill around 75,000 people and affect over 200 million people (Van Wassenhove 2005). Disaster logistics play a significant role in minimizing the losses following these events. Broadly speaking, these relief efforts can be divided into three phases: phase 1 corresponding to the preparation phase before disaster strikes, phase 2 corresponding to the immediate response phase after a disaster, and phase 3 corresponding to the reconstruction phase following a disaster (Kovács and Spens 2007). During Phase 1, the preparation phase, efforts focus on minimizing the impact of a disaster and in staging supplies for relief operations. Phase 2 of a relief operation is the immediate response phase, where emergency relief plans come to action. The response phase commences with search and rescue, but quickly focuses on fulfilling the humanitarian needs of the affected population. Phase 3 of a relief operation is the reconstruction phase, where the disaster location is re-developed.

Figure 2.1 describes the flow of supplies in supply chain distributing aid and relief supplies following a disaster. Very often, supplies are received at a primary hub (seaports, airports) and stocked at a central warehouse. From this location, supplies are distributed to small local warehouse locations, which are situated closer

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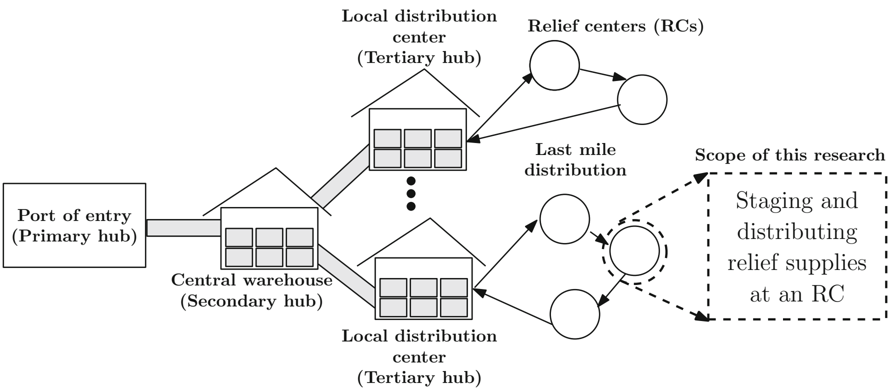


Fig. 2.1 Flow of supplies in the relief supply chain and focus of this research. (Modified from Balcik and Beamon 2008)

to the disaster sites. From the local warehouses, supplies are loaded into trailers and transported to disaster relief centers (RCs) where they are unloaded and staged at pods prior to distribution. The delivery and distribution of the supplies from the local distribution sites to the disaster relief centers are termed as last-mile operations (Balcik and Beamon 2008). In recent years, there has been significant amount of research focusing on planning for disaster response, pre-positioning inventory at strategic locations, routing supplies to affected areas and relief centers in the region. This research complements this existing body of work by focusing on the operations at the relief center itself.

At most disaster affected sites, relief centers are often temporary structures setup in open parking lots, school play grounds, in the immediate hours following the a disaster. The nature and intensity of the disaster and the demographics of the affected area significantly impact the amount and urgency with which aid must be distributed to the victims at these disaster relief centers. Efficient operation of RCs at the disaster area can play an important role in saving lives and minimizing public loss (Holguin-Veras et al. 2007). Recent studies that investigate what went wrong after disasters such as Katrina reveal that "… in addition to having inadequate facilities for storing donations… there was no clear plan for the distribution of donations. Some evacuees were sent from place to place in search of assistance. … Agencies improvised and set up tents to distribute items such as clothing, medical kits, cleaning supplies, and diapers". Although relief agencies such as Red Cross, Salvation Army and others have established procedures that need to be followed in distributing aid and relief, the main challenge is that each disaster presents its unique needs and "… volunteers on the field need to quickly adapt to unknown situations assess the important needs … and set up operations to allow rapid distribution of relief in a timely manner…" (Jody Glynn Patrick, The Salvation Army).

Most RCs often experience a sudden influx of victims requiring immediate attention and this creates a unique queuing phenomena, since RCs are often constrained

Fig. 2.2 Members of world food program distribute vitamin-enriched biscuits to Haitians while United Nations soldiers control the crowd in a tent city in Port-au-Prince, Haiti. (www.csmonitor.com)

in space (see Fig. 2.2). In order to control these queues, volunteer organizations involved in these efforts setup these RCs to control victim movement, yield high efficiency of distribution operations and minimize waiting of victims. This research develops analytical models to quantify these congestion effects at relief centers and the assess the impact of its layout on the efficiency of operations. Using knowledge from studies on pedestrian traffic flow, specialized state dependent queuing models are developed to model the flow of victims along the walkways setup at a relief center. These queuing models are then used as a building block in a larger multi-class open queuing network model of a relief center that distributes multiple items to victims. The queuing network configuration changes based on the layout of the relief center, the items distributes at each pod, and the needs of the different types of the victims. These queuing network models are analyzed to derive expressions for the average times that victims might experience before they receive the service at the relief center. Using this as a key metric, relief center operations are studied. The studies show that crowd density effects lead to significant increase in congestion and queuing delays underscoring the importance of developing specialized queuing models that capture these effects. The studies also show that by choosing appropriate layouts of the relief center, queuing delays can be reduced significantly. The layout and corresponding flow of victims also seem to have a significant impact on the utilization levels of the staff supporting the center, which has a direct influence on the staffing needs at these centers. We believe that these insights could form the basis for establishing guidelines and best practices that volunteer agencies could follow while setting up relief centers.

The rest of this chapter is organized as follows. Section 2.2 reviews the relevant literature. The queuing model of a relief center is analyzed in Sect. 2.3. The model consists of two key components, a queuing model of a walkway, and a queuing model of a pod distributing aid and relief supplies. These are described in Sect. 2.3.1 and 2.3.2, respectively. Expressions for the waiting times of victims at a relief center are derived in Sect. 2.3.3. Alternative layout configurations for relief centers are analyzed in Sect. 2.4, and the corresponding queuing network models analyzed to determine expressions for average waiting time of victims in these settings in Sect. 2.4.1 and 2.4.2. Section 2.5 reports the results of numerical studies conducted to evaluate the various design and performance tradeoffs at relief centers. Section 2.6 summarizes the main conclusions of this study.

2.2 Literature Review

This research lies at the intersection of two main areas, namely disaster logistics and facility design. Consequently, the review of literature is structured to present the relevance of the work in relation to these different areas.

Disaster logistics We briefly review the literature addressing issues in the three phases of disaster logistics operations, namely, phase 1—the preparation phase before disaster strikes, phase 2—the immediate response phase after a disaster, and phase 3—the reconstruction phase following a disaster. The purpose of reviewing work related to disaster logistics is to illustrate the breadth of issues and highlight the larger context in which operations of a relief center need to be considered. The reader can refer to Larson et al. (2006), Simpson and Hancock (2009), Altaya and Green (2006), and de la Torre et al. (2011) for a comprehensive review of issues and mathematical models related to humanitarian and disaster logistics operations.

A key aspect in planning for disasters is ensuring that inventory of critical relief supplies are pre-positioned in adequate quantities at strategic locations. Prior research in this area focuses on estimating optimal inventory levels required at various nodes along a supply chain, purchasing quantities and frequencies, and optimum of safety stock levels. Beamon and Kotleba (2006) develop a stochastic inventory control model to determine optimal order quantities and reorder points for a long-term emergency relief response. In a subsequent work, they compare the optimal solution of the previous model with a heuristic based inventory model. Akkihal (2006) determine the optimal warehouse location for inventories to support disaster relief by solving a p-median problem. Balcik and Beamon (2008) determine the optimal location for distribution centers in a network with a known set of suppliers and determine strategies to minimize response times. Duran et al. (2011) develop a mixed integer programming model to evaluate the effect of pre-positioning relief items on reducing response times.

Two key issues in the immediate response phase correspond to (i) the design of relief distribution systems focuses on the flow of relief supplies into a disaster affected zone, and (ii) the design of evacuation systems. Knott (1987) analyzes the problem of delivering food items from a distribution center to relief camps at the disaster zone using a linear programming formulation that maximizes the amount of food delivered. Haghani and Oh (1996) analyze a variation of this problem as a multiple commodity network flow problem with time windows and develop strategies that minimize loss of life. Barbarosoglu et al. (2002) and Barbarosoglu and Arda (2004) formulate a two-stage stochastic program to analyze a multi-commodity, multi-modal network formulation that evaluates the impact of demand uncertainty and network reliability on the distribution of relief. Özdamar et al. (2004) investigates the logistics of dispatching commodities to warehouses near disaster affected areas. Tzeng et al. (2007) use multi-objective programming methods to design delivery systems for relief supplies. The model is evaluated on three objectives: minimizing the total cost, minimizing the total travel time, and maximizing the minimal satisfaction during the planning period. Balcik et al. (2008) propose a mixed integer programming model that determines the delivery schedules for vehicles that would equitably allocate resources so as to minimize transportation costs and maximize benefits to aid recipients. Lin et al. (2011) propose a multi-item, multi-vehicle, multi-period logistics model for delivery of prioritized items in disaster relief operations that incorporates time windows and a split delivery strategies. Horner and Downs (2010) analyze a variant of the capacitated warehouse location model to analyze the flow of goods from logistical staging areas to the victims via intermediate points of distribution.

The design of evacuation systems focuses on the flow of victims out of a disaster affected zone. Sheffi et al. (1982) investigate the effect of spatial and temporal profiles of the loads on an evacuation network through a simulation based model and estimate their effect on total evacuation times. Kimms and Maassen (2011) develop a heuristic using a combination of simulation and optimization for optimal routing the traffic flows during a disaster relief operation. Cova and Johnson (2003) analyze a network flow model to identify the optimal lane-based evacuation routing plans in a complex road network and Fanga et al. (2011) develop heuristic algorithms for evacuation networks. Smith (1991) utilizes state-dependent queueing network models to design of emergency evacuation plans and model the nonlinear effects of increased occupant traffic flow along emergency evacuation routes. At a facility level, Smith and Towsley (1981) derive queuing models to model the egress of victims from a building affected by a disaster. A common aspect to relief center operations and the evacuation models existing in the literature is the crowd management challenges created by the sudden influx of victims. Our analysis of the layout and operations of a relief center draws upon the knowledge related to the design of evacuation systems and queuing models for evacuation networks to build realistic models that capture the crowd effects due to influx of victims at a relief center.

Facility Design This research also bears close relevance to facility design issues related to traditional distribution center (DC), that has been and continues to be the focus of several research studies. Although both the traditional DC and the RC at a disaster site are essentially setup to distribute goods and services, RC operations are considerably different and in some ways more complex compared to operations in a traditional DC. For example: multiple criteria (costs, tax incentives, labor, and infrastructure) are considered while determining the location and layout of a DC; however, the nature of the disaster affected region constrains the choice on the available locations for an RC. Moreover, there is very little time to conduct analysis on the optimal choice of location for an RC. In most cases, RCs must be setup and operational within hours of the disaster. Further, in traditional DCs, automation technologies (conveyors, cranes) can be implemented to increase throughput and reduce transaction cycle times. However, automation is often not feasible in an RC. Almost all activities in RC are manual. Also, generally well established infrastructure and information systems are available in DCs whereas in RCs, they are often unreliable, incomplete or non-existent; many RCs operate on temporary or limited power. Finally, the primary performance metric in traditional DCs is reducing operating costs and maximizing profitability whereas the performance metric in RCs is to deliver relief supplies to as many as possible, minimize loss of life, and alleviate suffering. These differences make the facility design of an RC an interesting research problem of immense practical relevance.

Through our research we intend to capture some of these unique characteristics of an RC and develop performance evaluation models that could be used to compare alternative layouts of RC. In that sense, we do build on the existing principles of facility design. This work also builds on the principles of design of evacuation systems and the queuing model constructs used to analyze relief centers builds upon the knowledge used to model crowd effects in evacuation systems. By bridging the theory in the areas of disaster logistics and facility design, we provide insights that not only improve our understanding of the research issues related to the design and operations of relief centers, but also provide guidelines that would influence practice. Sections 2.3, 2.4, and 2.5 provide details of the analysis.

2.3 Queuing Analysis of a Relief Center

Immediately following a disaster, relief agencies survey the affected area, assess potential sites for a disaster relief center and set them up as temporary structures in an a safe area such as an open parking lot or school yard. Figure 2.3a shows a layout used for disaster relief center commonly used by relief agencies and Fig. 2.3b shows the corresponding queuing model. In this section, we first develop the queuing model for performance evaluation of relief centers using this example layout. Subsequently, in Sect. 2.4, the queuing analysis is extended to analyze the performance of two alternative layouts.

Referring to Fig. 2.3a, note that the relief center consists of multiple pods that distribute a variety of items to the victims. For illustrative purposes, it is assumed that the relief center has four distribution pods. Each distribution pod is staffed by a single volunteer who distributes one or all of four items (for instance: Water-1, Ice-2, MRE-3, and Tarp-4) to each victim at each pod. In the figure, z_{11}, z_{21}, z_{31}, and z_{41} denote the coordinates where victims enter the relief center, z_{14}, z_{24}, z_{34}, and z_{44} denote the coordinates where victims exit the relief center, and x_1, x_2, x_3, and x_4 denote the coordinates of the four distribution pods. Victims that arrive at the relief center are categorized into distinct classes based on the items requested. It is assumed that here are $(2^4 - 1)$ i.e. 15 classes of victims and let $S = \{(1), (2), (3), (4), (1, 2), (3, 4), (1, 3), (1, 4), (2, 3), (2, 4), (1, 2, 3), (2, 3, 4), (3, 4, 1), (4, 1, 2), (1, 2, 3, 4)\}$ denote the set of victim classes.

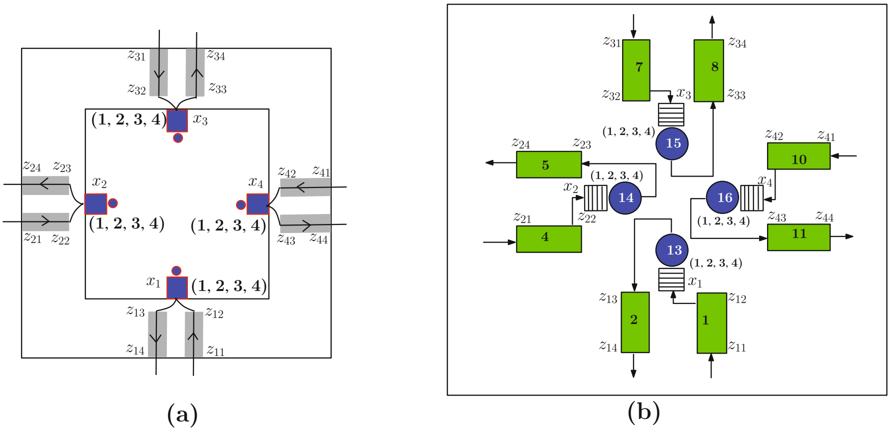


Fig. 2.3 Queuing network model of a relief center

Victims approach a distribution pod in the relief center via one of the four entry walkways in the direction: $\overrightarrow{z_{11}z_{12}}$, $\overrightarrow{z_{21}z_{22}}$, $\overrightarrow{z_{31}z_{32}}$, or $\overrightarrow{z_{41}z_{42}}$, queue at the corresponding distribution pod (located at coordinates x_1, x_2, x_3, or x_4), receive their supplies, and leave the relief center using the corresponding exit walkway in the direction $\overrightarrow{z_{13}z_{14}}$, $\overrightarrow{z_{23}z_{24}}$, $\overrightarrow{z_{33}z_{34}}$, or $\overrightarrow{z_{43}z_{44}}$. Each walkway corresponds to a segmented area in the open parking lot or school yard that guides the flow of victims in and out of the relief center. Since all four items are available at each distribution pod, a victim needs to visit only one pod to receive service. While this could have advantages, the queues in the walkways and at each distribution pod could be potentially longer because victims with different requirements share a common queue to receive service. Alternative layouts that explore these tradeoffs are examined discussed further in Sect. 2.4.

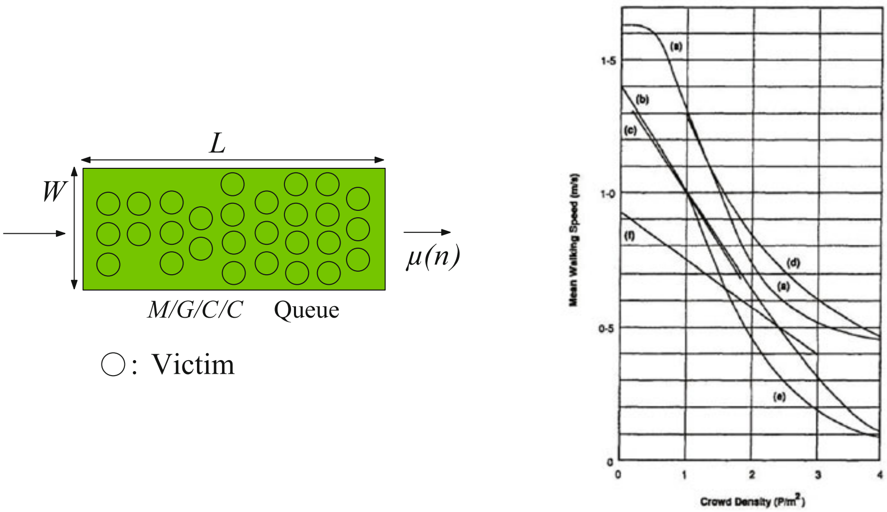
The queuing delays at the relief center depend on several factors including (i) the number of items distributed at each pod, (ii) the routing of the victims in the layout, (iii) the dimensions (length and width) of the walkways, (iv) arrival rate of victims, and (v) service times at each distribution pod. These queuing delays are analyzed by separately modeling the congestions on the walkways (where movement of victims is less coordinated) and congestions in front of the distribution pods (where the movement of victims are more coordinated). The dimensions of the walkways determines its capacity (the number of victims per square unit area). At each walkway, the movement of the victims towards the distribution pod is less coordinated. Consequently, the arrival rate of victims and capacity of the walkways determine the crowd density at each walkway. These crowd densities in turn affect the travel time of the victims through the walkway; with the travel times increasing as the crowd density increases. This effect of crowd density on queuing delays experienced by victims on the walkway is captured by modeling each walkway as an *M*/*G*/*C*/*C* queue with state dependent service rates. The *M*/*G*/*C*/*C* queues representing the walkway between the two coordinates *a* and *b* (with a direction of travel $\overrightarrow{ab}$) is denoted by ab. Closer to the distribution pod, the victim movement is more coordinated (typically through the use of ropes or barriers) and crowd density effects on queuing delays are negligible. Hence, the queuing effects closer to a distribution pod are modeled using an $M/M/1/K$ queue.

In Fig. 2.3b, the nodes 1, 4, 7, and 10 (2, 5, 8, and 11) correspond to the $M/G/C/C$ queues that model the four walkways through which the victims enter (exit) the relief center. The nodes 13, 14, 15, or 16 denote the four $M/M/1/K$ queues in front of the four distribution pods located at coordinates x_1, x_2, x_3, and x_4 respectively. The arrival process of victims is assumed to be Poisson with parameter λ_0. An arriving victim is assumed to belong to any particular class with equal probability. Hence, the arrival process of each victim class is assumed to be Poisson with parameter $\frac{\lambda_0}{15}$. Under these assumptions, the queuing network shown in Fig. 2.3b is analyzed to determine performance measures such as expected waiting times of the victims (from entry to exit), utilization of the distribution pods, and the distribution of victims at different pods and walkways. The approach used to determine these performance measures is as follows. First, queuing models for individual walkways and distribution pods are developed. The details are described in Sect. 2.3.1 and 2.3.2 respectively. Subsequently, using routing information of each class of victims, expected waiting times for each class of victim is obtained. The details are described in Sect. 2.3.3. Finally, based on the performance measures, the efficiency of this layout as well as the quality of service received by the victims at this relief center are investigated through numerical experiments in Sect. 2.5.

2.3.1 Queuing Analysis of an Individual Walkway

Each walkway is modeled as an $M/G/C/C$ queue with state-dependent travel times that have a general distribution. The main reason for modeling them as $M/G/C/C$ queue with state-dependent travel times is because the congestion delays on the walkways is affected by the crowd density at the walkway. One would expect that, with the increase in the number of victims using the walkway, the effective walking velocity of the victims decreases. Consequently, the average total travel time on the walkway would increase with crowd density on the walkway. This phenomenon was captured in an empirical state-dependent curve derived in Tregenza, 1976 and is shown in Fig. 2.4. In the figure, the y-axis denotes the speed of an individual pedestrian and the x-axis denotes the density of the number of pedestrians, so that the travel speed decreases with increasing crowd density. The curves corresponding to the letter (a) in Fig. 2.4 represents an empirical study referenced by Tregenza (1976).

Let L and W denoted the length and width of the walkway (expressed in meters) and C denote the capacity of the walkway. The C parallel servers of the $M/G/C/C$ model of the walkway denotes that C victims can travel on the walkway simultaneously. However, the travel times would vary depending on the number of victims present in the walkway. According to Tregenza (1976), the pedestrian traveling speed $V(n)$ decreases exponentially with the increase in the number of victims, n and



Pedestrian traffic flows vs. crowd density

Fig. 2.4 *M/G/C/C* model of the walkways (*left*) and empirical pedestrian speed-density curves (*right*). (Adapted from Smith (2010))

the pedestrian traffic flow comes to a relative halt when the population density approaches five pedestrians per square meter (5 peds/m^2). Thus, the walkway capacity, $C = \lfloor 5LW \rfloor$. Let the average walking velocity, $A = 1.5$ m/s; L, the length of the walkway; W, the width of the walkway (1 m); V_a, the average walking speed (0.64 m/s) when number of people per sq m = 2; V_b, the average walking speed (0.25 m/s) when number of people per sq m = 4; $a = 2LW$, and $b = 4LW$. Then, based on the analysis in Cheah and Smith (1994) and Smith (1994), the traveling speed $V(n)$ when there are n victims on the walkway is given by

$$V(n) = Aexp\left[-\left(\frac{n-1}{\beta}\right)^{\gamma}\right] \tag{2.1}$$

and the state-dependent service rate, $\mu(n)$ is given by expressed by

$$\mu(n) = \frac{nV(n)}{L} \tag{2.2}$$

$$\text{where } \gamma = \frac{ln\left[\frac{ln(V_a/A)}{ln(V_a/A)}\right]}{\left[ln\left(\frac{a-1}{b-1}\right)\right]} \quad \text{and} \quad \beta = \frac{a-1}{[ln(A/V_a)]^{1/\gamma}}.$$

Then, for each walkway i, the distribution of customers $P_i(n)$ on the walkway is provided by

$$P_i(n) = \frac{[\lambda_i E(S)]^n / n! f(n) \ldots f(2) f(1)}{1 + \sum_{i=1}^{C} [\lambda_i E(S)]^i / i! f(i) \ldots f(2) f(1)} \quad \text{for} \quad i = 1, \ldots, 12 \tag{2.3}$$

and the expected waiting time of a victim on the walkway (W_i) is given by

$$W_i = \frac{\sum_{n=1}^{C} nP_i(n)}{\sum_{n=1}^{C} P_i(n)\mu_i(n)} \quad \text{for} \quad i = 1, \ldots, 12 \tag{2.4}$$

where λ_i is the arrival rate of victims to queue i, $E(S) = \mu_i(1)^{-1}$ is the average travel time on the walkway, and $f(n) = \frac{V(n)}{V(1)}$ denotes the service rate of each server in the $M/G/C/C$ queue.

The $M/G/C/C$ queuing model for congested walkways has been used to model the critical impact of crowd density effect in a variety of settings. Smith and Towsley (1981) use $M/G/C/C$ in closed queuing network models for evacuation from high-rise buildings, while Smith (1994) use state dependent $M/G/C/C$ queues to model traffic congestion in highway networks. In that work, the state dependent $M/G/C/C$ queues model the reduced speeds in highways during rush hour traffic. State dependent $M/G/C/C$ queues have also been used to model variable conveyor speeds in material handling systems by Smith (2010). In their model, conveyor speeds decrease as the load (often bulk material such as coal, ore) on the conveyor increases. Therefore, we believe that state dependent $M/G/C/C$ queues form an appropriate building block to model pedestrian congestion and crowd density affects at disaster relief centers.

2.3.2 *Queuing Analysis of an Individual Distribution Pod*

As mentioned earlier, the four distribution pods at x_1, x_2, x_3, and x_4 are denoted by nodes with indices $i = 13, 14, 15, 16$. For simplicity of analysis, the internal traffic flows in the network are assumed to be Poisson processes. Consequently, the arrival process of victims of different classes to these distribution pods are assumed to be Poisson with rate λ_i. Further, each distribution pod is served by a single volunteer and the service time is assumed to have an exponential distribution with mean μ_i^{-1}. Note that μ_i^{-1} is assumed to be independent of the number of items requested by the victim (This assumption is relaxed in a later section). The queue at each distribution pod has a finite capacity K. Based on these assumptions, the queuing dynamics at each pod is analyzed as an $M/M/1/K$ queue. The queue length distribution and the expected waiting time at the $M/M/1/K$ queue is given by Eq. 2.5 and 2.6 respectively (Gross et al. 2008).

$$P_i(n) = \frac{(1-\rho_i)\rho_i^n}{1-\rho^{N+1}} \quad \text{for} \quad n = 0,1,\ldots,K;\ i = 13,14,15,16 \tag{2.5}$$

$$W_i = \frac{1-\rho_i^K - K\rho_i^K(1-\rho_i)}{\mu_i(1-\rho_i)(1-\rho_i^K)} \quad \text{for} \quad i = 13,14,15,16 \tag{2.6}$$

where $\rho_i \left(= \frac{\lambda_i}{\mu_i}\right)$ denotes the utilization of pod i. Using the expressions for the mean waiting times at each walkway and at each distribution pod, in the next section, expressions for the mean waiting time in the network are derived for each class of victims.

2.3.3 Analysis of Waiting Times in the System

As seen in Fig. 2.3b victims enter the relief center through one of the nodes 1, 4, 7, or 10, wait at one of the nodes 13, 14, 15, or 16 to receive their supplies, and leave the relief center using the corresponding exit node 2, 5, 8, or 11. For each class of victim, the average waiting time in the network equals the sum of (i) the average queue time in the walkway used to reach the distribution pod, (ii) the average waiting time at the distribution pod (queue time and service time), and (iii) the average queue time in the walkway used to exit the relief center. By symmetry in the layout shown in Fig. 2.3b, the total arrival rate of victims at each of the four pods is $\frac{\lambda_0}{4}$. This also leads to the following equalities:

$$
\begin{array}{ccccccc}
W_1 & = & W_4 & = & W_7 & = & W_{10} \\
W_2 & = & W_5 & = & W_8 & = & W_{11} \\
W_{13} & = & W_{14} & = & W_{15} & = & W_{16}
\end{array}
$$

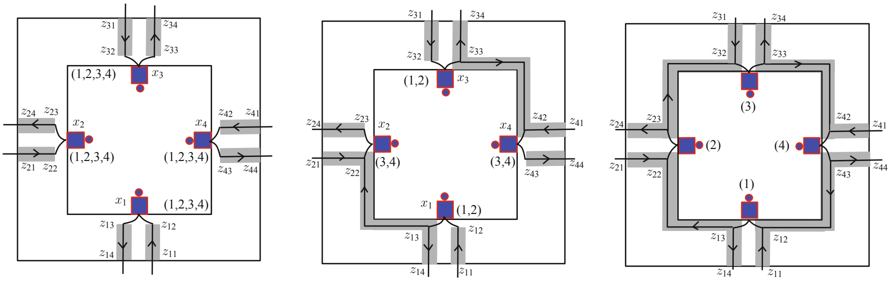
Therefore the waiting time for any class of victim receiving items from node 13 (or by symmetry from nodes 14, 15, or 16) is given by:

$$\overline{RT} = W_1 + W_{13} + W_2 \tag{2.7}$$

This completes the queuing network analysis of a relief center. As seen from the analysis above, the waiting time of victims depend on the dimensions (length and width) of the walkways, arrival rate of victims, and service times at each distribution pod. Three other factors that could have significant impact on the waiting times, namely, the layout of the relief center, the number of items distributed at each pod, and the routing of the victims in the layout. To illustrate how these parameters impact the waiting time at the relief center, two alternative layouts of the relief center are analyzed in the next section.

2.4 Analysis of Alternative Layouts of a Relief Center

Figure 2.5 shows two alternative layouts for a relief center. These layouts differ from the layout described in Sect. 2.4 in terms of the items available at the different pods as well as in the flow of victims. These layouts are analyzed to determine expressions for the average waiting times for each class of victims. These expressions are subsequently used in numerical studies to examine the impact of the differences in the layout on the relevant performance measures. Note that our intent is not to



Layout 1
Distributes four items at each pod

Layout 2
Distributes two items at each pod

Layout 3
Distributes one item at each pod

Fig. 2.5 Alternate layouts for a relief center

conduct an exhaustive evaluation of several alternative layouts for a relief center, but instead to illustrate how the queuing analysis described in the previous section could be generalized to evaluate alternatives layouts of a relief center.

Layout 1 corresponds to the layout shown in Fig. 2.3. In Layout 2 shown in Fig. 2.5, both the pods located at x_1 and x_3 distribute only items 1 and 2 whereas both the pods located at x_2 and x_4 distribute only items 3 and 4. Victims enter the relief center through either of the two entry walkways in the direction $\overrightarrow{z_{11}z_{12}}$ and $\overrightarrow{z_{31}z_{32}}$. If the victims require only item 1, or only item 2, or both items 1 and 2, then, they leave the relief center using the corresponding exit walkway in the direction $\overrightarrow{z_{13}z_{14}}$ or $\overrightarrow{z_{33}z_{34}}$. However, if the victims require items 3 and/or 4, they proceed toward the distribution pods located at x_2 (x_4) from the distribution pods located at x_1 (x_3). After receiving the supplies they leave using the exit walkways in the direction $\overrightarrow{z_{23}z_{24}}$ $(\overrightarrow{z_{43}z_{44}})$. In this layout, the distribution pods are specialized to meet certain requirements of the victims. However, some victim classes might need to visit multiple queues to satisfy all their needs.

In Layout 3 shown in Fig. 2.5, only one item is distributed at each pod. The pods located at x_1, x_2, x_3, and x_4 distribute items 1, 2, 3, and 4 respectively. Similar to Layout 1 and Layout 2, there are four entry walkways and four exit walkways. Based on the needs of the victim, they are directed to enter the relief center through an appropriate entry walkway. For instance, a victim that requires items 1, 2, and 3, enters the relief center through the entry walkway in the direction $\overrightarrow{z_{11}z_{12}}$, collects item 1 from pod located at x_1, then proceeds to pod x_2 to collect item 2, then proceed to pod x_3 to collect item 3, and then leave the relief center using the exit walkway in the direction $\overrightarrow{z_{33}z_{34}}$. The flow of victims in this layout mimics the flow of vehicular traffic at a traffic roundabout. In this layout, the distribution pods are specialized to meet unique requirements of the victims. However, in comparison to layout 2, a larger proportion of victims would need to visit multiple queues to receive satisfy all their needs.

The distribution layouts described in Fig. 2.5 are analyzed using the model building approach described in Sect. 2.3. Figure 2.6 illustrates the routing followed by a

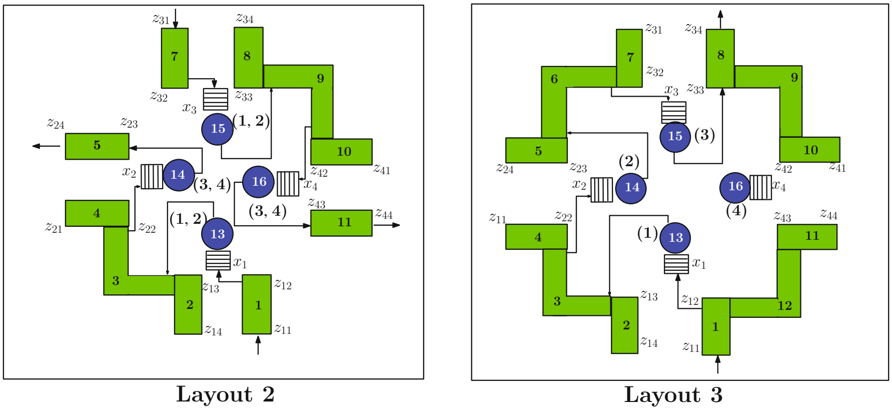


Fig. 2.6 Queuing network for alternate layouts showing routing for class of victims requesting items 1, 2, and 3

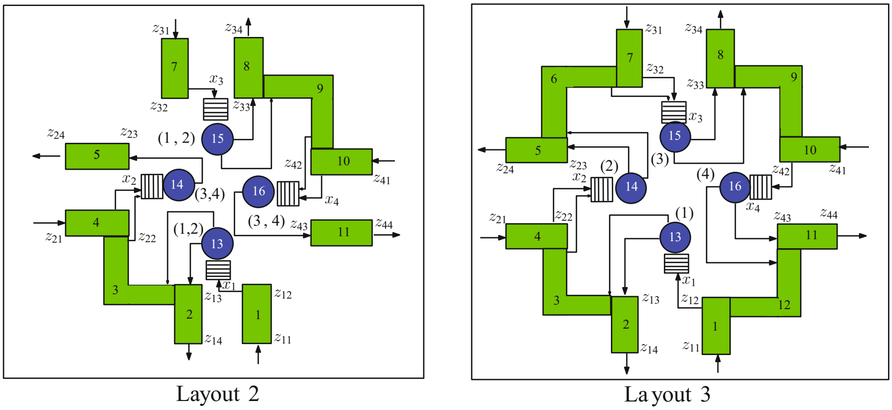


Fig. 2.7 Queuing network for alternate layouts showing routing for class of victims requesting all items

class of victims requesting only items 1, 2, and 3. Figure 2.7 illustrates the routing followed by a class of victims requesting all four items. In Layouts 2 and 3, since items are dedicated to particular pods, certain classes of victims would need to visit multiple pods to satisfy all their needs. However, the waiting times at the individual pods are likely to be lower due to the specialized nature of these pods. Further, having pods with specialized items also has the effect of 'thinning' the crowd at the relief center and regulating the flow of victims, which could reduce overall waiting times for victims at the relief center. The subsequent sections derive mean waiting time expressions for both these layouts to quantify these tradeoffs.

Table 2.1 Routing for each victim class in layout 2

Class (j)	Items required	Routings	Set of walkways (W_j)	Set of pods (P_j)
1	1	1-13-2	1, 2	13
2	2	1-13-2	1, 2	13
3	3	4-14-5	4, 5	14
4	4	4-14-5	4, 5	14
5	1, 2	1-13-2	1, 2	13
6	3, 4	4-14-5	4, 5	14
7	1, 3	1-13-3-4-5	1, 3, 5	13, 14
8	1, 4	1-13-3-14-5	1, 3, 5	13, 14
9	2, 3	1-13-3-14-5	1, 3, 5	13, 14
10	2, 4	1-13-3-14-5	1, 3, 5	13, 14
11	1, 2, 3	1-13-3-14-5	1, 3, 5	13, 14
12	1, 2, 4	1-13-3-14-5	1, 3, 5	13, 14
13	1, 3, 4	1-13-3-14-5	1, 3, 5	13, 14
14	2, 3, 4	1-13-3-14-5	1, 3, 5	13, 14
15	1, 2, 3, 4	1-13-3-14-5	1, 3, 5	13, 14

2.4.1 Analysis of Waiting Times for Layout 2

Note that in Layout 2, both pods 13 and 15 distribute items 1 and 2 whereas both pods 14 and 16 distribute items 3 and 4. Further, due to symmetry, it suffices to analyze the mean waiting time for victim classes that visit pods 13 and 15. The network is analyzed as a multi-class open queueing network. Table 2.1 shows the routing in Layout 2 for each of the 15 classes of victims. For example, a victim that needs items 1 and 3 would visit nodes 1, 13, 3, 14 and 5 respectively. This routing is denoted by the sequence 1-13-3-14-5. The table also lists two sets, W_j and P_j, of indices corresponding to the walkways and pods visited by class j, respectively.

The average waiting time for victims can be computed using the routing information for each class and the expressions for the mean waiting times at the walkway and pod derived in Sect. 2.3. Using these expressions, the average waiting time RT_j for victims of class j is given by

$$RT_j = \sum_{i \in P_j} W_i + \sum_{i \in W_j} W_i \quad \text{for} \quad j = 1, \ldots, 15 \tag{2.8}$$

where the mean waiting time, W_i, of victim of class j at walkway i in W_j and the mean waiting time, W_i, of victim of class j at pod i in P_j are obtained using the equations in Sect. 2.3.1 and 2.3.2 respectively with appropriate arrival and service time parameters. Then, for a relief center with Layout 2, the average waiting time for a victim is given by Eq. 2.9.

$$\overline{RT} = \frac{1}{15} \sum_{j=1}^{15} RT_j \tag{2.9}$$

Next, a similar analysis is conducted for Layout 3.

Table 2.2 Routing for each victim class in layout 3

Class (j)	Items required	Routings	Set of walkways (W_j)	Set of pods (P_j)
1	1	1-13-2	1, 2	13
2	2	4-14-5	4, 5	14
3	3	7-15-8	7, 8	15
4	4	10-16-11	10, 11	16
5	1, 2	1-13-3-14-5	1, 3, 5	13, 14
6	3, 4	7-15-9-16-11	7, 9, 11	15, 16
7	1, 3	1-13-3-6-15-8	1, 3, 6, 8	13, 15
8	1, 4	10-16-12-13-2	10, 12, 2	16, 13
9	2, 3	4-14-6-15-8	4, 6, 8	14, 15
10	2, 4	4-14-6-9-16-11	4, 6, 9, 11	14, 16
11	1, 2, 3	1-13-3-14-6-15-8	1, 3, 6, 8	13, 14, 15
12	1, 2, 4	10-16-12-13-3-14-5	10, 12, 13, 3, 5	16, 14
13	1, 3, 4	7-15-9-16-12-13-2	7, 9, 12, 13, 2	15, 16
14	2, 3, 4	4-14-6-15-9-16-11	4, 6, 9, 11	14, 15, 16
15	1, 2, 3, 4	1-13-3-14-6-15-9-16-11	1, 13, 3, 6, 9, 11	14, 15, 16

2.4.2 Analysis of Waiting Times for Layout 3

Note that in Layout 3, each pod distributes only one item. In particular, pods 13, 14, 15 and 16 distribute items 1, 2, 3 and 4 respectively. The network is analyzed as a multi-class open queueing network. Table 2.2 shows the routing in Layout 3 for each of the 15 classes of victims. For example, a victim that needs items 1, 2, 3, and 4 would visit nodes 1, 13, 3, 14, 6, 15, 9, 16, and 11 respectively. This routing is denoted by the sequence 1-13-3-14-6-15-9-16-11. The table also lists two sets, W_j and P_j, of indices corresponding to the walkways and pods visited by class j, respectively.

As with Layout 2, the average waiting time for victims is computed using the routing information for each class and the expressions for the mean waiting times at the walkway and pod derived in Sect. 2.3. Using these expressions, the average waiting time RT_j for victims of class j is obtained using Eq. 2.8 where the mean waiting time, W_k, of victim of class j at walkway k in W_j and the mean waiting time, W_k, of victim of class j at pod k in P_j are obtained using the equations in Sect. 2.3.1 and 2.3.2 respectively with appropriate arrival and service time parameters. Subsequently, the average waiting time, $\overline{RT}$, for a victim is given by Eq. 2.9.

2.5 Numerical Experiments

This section describes the numerical experiments that investigate how the average waiting times at a relief center depends on factors such as (i) the number of items distributed at each pod, (ii) the dimensions (length and width) of the walkways, (iii) the routing of the victims in different layouts, and (iv) the service times at each

Table 2.3 Parameter setting for numerical experiments

Parameter	Value
Walkway width W	1 m
Walkway length L	10, 30 m
Traveling velocity of victims v	1.5 m/s
Size of the finite buffer in front of the pods K	100
Rate of victims arriving at the relief area λ_0	330 victims/h
Service rate at each pod μ	360 victims/h

distribution pod. The parameters used in the numerical experiment are summarized in Table 2.3. In this section, the average waiting time for customers in Layout i is denoted by $\overline{RT_i}$ for $i = 1, 2, 3$.

Experiment 1 focuses on Layout 1. Recall that, in this layout all four items are distributed at each pod. One of the key features of the queuing network model for the relief center, is the use of state dependent $M/G/C/C$ queue to model the effects of crowd density on walkway delays. The results from Experiment 1 illustrate the importance of modeling the effect of crowd density while estimating waiting times for the victims. To illustrate this importance, the estimates of average waiting times obtained from this queuing network are compared the average waiting time estimates obtained from analysis of a queuing network where the walkways are modeled as state independent $M/G/C/C$ queues.

Further, the experiment also considers two scenarios of service times. In the first scenario, when $\alpha = 1$, the service times at a pod are independent of the number of items being distributed at the pod. In the second scenario, the service times at a pod increases with the increase in the number of items. In particular, the service rates are $\alpha^2\mu$ when four items are distributed at a pod, and $\alpha\mu$ when two items are distributed at a pod.

Table 2.4 reports results for two values of L, $L = 10$, 30 and two values of α,$\alpha = 1.0$, 0.5. The results lead to three main observations. First, it can be noted that increasing crowd density leads to significant increases in the expected waiting time in the network. From an expectation management point of view, this observation would be very valuable in guaranteeing a certain quality of service. Using waiting times from queuing models that incorporate the effect of crowd density on waiting times, volunteers from relief agencies could communicate more reliable estimates of waiting times to victims arriving at the relief center, thereby reducing frustration and

Table 2.4 Effect of crowd density on mean waiting times

Walkway length (m) L	Service time factor α	Walkway travel time dependent on crowd density (mins) $\overline{RT_1}$	Walkway travel time independent of crowd density (mins) $\overline{RT_1}$	Utilization $\rho_{13,1}$
10	0.50	9.97	8.21	0.92
30	0.50	14.33	8.66	0.92
10	1.00	2.19	0.44	0.23
30	1.00	6.55	0.88	0.23

Table 2.5 Effect of layout configuration on mean waiting times

Walkway length (m)	Service time factor	Walkway travel time dependent on crowd density (mins)			Walkway travel time independent of crowd density (mins)			Utilization		
L	α	$\overline{RT_1}$	$\overline{RT_2}$	$\overline{RT_3}$	$\overline{RT_1}$	$\overline{RT_2}$	$\overline{RT_3}$	$\rho_{13,1}$	$\rho_{13,2}$	$\rho_{13,3}$
10	0.50	9.97	4.34	3.39	8.21	2.29	1.06	0.92	0.73	0.49
30	0.50	14.33	9.21	8.81	8.66	2.87	1.78	0.92	0.73	0.49
10	1.00	2.19	2.76	3.39	0.44	0.71	1.06	0.23	0.37	0.49
30	1.00	6.55	7.63	8.81	0.88	1.29	1.78	0.23	0.37	0.49

improving the overall experience for the victim under stress. Second, it is observed that as the length of the walkways increase, the average waiting time increases significantly. The specialized state dependent $M/G/C/C$ queues provide better estimates of how the length of the walkway impacts the waiting times for victims, suggesting that the model could be used to investigate optimal length of walkways. Insights from such an analysis could be incorporated in the guidelines established by agencies involved in relief efforts. Third, the results also indicate that when the service rate at a pod decreases with the number of items, average waiting times and pod utilizations increase considerably. This illustrates another important decision faced by relief agencies in terms of staffing and organizing items at various pods at a relief center. The queuing models discussed here could be used to evaluate such tradeoffs related to crowd density and walkway lengths on waiting times at a relief center.

Experiment 2 focuses on comparing Layouts 1, 2 and 3. Recall that the allocation of items and the flow of victims in these layouts are different. In Layout 2, two items are distributed at each pod, while in Layout 3, only one item is distributed at each pod. As in Experiment 1, two scenarios of service rates considered. In the first scenario, when $\alpha = 1$, the service rate at a pod are independent of the number of items being distributed at the pod. In the second scenario, the service rate at a pod decreases with the increase in the number of items. In particular, the service rates are $\alpha^2\mu$ at each pod in Layout 1 when four items are distributed at each pod, and $\alpha\mu$ at each pod in Layout 2 when two items are distributed at each pod.

Table 2.5 reports results for two values of L, $L = 10, 30$ and two values of α,$\alpha = 1.0$, 0.5. The results indicate that increasing crowd density leads to significant increases in the expected waiting time in the network for all three layouts. This reinforces the point made earlier with Experiment 1, that using waiting times from queuing models that incorporate the effect of crowd density on waiting times is important so that volunteers from relief agencies could communicate more reliable estimates of waiting times to victims arriving at the relief center. Second, it is observed that as the length of the walkways increase, the average waiting time increases. Therefore, the models could be used to investigate the optimal length of walkways that would be necessary to meet service time needs of victims. Interestingly, Experiment 2 also indicate situations where that Layouts 2 and 3 are superior to Layout 1 in terms of average waiting times for a victim.

In particular, when the service times at a pod is independent of the number of items distributed at the pod ($\alpha = 1$), the average waiting times in Layout 1 is less than that in Layout 2 and Layout 3; i.e. when $\alpha = 1$

$$\overline{RT_1} < \overline{RT_2} < \overline{RT_3} \tag{2.10}$$

However, when the service rate at a pod decreases with the number of items ($\alpha < 1$), the the average waiting times in Layout 3 are the least, i.e., when $\alpha < 1$

$$\overline{RT_3} < \overline{RT_2} < \overline{RT_1} \tag{2.11}$$

Note that in Layout 3, the use of specialized queues to distribute particular items has the effect of 'thinning' the crowd. Therefore, although victims might need to visit multiple queues to receive all their items, these queues tender service quicker due to the improved flow of victims at each pod, thereby reducing the overall waiting times at the pod. These results suggest that both crowd density effects and layout of the relief center could have significant effect on average waiting times of victims. The queuing network models proposed in this research capture these important tradeoffs and could be used for deciding efficient configurations for distributing aid at relief centers.

2.6 Conclusions and Extensions

This research investigates the effect of layout of a relief center on the expected waiting times experienced by victims that queue to receive aid at these relief centers. Using a representative layout of a relief center as an example, the queuing delays at a disaster relief center modeled in detail by using a multi-class closed queuing network model. A distinguishing feature of the queuing model is the use of state dependent $M/G/C/C$ queues to capture the impact of crowd density on waiting times at the walkways. Closer to the distribution pod, where the victim movement is more coordinated, the queuing effects are modeled using an $M/M/1/K$ queue. Exact analysis of the queuing network yields analytical expressions for the average waiting times of the victims at the relief centers. The analysis reveals several important observations.

Numerical studies show that increasing crowd density leads to significant increases in the expected waiting time in the network. This observation has important implications for volunteers from relief agencies that would want to communicate more reliable estimates of waiting times to victims arriving at the relief center. Using waiting times from queuing models that incorporate the effect of crowd density on waiting times, volunteers can provide estimates that lead to better quality of service guarantees. Second, the results also indicate that when the service rate at a pod decreases with the number of items, average waiting times and pod utilizations increase considerably. This has important implications for relief agencies in terms of staffing and organizing items at various pods at a relief center. Third, the queuing models developed in this research could be used to evaluate tradeoffs related to crowd density and walkway lengths on waiting times at a relief center. Fourth, the models suggest the impact of alternative layouts on waiting times for victims. The studies show that when the service times at a pod is independent of the number of items distributed at the pod, the average waiting times in Layout 1 is less than that in Layout 2 and Layout 3. However, when the service rate at a pod decreases with the number of items, the the average waiting times in Layout 3 are the least. Layout 3 is inspired by the roundabouts used to regulate vehicular traffic. The study reveals that the use of specialized queues to distribute particular items in layout 3 has the effect of 'thinning' the crowd and improving victim flow. Although victims might need to visit multiple queues to receive all their items, these queues offer shorter waiting times thereby reducing the overall waiting times at the pod, in some cases. These results suggest that both layout and crowd density effects can be significant, thereby underscoring the importance of queuing network models that capture these effects explicitly. The insights obtained from this research can be useful to relief agencies that could use performance evaluations models like those presented here to develop guidelines to setup as well as operate relief centers following disasters.

There are several ways in which this research can be extended to conduct a more thorough investigation of the impact of layouts on waiting times for victims. First, the analysis was presented for only three types of layouts. In practice there are several other possible layouts for a relief center. The queuing models presented here could be extended to evaluate these alternative layouts and provide a more exhaustive comparison of alternatives. Next, the model could be extended to include more types of items, victim classes, and the differences in the demands of types of items. These differences in demand might drive alternative allocation strategies of items to the various pods at the relief center. We believe our model could be extended to explore such generalizations as well. Third, the layout comparisons were carried out based on mean waiting times. It would be useful to conduct similar comparisons in terms of the tail probabilities of the distributions of the waiting time. These could have stronger implications in terms of quality of service guaranteed to victims at a relief center. All these extensions are the focus of our ongoing investigations.

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Chapter 3
Multiple Location and Routing Models in Humanitarian Logistics

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3.1 Introduction

International humanitarian organizations aim to mitigate human suffering through relief operations, often combining development programs with disaster response. These organizations do not follow standard market principles and their field operations are usually established in volatile and unstable regions within an atypical context, facing many challenges (Van Wassenhove 2006). They are non-profit oriented, actually reporting to three groups: donors (governments, private foundations, individuals and firms) who finance the operations and are the main funding source, beneficiaries representing demand, and the international community.

In both cases of disaster response operations and development programs, road transportation of people and aid across developing territories is most often considered, using reliable 4×4 vehicles, since driving conditions are poor compared to those in developed countries. These vehicles serve to transport personnel, aid and beneficiaries in the action field. Humanitarian organizations' distribution needs in terms of transportation for disaster response and development programs are empirically assessed, calculating the fleet size required according to on-going demand. The Fleet Forum, a humanitarian interagency association, estimates that the total number

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of 4 × 4 vehicles in the international humanitarian sector is between 70,000 and 80,000 units (Pedraza Martinez and Van Wassenhove 2009).

One of the most important humanitarian organizations' operations is the 'last mile distribution', i.e. the delivery of aid to beneficiaries. This means transporting relief supplies and services from local distribution centres (depots or hubs) to beneficiaries, experiencing a twofold demand uncertainty: a) one part is derived from unpredicted disasters, which can generate an uncertain increase in the demand of disaster response operations. Transportation requirements for development programs are more stable in a short time horizon, although stochasticity occurs (due to beneficiaries' mobility, weather unpredictability, road network condition, (possible) unavailability of vehicles, etc.; Pedraza Martinez et al. 2010); b) the other part is derived from lack of effective coordination and planning between programs, which allows the local decision makers to dynamically allocate vehicles to routes not included in the original schedule (Pedraza Martinez et al. 2009).

The 4 × 4 vehicles' supply chain must be able to demonstrate cost effectiveness to donors who demand accountability (Tomasini and Van Wassenhove 2006). However, humanitarian organizations face operating conditions that are very different from those of commercial fleets in developed countries. The lack of stability, security, local infrastructure and facilities, combined with the huge difficulty in gathering reliable field data, makes the fleet optimization hard, even though fleet costs are high and transportation is the second largest cost in humanitarian operations after personnel (Pedraza Martinez and Van Wassenhove 2009). This fact, together with the uncertainty of transportation demand have as a consequence non-optimal last mile distribution and a significant increase of the fleet's running costs (more than 50 % according to the Fleet Forum). This uncertainty could be reduced through information sharing, scheduling and route planning, thus having a positive impact on last mile distribution performance.

Until now, humanitarian organizations have not directly assessed the impact of optimizing their vehicles routing and scheduling and operational research techniques are rarely applied, although this could prevent purchasing new vehicles and increasing fleet's size and cost unnecessarily. In fact there are estimates, e.g. from the global fleet manager of the International Committee of the Red Cross, that optimizing routing and scheduling would reduce their fleet size by 15 %. If this holds for all humanitarian organizations and, since the total current purchasing plus transportation and preparedness cost is approximately $30,000 per vehicle, the total savings would be in a magnitude of millions of dollars, without including running costs (Stapleton et al. 2009).

Currently, in some organizations (e.g. International Federation of the Red Cross and Red Crescent Societies), allocation and routing of the vehicles take place on a weekly basis at program level and is approved at a national level. Car-pooling is explicitly recommended but it is not monitored centrally. There are some additional constraints, e.g. in several cases and for security reasons vehicles in the same location are required to travel in pairs. In other cases (e.g. World Vision International), the allocation and routing of the vehicles is at regional programs coordinators' discretion and vehicles are not generally shared due to donor constraints or lack of information about overlapping routing. In periods without disaster operations, transportation needs are planned on a short term basis.

Most of the literature on humanitarian transportation and logistics has been focused on theoretical models for evacuating victims, preparedness and efficient response to disasters, optimizing routing and resources' deployment and distributing aid. Altay and Green (2006) identify acquiring vehicles as one of the typical activities for disaster response preparedness. Mathematical models for victims' evacuation can be found in (Sheffi et al. 1982; Sherali et al. 1991; Barbarosoglu et al. 2002; Kimms and Maassen 2011; Bish 2011). Aid distribution models can be found in (Barbarosoglu and Arda 2004; Yi and Kumar 2007; Tzeng et al. 2007). Most of these papers formulate optimization models to maximize the amount of aid delivery or minimize casualties and response time or cost. Viswanath and Peeta (2003) identify critical routes for earthquake response by using a multi-commodity network flow model. Sheu (2007) models the response to urgent relief demands during the first 3 days of disaster response. Yi and Ozdamar (2007) model the victim evacuation and medical personnel transportation after disasters using a mixed integer multi-commodity network flow model. Campbell et al. (2008) explore the impact of having different strategic goals on delivering aid vehicles' routing in the first stage of relief operations. Balcik et al. (2008) model aid distribution considering two objectives: minimizing transportation cost and maximizing benefits for aid recipients. Nolz et al. (2011) study the problem of designing a logistic network for distributing relief aid in a post-natural-disaster situation. Possible damages to infrastructures are taken under consideration for developing the model. Berkoune et al. (2012) examine the problem of transportation of several humanitarian supplies (e.g., water, food, medical goods and survival equipment) to people at fixed distribution points. Ozdamar (2011) presents a planning system for the coordination of helicopters' operations in disaster relief. Last mile distribution and pickups for post-disaster medical treatment and injured evacuation are taken into account. A review regarding optimization models in the context of emergency logistics can be found in (Caunhye et al. 2012). Finally, De la Torre et al. (2012) present a survey of operations research models developed for tackling vehicle routing problems in the generic context of disaster response.

The aim of this chapter is to model the last mile distribution fleet management problem at a regional level. A stochastic model is proposed for locating vehicles hubs, allocating demand areas and vehicles scheduling and routing in the case of development programs, allowing resources' sharing between them, the criterion being travelling time minimization under several side constraints. The model is modified in the case where disaster response operations are taking place simultaneously with development programs and the objective is to maximize the amount of supplies and/or services delivered to beneficiaries. The model's implementation and efficiency testing remains open for future research.

The remainder of the paper is structured as follows: First the statement of the problem in the case of development programs is presented in Sect. 3.2. Then the case of emergency response is incorporated in Sect. 3.3. The paper concludes with some remarks and suggestions for future research in Sect. 3.4. Finally, the two problems' deterministic (instance) versions mathematical models are presented in Appendices I and II, respectively.

3.2 The Case of Development Programs

International humanitarian organizations development programs (in sectors like health, nutrition, water supply, sanitation, etc.) are implemented in order to improve life quality in developing countries. They are long-termed and not highly urgent. In their operating practice, a number of available 4×4 vehicles are assigned to a region according to assessments regarding development programs' demand and in requisition order, where the major activity is to deliver supplies and services (including staff transportation) from local distribution centres (depots or hubs in vehicle routing problems terminology) to the end customers who are the beneficiaries located in several demand points (villages, refugee camps, etc.). These may not be directly connected to each other due to the road network condition, the regional topology, etc. All vehicles have a known capacity and a maximum accepted travelling time (tour time-limit or range) per day.

While transportation requirements for development programs are quite stable in a short time horizon, stochasticity occurs due to the mobility of beneficiaries and the uncertain demand that occasionally appears, the unpredictability of weather and road network condition that cause random travelling times, and the (possible) unavailability of vehicles (Pedraza Martinez et al. 2010).

The problem is to, simultaneously: a) determine the number and the locations of depots, which are a subset of the demand points' set, b) assign beneficiaries to depots and c) determine the vehicles' fleet size and schedule them to routes, with the objective to minimize the total travelling times, under several side constraints, such as:

- The total available budget for setting up depots and operating vehicles per day. This depends directly on the organization's available funding and it affects the capability of satisfying the total demand. It must be sufficient to cover the depots' set up and operational costs, the vehicles' operating cost, which is the sum of their running cost (including maintenance, repairs and fuel costs) plus their management cost (including the cost of vehicle drivers, utilization of information systems like GPS, transportation managers salaries' proportion for activities related to vehicle's scheduling and routing), etc.
- The fleet size capacity of all potential depots.

A planning period of one day can be considered, since this is a common time interval for humanitarian organizations logistics managers in order to schedule their vehicles' development programs operations.

The random elements of the problem examined here are:

- Travelling times. Their stochasticity is due to the unpredictability of weather and road network conditions. They are continuous random variables with unknown distribution that could be exactly calculated or approximated, by gathering data from humanitarian organizations' field operations using information systems for tracking their vehicles' fleet (GPS, etc.)

- Demands. Their stochasticity is due to the mobility of beneficiaries and their requests' differences that occasionally appear. If demands are equal to zero for a specific location, it means that the beneficiaries stationed there are absent. In general, demands can be estimated before vehicles' location and routing decisions, but their exact values are revealed upon arrival to the spot. They are discrete random variables with unknown distribution, which could be numerically approximated by statistical sampling from field data.
- The fleet size upper limits at the depots. It reflects vehicles' availability due to (possible) failures, maintenance, use for other purposes, etc. They are discrete random variables with unknown distribution that could be numerically approximated from past historical data kept by humanitarian organizations' logistics managers.

The mathematical model for the deterministic (instance) version of the problem described, where a specific realization (value) of the random parameters is considered, is presented in Appendix I.

3.3 The Case of Emergency Response

For humanitarian organizations, setting up an efficient supply chain in general and more specifically a last mile distribution network is always a complex operation after a man-made or a natural disaster. A successful humanitarian disaster operation mitigates the urgent needs of a population reducing vulnerability under time and resources constraints (Van Wassenhove 2006). Unlike logistics managers in the private sector, humanitarians face difficulties due to their operations' nature. In addition, even with accurate data, both demand and supply can vary significantly during the response operation period. Unexpected events also force resources to move out of one operation field and head off to another, even overnight.

The first three days after the disaster are crucial and during them supplies arrive to the operation field by air, by land or by sea from abroad as quickly as possible. Then, during the next three months approximately, it is a balancing effort between effectiveness in helping people and minimizing cost, considering that development programs operations may continue in parallel.

A decision-making tool in the case where disaster response operations are simultaneously taking place at a one-depot regional level together with development programs over a time period is necessary. There is an amount of disaster relief supplies arriving at the beginning of each day of the planning horizon (its magnitude can be a few months). Obviously, the demand in such cases may be satisfied only partially, but generally there is an upper acceptable limit of unsatisfied demand according to humanitarian organizations decision makers' tolerances and priorities in a case of emergency (Balcik et al. 2008). If unsatisfied demand exceeds a certain threshold, then the budget available for the next day may decrease, because the humanitarian organization will not be able to maintain a good image (media play a very important role to this) and donors will be more reluctant in their funding.

The objective is to maximize the amount of total beneficiaries supplies/services delivered by the vehicles' fleet in a planning horizon, under random disaster response and development programs demand, travelling times and vehicles' availability. The problem can easily be extended in the case where there are multiple depots, which are located according to the location-allocation model presented in the previous section.

The mathematical model for the deterministic (instance) version of the problem described is presented in Appendix II.

3.4 Discussion and Conclusion

Natural and man-made disasters increasingly occurring during the last decade due to environmental degradation and climate change, rapid urbanization, disease and poverty and the need to support disaster response operations and development programs, have increased the volume of humanitarian activities along with the needs for efficient transport capacity and fleet management.

In general, humanitarian organizations are quite difficult to operate under a standard rules and procedures framework. Many of their employees are independent and creative, which can be helpful under the non-trivial situations they face, but on the other hand such behaviour usually decreases relevant data reliability. Collecting accurate and adequate field data is quite difficult, since the nature of the operations makes access to information hard and enough time must be spent for preparing and interpreting data before feeding it to a decision support model. In disaster response operations, data collection is certainly not the main priority for the involved personnel and even in the most advanced humanitarian organizations field data are noisy, incomplete or unavailable. Quite often lots of data are collected, mostly for administrative reasons, but they are not used for optimizing decision making. If the data capturing problem is solved, then even simple optimization models can provide significant results.

It is obvious that data capture and, more generally, professional fleet management is largely absent in the hundreds of small humanitarian organizations. Development programs often avoid supplying their vehicles to the response team during disaster response in order to continue running their operation as smoothly as possible. There is a huge need for more work in this area considering that any savings resulting from better fleet management will be invested in increasing the number of beneficiaries of humanitarian operations. Considering the complexity of humanitarian operations, more research is necessary on this topic in operations management/operational research in order to improve efficiency. Theoretical optimization models are valuable and for their implementation it is first necessary to examine the way humanitarian organizations operate. At the moment managerial structures and objectives, incentive systems and key performance indicators are misaligned, strongly reducing their capability to implement these models (Pedraza Martinez et al. 2010).

Although it is difficult to conclude whether optimization methods could be eventually used to improve last mile distribution performance or whether unpredictable operating conditions, complex organizational structures, vague objectives, or donor constraints would make the use of optimization decision tools prohibitively expensive or simply impossible, there is a strong evidence that improving the way the fleet vehicles are managed at a regional, national or international level will reduce costs and increase the efficiency of the fleet.

The theoretical models proposed in this chapter can be utilized as generic decision making tools by a humanitarian organization, as long as they are fed with its operational data. They can be used in any planning horizon, since for example, if the demand or the number of development programs changes, the model can be resolved. It should be noted that it was not possible until now to find real data to test the efficiency of the proposed models, since in the generic context of humanitarian logistics both the accuracy and availability of real data are rather scarce (Van Der Laan et al. 2009).

The next research steps include solving the models and testing their efficiency in the case of actual development programs/disaster response operations of a humanitarian organization. If the real-world case study dimensions exceed the proposed models optimal solution yielding capability, several heuristics could be utilized, e.g. simulated annealing and tabu-search (Wu et al. 2002; Laporte et al. 2000), using the instance models as the lower bound for heuristic-validation purposes, at least for small networks. Other options could be to examine not only delivery to beneficiaries but also backhauling, e.g. rescuing people, possible in time windows. Finally, another interesting topic is the incorporation of disaster forecasting into the model.

3.5 Appendix I

Considering the randomness of the demand, the travelling times and the vehicles' availability, the problem in Sect. 3.2 can be defined as a stochastic multiple-depot multiple-vehicle location-routing one (Chan et al. 2001). A deterministic (instance) version of the model, where a specific realization (value) of the random vector that consists of the demands, the travelling times and vehicles' availability, is considered.

Let G(N, E) be a graph, where N is the set of nodes (demand points) and E the set of edges (i, j), $i, j \in N$. The travelling times from i to j, $i, j \in N$ are t_{ij} (it is $t_{ij} = 0$ for $i = j$. For cases where there is not a direct connection between i and j, the respective arcs are removed from the graph). Let D be the set of potential depots locations, $D \subseteq N$.

Furthermore, let:

P be the set of regional development programs

R be the maximum accepted travelling time for all vehicles (tour time-limit or range) per day. It is $t_{ij} \leq R$, $i, j \in N$

d_{ip} be the demand of demand point i for project p, $i \in N$, $p \in P$

V be the vehicle's capacity
c_i be the fixed cost of setting up a depot $i \in D$ per day
c_v be the vehicle's operating cost per day
B be the total available budget for setting up depots and operating vehicles per day
M_i be the fleet size upper limit at depot $i \in D$.

Variables

$y_i = 1$, if a depot is established in location $i \in D$; 0, otherwise.
$z_{ij} = 1$, if demand point $j \in N$ is allocated to depot $i \in D$; 0, otherwise.
$x_{ij} = 1$, if the route (i, j) is used in the optimal solution by a vehicle, $i, j \in N$; 0, otherwise.
m_i the number of vehicles stationed at depot i, $i \in D$.
t_i a vehicle's arrival time at demand point i, $i \in N$.

Assumptions

- All 4 × 4 vehicles are considered to be of the same type running with the same speed and having the same capacity (the model can easily be modified for different types of vehicles).
- The demand of a specific location for all programs is served by one depot.
- All depots can facilitate vehicles and supplies for every program. If this is not the case, then they are excluded from the set of potential depots locations for some or every demand point.
- Vehicles pooling and sharing between different programs is allowed.
- Within the planning period of one day, each vehicle is making only one tour before returning to the same depot where it departed from.
- Travelling times t_{ij} are non-symmetric and they do not satisfy the triangular inequality $t_{ij} \le t_{ik} + t_{kj}$, $i, j, k \in N$, $i \ne j \ne k$. The idle times while demand points are served are incorporated in travelling times.

The mathematical model is the following:

$$\min \sum_{i,j \in N} t_{ij} x_{ij}$$

s.t.

$$\sum_{i \in N-D} x_{ij} = 1,\ j \in N-D \tag{3.1}$$

$$\sum_{j \in N-D} x_{ij} = 1,\ i \in N-D \tag{3.2}$$

$$t_{j_l} \ge t_i + t_{ij_l} - (1 - x_{ij_l})R,\ i \in N, j_l \in N - D,\ l = 1, ..., k,\ k = \left\lceil \frac{\sum_{p \in P} d_{jp}}{V} \right\rceil \tag{3.3}$$

$$t_{j_l} \le t_i + t_{ij_l} + (1 - x_{ij_l})R,\ i \in N, j_l \in N - D,\ l = 1, ..., k,\ k = \left\lceil \frac{\sum_{p \in P} d_{jp}}{V} \right\rceil \tag{3.4}$$

$$t_{i_l j} x_{i_l j} + t_{i_l} \le R,\ i_l \in N - D, j \in D,\ l = 1, ..., k,\ k = \left\lceil \frac{\sum_{p \in P} d_{ip}}{V} \right\rceil \tag{3.5}$$

$$\sum_{i,j \in S} x_{ij} \le |S| - r(S),\ S \subseteq N - D,\ |S| \ge 3 \tag{3.6}$$

$$x_{i_1 i_2} + x_{i_2 i_1} + 3(x_{i_2 i_3} + x_{i_3 i_2}) + x_{i_3 i_4} + x_{i_4 i_3} \le 4,\ i_1, i_4 \in D,\ i_2, i_3 \in N - D \tag{3.7}$$

$$x_{i_1 i_2} + x_{i_2 i_1} + x_{i_{h-1} i_h} + x_{i_h i_{h-1}} + 2 \sum_{i,j \in \{i_2, ..., i_{h-1}\}} x_{ij} \le 2h - 5,\ h \ge 5,$$
$$i_1, i_h \in D,\ i_2, ..., i_{h-1} \in N - D \tag{3.8}$$

$$y_i \le \sum_{j \in N - D} x_{ij} \le m_i,\ i \in D \tag{3.9}$$

$$y_j \le \sum_{i \in N - D} x_{ij} \le m_j,\ j \in D \tag{3.10}$$

$$\sum_{\substack{i \in D \\ j \in N - D}} x_{ij} = \sum_{\substack{i \in N - D \\ j \in D}} x_{ij} \tag{3.11}$$

$$\sum_{i \in D} z_{ij} = 1,\ j \in N - D \tag{3.12}$$

$$\sum_{j \in N - D} z_{ij} = m_i,\ i \in D \tag{3.13}$$

$$\mathrm{y_i \le m_i \le M_i y_i, i \in D} \tag{3.14}$$

$$\sum_{i \in D} c_i y_i + c_v \sum_{i \in D} m_i \le B \tag{3.15}$$

$$\mathrm{x_{ij} \in \{0, 1\}, i, j \in N}$$

$$\mathrm{y_i \in \{0, 1\}, i \in N}$$

$$\mathrm{z_{ij} \in \{0, 1\}, i \in D, j \in N - D}$$

$$m_i \in \mathbb{N}, i \in D$$

$$t_i \geq 0, i \in N.$$

Constraints sets (3.1) and (3.2) specify that each location not used as a depot must be serviced exactly once by any vehicle. Of course, any location may be visited more than once if this saves time, but this need not appear explicitly in the model.

Constraints' sets (3.3)–(3.5) are formulated as sub-tour breaking and maximum travelling times in the case when the demand of a point j is greater than the available vehicles' capacity (Chan et al. 2001; Laporte 1992). In this case more than one vehicles may visit point j (assumed to arrive at the same time), which is 'split' to the artificial points $j_1, j_2, \ldots, j_k$, where $k = \left\lceil \frac{\sum_{p \in P} d_{jp}}{V} \right\rceil$. These are assumed to have a uniform demand, zero travelling times from one to another and the same travelling time from other demand points as point j. Note that if the route (i, j) does not appear in the solution, then $x_{ij} = 0$ and the constraints are non-binding; otherwise, $x_{ij} = 1$ and then $t_j = t_i + t_{ij}$.

Constraints set (3.6) is a sub-tour elimination constraint with a twofold meaning (Laporte 1992): a) r(S) is the minimum number of vehicles needed to serve all points in set S. It is a lower bound of the number of required vehicles so as to visit all locations in S in the optimal solution, under vehicles' capacity and operating times' constraints. An initial easy to calculate lower bound, compatible with constrains sets (3.3)–(3.5) is $r(S) = \sum_{i \in S} \left\lceil \frac{\sum_{p \in P} d_{ip}}{V} \right\rceil$, b) they also guarantee that the solution contains no "illegal" sub-tour disconnected from the hub.

Constraints sets (3.7)–(3.8) are chain-barring constraints. They ensure that each route starts and ends at the same depot. For a detailed explanation of these constraints see (Laporte et al 1986; Chan et al. 2001).

Constraint sets (3.9)–(3.11) express the fact that the vehicles stationed at a depot must leave and enter this depot, provided that this depot is utilized.

Constraints set (3.12) ensures that all the demand points are allocated to one and only depot.

Constraints set (3.13) states that all the vehicles stationed at a depot are utilized.

Constraints set (3.14) means that no vehicle can be based at a location which is not used at a depot. Additionally, if a location is used as a depot, the number of vehicles assigned to it is bounded between one and the pre-specified upper limit. Combined with constraints set (3.13) it ensures that a demand point is allocated to a hub only if this hub is actually established.

Finally, constraint (3.15) is the available budget constraint.

3.6 Appendix II

First a version of the stochastic problem, where a specific realization (value) of the random vector that consists of the demands, the travelling times and vehicles' availability, is considered. The model uses some ideas from the formulation used in (Balcik et al. 2008).

Notation:
Parameters

T	the planning horizon. Its magnitude can be a few months
t	time instances, $t = 1, \ldots, T$. Although any time period can be used, the most suitable unit of measurement during periods of disaster response operations is a day
N(t)	the set of demand points at time period t ($N(1) = N_0$). It is $N(t) = \{1, 2, \ldots, \lvert N(t) \rvert\}$, where the first point is set as the depot
P	the number of regional development programs
J	the set of demand types. It is $J = \{1, 2, \ldots, P+1\}$, where 1 corresponds to disaster response demand and $2, \ldots, P+1$ to the P development programs demand
$d_{i\zeta}(t)$	the demand of type $\zeta \in J$ at point $i \in N(t)$ at day t. For the sake of homogeneity a unit of measurement named "beneficiaries supply units" is utilized
t_{ij}	travelling times from i to j, $i, j \in N(t)$
R	the maximum accepted travelling time for all vehicles (tour time-limit or range) per day. It is $t_{ij} \le R$, $i, j \in N(t)$, $t = 1, \ldots, T$
V	the vehicles capacity
$c_v(t)$	the vehicles operating cost at day t
b(t)	the total available budget at day t
M(t)	the fleet size upper limit at the depot at day t
$\Pi(t)$	the amount of disaster relief supplies arriving at the beginning of day $t \in T$
$c_p(t)$	the purchase cost of a vehicle at day t
$u_{i\zeta}(t)$	The upper acceptable limit for unsatisfied type $\zeta \in J$ demand at demand point $i \in N(t)$ at time period $t \in T$.

Variables

$B_{i\zeta}(t)$	the number of beneficiaries' supply units of type $\zeta \in J$ delivered to demand point $i \in N(t)$ at day $t \in T$
$x_{ij}(t) = 1$	if the route (i, j) is used in the optimal solution by a vehicle, $i, j \in N(t)$; 0, otherwise
m(t)	the number of vehicles stationed at the depot at day t. It is $m(1) = m_0$
A(t)	the number of purchased vehicles at day $t \in T$
$I_{i\zeta}(t)$	the inventory level of type $\zeta \in J$ supplies at point $i \in N(t)$ at the beginning of day $t \in T$. It is $I_{i\zeta}(1) = I^{\zeta}{}_0$, $i \in N(t)$, $t \in T$, $\zeta \in J$
$U_{i\zeta}(t)$	the fraction of unsatisfied type $\zeta \in J$ demand at demand point $i \in N(t)$ at day $t \in T$.

t_i a vehicle's arrival time at demand point i, i ∈ N(t). These arrival times obviously depend on the time instance t.

Assumptions
The assumptions stated in Appendix I also hold here. It is additionally assumed that during disaster response time periods, humanitarian organizations do not sell their vehicles, as they do in other periods when they are involved only in development programs.

The mathematical model is the following:

$$\max \sum_{i \in N(t)} \sum_{\zeta \in J} B_{i\zeta}(t)$$

s.t.

$$\sum_{i \in N(t)-\{1\}} x_{ij}(t) = 1,\ j \in N(t) - \{1\},\ t = 1, ..., T \tag{3.16}$$

$$\sum_{j \in N(t)-1} x_{ij}(t) = 1,\ i \in N(t) - \{1\},\ t = 1, ..., T \tag{3.17}$$

$$t_{j_l} \geq t_i + t_{ij_l} - (1 - x_{ij_l}(t))R,\ \ t = 1, ..., T,\ i \in N(t),$$
$$j_l \in N(t) - \{1\},\ l = 1, ..., k,\ k = \left\lceil \frac{\sum_{\zeta \in J} d_{j\zeta}}{V} \right\rceil \tag{3.18}$$

$$t_{j_l} \leq t_i + t_{ij_l} + (1 - x_{ij_l}(t))R,\ t = 1, ..., T,\ i \in N(t),$$
$$j_l \in N(t) - \{1\},\ l = 1, ..., k,\ k = \left\lceil \frac{\sum_{\zeta \in J} d_{j\zeta}}{V} \right\rceil \tag{3.19}$$

$$t_{i_l 1} x_{i_l 1}(t) + t_{i_l} \leq R,\ t = 1, ..., T,\ i_l \in N(t) - \{1\}, l = 1, ..., k,\ k = \left\lceil \frac{\sum_{\zeta \in J} d_{i\zeta}}{V} \right\rceil \tag{3.20}$$

$$\sum_{i,j \in S} x_{ij}(t) \leq |S| - r(S),\ t = 1, ..., T,\ S \subseteq N(t) - \{1\},\ |S| \geq 3 \tag{3.21}$$

$$1 \leq \sum_{j \in N(t)-\{1\}} x_{1j}(t) \leq m(t),\ t = 1, ..., T \tag{3.22}$$

$$1 \leq \sum_{i \in N(t)-\{1\}} x_{i1}(t) \leq m(t),\ t = 1, ..., T \tag{3.23}$$

$$\sum_{j \in N(t)-\{1\}} x_{1j} = \sum_{i \in N(t)-\{1\}} x_{i1},\ t = 1, \ldots, T \tag{3.24}$$

$$\mathrm{m(t) \le M(t), t = 1, \ldots, T} \tag{3.25}$$

$$c_v(t)m(t) + c_p(t)A(t) \le b(t), \mathrm{t} = 1, \ldots, \mathrm{T} \tag{3.26}$$

$$\sum_{i \in N(t)} B_{i1}(t) \le \Pi(t),\ t = 1, \ldots, T \tag{3.27}$$

$$\sum_{t=1}^{T} B_{i1}(t) \ge d_{i1}(t), \quad i \in N(t) \tag{3.28}$$

$$m(t) = m(t-1) + A(t),\ \mathrm{t} = 1, \ldots, \mathrm{T} \tag{3.29}$$

$$U_{i1}(t) = \frac{d_{i1}(t) - B_{i1}(t)}{d_{i1}(t)} \le u_{i1}(t), \quad i \in N(t), t = 1, \ldots, T \tag{3.30}$$

$$U_{i\zeta}(t) = \frac{d_{i\zeta}(t) + I_{i\zeta}(t+1) - B_{i\zeta}(t) - I_{i\zeta}(t)}{d_{i\zeta}(t)} \le u_{i\zeta}(t), i \in N(t),$$
$$\zeta \in J - \{1\},\ t = 1, \ldots, T \tag{3.31}$$

$$\mathrm{x_{ij}(t) \in \{0, 1\}, i, j \in N(t)}$$

$$\mathrm{m(t), A(t)} \in \mathbb{N}$$

$$\mathrm{B_{i\zeta}(t), I_{i\zeta}(t), t_i \ge 0, i \in N(t).}$$

Constraints sets (3.16)–(3.26) are identical or very similar to the ones discussed in Appendix I model formulation. Constraints set (3.27) state that the total number of beneficiaries supply units delivered in the case of disaster relief in any day is not greater than the available supplies. Constraints set (3.28) ensure that the entire demand in the case of disaster response will be met at the end of the planning horizon. Constraints set (3.29) capture the vehicle fleet size for the planning horizon. Constraints sets (3.30) and (3.31) ensure that the unsatisfied demand fractions are less or equal than the acceptable upper bounds, according to humanitarian organizations decision makers tolerances and priorities in a case of emergency. Tuning $u_{i\zeta}(t)$ allows the 'weighting' between disaster response and development programs demand. It is also interesting to notice that, if $\sum_{i \in N(t)} \sum_{\zeta \in J} u_{i\zeta}(t),\ t = 1, \ldots, T$ exceeds a certain threshold, then the budget available for the next day $b(t+1)$ may decrease, because the humanitarian organization will not be able to maintain a good image (media play a very important role to this) and donors will be more reluctant in their funding.

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Chapter 4
Preparedness Measures for Emergency and Disaster Response

Tobias Andersson Granberg

4.1 Introduction

4.1.1 Background

If you ask one ambulance dispatcher about the current preparedness in the area, he or she might answer that it is good, everything is under control. If you ask another dispatcher the same thing, for the same area, the same time, he or she may say that the situation is strained, the preparedness is low, additional resources may need to be called in. Two different people may conceive a situation differently, even if they are both professionals. Furthermore, since no accepted and utilized definition of emergency medical preparedness exist, both of them are correct (Andersson et al. 2007).

In the example above, both ambulance dispatchers will have an opinion considering the preparedness, even though they might not agree on the specifics. The dispatchers know that emergency medical preparedness is a description of the ability to serve people in need of out of hospital medical care, now and in the future. There are relatively few factors that affect this preparedness, the most obvious being the number of available ambulances (and the expected number of available ambulances in future) together with their expected response times, and the expected call frequency.

When considering preparedness for more severe events, the situation becomes more complex. If you were to ask somebody in the crisis management organization for an arbitrary municipality to describe the state of the municipality's disaster preparedness, there is a good chance that the answer would be "I don't know". If you ask somebody which of two cities that has the best preparedness for handling a major storm or a severe act of terrorism, the answer might evolve to "I have absolutely no idea" (Simpson 2008).

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It is more difficult to define what encompasses disaster preparedness than emergency medical preparedness, since many more factors affect the disaster preparedness. Factors for handling a major storm would for example include response resources like fire and rescue services, ambulances and police, available disaster plans and crisis management organizations, alarm systems and many more. Also, some sort of measure of the risk that a major storm will occur, and the magnitude of the storm is needed.

Thus, it is not trivial to define, and perhaps even more difficult to quantify, the concept of preparedness. Still, it is—or at least should be—necessary when making plans and constructing methods for emergency and disaster response and management. If you can measure the preparedness, it will give you an indication of how prepared you are for handling a certain type of event. If you cannot measure the preparedness, it will be more difficult to assess the potential impact of an event, or to compare different plans, systems or solutions with each other.

4.1.2 Chapter Purpose and Outline

The purpose of this chapter is to introduce the concept of quantitative preparedness measures, and suggest a general methodology for constructing such measures. The next sub section will go through a number of definitions and expressions related to preparedness measures. While not aiming to review all the related literature, Sect. 4.1.4 will give a few examples of case studies, projects and initiatives where some sort of preparedness measures are constructed or used.

In Sect. 4.2, a general methodology for constructing a preparedness measure is presented. This methodology is then exemplified in Sect. 4.3, where it is applied on two cases studies (which were carried out before the development of the general methodology). The first case study, described in Sect. 4.3.1 is performed by Davidson and Lambert (2001). The second, described in Sect. 4.3.2, is partly an original contribution to this chapter, although some of the contents have been previously published in Andersson et al. (2007) and Andersson and Värbrand (2007).

This chapter ends with Sect. 4.4, which contains conclusions and some recommendations for further studies.

4.1.3 Preparedness Definitions

There exists no general definition of preparedness that is useful for actually evaluating the preparedness in a certain situation. One example of a general definition is “the state of being prepared or ready, esp. militarily ready for war” (Collins English Dictionary 2011), which does not tell us anything of what is needed for the preparedness to be high or low, good or bad. A definition from the secretariat of the International Strategy for Disaster Reduction (UNISDR 2011) states that preparedness is “The knowledge and capacities developed by governments, professional response and recovery organizations, communities and individuals to effectively anticipate, respond to, and recover from, the impacts of likely, imminent or current hazard events or conditions." This gives some clues to which resources that might be necessary, and highlights that preparedness may be viewed from different perspectives, but we still need to know the details regarding the incidents.

For a preparedness measure to be useful, it is necessary to define the event you would like to be prepared for, as well as the perspective from which the measure will be used. Two examples of more practically useful definitions are "Tsunami preparedness refers to an individual's perception of the extent of being prepared to confront with future tsunami." (Rachmalia et al. 2011) and "Strategic preparedness connotes a set of policies, plans, and supporting infrastructure that is implemented in advance of a natural or man-made disaster." (Haimes et al. 2008). In the latter case however, the policies and plans will vary significantly if the disaster is flood or if it is a train bombing.

Preparedness measures and indicators are used to evaluate the situation before an emergency or a disaster has occurred. Depending on the event under consideration, different factors will affect the preparedness. It is also possible to view preparedness from different perspectives, e.g.:

- *Personal preparedness*. A person's or a household's preparedness for handling a certain type of event.
- *Organizational preparedness*. A response organization, e.g. the police, might be interested in the preparedness for helping people, while a company may have their own preparedness for dealing with disasters, emergencies or economic crises.
- *Society preparedness*. On a larger scale, society preparedness can be a nation's ability to handle a major disaster, i.e. national disaster preparedness. On a regional scale, it may be a measure of how the region, e.g. a county or a municipality, is organized to ensure the safety and security of its inhabitants in case of accidents.

Risk, hazard and *vulnerability* are concepts that are closely related to preparedness. They share a characteristic in that there exist no universal—but a multitude—of definitions for each expression.

Once again falling back the UNISDR definitions (UNISDR 2011), they state that:

- Hazard is "A dangerous phenomenon, substance, human activity or condition that may cause loss of life, injury or other health impacts, property damage, loss of livelihoods and services, social and economic disruption, or environmental damage."
- Vulnerability is "The characteristics and circumstances of a community, system or asset that make it susceptible to the damaging effects of a hazard."
- Risk is "The combination of the probability of an event and its negative consequences."

Thus, an earthquake is a hazard, and the hazard probability in an area together with a measure of the potential negative consequences (which are directly dependent on the vulnerability), make up the risk. Furthermore, it is argued that vulnerability must be discussed within a hazard context, and that response and recovery constitutes important parts of the vulnerability (Birkmann 2007). That is, an area with plenty of emergency response resources is less vulnerable to a forest fire, than a similar area with fewer resources. Measuring risk and vulnerability is similar to measuring preparedness, and in some cases it can easily be argued that a preparedness measure could be denominated a vulnerability measure or a risk measure.

4.1.4 Relevant work

Table 4.1 summarizes a number of studies where preparedness (or in some cases risk or vulnerability) measures are developed. More examples of work done to measure the risk, vulnerability and preparedness for disasters can be found in Birkmann (2007). Similar studies regarding everyday emergencies are scarcer; in Table 4.1, only Andersson and Värbrand (2007) clearly focus on routine emergencies, although it may be possible to view the road tunnel accidents considered in Manca and Brambilla (2011) as less severe emergencies as well.

The studies in Table 4.1 are classified according to *Event, Perspective* and *Purpose* of the measure. When the event is *General disaster*, this may mean that the measures in the study include multiple disasters, like in Cardona (2005) and Simpson (2008). Markenson and Krug (2009) do not develop a measure, but discuss pediatric care in the aftermath of events like hurricanes and terrorist attacks. The perspective (see Sect. 4.1.3) is selected based on the potential users and application of the measure. In Manca and Brambilla (2011), the perspective can be societal or organizational depending on who is responsible for the road tunnel safety. Most of the measures are used for comparing different areas (zones, cities, counties, countries) with each other. This is however often just one of the purposes; the comparison can then be used as a base for improving the preparedness.

4.2 How to Measure Preparedness

4.2.1 Methodology

A general methodology for constructing a preparedness measure is suggested below. It consists of four steps, each of which will be further discussed in the following sub sections:

1. Select event and perspective
2. Select indicators
3. Combine the indicators
4. Validate the measure

Table 4.1 Event and perspective for some preparedness measure studies

Source	Event	Perspective	Purpose of measure
Andersson and Värbrand (2007)	Routine ambulance calls	Organizational	Calculate preparedness levels within a county to support dispatching and relocation
Baker (2011)	Hurricanes	Personal	Analyze household preparedness, to find relationships between preparedness and demographic variables, and between preparedness and demand for relief materials
Cardona (2005)	General disaster	Society	To compare the disaster preparedness between countries
Davidson and Lambert (2001)	Hurricanes	Society	To compare in U.S. counties' preparedness for handling hurricanes
Manca and Brambilla (2011)	Road tunnel accidents	Society, organizational	Evaluate tunnel safety by comparing it to an optimum level
Markenson and Krug (2009)	Pediatric care in case of general disaster	Organizational	No specific measure developed: discussion and recommendations
Rachmalia et al. (2011)	Tsunami	Personal	Analyze the relationship between personal tsunami experience and preparedness for a tsunami
Simpson (2008)	General disaster	Society	To compare the disaster preparedness between cities
WHO (2011)	Pandemic influenza	Society	To evaluate and compare different countries' preparedness for handling an influenza pandemic

4.2.2 Select Event and Perspective

As described in Sect. 4.1.3, it is necessary to decide which event to prepare for, and which perspective that should be used. In many cases, this might be a straightforward decision. A response organization, like the fire and rescue services, are probably primarily interested in the organizational preparedness, and the events that they are responsible for. However, if they want to construct a measure encompassing multiple events, e.g. the preparedness for handling all types of fires, traffic accidents, landslides and drowning accidents, the number of factors that need to be involved in the measure increases. It becomes even more complicated if you want to construct a measure for (general) disaster preparedness for a city. Then it is necessary to calculate the occurrence probability for all types of disasters that might affect the city. It is also necessary to select the perspective; in the society preparedness which is the natural choice for this example, the inclusion of both the organizational preparedness for the response organizations and the personal preparedness for the citizens might be required.

In short, the complexity of the preparedness measure rapidly increases with the number of events and the number of perspectives that the measure should be able to incorporate.

4.2.3 Select Indicators

A preparedness measure is typically constructed by a set of indicators. A couple of examples of indicators that can be used for different kinds of events are:

- (Personal) tsunami preparedness: Knowledge, individual emergency planning and resource mobilization capacity (Rachmalia et al. 2011).
- (Personal) hurricane preparedness: Food for three days, flashlight with batteries for three days, medicines, drinkable water, important papers on hand, an outdoor grill, a generator (Baker 2011).
- (Organizational) road tunnel accident preparedness: tunnel length, emergency exists, tunnel manager experience, training of emergency personnel, first aid support, and many more (Manca and Brambilla 2011).
- (Organizational) pediatric emergency preparedness: pediatric providers available for emergency preparedness, specific numbers of pediatric patients who can be treated, number of children that the triage providers can triage per hour, etc. (Markenson and Krug 2009).
- (Society) national pandemic influenza preparedness: how often the national committee/task force meets, surveillance measures during a pandemic, health facilities priorities and response strategies, etc. (WHO 2011).

Furthermore, although they may not be directly used as preparedness measures, operations research methods applied to the preparations phase of disaster or emergency management usually have some criteria for evaluating proposed solutions. Some of these criteria may well be used as preparedness indicators, e.g. coverage measures, expected response times or satisfied demand.

When constructing a quantitative measure, it is necessary to use indicators that can be quantified. For instance, the indicator *Knowledge*, used in Rachmalia et al. (2011), was measured using a questionnaire where each respondent got a score depending on the level of knowledge. It is also necessary to select indicators for which reliable data is available, or possible to collect.

4.2.4 Combine the Indicators

Assuming that there exist a set of sensible indicators, they will most probably vary in units, including time measures, monetary units, binary units and percentages. If these indicators are to be combined into an index, or some other sort of measure, or if they are to be directly compared to each other, it may be necessary to weight or scale them. There are many methods for this, and a nice overview is given in Cardona (2005), where the advantages and disadvantages of methods like regression models, factor analysis, multi-criteria decision making, expert judgment, and analytic hierarchy process, among others, are discussed.

For a certain event or set of events and perspectives, it may not be enough to construct just one measure. It may even be contra productive for the intended purpose of the measure; e.g. creating a measure for all kinds of disasters that may affect a city can be useful if the main purpose is to compare different cities' disaster preparedness. It will however not necessarily give any guidelines as to how the preparedness can be improved. For the latter purpose, one measure for each type of disaster that may affect the city would be more useful.

4.2.5 Validate the Measure

When the selected indicators have been combined into a preparedness measure, it needs to be validated. A successful validation means that the measure fulfills its intended purpose. There are a number of methods and techniques available for validating quantitative models, and especially the validation of simulations models has been a thriving research area, see e.g. Sargent (2005). Although not all technics commonly used for validating simulation models are applicable here, a number of them can still be used to ensure that the developed measure produces reasonable and useful results.

Two examples of techniques mentioned in Sarget (2005), that can easily be applied to the validation of preparedness measures are:

- *Sensitivity analysis*: The parameters that constitute the input data to the measure are changed, and the output from the measure is studied. This is applied in the first case study (Sect. 4.3.1).
- *Face validity*: System experts are asked to study and comment the results produced by the measure. This is applied in the second case study (Sect. 4.3.2).

4.3 Case Studies

Two cases studies are presented to illustrate how the proposed methodology can be used in practice. The first study concerns hurricane disasters, and is an example of a measure for disasters while the seconds study deals with emergency medical services concentrating on routine emergencies. It should be noted that the cases studies were performed before the development of the methodology.

4.3.1 Development of a Hurricane Disaster Risk Index

In Davidson and Lambert (2001), a hurricane disaster risk index (HDRI) is developed for comparing the risk of hurricane disasters in counties in the U.S.A. The authors point out that they use the term hurricane disaster risk instead of hurricane risk, to make it clear that the response and recovery capability is included in the measure.

Thus, it is quite possible to regard the index as a preparedness measure, since it also gives an indication on how prepared a county is for handling a hurricane.

4.3.1.1 Selection of Event and Perspective

The first step in the methodology described in Sect. 4.2 is to select the event and the perspective for the measure. The event type in this study is easily identified as a hurricane, i.e. a single specific event. The perspective should be regarded as societal, since the main intended purpose is to compare different counties.

4.3.1.2 Selection of Indicators

The second step is to select appropriate indicators. Davidson and Lambert (2001) include four main factors in the study, each with a number of subfactors, which are made up by a number of indicators (see Table 4.2).

4.3.1.3 Combining the Indicators

The third step is to combine the indicators to construct a measure that can be used to compare different counties. However, the indicators in Table 4.2 vary in units including knots, dollars and percentages. So, before the indicators are combined into an index, they are scaled using a linear function:

$$X_{ij} = \frac{\left(X'_{ij} - minposs_i\right) \times 10}{(maxposs_i - minposs_i)} \tag{4.1}$$

where X'_{ij} is the unscaled value of indicator i for county j. $maxposs_i$ is the maximum expected value for the indicator that are likely to occur in any U.S. county in the next ten years, and $minposs_i$ is the minimum expected value. However, for indicators that have a positive impact on the preparedness, $minposs_i$ will have the larger value of the two. Thus, for the indicator *Resident population*, minposs is zero while maxposs is 2.3 million. Supposing a county has an unscaled indicator value of 750,000, the scaled value for the indicator will be $750{,}000 \times 10/2{,}300{,}000 = 3.26$. The indicator *Num. physicians per 100,000 people* has a minposs of 690 and a maxposs of zero. Given that the unscaled indicator value is 150, the scaled counterpart will become $(150 - 690) \times 10/-690 = 7.82$. After scaling, the indicators take values from 0 to 10, where less is good. A value close to zero for an indicator means that the risk is low, or that the preparedness is good, in regards to that specific indicator.

The indicators are then weighted and additively combined into a value for each factor, e.g. $\mathrm{V} = \mathrm{w_{V1}X_{V1}} + \cdots + \mathrm{w_{V6}X_{V6}}$, where V is the vulnerability factor and $\mathrm{w_{V1}}$ is the weight for the first vulnerability indicator (% population aged 0–4 or 65 +). Finally the factors are multiplicatively combined into an index value with a

Table 4.2 Indicators for hurricane disaster risk used in Davidson and Lambert (2001)

Factor	Subfactor	Indicator
Hazard	Wind hazard	Mean return period of hurricanes Cat 1–2
		Mean return period of hurricanes Cat 3–4
		Mean return period of hurricanes Cat 5
	Storm surge	% area below 50-year stillwater elevation
	Rainfall	Average forward speed of hurricanes (knots)
Exposure	Population exposure	Resident population
		Average daily num. of tourists, June-Nov
	Building exposure	Number of housing units
		Median home value (dollars)
	Economic exposure	Income from agriculture ($1000s)
		Number of business units
	Lifeline exposure	Value of power lines (dollars)
Vulnerability	Population vulnerability	% population aged 0–4 or 65 +
		% population (aged 16–64) w/mobility limitation
		Public education indicator
	Building vulnerability	Average BCEGS grade
		% of homes that are mobile homes
	Economic vulnerability	% businesses with less than 20 employees
Emergency response & recovery capability	Connectivity	% county land detached from mainland
	Evacuation & shelters	Number of shelters available
		Evacuation clearance time (hours)
		% population expected to evacuate
	Mobility	Population density (people per sq. km)
		City layout (roads in grid = 0; otherwise = 1)
	Resources	Num. hospital beds per 100,000 people
		Num. physicians per 100,000 people
		Per capita state gross product (constant 1990 US$)

weight for each factor. To determine the weights, the analytic hierarchy process is used, where the indicators are compared pairwise. Index values are calculated and analyzed for 15 U.S. counties.

4.3.1.4 Validation of the Measure

The last step is to validate the measure, to make sure that the results are credible. Davidson and Lambert (2001) point out that

> Just as the indicator set is part of the definition of the concept that is being measured, so are the weight values. If the weights are changed, the concept being measured is also, and the county rankings corresponding to the new concept should not necessarily equal those associated with the original concept.

That is, changing anything in the measure—indicators, parameters, or weights—might alter the results that the measure is used to produce. So, in order to analyze the results' sensitivity to changes in the weights, they perform an uncertainty analysis using Monte Carlo simulation, and conclude that the results are stable. The same type of validation is performed for uncertainty in input data, but here the results indicate that uncertainty in data might indeed affect the ranking of counties produced by the measure. Therefore, it may be beneficial to reduce data uncertainty.

In conclusion, the hurricane disaster risk index constructed by Davidson and Lambert (2001) is a nice example of a disaster preparedness measure that could well have been developed using methodology proposed in Sect. 4.2.

4.3.2 An EMS Preparedness Index

Keeping an adequate preparedness is one of the most complex tasks for an ambulance dispatcher. It requires knowledge of where call sites are likely to appear and of how fast the ambulances can travel through different parts of the area, as well as knowledge of where the ambulances currently are located and if they are available. Today, many ambulances have satellite navigation system receivers and transmit their position and status to an emergency center. Still, to know where ambulances might be needed in the future, and how fast they can get there, requires experience. We will develop a preparedness measure for emergency medical services that can be used to support these decisions.

4.3.2.1 Selection of Event and Perspective

When selecting the event and the perspective for the measure (Step 1 of the methodology in Sect. 4.2), a definition for emergency medical services preparedness can be useful. A suggestion is that:

> In emergency medical services, preparedness refers to the ability of being able to, within a reasonable time, offer qualified emergency medical care to the inhabitants in a specific geographical area.

The definition is purposely vague, leaving it to the politicians to decide how long time that is reasonable, and what qualified means. Still, it is possible to use as a base for building a preparedness index.

The event in this case is any daily event that ambulances respond to, and the intended use for the measure is daily operations, i.e. routine emergencies. Here we assume that all events that ambulances respond to require just one ambulance, and that all ambulances in the system can be considered equally qualified to handle an event. Therefore, it is not necessary go into detail concerning the events, since they all require the same type and amount of resources. The perspective is organizational, since the intended users are ambulance dispatchers, who are responsible for maintaining the preparedness in a particular area.

4.3.2.2 Selection of Indicators

In order to select indicators (Step 2), the geographical area is divided into a set of zones, *N*. A weight c_j is assigned to each zone *j*. This weight mirrors the probability that an ambulance will be needed in the zone and can for example be calculated as c_j = (*the expected number of calls in zone j*) where a forecast for the number of calls must be performed. It is also possible to base the weight on the population, advance knowledge of special events and other information that may affect the need for ambulances in the zone. The weights can also be time dependent, e.g. c_{jt} = (*the weight for zone j in time period t*), as the need for ambulances often varies with time. For simplicity, we will now however concentrate on static weights.

We assume that the preparedness in a zone mainly depends on three indicators:

1. The number of ambulances that can reach the zone (within a certain time).
2. The time it takes for the ambulances to reach the zone (i.e. the expected travel time).
3. The expected need for ambulances in the zone (i.e. c_j).

4.3.2.3 Combining the Indicators

Using the three selected indicators, it is possible to construct a measure in a number of different ways. Depending on the construction, the different measures will have different qualities. This makes it important to carefully consider what the measure can and will be used for. The measure then has to be tested to see if it possesses the desired qualities.

The measure suggested here, is that the preparedness in a zone *j* can be calculated as:

$$p_j = \frac{1}{c_j} \sum_{l=1}^{L_j} \frac{\gamma^l}{t_j^l} \tag{4.2}$$

where c_j = the demand for zone *j*; L_j = the number of ambulances that contribute to the preparedness in zone *j*; γ^l = the contribution factor (the weight) for ambulance *l* ($l = 1$ is the closest, 2 the second closest etc.) and t_j^l = the travel time to zone *j* for ambulance *l* and the following properties hold:

$$t_j^1 \leq t_j^2 \leq \cdots \leq t_j^{L_j} \tag{4.3}$$

$$\gamma^1 > \gamma^2 > \cdots > \gamma^{L_j} \tag{4.4}$$

Thus, the preparedness is calculated by letting the L_j closest ambulances to zone *j* contribute to the preparedness with an impact that is decreasing as the travel time to the zone increases.

The basic idea behind the measure is that the closest ambulance is the most important and therefore should give the largest contribution to the preparedness. More ambulances than one might however be needed to ensure a high preparedness.

If the demand c_j is large, this indicates that the frequency of calls in the zone is relatively high, which means that one ambulance probably will not be able to serve one call and become available again before the next call arrives. In this case there is a need for backup ambulances in, or close to, the zone to ensure that the preparedness does not drop to an unacceptable level.

We let each L_j be constrained by $L_j \leq L$, where L is a positive integer. It is not necessary to use a very large L, since ambulances that become busy will be available again when they have completed their call. Suppose, for example, that the three closest ambulances in a specific case are located at 5, 10 and 15 min respectively from zone 23 and that $\gamma^l = 1, 0.5, 0.25$ for $l = 1, 2, 3$. With a demand, c_{23}, equal to 0.1, this would give a preparedness of $p_{23} = (1/0.1) \times (1/5 + 0.5/10 + 0.25/15) \approx 2.67$. However, the value 2.67 does not tell us anything if it cannot be put into a context, which is characteristic for most index measures. Thus, we need a calibration and a validation procedure to find relevant values for the parameters and to make sure that the measure is useful.

4.3.2.4 Validation of the Measure

As for the final step in the methodology, the preparedness measure is validated using three different methods:

A. Comparison with coverage measures
B. Validation by simulation
C. Validation by dispatcher evaluation

First, the measure is calibrated for the county of Stockholm in Sweden. The area is divided into 1240 zones, and a travel time matrix is produced containing deterministic travel times from each zone to each other zone. Population data for each zone is used to calculate c_j. γ^l is set to $1/2^{l-1}$ for $l = 1, 2, \ldots, 7$, i.e. $\gamma^1 = 1$, $\gamma^2 = 0.5$, $\gamma^3 = 0.25$, $\gamma^4 = 0.125$, etc. A maximum of seven ambulances are used to calculate the preparedness for a zone. The objective in Method A is to see if the measure behaves similar to other preparedness measures, in this case coverage. Thus, we would like to see that for increasing values on p_j, we also get an increase in the coverage.

Coverage is calculated as the number of people (in percent) that can be reached by one ambulance, within 10, 15 and 20 min respectively. This makes coverage a measure for the entire area, while the preparedness is calculated per zone. Therefore we define the area preparedness P as:

$$P = \min_{j \in N} p_j \tag{4.5}$$

where N is the set of zones. Other ways of aggregating the zone preparedness values into area preparedness are discussed in Lee (2011). A mathematical model is formulated to maximize the area preparedness P, and solutions for a number of test cases involving a varying set of ambulances are obtained using a simulated annealing

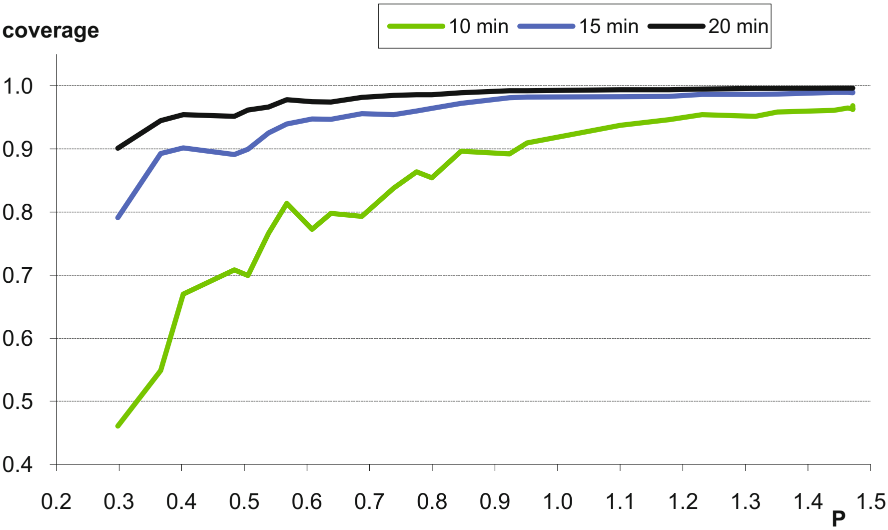

Fig. 4.1 The coverage increases when the area preparedness increases

heuristic. The coverage is calculated for the resulting location solutions and the result can be seen in Fig. 4.1. It is clear that the coverage in the area increases when the area preparedness P increases.

The results from validation method A indicate that the construction of the preparedness measure, and the parameter settings, make sense when compared to coverage. It should be noted that the coverage measure used here only include first response coverage, and does not take into account the possibility that an ambulance might become busy, something that is built into p_j.

Method B involves validating the preparedness measure using simulation. Using the measure as a base, an ambulance dispatch algorithm and a relocation algorithm are developed. The ambulance dispatch algorithm will dispatch the closest ambulance for all priority 1 calls (life threatening). When faced with less urgent calls, the algorithm will select all ambulances that are reasonably close (e.g. within 20 min) to the call site, and recalculate the preparedness in all zones given that one of these ambulances are dispatched. Finally, the ambulance that has the least impact on the area preparedness will be dispatched.

The ambulance relocation problem occurs when one or more zones have a preparedness level less than a certain threshold, P_{min}. The objective is then to reach the P_{min} level in all zones as quickly as possible. The preparedness is increased by relocating one or more ambulances closer to the zones that suffer from a low level of preparedness. The relocation problem is solved using a greedy tree search heuristic.

Both algorithms are incorporated into a simulation model which is run using the same input data (although somewhat refined, especially the demand data) as in Method A. The results show that the response times decrease with more sophisticated dispatching (when evaluating the preparedness before dispatching to low priority calls, instead of just sending the closest ambulance) and when using relocations. However, a lot of relocations are needed to get significant reductions in response time. More details on the validation work using Method B can be found in Andersson and Värbrand (2007).

The results from Method B indicate that if the preparedness measure is used practically, the main performance parameter in EMS—the response times (or more accurately the patient waiting times)—should benefit. The preparedness measure can be implemented into a geographical information system (GIS), visualizing zones with preparedness less than P_{min} as red. The dispatchers can then manually act upon this information and take it into account when selecting units to dispatch, or trigger relocations to preserve the preparedness in the area.

In Method C, the main users of the EMS preparedness index, i.e. the ambulance dispatchers, gets to evaluate the measure. The preparedness measure, with a corresponding visualization feature, the dispatcher algorithm and the relocation algorithm, are implemented in the GIS used in emergency centers in Sweden, operated by the company SOS Alarm. Eleven scenarios are constructed, where in each scenario, 3–6 areas are marked. The scenarios consist of a map screenshot from the GIS with a set of available ambulances, the day and the time. Twenty dispatchers, who all have experience of working with the areas in the scenarios, have to decide if the preparedness in each area is good (1) or bad (0). The result is shown in Fig. 4.2. It is obvious from the result that different ambulance dispatchers may have different opinions regarding EMS preparedness. Dispatcher 4 (Op4) thinks that the preparedness is less than acceptable in 37 of the 48 areas, while dispatcher 11, 14 and 16 only think it is bad in six areas. Not for one single area, all dispatchers agree that the preparedness is inadequate; even for the worst area (Area 8-2) one dispatcher (Op2) considers the preparedness to be acceptable. However, the preparedness is considered good enough by all the dispatchers in ten of the 48 areas.

The preparedness p_j for the areas are calculated for different choices of parameters and are compared to the mean values of the dispatchers' results. The parameter settings that are tested include different values on γ as well as the squaring of the travel times. Comparing the dispatchers perception of what entails EMS preparedness, with the values that are produced by the quantitative measure, reveals that using contribution factors $\gamma = 1, 0.5, 0.25,$ etc. reduce the contribution from the second and the third ambulance too quickly. Thus, for an area with high demand, it might never be possible to reach an adequate preparedness level, no matter how many ambulances that are available. Contribution factors $\gamma = 1, 0.9, 0.8,$ etc. give a better correspondence to how the ambulance dispatchers perceive preparedness. Another result of Method C is that by squaring the travel times, i.e. using a measure like:

$$p_j = \frac{1}{c_j} \sum_{l=1}^{L_j} \frac{\gamma^l}{\left(t_j^l\right)^2} \tag{4.6}$$

the preparedness measure is enhanced even further. This becomes evident when studying some of the areas where the preparedness measure fails, and realizing

Area	Op4	Op3	Op5	Op20	Op7	Op9	Op18	Op13	Op2	Op8	Op17	Op1	Op12	Op6	Op15	Op19	Op10	Op11	Op14	Op16	Mean
8-2	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0,05
6-2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0,10
11-2	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0,10
7-2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	1	0	0,15
11-4	0	0	0	0	0	0	0	0	0	0	1	1	0	0	1	1	0	0	0	0	0,20
6-1	0	0	0	1	0	0	0	1	0	0	0	1	0	0	0	0	0	1	0	1	0,25
2-4	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	1	1	1	1	0,35
4-2	0	0	0	0	0	0	1	1	1	0	0	0	1	0	1	1	0	0	0	1	0,35
9-1	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	1	1	1	1	1	0,35
9-2	0	0	1	0	0	0	0	0	0	1	0	0	1	1	0	0	1	1	1	1	0,40
7-3	0	0	1	0	0	0	0	1	0	0	1	0	1	1	1	1	1	0	1	1	0,50
9-3	0	0	1	0	0	0	1	0	0	1	0	0	1	1	0	1	1	1	1	1	0,50
3-2	0	0	0	0	0	0	0	1	1	1	1	1	0	1	1	0	1	1	1	1	0,55
10-1	0	1	0	0	0	0	1	0	1	1	0	1	1	1	1	1	1	1	1	0	0,60
11-5	0	0	1	0	1	1	0	0	0	0	1	1	0	1	1	1	1	1	1	1	0,60
1-3	0	0	0	0	0	1	0	0	1	1	1	1	1	1	1	1	1	1	1	1	0,65
4-3	0	0	0	0	1	0	1	1	1	1	1	0	0	1	1	1	1	1	1	1	0,65
6-5	0	1	0	0	1	0	1	1	0	0	1	1	1	1	1	1	1	1	1	1	0,70
10-2	0	1	0	0	1	0	1	1	1	1	0	1	1	1	1	1	1	1	1	0	0,70
2-3	0	1	0	0	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	0,80
4-4	0	0	0	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	0,80
4-5	0	0	1	1	0	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	0,80
6-3	0	0	1	1	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0,80
6-4	0	0	1	1	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0,80
8-5	0	1	0	1	0	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	0,80
1-2	0	1	1	1	1	1	0	0	1	1	1	1	1	1	1	1	1	1	1	1	0,85
3-1	0	0	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0,85
7-1	0	1	0	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0,85
11-6	0	1	0	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	0,85
4-6	0	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0,90
5-1	0	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0,90
11-1	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0,90
4-1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0,95
5-3	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0,95
8-1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0,95
8-4	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0,95
8-6	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0,95
9-4	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0,95
1-1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1,00
2-1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1,00
2-2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1,00
3-3	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1,00
5-2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1,00
8-3	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1,00
10-3	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1,00
10-4	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1,00
10-5	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1,00
11-3	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1,00
Mean	0,23	0,52	0,54	0,58	0,60	0,60	0,69	0,73	0,75	0,75	0,75	0,77	0,79	0,81	0,83	0,85	0,88	0,88	0,88	0,88	0,72

Fig. 4.2 Dispatcher perception regarding EMS preparedness

that it is because there are two or three ambulances at some distance (e.g. 30 min) from a fairly, not overly, demand intensive area. The preparedness measure without the squared travel times will then calculate the preparedness as adequate, since the ambulances together make up a good preparedness. A majority of the dispatchers, on the other hand, would like to have at least one ambulance closer to the area for the preparedness to be adequate. One option to mirror the dispatchers' opinions in this case is to lower the threshold level, P_{min}, until the preparedness is low in this area as well, but this will result in a low preparedness also in high demand areas, that actually have plenty of ambulances nearby. By squaring the travel times, the preparedness will drop rapidly when the ambulances are further away. This way, it is possible for multiple ambulances to build up a good preparedness in areas where the demand is high, by being located close to that area. However, the preparedness in areas with a medium demand and no ambulances close by will be inadequate, just like the dispatchers perceive it.

The next logical step in the validation process would be to repeat Method A and B with the new preparedness measure and the new parameter settings, to ensure that these results still hold. Furthermore, the dispatcher evaluation should be repeated with dispatchers from other emergency centers, working with other geographical areas.

The method proposed in Sect. 4.2 can thus be used to develop a preparedness measure for emergency medical services, focusing on daily events. Similarly, it is possible to construct a measure for e.g. fire and rescue services. However, this would have to take into account that the events considered might differ quite a lot in regards to which and how many resources that are needed in the response.

4.4 Conclusion

This chapter gives an introduction to the concept of measuring preparedness. It is easy to convince someone that it is beneficial to measure preparedness, risk and vulnerability, but most of the preparedness measures available have a clear disadvantage. They do not say anything by themselves, they lack units and they are difficult to understand and interpret. Both of the preparedness measures presented in more detail in this chapter are unit-less, and the preparedness needs to be calculated for number of counties (in the hurricane measure) or for a number of zones (in the EMS case). When this has been done, it is possible to compare different counties or zones, and define a level of standard for the preparedness.

What would be useful for a decision maker is a measure that can be applied without the need for benchmarking. But then the measure would have to have a unit that can easily be interpreted, e.g. cost or expected number of lives lost. The main difficulty with constructing such a measure is the complex relations between the event, the response, the vulnerability, and the consequences. It is extremely difficult to say, with some certainty, how many people in a specific city that will die in an earthquake. It is even more difficult to say how many that will be saved with the introduction of an early warning alarm system, or if the number of emergency response resources are increased by 10 %. Even for systems dealing with everyday accidents, where historical data is available, this is not trivial. Consider for example a housing fire. The consequence of the fire can be measured in lives lost, people injured, property value destroyed, and environmental damages. However, how many lives that are lost will depend on how many people that were inside when the fire started (which is correlated to the time of day), the material and the construction of the house, how quickly the fire services arrive, how many firefighters that respond, which kind of vehicles and equipment they have, and many other factors. This makes it difficult to find a model that can predict the consequences given that we have all the input values, though such a model would very useful.

Consequently, there is need for more research investigating the relations between emergencies, disaster and other events, the preparedness for handling them, and the consequences. Given that we can find, and quantify these relations, it will—to a much larger extent—be possible to measure and optimize the preparedness, and also get acceptance for the results.

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Chapter 5
Military Logistics Planning in Humanitarian Relief Operations

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5.1 Introduction

The 2011 triple disaster (earthquake, tsunami, and leaks of nuclear radiation) in Japan, the 2010 earthquake in Haiti, the devastating floods in Pakistan, the Sichuan earthquake, the 2005 Hurricane Katrina, and the 2004 Indian Ocean earthquake and tsunami, to name only a few, are among the most devastating natural disasters the last decade has seen. Disasters, when they strike, leave people without shelter, food, and in urgent need of medical assistance. In these situations, regional and international aids are necessary to supplement the local government and humanitarian organizations in absorbing the surge in demand for supplies. A disaster is defined by Centre for Research on Epidemiological Disasters (CRED) as a "situation or event, which overwhelms local capacity, necessitating a request to national or international level for external assistance; an unforeseen and often sudden event that causes great damage, destruction and human suffering" (CRED http://www.cred.be). Disasters are on the rise[1] and they are more complex (Tomasini and Van Wassenhove 2009). Disasters are termed *natural* if caused by an uncontrollable natural force and *man-made* if caused by human interference or the consequences of technological failures such as toxic material and gas releases. The frontier between the two types of disasters is not very clear. For example, the 2011 Japan's earthquake triggered a massive

[1] The increase in the number of disasters is explained partly by better reporting of disasters in general and partly due to real increases in both the frequency and the impact of certain types of disasters.

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tsunami and several explosions at the Fukushima nuclear power plant. Added to this tremendous disaster, Japan has endured in 2011 one of its coldest winter. Indeed, winter storms complicated rescue and recovery after the Tsunami and the earthquake. Beyond these types of disasters, complex emergency, resulting from conflict induced conditions and very often coming with natural disasters, have intensified over the last decades in many regions of the world (CRED http://www.cred.be). A complex emergency is defined by the Inter-Agency Standing Committee Working Group (IASC) as "a humanitarian crisis in a country, region or society where there is total or considerable breakdown of authority resulting from internal or external conflict and which requires an international response that goes beyond the mandate of any single United Nations (UN) country program" (IASC http://www.humanitarianinfo.org/iasc). In complex emergencies, affected populations are very often cut off from their sources of income and lose their security, owing to displacement of populations. Wars and civil disturbances that destroy homelands and displace people are considered by certain organizations among the causes of complex disasters (CRED http://www.cred.be). In addition to the direct impact on the affected populations, there is increasing awareness that both natural and complex disasters have significant environmental consequences and long-term implications of those affected populations.

Use of Military Forces (MF) in support of humanitarian operations is a long-established practice. In the public belief, there is often a high expectation that the military will be involved in the immediate aftermath of conflicts and large-scale disasters. From the Canada's allies military perspective, a dominant paradigm driving perspectives on future humanitarian military missions is the *Comprehensive approach* (Chief of Force Development 2009a, b), which argues that to meet the challenges of the future security environment it is required the participation of, and cooperation with, allied defence teams, other government departments, the private sector and, where applicable, Non-Governmental Organizations (NGOs). In order for this approach to be effective, involved actors need to be adaptive to changing situations and find the means of creating a more networked focus in order to benefit from the strength and capabilities of all active actors. The requirement for military support in Humanitarian Relief Operations (HROs) is situation dependent and is determined by a number of parameters including the type, scale, and location of the disaster, impact of the disaster on the stricken state coping mechanisms, and the assessed shortfall between disaster relief and victims' needs. The frequency of military intervention in HROs is expected to increase since it has been estimated that the number of disasters (natural, human made, and complex) will increase over the next 50 years (Thomas and Kopczak 2005).

Military involvement in HROs should be driven by need and be respectful of the principals of humanity, neutrality and impartiality. In HROs, any military–civil coordination must first serve the prime humanitarian principals of humanity. Determining the extent to which humanitarian agencies should coordinate with MF to minimize the consequences of close affiliation, or even perception, as these could jeopardize the humanitarian principals of neutrality and impartiality, is not obvious. In some disaster situations there may be some tensions that may be exacerbated by the presence of MF. To establish a climate of confidence among the different actors and the stricken state government it is necessary that the intent of the force is clearly understood by all involved actors. Transparency of intent is crucial to a successful coordination among the involved actors, and required to reduce the mistrust that may result from the military presence.

Humanitarian logistics is one of the most important aspects of disaster management systems. Civilian agencies ask for military help in HROs for several reasons, among which their logistics capabilities. Among the most wanted capabilities are transport (land, air, and sea), communications, medicines, tools and equipment, and security. Military humanitarian logistics is defined as the functions, within the military logistics branch, dealing with the preparedness and responses phases of a disaster. The military emergency logistics encompasses the process of planning, implementing, and controlling the efficient flow and storage of goods and material as well as provisioning of infrastructure engineering support.

This chapter discusses some emerging challenges facing the military in HROs, and proposes logistics optimization models for planning of HROs. The remainder of this chapter is organized as follows. Section 5.2 discusses the military involvement and roles in HROs. The potential areas of collaboration/cooperation are discussed as well in this section. Section 5.3 details the military role in HROs from a logistics perspective. Section 5.4 presents mathematical models and a solution approach based on Column Generation (CG) for scheduling HROs in a disaster relief operation. Several aspects of the HROs are included in the optimization model and discussed with their effects on the global HROs efficiency and effectiveness. Computational results are presented and briefly discussed in Sect. 5.5. Finally some concluding remarks and future research trends in the field of military HROs are given in Sect. 5.6.

5.2 Military and the Humanitarian Relief Environment

In this section, we discuss some characteristics of the emerging environment where the MF will continue to intervene and their impacts on the HROs. We also discuss the military role in the disaster response cycle and their carried activities in HROs. The interaction between military and civilian Humanitarian Relief (HR) organizations is also discussed at the end of this section.

5.2.1 Emerging Environment Characteristics

The characteristics or the trends of the emerging humanitarian environment, in which the MF and humanitarian relief actors are operating, can be described as follows:

5.2.1.1 Volatility and Uncertainty

Involved actors in HROs are facing several challenges in building their relief plans due to the uncertainty and volatility characterizing most of the HROs activities.

Uncertainties about the location and intensity of the disaster, volatility of demands, aid volatility and uncertainty, imbalance between supply and demand, and disruptions in the distribution system are all factors that affect military and civilian HR supply chains. These factors have often complicated relief policy implementation, especially in countries where a large part of government spending is financed by international aid. Along with natural disasters, food scarcity and price volatility will continue to affect food and other basic goods for the next decades in HROs.

5.2.1.2 Globalization

It refers to the increased mobility of goods, services, technologies, etc. around the world. Globalization goal is to increase material wealth, goods, and services through an international division of labour by efficiencies catalyzed by international relations and signed agreements. As consequences of globalization, societies have become integrated through communication, transportation, and trade. Globalization can increase interdependence of MF of different countries and encourages them to adopt shared processes and resources for emergency relief operations. Globalization also will facilitate the transfer between the military institutions and allies of the technological innovations useful for HROs.

5.2.1.3 Multinational and Public Humanitarian Environment

States will continue (via their MF, etc.) to represent the key actors in HROs. However, non-state actors will continue to function as significant players in the theatre of operations. These non-state actors are represented by international organizations such as the United Nations (UN) and its agencies as well as NGOs, multinational corporations, and humanitarian organizations engaged in the provision of humanitarian aid and assistance to the victims. The need for more coordinated and holistic approach to operations is ever more evident. The Departments of Defence of different NATO countries called for a force that is joint, interagency, multinational and public-enabled. Such a force would see the resources and processes (dedicated for HROs) aligned with those of other agencies and coordinated through a global plan and applied in the areas of operations. As such, the approach would see the military activities being carried out collaboratively within a context of a comprehensive approach involving the coordinated actions of the military with the other instruments of national power.

5.2.1.4 Rapid Scientific and Technological Innovation

Strategic science and technology programs put forward last decade by different governments in the public safety and emergency management fields are contributing significantly to technological innovation and rapid scientific growth (Chang et al. 2007;

Tzeng et al. 2007). The aim of these programs is to gather the scientific expertise in order to solve the major scientific problems encountered during emergency relief operations and to develop forecasting models for effective and efficient relief operations management. Typical problems include automated identification (e.g., emergency supply such as food/water, clothes, shelter or ambulance and health experts' location), transportation routing and scheduling (e.g., efficient patient evacuation or food delivery to demand sites), demand forecasting (basic commodities such as water, food, and blankets/tents), monitoring (disaster evolution and demand satisfaction and impact on recovery, anticipated undesirable situation), automated assistance to demand response (e.g., the use of cheap robots to deliver supply, sustain demand and rescue). Different defence departments (e.g., DND) are involved in these research programs. Recent technology developments to assist emergency logistics supply chain management enhancing supply chain visibility/optimality, and reducing logistics costs and footprint are numerous. Automated identification, Radio Frequency Identification (RFID) mesh, and most generally sensor network technology look particularly promising and helpful in providing total asset and resource visibility and ultimately end-to-end supply chain visibility, while facilitating near real-time asset readiness assessment and management. Emerging problem-solving procedures based on meta-heuristics and agents, and the synergy of available analysis methods (through supply network simulation; asset, situation and plan execution monitoring; model checking for situation assessment, data mining and demand/plan execution forecasting) are increasingly applicable to the human relief operation context to take on integrated logistics decision challenges leading to supply network optimality. In contrast, green logistics and sustainable development practices represent promising approaches in significantly reducing logistics costs and footprint. Robotic systems (e.g., unmanned autonomous systems) able to achieve multiple roles concurrently (e.g., tactical airlift cargo transportation, logistics route reconnaissance, medical evacuation, and search and rescue) constitute an alternate technology to reduce the logistics footprint.

5.2.1.5 Complex In-theatre Relief Operations

The involved humanitarian and military actors have fundamentally different thinking and cultures, mandates, objectives, and working methods. Coordinating the different actors in order to increase the relief efficiency and effectiveness of the combined efforts to serve the common humanitarian objective is among the most challenging in-theatre operations. Within the context of military–civil relations, there are different kinds of operations where humanitarian actors and military may coordinate their efforts. Given the large difference in working methods and culture, cooperation between military and humanitarian agencies is not appropriate or possible. However, collaborations where each actor pursues a specific objective, are encouraged and necessary to minimize competition and conflicts. From the logistics perspective, the lack of coordination and cooperation among the humanitarian actors may cause some problems in the relief distribution chain. These problems include congestion in the relief distribution network (Thomas and Kopczak 2005), storage capacity of distribution centres and depots (Balcik et al. 2008), and safety of supply, vehicles, humanitarian organizations and their personnel. The congestion problem may happen at different locations in the supply topology, e.g., depots, Local Distribution Centres (LDCs), and routes. This problem is mainly due to the difficulty to coordinate the HR efforts in disaster areas. Congestion may limit the availability of supplies, and causes ineffective distribution of aids (Thomas 2008). The problem of planning the storage capacity of the support network nodes is closely related to the congestion problem at those nodes. This problem, not well studied in the context of HROs, needs more attention to ensure fair and effective distribution of supplies through pre-positioning of supplies during the disaster relief operation.

5.2.1.6 Threat

Some humanitarian environments are characterized by threats to affected population and humanitarian relief agencies. They are usually due to conflicts where civilian are located in areas difficult to access. The threat environment is characterized as being (1) permissive: The host nation has power to maintain order in the afflicted area, and the government has the capability to assist in the HROs. Therefore, humanitarian actors may provide assistance with less worry about their safety; (2) uncertain: the host nation does not have full control of the afflicted territories and populations. The possibility of obstruction from individuals, crowds or mobs, or organized factions are not inexistent; (3) hostile: hostile forces have control over the afflicted areas and have capabilities to obstruct and deny any assistance to an at risk populations. The nature of the environment may also decide on the involvement of military in HROs. In hostile environments where humanitarian organizations are denied access to afflicted populations and supplies might be used by belligerents for their own purpose, the military involvement might the only alternative for humanitarian organizations and the host nation.

5.2.2 Military Involvement and Role in Humanitarian Relief Operations

Most often military involvement is requested in response to a sudden and unexpected disaster. The magnitude of a disaster and the threat environment may also call for military involvement. For example, the Canada's current foreign policy is to ensure an effective, appropriate, coordinated and timely response to emergency relief, humanitarian assistance, peacekeeping (stabilization) and peacemaking (peace enforcement) needs around the world. Indeed, through its engagements with the UN and the North Atlantic Treaty Organization (NATO), Canada is likely to be involved in these three types of missions. When not directly involved in providing security to humanitarian organizations, Canadian Forces (CF) may be required to assist in planning or providing advice on security for governmental and non governmental humanitarian organizations.

In some situations, it is important to maintain a clear separation between the military and humanitarian organizations by separating their respective duties and responsibilities. This is especially important in some particular conflict areas. Any coordination with a party involved in a conflict must be carefully studied given that a perceived affiliation with a belligerent might lead to the loss of neutrality and impartiality of the humanitarian organization. This in turn may affect the security of beneficiaries and humanitarian staff. However, at the same time humanitarian actors need to find efficient and effective ways to ensure delivery of vital assistance to afflicted populations. Therefore, a balance has to be found for each situation between the perceived affiliation with the military and the safety/effectiveness of the relief operations. To stick to their principles of humanity, neutrality, and impartiality, most humanitarian organizations perceive the decision to seek military-based assistance as the last resort option when other mechanisms are unavailable or inappropriate.

It is well accepted that where and when humanitarian capacities are not adequate and cannot be obtained in a timely manner, military capabilities may be deployed in accordance with the *Guideline On The Use Of Military and Civil Defence Assets to Support United Nations Humanitarian Activities in Complex Emergencies* (Center for excellence in disaster management & humanitarian assistance http://www.coe-dmha.org/media/guidance/3MCDAGuidlines.pdf). The key criteria in the guidelines include (1) unique capability, i.e., no appropriate alternative civilian resources exist, (2) timeliness, i.e., the urgency of the operation requires immediate action; (3) clear humanitarian direction, i.e., military assets remain under the military control, but the control over the use of military assets is under the civilian (humanitarian organization) control; (4) time-limited, i.e., the use of military assets to support humanitarian activities should be limited in time and scale.

MF when deployed in disaster areas may carry out humanitarian tasks themselves or support the efforts of other agencies involved in the HR efforts. The tasks may therefore cover a large spectrum of activities ranging from the distribution of provision to simply providing security to tierce organizations. The military support can be classified, based on the degree of implication of the military in the relief efforts, as follows:

- Direct support: this is the peer-to-peer distribution of supplies and services. This activity in common in HROs, where MF are highly involved, and imply direct delivery of good to affected people.
- Indirect support: support is provided to agencies directly involved in distribution of goods to population. This way of support involves such activities as transporting relief goods, security, and protection to humanitarian activities. This is very common in hostile areas where military support is required to protect convoys and ensure safety of personnel.
- Infrastructure support: this involves providing services in the direct and indirect ways. Activities such as road and bridge repair, airspace management, water, and power generation are provided both to affected population and to help relief organizations.

Table 5.1 Military activities in support of HROs

Name	Description
Field engineering	Provide general military engineering capabilities, e.g., bridge construction for vehicles and/or pedestrian
Latrine construction	Construct latrines to prevent the spread of disease, and ensure a hygienic disposal of human faeces
Road/airfield construction	Prepare and conduct road/airstrip repair/construction to improve existing transportation systems
Training mine awareness/clearing	Provide mine awareness/clearing training support to population and/or HR personnel
Water treatment/purification	Operate water purification equipment to provide potable water
Field hospital	Provide full range of military medical support in austere environment
Radio and satellite communication	Establish a radio communication system to support information exchange within the area of operations, and satellite communication to support information exchange both within and out of the area of relief operations
Fixed wing strategic airlift	Provide strategic airlift of humanitarian goods/cargo and the transportation of emergency personnel and equipment to the crisis area
Tactical support phase	Provide personnel, vehicles and communications equipment to support a filed mission headquarters
Fixed wing/helicopter theatre airlift	Provide regional airlift (short-haul) capability for delivery of personnel, equipment, and/or humanitarian cargo within the crisis region in coordination with the UN Air Operations Centre, local authorities and humanitarian organizations involved
Mine clearing	Provide mine clearing services in support of HROs

Table 5.1 presents some of the traditional and non-traditional military operations which are conducted in a direct, indirect, and as infrastructure support ways.

In addition to their traditional tasks (i.e., civil engineering, logistics, security) MF involved in HROs have been allocated tasks that are non-traditional military tasks. Among these tasks:

- Providing protection for humanitarian assistance: because of the uncertainty and hostility of the crisis area, humanitarian aid might not reach the needy people. In this case, military protection may be needed to ensure effective delivery of the goods to the various elements in the whole relief system. Some sensitive points in the relief chain need more security than others, e.g., airports and seaports where aids enter the country and distribution centres so they are not stolen. Furthermore, aid in transit might also need close protection depending on the areas they must transit to reach their destinations or distribution points. Protection for non-military personnel is also an issue MF are usually allocated during HROs.
- Humanitarian interventions: they are launched to gain humanitarian access to an at-risk population when the host nation is enable or refuses to take action to alleviate human suffering or protect the local population. This type of intervention is

a combat oriented operation intended to provide protection to the affected population and humanitarian aid workers by establishing favourable security conditions to HR activities.
- Protection of refugees and displaced people: this activity involves constructing and maintaining camp to concentrate individuals to ensure their safety. Security may be provided for the camp during the whole humanitarian crisis, or during some specific period corresponding to the return of refugees to their places of origin.
- Restoration of civil infrastructures: military resources are very often dedicated to the repair of some sensitive areas to guarantee operational flexibility of the ongoing HROs.

5.2.3 Military and Humanitarian Relief Mission Cycles

In this section, we review and compare some military deployment phases during classical and humanitarian missions.

5.2.3.1 Military Mission

Table 5.2 presents a description of the standard MF mission phases. A typical mission includes 5 phases: warning, preparation, deployment, employment, and redeployment. During the warning phase, the MF gather relevant data and conduct a mission analyses leading to decisions on the deploying force structure and tasks. The preparation phase starts when the Government gives a go ahead for the mission. Depending on the mission, units may train before they leave and a Theatre Activation Team (TAT) may deploy to ensure that the incoming troops will find proper shelter and basic commodities when they arrive. Some heavy equipment may also be transported in advance. During the deployment phase, units and their equipment are moved from their home bases and transported to the mission area. The employment phase is the main phase of the mission where the MF executes its assigned tasks. If the mission lasts more than 6 months, some personal rotations are required. The logistics support role during this phase is to support rotations and to resupply the goods consumed during the mission to sustain the force. Some equipment may also be repaired in theatre maintenance facilities, or shipped back for repair or overhauling, and new equipment may be brought in. The redeployment phase occurs when the mission is over.

The actual timing of these phases can vary depending on the mission type. For example, within the CF, the Disaster Assistance Response Team (DART) missions arise virtually without warning, and there may be only a few days between the warning and the employment phases. For recent DART missions in response to major natural disasters, the actual preparation and deployment time has rarely been less than 6 days, which is relatively long considering the fact that people rarely survive if not rescued within 72 h. For other humanitarian crisis such as famine and

Table 5.2 Military deployment phases

Warning	Government asks for analysis of the potential operations profile
Preparation	Units train for the mission's objectives according to the projected conditions. A theatre activation team deploys to prepare the full deployment of the mission. Some heavy equipment is deployed
Deployment	Units and their equipment are deployed
Employment	The mission is sustained from home and local suppliers
Redeployment	All units and their equipment are moved back home, sold, donated, or disposed

extensive refugee movements, deployed MF units were operational between 7 and 19 days after the warning phase (Dickson and Mason 2007). On the other hand, due to logistics requirements, more than a month can be required for the deployment, reception and preparedness for a mission engaging a full battle group in a land-locked theatre.

5.2.3.2 Humanitarian Relief Mission

HR missions are more spontaneous and less structured than military missions. In HROs, the disaster response cycle is usually composed of a set of activities that are performed before, during, and after a disaster with the goal of preventing loss of human life, reducing its impact on the economy, and returning to a state of normalcy as disaster operations (Altay and Green 2006). The disaster response cycle in HROs can be divided into three stages, each demanding different types of assistance, different requirements, and capabilities (Tomasini and Van Wassenhove 2009).

- Life saving phase: called also in the literature the ramp-up stage, it covers the first few days after the onset of the disaster. Getting access to the field and setting up operations as fast as possible is the highest main objective. During this phase, the military participates in traditional and non-traditional operations, e.g., search and rescue, medical assistance, delivery of water and emergency shelter, emergency engineering and communication support.
- Stabilization phase: is also called the sustainment phase. During this phase agencies focus on implementing their programs, while cost and efficiencies gain importance. Activities such as delivery of food and medical aid, development of local capacities such as water and sanitation, and the construction of emergency shelters, are among the activities aimed to stabilize the affected crisis areas.
- Recovery phase: also called the ramp-down phase, agencies are focusing on their exit strategy including transfer of operations to local actors. Rehabilitation and reconstruction activities aimed at community self-sufficiency and restoration of local/national governance are the ultimate activities of the disaster response cycle.

However, because the whole disaster response is a continuous cycle, these phases are very often undertaken concurrently. In response of any disaster, these phases are conducted to save and protect lives, though, most of these activities are conducted at the same time. In terms of operational performance the interesting part about the transition between the different phases is the shift in focus from speed to cost reduction. The life saving phase is driven by the urgency of the needs and high levels of uncertainty. The focus on speed and cost is usually not considered during this phase. Humanitarian agencies prioritize (during this phase) the need to get to the area, observe and assess how many resources are needed, and implement immediate solutions. Optimizing the cost of operations is usually considered in the last phase.

5.2.4 Cooperation and Coordination in Decision-making

Humanitarian relief environments may intrinsically engage multiple decision-makers and a variety of actors each with different missions, goals, capacity, and logistics capabilities (NGOs, joint, inter-agency, multinational and public, multinational coalition) that need to be explicitly coordinated in order to manage interdependencies (e.g., due to resource-sharing, task precedence or expertise constraint requirements). As reported in Kovács and Spens (2009) and Balcik et al. (2008), a variety of recent work and publications on human relief operations recognize coordination as a key challenge. Multiple organizations at various levels may be concurrently working at a major disaster site. These entities must collaboratively set up suitable facilities and infrastructure and efficiently supply and service affected people in disaster zones. Congestion may seriously impact relief supply availability, as shown in the Gujarat earthquake case, in which a single airport with few officials, land vehicles, and warehouses represented the main entry point for 50 organizations delivering goods over a 10-day period (Thomas 2008). Intrinsic contention for local commodities and service providers (e.g., sheltering, vehicle purchase/lease) dramatically conducted inflation rate up by an order of magnitude in comparison to normal conditions.

Competition between HR organizations to get most visibility first in order to obtain preferential resource access from public and private donors further emphasizes the need for better coordination and cooperation between different actors/echelons along the supply network (vertical), or over a given level/echelon (horizontal). Cases calling for better coordination needs are presented in more details in Oloruntoba (2005); Thomas and Kopczak (2007); Van Wassenhove (2005). In Cruijssen et al. (2007) the nature of benefits horizontal cooperation may bring to disaster relief logistic operations between humanitarian organizations, as well as the practical obstacles impeding the delivery of the expected payoff, are briefly reported. Accordingly, the authors contend that coordination between humanitarian organizations contributes improving overall operation efficiency, as insufficient or sub-optimal coordination wastes resources or puts at risk valuable response time unnecessarily. Thereby, cost reductions expected through price stabilization and warehouse network decentralization for supply and capability pre-positioning are recognized as key potential benefits. However, important or additional gains may be anticipated for lead-time reductions, quality control and capacity assurance through consolidation and standardization of procurement volumes, logistics process streamlining and possible stock exchange between individual humanitarian organizations. As a result, horizontal cooperation expectations include increased company's productivity (e.g., decrease in empty hauling, better usage of storage facilities), cost reductions of non-core activities (e.g., organizing safety trainings, joint fuel facilities), purchasing cost reductions (e.g., vehicles, on-board computers, fuel, maintenance), cheaper, faster and higher quality of service (e.g., frequency of deliveries, geographical coverage, reliability of delivery times), shorter response time.

Coordination may however be hindered by multiple impediments such as payoff distribution or reward sharing, implicit competition among similar HROs supply/service providers, organization dominance over others and unbalanced visibility. Organizations attitudes and positions toward military HROs may also induce competition, opportunity losses or credibility concerns. Further obstacles impacting coordination and cooperation between humanitarian organizations include organizations' mandates, organizational structure, advocated information technology, real and perceived competition between humanitarian contributors, and the timeliness and accuracy of information exchanged during HROs (Cruijssen et al. 2007).

5.3 Military and Humanitarian Relief Logistics

In this section, we focus on humanitarian relief logistics and highlight some aspects of the problem where the contribution of the military is of high value.

Humanitarian logistics is defined by Thomas (2004) as "the process of planning, implementing and controlling the efficient, cost effective flow and storage of goods and materials as well as related information from the point of origin to the point of consumption for the purpose of alleviating the suffering of vulnerable people. The function encompasses a range of activities, including preparedness, planning, procurement, transport, warehousing, tracking and tracing, customs and clearance" (Thomas 2004). In-theatre humanitarian relief operations, which include a variety of operation in the field (e.g., distribution of relief supplies) present multiple logistics aspects and challenges with limited communications and usually damaged transportation infrastructure. In such environments, military have proven to be better placed to quickly deploy capabilities to conduct activities such as air and land transportation of aid, air drops, airport improvement and navigation aid, electricity generation infrastructure repair, and water purification.

The distribution of relief supplies in typical large-scale HROs involving international actors is shown in Fig. 5.1 (Balcik et al. 2008). In this configuration, supplies received from international and local/regional donors are transported and stocked in depots, via air or land routes then, distributed to LDCs. The supplies reach the beneficiaries by local distribution from the LDCs. In our case, different classes of trucks and helicopters may be used to convey the different classes of commodities to the beneficiaries.

This relief distribution topology resemble closely to a military tactical logistics topology where LDCs and beneficiaries in the HR domain are replaced by forward operating bases and deployed troops, respectively (Sebbah et al. 2011).

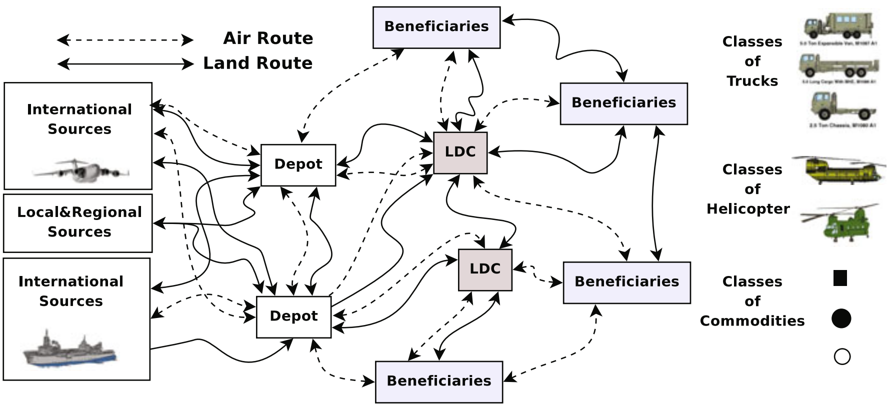

Fig. 5.1 Reliefs distribution topology

5.3.1 Military and Humanitarian Supply Chains

The particular needs for humanitarian relief operations have resulted in the development of emergency-relief organization networks. These networks involve UN agencies such as the World Food Programme (WFP), NGOs such as the Red Cross, Médecins Sans Frontières (MSF), CARE and OXFAM, as well as governmental organizations (such as the Stabilization and Reconstruction Task Force (START) in Canada), but they rely heavily on MF support. One of their aims is to setup emergency logistics networks to minimize the response time by bringing relief quickly and to maximize the relief in the disaster zone. To be efficient in their activities, the involved organizations should coordinate their actions. Previous studies on such networks showed that "even if there has been improvement in evacuation and emergency preparedness systems, it is apparent that with the current resources and operating policies the emergency management offices are not achieving their objectives. Even more, the cited researches show that no increased transportation or road building would allow evacuating the population in a timely manner" (Tovia 2007). The road ahead is therefore quite challenging. The current situation of the logistics function in the humanitarian sector is similar to logistics in the corporate sector in the 1980s. Indeed, the logistics function in the humanitarian sector is under-recognized, under-utilized and under-resourced (Fritz Institute http://www.fritzinstitute.org).

Given the commitment of certain countries to continue contributing to emerging international conflicts, crisis and disasters, it seems clear that the global reach capabilities of these countries must be enhanced. International missions are complex and diverse, and it is important for their success to improve the overseas mission deployment speed and sustainability. Improving the global reach capabilities will improve the ability of the engaged countries in the humanitarian efforts to deploy quickly. A study examining the option of developing an overseas network of Operational Support Hubs (called also Intermediate staging base) to improve the CF global reach is given by Ghanmi et al. (2009). Some larger countries have existing capabilities of this type, such as the United States military global en-route infrastructure, the United Kingdom legacy of permanent overseas bases, and France's African bases are good examples. These countries also possess MF that are configured for rapid deployment. This option has the potential of improving deployment speed, sustainment efficiency, as well as the supply network robustness and resilience. Although the concept of an overseas supply network is relatively easy to value, the specific question of the number, location and mission of the depots to implement is much more difficult to answer.

Regarding inventory management in HROs, a certain amount of insurance inventory needs to be kept in anticipation of future needs. However, keeping an excessively high insurance inventory is very expensive; both from the point of view of the capital immobilized and of the warehousing facilities required for its storage. This implies that a proper balance between readiness and inventory investments must be reached. A similar trade-off must be made for transportation assets: if the required planes are not available when needed, serious delays may be incurred. In both cases, if the level of resources available is insufficient, recourse actions are possible. Some material can be procured from external suppliers and some transportation assets can be leased, but this requires time and it may be very expensive.

5.3.2 Logistics Problems in Humanitarian Relief Operations

Although each crisis is unique in its details, most exhibit some similarities in the logistical response and the challenges they are facing. In the immediate aftermath of a disaster, military and humanitarian organization's staff must work under chaotic conditions. Local infrastructure such as roads, bridges, hospitals, and airports are often destroyed. Transport capacity is scarce. Local representatives of the population, to coordinate the relief efforts, are usually overwhelmed and cannot coordinate all the efforts. Within a disaster relief operation cycle, involved organizations are facing several logistics challenges. They are summarized as follows:

- Assessment: following a disaster, usually within a few hours, humanitarian organizations send assessment teams to assess the needs of the afflicted population in terms of health care, water and nutrition. Because this information is required within very short time and the chaotic conditions following directly the disaster, deployed logisticians estimate the needs based on rough estimation of the numbers of beneficiaries that may change drastically as new information emerges. Military are not usually involved in this step. During this phase, logisticians also select potential locations for installing crisis infrastructure including field hospitals, temporary depots, and distribution centres.
- Planning of operations: in order to provide effective relief, there is a critical challenge inherent to coordination of the relief distribution operations with other relief activities, such as infrastructure repair and construction, e.g., field hospitals.

Several parameters need to be taken into consideration during this step, such as weather, safety issues, and the nature of the disaster.

- In-theatre operations: once supplies arrive at the local port of entry, the challenge of distributing them to the needy population becomes an issue. Given the uncertainty characterizing the demands, the number and distribution of beneficiaries, providing effective and fair relief support is not guaranteed with the lack of accurate information. Furthermore, because of the limited available resources, e.g., transportation assets and storage capacity, conducting in-theatre operations becomes a hard planning and scheduling problem. In this phase, MF have a long history and can provide valuable assistance to afflicted people as well as to other relief agencies.
- Coordination with other HR actors: in some relief operations, hundreds of organizations are involved in the relief operation, all seeking to set up facilities and infrastructure, and to distribute supplies and save people. However, due to the difficulty in coordinating the activities of all these agencies, several problems may appear at different levels during the relief activities. Problems that may result from the lack of coordination efforts are: unfair and inefficient distribution of supplies and congestion in the distribution chain. These problems are mainly due to the non-uniform distribution of relief agencies over the disaster area, which creates unfair distribution of supplies with some congested areas and some other less covered. As happened during the Gujarat earthquake when a single airport with few officials, transportation assets, and warehouses served as the entry point for more than 50 organizations flying in supplies over a period of 10 days (Thomas 2008).

Facing such unpredictable conditions and these hard coordination and planning problems, logisticians continually need to create new strategies to overcome these new obstacles. In HROs, logisticians must get the right goods, to the right place, at the right time, within the limits of the budget, although, at the very beginning they do not know exactly what they need, where and when they need it.

5.3.3 Planning Factors in Humanitarian Relief Logistics

In the planning process of HROs, there are a number of key metrics that could be considered to achieve effective logistics planning. As opposed to its commercial counterpart, in the HR context, profit is not the motive. In HROs, the objective is usually to do get the job done while satisfying some extra constraints and objectives. These are addressed below.

- Timeliness: to be effective, a relief support needs to get on-time to its beneficiaries in order to save lives. This is especially true during the period following directly the disaster.
- Budgetary constraints: perceived aids from donors and governments do not match the required need of afflicted population. HR organizations involved in HROs need to target objectives reachable with their allocated budgets.

- Fairness in supply delivery: depending on its definition, fairness is usually intended to equally help afflicted people without any discrimination.

These objectives and constraints are addressed in the mathematical models of Sect. 5.4 for relief distribution scheduling.

5.4 Military Relief Distribution Scheduling: Mathematical Models

This section is concerned with developing mathematical models for designing HR network topology and scheduling relief distribution in a large-scale natural and/or complex disaster. The focus is on efficient ways to schedule relief distribution in the fields. Although we tailored the optimization models to military relief distribution missions (mainly using military assets), they can be used in any humanitarian relief scheduling operations by relaxing and/or adding some operational constraints to meet the new needs. In this part of the chapter, we assume that MFs are in charge of logistics planning for reliefs' distribution. Therefore, the commander has possession of the available logistics resources that he can use in the execution of the established relief plan (i.e., a centralized scheduling approach).

5.4.1 Literature Review

Several aspects of the planning and scheduling of supply distribution problem have been addressed in the literature with different assumptions, objectives, and constraints. The collaboration between military and humanitarian actors is discussed in Beresford and Rugamba (1996). In this section, we discuss some of the key papers addressing some problems related to distribution of relief in some bodies of literature. For an overview and classification of papers in disaster relief operations, see the comprehensive surveys of Atlay and Green (2006) and Simpson and Hancock (2009). From the relationship between the HR participating bodies perspective, the authors in Pettit and Beresford (2005) examined the different aspects involving military and other humanitarian organizations.

The optimization problem in relief distribution and scheduling is to find the optimal loading and routing patterns of transportation assets subject to time schedule constraints, delivery delay constraints, transportation capacity, safety and security in the network, cost budget, storage capacity, and fairness in distribution of commodities. This problem of vehicle loading and routing is a particular case of the classical Vehicle Routing Problem (VRP) and Multiple Bin Packing Problem (MBPP), which have been proven NP-hard[2] problems (Iori et al. 2007; Laporte 1992; Toth and Vigo 2002).

[2] Non-deterministic polynomial-time hard. The optimization problem, "what is the optimal solution of the loading and routing problem in our tactical logistics problem?", is NP-hard, since there is no easy way (polynomial-time algorithm) to determine if a solution is the optimal one.

Research papers in relief distribution can be classified into two categories involving utilitarian and egalitarian policies, respectively. In egalitarian policies, the objective is to maximize equality of some metrics such as delivery time and amounts of delivered commodities. While in utilitarian policies, the objective is to maximize or minimize a global metric without requiring equality in distribution of relief supplies. Objectives that are utilitarian in delivery of relief support can be found in a number of research papers including (Campbell et al. 2008; Huang et al. 2011; Knott 1987; Mete and Zabinsky 2010; Nolz et al. 2010). In Campbell et al. (2008) focused on the service time and proposed two objective functions: minimizing the maximum arrival time and minimizing the sum of arrival times of supplies. Therein, each demand location is visited exactly once, and demands are satisfied with one visit. Equity in the delivery time was not considered in this work. Knott (1987) proposed an Integer Linear Programming (ILP) model to find the number of trips a vehicle has to make in order to maximize the amount of delivered commodities while minimizing the transportation cost. In Nolz et al. (2010), the focus is on minimization of the total amount of unsatisfied demands while minimizing the latest arrival time at each destination. This last metric is an egalitarian measure of delivery speed. In Barbarosoglu et al. (2002), a modeling framework to address the crew assignment, and routing of helicopters during the initial response phase of disaster management is proposed. The authors developed ILP models to minimize the number of tours each helicopter performs and optimize the assignment of pilots to helicopters. A solution approach based on heuristics was developed as the size of the resulting ILP models is huge and no exact solution method was proposed to solve the models. Other research papers with utilitarian objectives focused on minimizing the amount of unsatisfied demands include (Mete and Zabinsky 2010; Özdamar et al. 2004; Salmerón and Apte 2010; Van Hentenryck et al. 2010), on minimizing logistics costs (Haghani and Oh 1996; Rawls and Turnquist 2010; Shen et al. 2009; Van Hentenryck et al. 2010), and on minimizing completion delay (Barbarosoglu et al. 2002; Yi and Ozdamar 2007).

In HROs, very often, the needs of beneficiaries exceed the available relief supplies, and involved humanitarian organizations have to choose allocation strategies to impartially distribute the aids according to the needs. In order to ensure a fair distribution of supplies, equity is a critical metric in HROs (Balcik et al. 2008). There are some relief distribution models using egalitarian policies to maximize the equality of some measures. Huang et al. (2011) extended the work of Campbell et al. (2008) by weighting the arrival time by the amount of commodities required at each destination. Therein, three metrics are introduced to measure equity in relief distribution. The first two are deviation-type equity metrics that measure the spread in service level across destinations, and the third calculates the equity in delivery time. A numerical study on small instances, in which it is possible to obtain an optimal solution, was conducted and heuristics were developed to solve large instances. In Tzeng et al. (2007), the authors consider the fairness problem under the problem of intermediate facility location problem in distributing supplies from a set of supply sources to demand points. A multi-period multi-objective model is developed where the objective is minimizing the logistics cost, travel time, and maximizing the minimum service satisfaction among demand points. In Balcik et al. (2008), it is proposed a joint model of routing and supply allocation in distributing multiple types of relief supplies. The authors minimize the maximum unsatisfied demand percentage over demand locations over a planning horizon.

5.4.2 Assumptions and Motivation

In this work, we consider the following characteristics and assumptions in modeling of the different aspects of the relief distribution problem.

- Two modes of transportation: air and land;
- Multiple classes of supplies;
- Transportation fleet of limited size: limited number of helicopters and trucks;
- Transportation assets may be pre-positioned at intermediate locations to increase the effectiveness of the distribution system;
- Storage capacity: depots are of limited capacities and can receive different quantities of each class of supplies;
- Land transportation routes are not necessarily safe during all the scheduling horizon;
- A security budget is available to secure some land routes during some scheduling intervals;
- Some beneficiaries can be reached only by air or land, or both;
- Total demand for relief supplies of each class of commodities is higher than the offer;
- Supplies are required within different time windows and may be delivered within different time windows;
- Multiple visits are required to each demand point to deliver all required commodities.

Given that, the needs of the different classes of commodities are not the same during the different phases of the disaster relief cycle, and the stages are very often undertaken concurrently, we develop a multi-period scheduling approach to effectively plan the overlapping of the periods and optimize the sharing of the limited resources, e.g., storage and transportation capacities.

5.4.3 Mathematical Models Description

A typical in-theatre relief topology is shown in Fig. 5.1. The entry points of goods are an airport, a seaport, and a local/regional source, all located in safe areas. The relief time horizon is divided into multiple periods of equal durations. The duration of each period is assumed to correspond to the time required to deliver commodities from one location to the next in the relief topology. Given that we have a limited number of transportation assets and storage capacity at intermediate locations, and those different commodities may be required within different time periods, we develop an optimization method that shares the logistics resources (transportation assets and storage capacities) and pre-positions transportation assets and commodities to anticipate future needs of beneficiaries.

Our model extends the classical Capacitated Vehicle Routing Problem with Time Window (CVRPTW) by allowing transshipment and change in transportation mode at intermediate nodes during transportation. Furthermore, we allow delivery of commodities within different time periods and allocate different rewards to the different deliveries within each time period. This variant of the multi time periods delivery is used because it models more accurately the reality of the HR environment and distribution model. A variety of solutions based on heuristics, and exact methods have been developed for different versions of the problem (Desrochers et al. 1992; Fisher 1995; Jimenez and Verdegay 1999; Laporte 1992; Ziliaskopoulos and Wardell 2000). With the objective to develop a flexible modeling and solution approaches that would scale in large relief support topology, we adopt a Column Generation (CG) decomposition approach. CG is an efficient optimization method for solving large scale Linear Programs (LP) and its performance unfolds in solving ILPs (Laporte 1992; Ribeiro and Soumis 1994).

5.4.4 Column Generation Decomposition Methodology

Our CG decomposition approach is based on the separation between the design and optimization of relief plans. A relief plan $p \in \mathcal{P}$ is a combination of transportation assets, trucks and helicopters, distributed along the network routes and pre-positioned at some nodes to transport different amounts of commodities to different beneficiaries during different time periods. Figure 5.2 presents an example of a relief plan. The distribution of transportation assets in a relief plan is performed in a way that sends *at most* one transportation asset during each time slot on each route, as illustrated in Fig. 5.2: from Main Depot to Depot 1 are sent on the same route a helicopter and a truck during time slot T_1 and T_2, and during the same time slot T_1 a helicopter and a truck but on two different routes from Main Depot to Deport 1 and Depot 2.

The different commodities and transportation assets could be either pre-positioned at intermediate nodes during some time slots, e.g., at Depot 1 during time slot T_2 and at Depot 2 during time slots T_2 and T_3, or on the road to the different destinations. The transportation assets are re-routed back to the main depot after delivering the commodities.

This decomposition is elaborated to address the computation of the operating cost and to break the symmetry in the ILP model due to the similitude of the trucks and helicopters of the same classes. To meet the demands of each destination, we assumed that multiple visits are required to deliver the whole demands. Therefore, multiple relief plans may be required to meet the whole demand of any destination. By doing so, we divide the whole scheduling problem into sub scheduling problems of limited sizes involving each a limited number of transportation assets and commodities. As the number of involved assets in each subproblem cannot exceed the number of routes, the size of a scheduling sub problem in this case is defined by the number of routes not the fleet size.

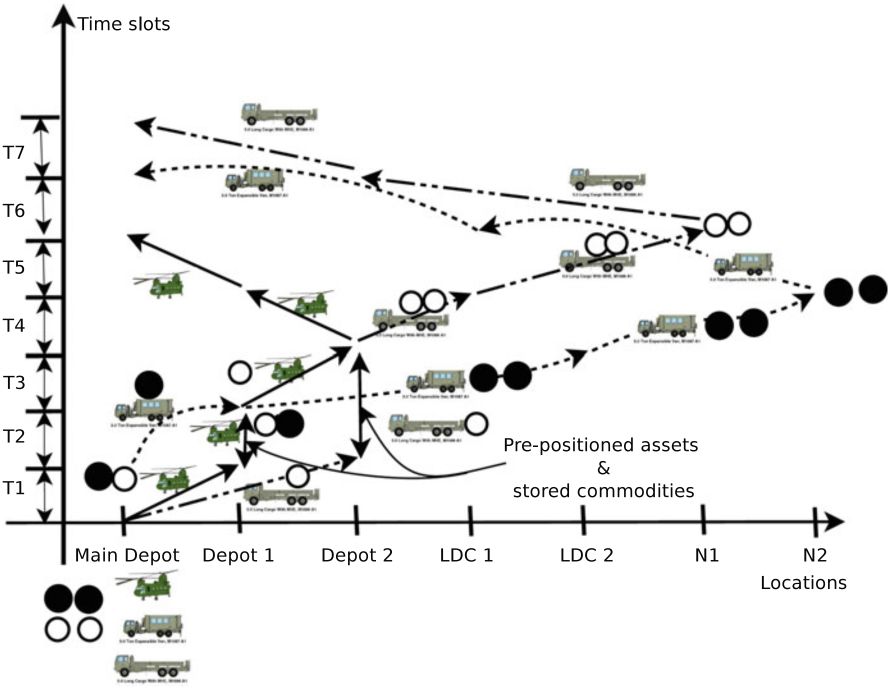

Fig. 5.2 A relief plan

In order to set up the mathematical models, we define the following sets and parameters:

Sets

$\mathcal{P}$	relief plans, indexed by p,
$\mathcal{M}$	intermediate locations, including depots, LDCs, indexed by m,
$\mathcal{N}$	destinations (beneficiaries), indexed by n,
$\mathcal{R}$	routes, including land and air routes, indexed by r,
$\mathcal{V}$	classes of transportation assets, trucks and helicopters, indexed by v,
$\mathcal{K}$	classes of commodities, indexed by k,
$\mathcal{T}$	time slots, indexed by t,
$\omega^+(m)$	set of outgoing routes from location $m \in \mathcal{M}$, similarly $\omega^+(n)$ for $n \in \mathcal{N}$,
$\omega^-(m)$	set of incoming routes to location $m \in \mathcal{M}$, similarly $\omega^-(n)$ for $n \in \mathcal{N}$.

Parameters

A_v^t	number of available trucks of class v during time slot t,
B_v	bulk capacity of transportation assets of class v (number of units),
$C_{v,r}^t$	operating cost of a transportation asset of class v on route r during time slot t ($)

C_p operating cost of relief plan p. It is equal to the sum over the cost of each transportation assets used on the different routes within the relief plan p ($),
d_n^k maximum amount of commodities of class k (offer) that could be transported to destination n,
D_r distance of route r (km),
H_v^t number of available helicopters of class v during time slot t,
I_m cost of building a depot at location m,
O_m storage capacity (number of units) of location m,
Q_v payload capacity of transportation assets of class v (ton),
S_v cruising speed of transportation assets of class v (km/h),
$U_{n,k}^t$ $\in \mathbb{R}_+$value of the utility function of delivering commodities of class k to destination n within time slot t,
U_p value of the utility function within the whole relief plan. It is equal to $\sum_{n\in\mathcal{N}}\sum_{k\in\mathcal{K}}\sum_{t\in\mathcal{T}} U_{n,k}^t$,
W_k weight of one unit of commodity of class k (ton),
$(a_v^t)_p$ number of trucks of class v used during time slot t within relief plan p,
$(E_n)_p$ binary parameter equal to 1 if node m is used in relief plan p,
$(F_{v,r}^t)_p$ equal to 1 if a transportation asset of class v is used on route r during time slot t within relief plan p, 0 otherwise,
$(h_v^t)_p$ number of helicopters of class v used during time slot t within relief plan p,
$(Q_{m,k}^t)_p$ number of commodity units of class k stored at node m during time slot t within relief plan $p \in \mathcal{P}$,
$(Q_{n,k}^t)_p$ number of commodities units of class k received at destination n during time slot t within relief plan $p \in \mathcal{P}$.

Index p is dropped from variables $(Q_{m,k}^t)_p$ and $(Q_{n,k}^t)_p$ in the pricing problem.

Given these parameters and variables, a relief plan p can be formally defined as a set of $(|\mathcal{K}|+3)-$tuple where $|\mathcal{K}|$ is the size of the set of classes of commodities and the 3 other elements refers to the route identity, time interval identity, and transportation assets class identity, respectively. A relief plan is defined formally as a set of $(|\mathcal{K}|+3)-$tuple of the following form: < route r, time interval t, one transportation asset of class $v_i (i = 1, \dots, |\mathcal{V}|)$, amount of commodities of classes $k_i (i = 1, \dots, |\mathcal{K}|)$ > . The key identity of each $(|\mathcal{K}|+3)-$tuple is the route identity and time interval identity. A relief plan may have several $(|\mathcal{K}|+3)-$tuples with the same route or same time interval but never the same route and time interval identities. The motivation behind this kind of decomposition is, in addition to practical complexity reduction, to ease the computation of the operating cost as it is a function of the used transportation asset (operating cost and cruising speed) and the distance of the used routes (see below for a mathematical formula for the operating cost computation).

The Operating Cost Model In the computation of the cost of each relief plan (C_p) we consider the operating cost of each of its transportation assets which is given as follows:

$$Operating\ cost\ (\$) = \frac{Hourly\ Cost\ Rate\ (\$/h) \times Distance\ (km)}{Cruising\ Speed\ (km/h)} \tag{5.1}$$

The selected transportation assets within each relief plan will ensure delivery of parts of the supplies to some destinations. It is a combination of relief plans that are needed to build up a global relief support strategy. In our CG approach, the optimization and design of relief plans are performed by the master and pricing problems, respectively. These two models are presented below.

5.4.4.1 Master Model

In the master model, we optimize the selection of relief plans $p \in \mathcal{P}$. We define the following variables:

Z_p $\in \mathbb{Z}^+$ is the number of copies of relief plan p. These variables allow us to construct global relief strategies by combining similar copies of the same relief plan. For example, if within a relief plan p a truck of class v is used on route r during time slot t and $Z_p = n(\in \mathbb{Z}^+)$, then, n similar trucks of class v will be used during the same time interval in the global support strategy on route r by combining n copies of relief plan p.

L_m is a binary variable to capture if a depot is installed at location m.

The Objective Function The objective function is composed of three terms: maximize the utility function of the relief plans, i.e., the delivery of commodities (during specific time periods) to beneficiaries; minimize the operating cost of the selected relief plans, i.e., the operating cost of the selected transportation assets in each relief plan, and minimize the capital cost of installing depots. The expression of the objective is given as follows:

Maximize:

$$z^{Master} = \overbrace{\sum_{p\in\mathcal{P}} U_p Z_p}^{Utility} - \overbrace{\sum_{p\in\mathcal{P}} C_p Z_p}^{Operating\ cost} - \overbrace{\sum_{m\in\mathcal{M}} I_m L_m}^{Capital\ cost}$$

where the first term is a real value measuring the whole utility of delivering the commodities to their destinations, and the second and third are dollar costs.

Using the above pre-defined parameters, the expression of the reduced cost can be re-expressed as follows:

$$\begin{aligned} z^{Master} &= \sum_{p\in\mathcal{P}}\sum_{n\in\mathcal{N}}\sum_{k\in\mathcal{K}}\sum_{t\in\mathcal{T}} (U^t_{n,k} Q^t_{n,k})_p Z_p \\ &\quad - \sum_{p\in\mathcal{P}}\sum_{v\in\mathcal{V}}\sum_{r\in\mathcal{R}}\sum_{t\in\mathcal{T}} (C^t_{v,r} F^t_{v,r})_p Z_p - \sum_{m\in\mathcal{M}} I_m L_m \end{aligned} \tag{5.2}$$

Constraints

- Location constraints of the depots.

$$\varepsilon \sum_{p\in\mathcal{P}} (E_n)_p Z_p \leq L_m \quad m \in \mathcal{M} \tag{5.3}$$

where $\varepsilon \ll 1$.

These constraints are used to capture whether or not a depot is installed at location n. If any relief plan p is routing assets through location n then, a depot is considered as installed at n.

- Storage capacity constraint of the depots.

$$\sum_{p \in \mathcal{P}} \left[\sum_{k \in \mathcal{K}} Q_{m,k}^{t} \right]_{p} Z_p \leq O_m \quad m \in \mathcal{M}, t \in \mathcal{T} \tag{5.4}$$

These constraints are used to set up an upper bound on the storage capacity of each depot $m \in \mathcal{M}$. The used storage capacity by all relief plans cannot exceed the specified value O_m.

- Offer and demand constraints.

$$\sum_{p \in \mathcal{P}} \left[\sum_{t \in \mathcal{T}} Q_{n,k}^{t} \right]_{p} Z_p \leq d_n^k \quad n \in \mathcal{N}, k \in \mathcal{K} \tag{5.5}$$

$$\sum_{p \in \mathcal{P}} [Q_{n,k}^{t}]_p Z_p \leq \overline{Q_{n,k}^{t}} \qquad n \in \mathcal{N}, k \in \mathcal{K},\ t \in \mathcal{T} \tag{5.6}$$

$$\sum_{p \in \mathcal{P}} [Q_{n,k}^{t}]_p Z_p \geq \underline{Q_{n,k}^{t}} \qquad n \in \mathcal{N}, k \in \mathcal{K},\ t \in \mathcal{T} \tag{5.7}$$

Constraints (5.5) set up an upper bound on the number of commodities delivered to each destination n (offer) during each time period $t \in \mathcal{T}$. Constraints (5.6) and (5.7) are used to set up an upper bound $\overline{Q_{n,k}^{t}}$ and lower bound $\underline{Q_{n,k}^{t}}$ on the number of required commodities at each destination n during each time period t.

- Fleet size constraints.

$$\sum_{p \in \mathcal{P}} (a_v^t)_p Z_p \leq A_v^t \quad \upsilon \in \mathcal{V}, t \in \mathcal{T} \tag{5.8}$$

$$\sum_{p \in \mathcal{P}} (h_v^T)_p Z_p \leq H_v^t \quad \upsilon \in \mathcal{V}, t \in \mathcal{T} \tag{5.9}$$

These constraints are used to set up an upper bound on the number of available trucks and helicopters of each class $\upsilon \in \mathcal{V}$ during each time slot $t \in \mathcal{T}$, respectively.

5.4.4.2 Pricing Model

The pricing problem, which is used to generate a promising relief plan each time it is run, corresponds to the maximization of the reduced cost of the restricted master problem subject to a set of relief plan design constraints. The expression of the reduced cost ($\overline{C}_p$) of a relief plan p is given as follows:

$$\begin{aligned}\overline{C}_p = \quad & \sum_{n\in\mathcal{N}}\sum_{k\in\mathcal{K}}\sum_{t\in\mathcal{T}} U^t_{n,k} q^T_{n,k} - \sum_{v\in\mathcal{V}}\sum_{r\in\mathcal{R}}\sum_{t\in\mathcal{T}} C^t_{v,r} F^t_{v,r} \\ & - \sum_{m\in\mathcal{M}} \varepsilon E_m(\theta_1)_m \\ & - \sum_{m\in\mathcal{M}}\sum_{t\in\mathcal{T}} \left[\sum_{k\in\mathcal{K}} q^T_{m,k}\right](\theta_2)^t_m \\ & - \sum_{n\in\mathcal{N}}\sum_{k\in\mathcal{K}}\sum_{t\in\mathcal{T}} q^T_{n,k}(\theta_3 - \theta_4)^t_{n,k} \\ & - \sum_{v\in\mathcal{V}}\sum_{t\in\mathcal{T}} a^t_v(\theta_3)^t_v \\ & - \sum_{v\in\mathcal{V}}\sum_{t\in\mathcal{T}} h^T_v(\theta_4)^t_v\end{aligned} \tag{5.10}$$

where $\theta_i (i = 1, 2, 3, 4)$ are the values of the dual variables associated with constraints (5.3) to (5.9). $E_m, F^t_{v,r}, q^T_{m,k}, q^T_{n,k}, a^t_v, h^T_v$ which were parameters in the master problem become variables in the pricing problem. In addition, we define the following variables of the pricing problem:

$y^t_{n,r,k}$: for each destination $n \in \mathcal{N}$, class of commodity $k \in \mathcal{K}$, route $r \in \mathcal{R}$, and time slot $t \in \mathcal{T}$ is the amount of commodities of class k transported to destination n along route r during period of time t.
$x^t_{v,m}$: number of trucks of class v pre-positioned at location m (including destinations) during time slot t.
$g^t_{v,m}$: similarly to $x^t_{v,m}$, is the number of helicopters of class v pre-positioned at location m during time slot t.

We define the constraints of the pricing problem as follows:

- For each $r \in \mathcal{R}, t \in \mathcal{T}$:

$$\sum_{v\in\mathcal{V}} F^t_{v,r} \leq 1 \tag{5.11}$$

$$\sum_{n\in\mathcal{N}}\sum_{k\in\mathcal{K}} W_k y^t_{n,k,r} \leq \sum_{v\in\mathcal{V}} Q_v F^t_{v,r} \tag{5.12}$$

$$\sum_{n\in\mathcal{N}}\sum_{k\in\mathcal{K}} y^t_{n,k,r} \leq \sum_{v\in\mathcal{V}} B_v F^t_{v,r} \tag{5.13}$$

  Constraints (5.11) state that at most one transportation asset (helicopter or truck) of a given class v could be used on route r during time slot t. Constraints (2.12) and (2.13) are payload and bulk transportation capacity constraints, respectively.
- For each $n \in \mathcal{N}, k \in \mathcal{K}, r \in \mathcal{R}, t \in \mathcal{T}$

$$y^t_{n,k,r} \leq \psi \sum_{v\in\mathcal{V}} F^t_{v,r} \tag{5.14}$$

  where $\psi \in \mathbb{Z}^+$ is an arbitrary large number.

Constraints (5.14) state that route r, land or air route, is used during time period $t \in \mathcal{T}$ to transport commodities of class k to destination n only if there is a transportation asset on r.

- For each $n \in \mathcal{N}, k \in \mathcal{K}, m \in \mathcal{M}, t \in \mathcal{T}$

$$Q^t_{m,k} = Q^{t-1}_{m,k} + \sum_{n \in \mathcal{N}} \sum_{r \in \omega^-(m)} y^{t-1}_{n,k,r} - \sum_{n \in \mathcal{N}} \sum_{r \in \omega^+(m)} y^t_{n,k,r} \tag{5.15}$$

Constraints (5.15) are used to record the amount of commodities of class k stored at each location m during each time period t. This amount is equal to what was at m during previous time period $m - 1$ plus the difference between the received amount during the previous period and the expedited amount during the same time period.

- For each $n \in \mathcal{N}, k \in \mathcal{K}, t \in \mathcal{T}$

$$Q^t_{n,k} = \sum_{r \in \omega^-(n)} y^{t-1}_{n,k,r} \tag{5.16}$$

Constraints (5.16) are used to record the amount of commodities of class k received at destination n during time slot t.

- For each $v \in \mathcal{V}, m \in \mathcal{M}, t \in \mathcal{T}$

$$x^t_{v,m} = x^{t-1}_{v,m} + \sum_{r(land) \in \omega^-(m)} F^{t-1}_{v,r} - \sum_{r(land) \in \omega^+(m)} F^t_{v,r} \tag{5.17}$$

$$g^t_{v,m} = g^{t-1}_{v,m} + \sum_{r(air) \in \omega^-(m)} x^{t-1}_{v,r} - \sum_{r(air) \in \omega^+(m)} x^t_{v,r} \tag{5.18}$$

Similarly to Constraints (5.15), constraints (5.17) and (5.18) are used to record pre-positioned trucks and helicopters, respectively.

- For each $k \in \mathcal{K}, m \in \mathcal{M}$

$$\sum_{n \in \mathcal{N}} \sum_{t \in \mathcal{T}} \left[\sum_{r \in \omega^+(m)} y^t_{n,k,r} - \sum_{r \in \omega^-(m)} y^t_{n,k,r} \right] = 0 \tag{5.19}$$

Constraints (5.19) are used to ensure relief flow conservation at each intermediate location for each class of commodities.

- For each $v \in \mathcal{V}, m \in \mathcal{M} \cup \mathcal{N}$

$$\sum_{t \in \mathcal{T}} \left[\sum_{r \in \omega^+(m)} x^t_{v,r} - \sum_{r \in \omega^-(m)} x^t_{v,r} \right] = 0 \tag{5.20}$$

$$\sum_{t \in \mathcal{T}} \left[\sum_{r \in \omega^+(m)} h^t_{v,r} - \sum_{r \in \omega^-(m)} h^t_{v,r} \right] = 0 \tag{5.21}$$

Constraints (5.20) and (5.21) are used to ensure transportation assets flow conservation at each location $m \in \mathcal{M} \cup \mathcal{N}$, respectively.

- For each $\upsilon \in \mathcal{V}, t \in \mathcal{T}$ correspondence between master and pricing variables

$$a_v^t = \sum_{m \in \mathcal{M}} x_{v,m}^t + \sum_{r(land) \in \omega^+(m)} F_{v,r}^t \tag{5.22}$$

$$h_v^T = \sum_{m \in \mathcal{M}} g_{v,m}^t + \sum_{r(air) \in \omega^+(m)} F_{v,r}^t \tag{5.23}$$

Constraints (5.22) and (5.23) are used to capture the number of trucks and helicopter used in the current relief plan. The number of trucks (respectively helicopters) used in the current relief plan is equal to the number of trucks (respectively helicopters) on the road plus those pre-positioned at the different locations.

- For each $n \in \mathcal{N}$

$$E_m \geq \in \sum_{n \in \mathcal{N}} \sum_{k \in \mathcal{K}} \sum_{r \in \omega(m)} \sum_{t \in \mathcal{T}} y_{n,k,r}^t \quad \in \ll 1 \tag{5.24}$$

Constraints (5.24) are used to capture if a potential location of a node is use in the routing of assets. If so, the variable E_n will be set to 1 to specify that by the current plan a node is required at the specified node.

To the best of our knowledge, this model is the first to address all these practical aspects of the relief distribution problem and to propose a CG modeling approach to scale the solution algorithm.

5.5 Computational Results

This section is divided into two subsections to illustrate the proposed methodology. In the first subsection, we assess the performance of the proposed CG algorithm. In the second, we simulate a HR environment and analyze the results obtained by the proposed solution algorithm.

5.5.1 Algorithmic Performance Assessment

The CG is extended with a Branch-and-Bound (B&B) algorithm to generate an integer solution once the optimal LP is obtained. The B&B algorithm operates on the so-far generated columns in the CG algorithm. Table 5.3 presents the results obtained using the CG algorithm involving 12 different patterns of demand generated for different HROs. The distributions of the required demands are randomly generated within approximated intervals. Therein, we measure the value of objective function of the optimal linear solution Z_{LP}, the integer solution Z_{ILP} (both numerical values), the integrality gap[3] between them (%), and the running time (in seconds) until the final

[3] Is the difference between the LP and ILP solution values.

Table 5.3 Performance measurements

	z_{LP}	z_{ILP}	Gap (%)	Time (s)
1	186,616	182,505	1.8	2,064
2	135,733	132,153	1.3	946
3	736,384	713,911	3.0	3,478
4	193,913	189,795	2.1	829
5	237,549	228,278	3.9	384
6	140,574	137,090	2.4	2,295
7	213,241	209,938	1.5	2,913
8	185,949	183,436	1.3	1,580
9	165,961	164,859	0.6	1,302
10	165,857	164,692	0.7	1,153
11	138,704	137,652	0.7	564
12	166,007	164,744	0.7	3,183

integer solution (Z_{ILP}) of the CG. Within these 12 instances, we relaxed the number of transportation assets constraints (5.8 and 5.9) by setting large bounds. Furthermore, for the multi delivery time, we set a similar utility of delivering commodities during different time periods.

The obtained results show how effective is the CG approach in obtaining optimal continuous solutions and deriving good integer ones. The integer solutions obtained by extending the CG algorithm with a B&B show a very low integrality gap in [0.6 %, 3.9 %]. The running time of all performed experiments is less than 1 h and is within the interval of time [384, 3,183] seconds.

5.5.2 A Humanitarian Relief Scenario

In this section, we demonstrate the proposed methodology by using a hypothetical example of scheduling of reliefs distribution in HROs.

5.5.2.1 The Logistics Network

The illustrative topology in Fig. 5.3 shows a relief distribution topology where the different locations are chosen to cover the scattered populations. While the locations of the LDCs are defined to cover the beneficiaries, the potential locations of the depots are identified for selection. In this scenario beneficiaries are aggregated into destination points and delivered relief commodities through Depots and LDCs. The arrows starting from the *Depots* ending at the LDCs indicate the direction of relief flow. Example, Depot 1 can be used to distribute reliefs to $\text{LDC}_\text{i}(i = 1, \ldots, 4)$. We assume that the entry points of supplies (Airport/Seaport of Disembarkation (A/S) POD and local sources) are collocated within the same place from which commodities are transported to LDCs through the depots.

Table 5.4 illustrate the capital cost (renting or construction) of the potential depots in Fig. 5.3 with the storage capacity of each (Table 5.5).

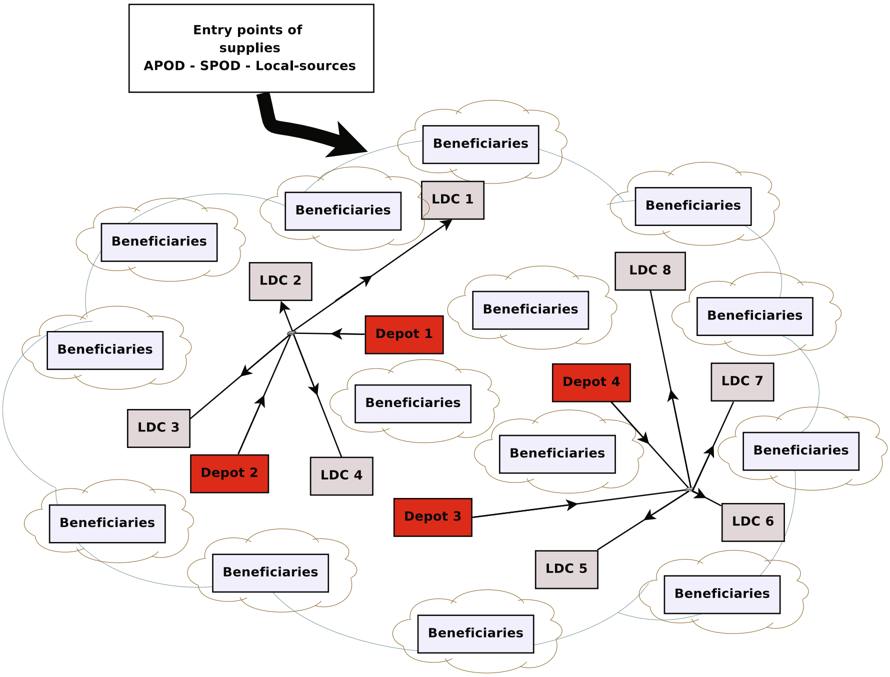

Fig. 5.3 A relief distribution topology

5.5.2.2 Commodities, Demands, and Offers

From a transportation requirement point of view, we grouped our commodities into three classes: general (e.g., food, clothing, medical material), refrigerated (e.g., fresh food, rations, medical material), and construction material, referred to by K_1, K_2, and K_3, respectively. In this study, we suppose that commodities are packed into pallets (standard transportation units) of similar size. The average weights of the pallets depend on their contained class of commodity and described as follows: refrigerated 0.5 Ton, general 1 Ton, and reconstruction 1.5 Ton.

To approximate the needs of afflicted populations in our hypothetical model, we used some military forecasting logistics models (Kaluzny and Erkelens 2008). Different scenarios were simulated with different population sizes and needs over the scheduling horizon. Table 5.6 illustrates the distribution of the demands over

Table 5.4 Depots: capital cost and storage capacity

Depots	Capital cost (renting, constructing) ($)	Storage capacity (pallets)
1	100,000	60
2	90,000	40
3	90,000	40
4	100,000	60

Table 5.5 Characteristics of classes of transportation assets

		Capacity				
		Payload (Ton)	Bulk (#Pallet)	Range (km)	Speed (km/h)	Cost per hour ($)
Helicopters	CH-147D Chinook	12.2	8	800	220	8,000
	CH-146 Griffon	1.9	1	550	200	5,000
Trucks	MLVW-Cargo	5.0	4	536	90	442
	HLVW-Cargo	10.0	8	732	85	517

the relief horizon. We support given (estimated) the demands of each destination (number of pallets) ∈ [min, max] for each class of commodities during each time slot. In each case of Table 5.6 are reported the min and max number of pallets of each class of commodities K_i required within the specified time slot.

The min and max amount of commodities of each class required by each destination and during each time slot are represented in the last column and line of Table 5.6, respectively.

Table 5.7 presents the offers of each class of commodities K_i versus the min and max amounts of demands of each class.

Table 5.6 Demand pattern

Destination	Class K	Time-slots						Total
		1	2	3	4	5	6	
1	K_1	(5, 8)	(5, 8)	(5, 8)	(5, 8)	(5, 8)	(5, 10)	(31, 50)
	K_2	(5, 10)	(5, 10)	(5, 6)	(5, 6)	(5, 8)	(5, 10)	(30, 50)
	K_3	(5, 6)	(5, 8)	(5, 6)	(5, 10)	(5, 10)	(5, 10)	(30, 50)
2	K_1	(3, 6)	(8, 15)	(6, 10)	(5, 8)	(5, 6)	(4, 5)	(30, 50)
	K_2	(5, 5)	(5, 15)	(5, 5)	(5, 7)	(5, 8)	(5, 10)	(30, 50)
	K_3	(5, 6)	(5, 8)	(5, 6)	(5, 10)	(5, 10)	(5, 10)	(30, 50)
3	K_1	(5, 8)	(5, 8)	(5, 8)	(5, 8)	(5, 8)	(5, 10)	(32, 50)
	K_2	(5, 10)	(5, 10)	(5, 6)	(5, 6)	(5, 8)	(5, 10)	(30, 50)
	K_3	(5, 6)	(5, 8)	(5, 6)	(5, 10)	(5, 10)	(5, 10)	(30, 50)
4	K_1	(3, 6)	(8, 15)	(6, 10)	(5, 8)	(5, 6)	(4, 5)	(31, 50)
	K_2	(5, 5)	(5, 15)	(5, 5)	(5, 7)	(5, 8)	(5, 10)	(30, 50)
	K_3	(5, 6)	(5, 8)	(5, 6)	(5, 10)	(5, 10)	(5, 10)	(30, 50)
5	K_1	(5, 8)	(5, 8)	(5, 8)	(5, 8)	(5, 8)	(5, 10)	(30, 50)
	K_2	(5,10)	(5, 10)	(5, 6)	(5, 6)	(5, 8)	(5, 10)	(30, 50)
	K_3	(5, 6)	(5, 8)	(5, 6)	(5, 10)	(5, 10)	(5, 10)	(31, 50)
6	K_1	(3, 6)	(8, 15)	(6, 10)	(5, 8)	(5, 6)	(4, 5)	(31, 50)
	K_2	(5, 5)	(5, 15)	(5, 5)	(5, 7)	(5, 8)	(5, 10)	(30, 50)
	K_3	(5, 6)	(5, 8)	(5, 6)	(5, 10)	(5, 10)	(5, 10)	(30, 50)
7	K_1	(5, 8)	(5, 8)	(5, 8)	(5, 8)	(5, 8)	(5, 10)	(30, 50)
	K_2	(5, 10)	(5, 10)	(5, 6)	(5, 6)	(5, 8)	(5, 10)	(30, 50)
	K_3	(5, 6)	(5, 8)	(5, 6)	(5, 10)	(5, 10)	(5, 10)	(31, 50)
8	K_1	(3, 6)	(8, 15)	(6, 10)	(5, 8)	(5, 6)	(4, 5)	(31, 50)
	K_2	(5, 5)	(5, 15)	(5, 5)	(5, 7)	(5, 8)	(5, 10)	(30, 50)
	K_3	(5, 6)	(5, 8)	(5, 6)	(5, 10)	(5, 10)	(5, 10)	(30, 50)
Total		112/164	132/256	124/164	120/196	120/200	117/220	728/1200

Table 5.7 Demand versus offer

Class-of-commodities	Demand (min, max)	Offer
K_1	246, 400	320
K_2	240, 400	320
K_3	242, 400	320
Total	728, 1200	960

After meeting the minimum amount of demands of each destination, the extra supplies left are distributed following some utility values illustrated in Table 5.8. A destination with a high utility value for a class of commodity during a given time slot will be allowed a higher priority, hence is more likely to receive an extra amount of supplies over a destination with a low utility. The utility values in Table 5.8 are elaborate based on a hypothetical model that allocates different priorities to different destinations for different classes of commodities during different time slots. The values in Altay and Green (2006); Campbell et al. (2008) are generated based on the vulnerability of the afflicted areas and populations. A matching function can also be developed between the priorities associated with the demands of the populations and any other interval of utilities. In our model, to have uniform terms in the optimization

Table 5.8 Delivery time utility

Destination	Class K	Time-slots					
		1	2	3	4	5	6
1	K_1	5	4	3	2	1	3
	K_2	5	1	2	3	4	5
	K_3	1	5	4	5	3	2
2	K_1	2	5	1	4	3	2
	K_2	2	3	4	5	2	3
	K_3	5	2	2	3	5	4
3	K_1	1	2	3	4	5	6
	K_2	5	4	3	2	1	6
	K_3	1	2	3	4	6	5
4	K_1	1	2	3	4	5	6
	K_2	5	4	3	2	1	6
	K_3	1	2	3	4	6	5
5	K_1	1	2	3	4	5	6
	K_2	5	4	3	2	1	6
	K_3	1	2	3	4	6	5
6	K_1	1	2	3	4	5	6
	K_2	5	4	3	2	1	6
	K_3	1	2	3	4	6	5
7	K_1	1	2	3	4	5	6
	K_2	5	4	3	2	1	6
	K_3	1	2	3	4	6	5
8	K_1	1	2	3	4	5	6
	K_2	5	4	3	2	1	6
	K_3	1	2	3	4	6	5

Table 5.9 Fleet mix and size

	Available	Used
MLVW-Cargo	50	5
HLVW-Cargo	50	50
CH-147D Chinook	40	34
CH-146 Griffon	40	0

objective, we set the value of each utility parameter $U^t_{n,k}$ of delivering a commodity of class K to destination n during time slot t, in the pricing objective function (5.10), as the product of the *cost of transporting a pallet* times the associated value in Table 5.8.

5.5.2.3 Scheduling of Operations

In this set of experiments, we consider a fleet mix and size of vehicles as presented in the second column of Table 5.9. In the third column are presented the number of used assets of each class.

Table 5.10 shows the optimal scheduling of the reliefs according to the demands/offers formulated in Tables 5.6 and 5.7, and the utility distribution in Table 5.8.

Table 5.10 Delivered commodities over the schedule time

Destination	Class K	Time-slots						Total
		1	2	3	4	5	6	
1	K_1	8	8	8	6	5	5	40
	K_2	10	5	5	5	5	10	40
	K_3	5	8	6	10	6	5	40
2	K_1	3	15	6	6	5	5	40
	K_2	5	10	5	7	8	5	40
	K_3	6	5	5	5	10	9	40
3	K_1	5	5	5	7	8	10	40
	K_2	10	5	5	5	5	10	40
	K_3	5	5	5	5	10	10	40
4	K_1	3	8	10	8	6	5	40
	K_2	5	10	5	5	5	10	40
	K_3	5	5	5	5	10	10	40
5	K_1	5	5	5	7	8	10	40
	K_2	10	5	5	5	5	10	40
	K_3	5	5	5	5	10	10	40
6	K_1	3	8	10	8	6	5	40
	K_2	5	10	5	5	5	10	40
	K_3	5	5	5	5	10	10	40
7	K_1	5	5	5	7	8	10	40
	K_2	10	5	5	5	5	10	40
	K_3	5	5	5	5	10	10	40
8	K_1	3	8	10	8	6	5	40
	K_2	5	10	5	5	5	10	40
	K_3	5	5	5	5	10	10	40
Total		136	165	140	144	171	204	960

The capital and operating costs of this solution are \$ 89,6474 and 2 × \$ 90,000 (cost of building/renting Depots 2 and 3).

5.6 Conclusion

This chapter presented some military logistics dimensions of HROs. It first described the context in which the military intervene in HROs and the roles they play. The characteristics and the trends of the emerging environment, in which the military and humanitarian relief actors are operating were presented. Some aspects of the interactions between military with other non-military organizations are discussed as well as logistics problems and planning factors involved in HR logistics.

This chapter proposes new mathematical models for scheduling HR distribution in a disaster relief operation over a multi-period horizon. It focused on planning and scheduling distribution of multiple classes of supplies to demand points in a disaster area using two modes of transportation including air and land. Several practical aspects of relief distributions are discussed and bottlenecks identified for future investigations. The mathematical models developed in this chapter for scheduling HR distribution address only the centralized case. Indeed, the decisions regarding the flows of relief and services from the points of origin to the points of destination to meet the urgent needs of the affected people under emergency conditions are supposed to be made by a single decision authority. This is not really the case in HROs field and the decisions and the process of planning HROs usually involve different entities (military and civilian) that should coordinate their efforts to perform effective and efficient distribution to suppliers. Mathematical models corresponding to this setting are naturally distributed and modelling should capture various and possibly conflicting decision level authorities.

One of the challenges will be to effectively consider the various (or even limited) dimensions of coordination in solving and developing the mathematical models for distributed HROs. This is exacerbated by inadequate coordination tools and mechanisms to properly support the ability of people or groups to actively coordinate their activities during HROs. There are processes in place but coordination mostly remains manual. The ability to manage tasks among multiple actors tends to improve overall operation efficiency. Given HROs complexity, a combination of optimization approaches with multi-agent coordination techniques may ultimately provide HRO planning benefits. Developing an information sharing environment to support distributed mathematical models and the automated coordination techniques deployment can also be considered as a R&D priority in this domain.

Future work will take on new challenges, increasingly paying attention to end-to-end global supply chain management, coordination and agility issues in distributed and risky environment settings over different types of disasters and scales. As a coalition of relief effort providers, net-centric agile military organizations need to develop and maintain a shared persistent situational awareness and rapid response capability to meet emerging and future HROs complexity.

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Chapter 6
A Procurement Auctions-Based Framework for Coordinating Platforms in Humanitarian Logistics

Mustafa Alp Ertem and Nebil Buyurgan

6.1 Introduction

A disaster is defined as "an unforeseen and often sudden event that causes great damage, destruction and human suffering with at least ten people reported killed, 100 people reported affected, a declaration of a state of emergency, and a call for international assistance" (CRED 2011). Last two decades have witnessed devastating floods, earthquakes, tsunamis following an earthquakes, famines, or refugee crises all over the world. Only in 2010, close to 300,000 people were killed and more than 200 million people were affected by disasters causing $124 billion worth of economic damage (ADSR 2011). Disasters are classified based on their source (natural or man-made), speed of onset (slow or sudden), or location (dispersed or localized) (Duran et al. 2013). Earthquakes, hurricanes, and floods are examples of sudden onset natural disasters. Famine is an example of slow onset natural disasters and a refugee crisis is an example of slow onset man-made disasters.

Although different types of disasters require different chain of relief operations, typical stages of disaster relief operations include mitigation, preparedness, response, and recovery (Altay and Green 2006). The mitigation phase is related to infrastructure investment for minimizing the damage of disasters such as building walls to the shoreline to prevent floods. The preparedness phase aims to develop means to get ready for a disaster strike. Disaster education, pre-positioned inventories, and early warning systems are major examples. The response phase comes immediately after the onset of the disaster. This is the most challenging phase of all phases. Urgent needs of affected people should be supplied in the shortest time. The recovery phase aims to rehabilitate the affected area by reconstructing bridges and buildings, cleaning up the rubble, and helping the injured and mentally traumatized people.

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Humanitarian logistics, which plays a key role in every stage of disaster relief operations, is defined as "the process of planning, implementing and controlling the efficient, cost-effective flow and storage of goods and materials, as well as related information, from point of origin to point of consumption for the purpose of meeting the end beneficiary's requirements" (Thomas and Mizushima 2005). When a state of emergency is declared and aid is appealed, resources such as relief personnel, relief goods and equipment are mobilized to the disaster location. By its definition, mobilization of resources as well as its predecessor and successor operations in a relief chain (Duran et al. 2013) can be categorized as humanitarian logistics, which contribute to more than 80 % of the total relief costs (Van Wassenhove 2006). Although local government of the disaster location is the main responsible to alleviate the suffering of its people (Thomas and Fritz 2006), Non-Governmental Organizations (NGOs) as well as other relief aid agencies offer their help to transport the right number of relief goods on time to the right place. NGOs and relief aid agencies spend about $20 billion annually to overcome those challenges (derived from Tatham and Pettit 2010).

Due to its nature and operating environment, humanitarian logistics have different characteristics than commercial logistics. The main difference is its objective of alleviating the suffering of beneficiaries. Several other characteristics of humanitarian logistics are summarized by comparison in Table 6.1. Among the topics listed in Table 6.1, the auction framework presented in this chapter aims to address the demand-supply imbalance, procurement activities using cash donations, ad-hoc delivery network structure, and stakeholder coordination. The motivation for using auctions for procurement operations is to utilize the inventory of suppliers more efficiently in a scarce resource environment by using special parameters for humanitarian logistics addressing these topics. The proposed auction is planned to take place after the first rush (i.e., 12–72 h) in the aftermath of a disaster.

Procurement in humanitarian logistics, which is the scope of this chapter, can be defined as acquiring the possession of relief goods or equipment by the humanitarian organizations by making monetary payments to the suppliers. Procurement is one of the first and perhaps the most overlooked step in the disaster relief operations. Procurement is necessary to have the required goods readily available for the successor relief operations including inventory pre-positioning, vehicle routing and assignment, transportation scheduling, and resource allocation. In some studies (Gong 2003; Coulter et al. 2007), procurement is seen as a means to help the recovery of the affected country. Estimates show that 65 % of the total disaster relief budget is dedicated to procurement of relief supplies and equipment (Schulz 2009, p. 97), which makes procurement the step of humanitarian logistics where majority of donor funding is spent. Organization of funding mechanisms, donor expectations, diversity of stakeholders, unpredictability of disasters and resource scarcity/oversupply are some factors (Balçik et al. 2010) that contribute to the complexity of the procurement operations in disaster relief. This complexity poses tough "what type, how much, when, from where, and how" questions for humanitarian organizations procuring relief goods.

In this chapter we propose a procurement method for humanitarian logistics that is based on auctions. The purpose of this auction-based approach is to address and

Table 6.1 Comparison of commercial and humanitarian logistics (Ertem et al. 2010)

Topic	Commercial logistics	Humanitarian logistics
Main objective	Maximize profit	Save lives and help beneficiaries
Demand pattern	Fairly stable and can be predicted with forecasting techniques	Irregular with respect to quantity, time, and place. Demand is estimated within the first hours of response
Supply pattern	Mostly predictable	Cash is donated for procurement. Unsolicited donations, and in-kind donations need sorting, prioritizing to decrease bottlenecks
Flow type	Commercial products	Resources like evacuation vehicles, people, shelter, food, hygiene kits, etc.
Lead time	Mostly predetermined	Approximately zero lead time, demand is needed immediately
Delivery network structure	Established techniques to find the number and locations of warehouses, distribution centres	Ad-hoc distribution facilities or demand nodes, dynamic network structure
Inventory control	Safety stocks for certain service levels can be found easily when demand and supply pattern is given	Unpredictable demand pattern makes inventory control challenging. Pre-positioned inventories are usually insufficient
Technology and information systems	Highly developed technology is used with commercial software packages	Less technology is used, few software packages that can record and track logistics data. Data network is non-existent
Performance measurement method	Based on standard supply chain metrics	Time to respond the disaster, fill rate, percentage of demand supplied fully, meeting donor expectation
Equipment and vehicles	Ordinary trucks, vehicles, fork-lifts	Robust equipment are needed to be mounted and demounted easily
Human resources	Commercial logistics is a respected career path	High employee-turnover, based on voluntary staff, harsh physical and psychological environment
Stakeholders	Shareholders, customers, suppliers	Donors, governments, military, NGOs, beneficiaries, United Nations etc.

promote the coordination among humanitarian organizations and suppliers during response and recovery operations after the first rush of the disaster onset. The auction model is developed to handle unique characteristics and restrictions of disaster relief environments using a single round sealed-bid auction. The next section overviews the procurement operations in humanitarian logistics to give some perspectives on timing of the procurement as well as supplier location. Then the proposed auction-based procurement framework is introduced with its operating mechanisms in Sect. 6.3. Considered system parameters that are unique for humanitarian logistics and models along with formulations that handle those parameters in the decision system are also discussed in Sect. 6.3. Section 6.4 gives the results of the study.

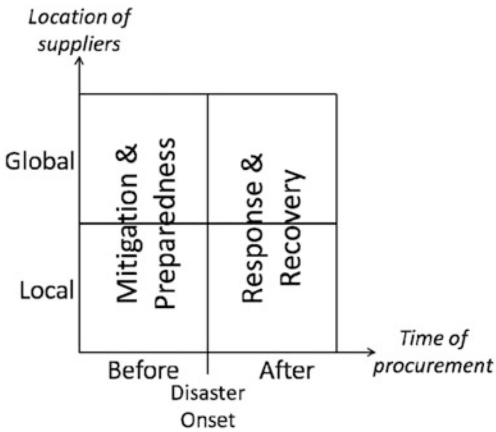

Fig. 6.1 Classification of procurement methods in humanitarian logistics

6.2 Procurement Operations in Humanitarian Logistics

Procurement methods in humanitarian logistics can be classified in two dimensions: (1) location of suppliers, and (2) time of procurement. Figure 6.1 illustrates these two dimensions with respect to disaster relief operations. Whether locally or globally supplied, procurement before the disaster onset addresses the mitigation and preparedness phases whereas procurement after the disaster onset addresses the response and recovery phases. Since the relief environment changes significantly with the disaster onset, the procurement methods change significantly, too. Moreover, operational procedures, contract types, resource availability, quality, and price of the relief goods change depending on the location of suppliers.

6.2.1 Procurement Before the Disaster Onset

Procurement before the disaster onset is necessary for prepositioning relief supplies in strategic locations near disaster-prone areas. The beneficiaries are supplied from pre-positioned inventory during the initial days after the disaster; therefore, having those supplies ready to dispatch is of critical importance. Nevertheless, only a small percentage of the total relief supply is sourced from the pre-positioned inventory (Balçik and Beamon 2008). Pre-positioning is a strategic decision which requires thorough analysis of relief operations. When humanitarian organizations decide to pre-position inventory, some issues such as the number of warehouse(s) and their locations as well as the types and the amount relief supplies to stock (Duran et al. 2013) should be considered which requires extensive investigation and management effort.

Procurement before the disaster onset from global suppliers has quality and availability advantages over other procurement methods. Before the disaster onset, humanitarian organizations have enough time to search through various suppliers, compare their quality and availability. Once purchased and stocked in the warehouse, relief goods should be tracked for their quantity, expiration dates, and location in the warehouse, which -often- is only possible by using proper information technology tools. However, pre-positioned inventory is a costly investment for humanitarian organizations. Safeguarding the relief goods, preserving their condition and transportation have considerable operational costs that add up to the total pre-positioning cost.

This type of procurement and prepositioning is practiced both by some large humanitarian organizations and military forces of all countries. Examples for large humanitarian organizations can be given as United Nations Humanitarian Response Depot (UNHRD) of World Food Programme (WFP), World Vision International (WVI), and CARE. For example UNHRD network consists of five global depots in Italy, Ghana, United Arab Emirates, Malaysia, and Panama (UNHRD 2011). WVI also manages four global warehouses in the USA, Italy, Germany, and Dubai. Similarly, CARE International has three global warehouses in Dubai, Panama, and Cambodia (Duran et al. 2011). Additionally, Pettit and Beresford (2005) analyse the current military practices in disaster relief operations using the UK military forces case and Ghanmi (2011) presents Canadian military forces hub location problem.

Procurement before the disaster onset from local suppliers is rarely applied, because the "locality" of the disaster is unknown before the disaster onset. Hence, there is no distinction between local or global suppliers before the disaster onset. One alternative definition for disaster locality can be the locality of the global warehouse of large humanitarian organizations. In this definition, procurement from the local suppliers near the global warehouse is considered. Using local suppliers before the disaster onset can be helpful for long-term economic development of the host country. Other advantages of using local suppliers are low transportation costs and fast delivery. On the other hand, quality may not be as expected or the capacity of local suppliers may not be enough for high volume demand (Balçik and Beamon 2008).

6.2.2 Procurement After the Disaster Onset

Procurement after the disaster onset is necessary because disasters are unpredictable in nature (Balçik et al. 2010). The location, timing, and severity of a disaster are unknown to the decision makers before the disaster. Inventory can be pre-positioned only when these aspects are estimated to an acceptable degree. Therefore, no matter how good the estimates are, there will be procurement after the disaster. Unlike the procurement before the disaster onset, more tactical and operational decisions have to be made by the humanitarian organizations. For example gifts-in-kind need to be sorted, prioritized, and stored (Duran et al. 2011). There is often a demand mismatch and operational problems in practice for gifts-in-kind (Tomasini and Van Wassenhove 2004; Thomas and Fritz 2006; Murray 2005). Also, funding for the disaster is proliferated after the disaster onset (Tatham and Pettit 2010) which requires dynamic spending strategies for the available funds. If there existed more funding in the mitigation and preparedness phases, not only the overall cost of a relief operation would be less, but also there would be fewer high-cost, agile procurement activity (Jahre and Heigh 2008). Therefore, the funding structure necessitates the procurement after the disaster onset.

Procurement after the disaster onset from global suppliers is mostly practiced by large humanitarian organizations. They usually send their personnel to the disaster area after the onset and assess the needs of the people. Depending on the type and severity of the disaster, they then decide whether to procure locally or globally. Since infrastructure is usually destroyed after the disaster, local suppliers may not always be easily accessible. Moreover, local supplier capacity might not be sufficient for sudden demand amplification. Large humanitarian organizations usually distribute kits (e.g., medical, hygiene, family, and kitchen) as a form of aid. These packaged kits might not be in the product spectrum of local suppliers; hence, they would have to produce such kits from scratch on demand. Therefore, large humanitarian organizations usually procure relief goods from global suppliers, but use local transportation and ad-hoc warehousing services.

Another variant of procurement after the disaster onset is procuring from already contracted global suppliers. In this approach, large humanitarian organizations establish Long Term Agreements (LTAs) with global suppliers to supply certain amount of relief goods on demand. LTAs create a common platform for attributes between global suppliers and humanitarian organizations for quality, price, packaging and labelling, lead time, and capacity. The suppliers to establish LTAs with can be determined using a multi-attribute auction mechanism. It is an efficient approach for humanitarian organizations, because they do not have to make the payment in advance and stock the relief goods (UNHRD 2011). One caveat of this approach for global suppliers is that they have to stock a certain amount of inventory on their premises for a possible disaster, which is actually transferring the inventory management cost to the supplier. The terms for LTAs should be defined clearly in order to protect both sides.

Procurement after the disaster onset from local suppliers is the most convenient method of supplying the immediate needs of beneficiaries, if only local suppliers have sufficient inventory in good condition. Procuring from local suppliers is encouraged especially in the recovery phase of disaster relief to support local economy and contribution of local people (Gong 2003; Coulter et al. 2007). The two most important criteria in deciding among local suppliers are price and timely delivery (Shahadat 2003). Reliability of the supplier and ability to offer quality products are also required by humanitarian organizations exercising procurement in developing countries (Shahadat 2003).

6.2.3 Procurement Coordinating Platforms

Some humanitarian organizations act as coordinating platforms for disaster relief procurement. For instance, UNHRD, Regional Logistics Units (RLUs) of the International Federation of Red Cross and Red Crescent Societies (IFRC) (Gatignon et al. 2010), and European Commission's European Community Humanitarian Office (ECHO)'s Humanitarian Procurement Centers (HPCs) function as coordinating platforms for different humanitarian organizations. Although UNHRD and RLUs can perform procurement on behalf of their partners, procurement is not among their primary functions. On the other hand, HPCs were primarily established to facilitate procurement operations of humanitarian organizations. Hence, some information on how HPCs work will be given in the following.

European Community Humanitarian Office (ECHO) distributed € 1.115 million in 2010 providing humanitarian assistance to about 151 million people (ECHO Annual Report 2011). ECHO initiated Humanitarian Procurement Centres (HPCs) which are defined as "not for profit organizations specialized in the technical and commercial management of supplies and services necessary for the implementation of humanitarian actions. They can provide Technical Assistance in procurement to Contracting Authorities or supply pre-established stocks, purchasing or logistics capacity (HPC Annex IV 2009)." Humanitarian organizations should be qualified by an assessment procedure to become HPCs for services like stockholding, procurement and consultancy.

ECHO partners conduct procurement by three procedures when using EU funding: (1) open procedure, (2) negotiated procedure, and (3) negotiated procedure with a single tender. Under the first procedure, all involved suppliers may offer a tender after the publication of a contract notice. Under the second procedure, only invited suppliers may offer a tender based on the qualifications (i.e., expertise, certifications, product quality, lead-time, etc.) on a contract notice. Third procedure is for several special circumstances including employing an HPC and for contracts less than € 60,000. Hence, employing an HPC facilitates the procurement operation for ECHO partners for contracts exceeding this threshold. Other advantages for ECHO partners include reduced costs, use of HPC's procurement expertise and broad supplier base, quality assurance, transparency in procurement activities, substitutability of relief goods, and cost savings regarding transportation (Schulz 2009).

6.3 A Procurement Auctions-Based Framework

One way to obtain the needs of beneficiaries is procurement auctions. An auction is a mechanism which provides procedures to establish resource allocation based on bids submitted by participants (McAfee and McMillan 1987). Two parties are defined for a specific auction: auctioneer and bidder. In selling auctions (i.e., forward auctions), there is one seller and multiple buyers. In procurement auctions (i.e., reverse auctions), there is one buyer and multiple sellers. Generally, procurement auction-based models include two main phases: (1) the bid construction phase and (2) the winner determination phase (de Vries and Vohra 2003, 2004). In the bid construction phase, the bidders evaluate the auction and construct a bid price considering a number of objectives and constraints. When the auctioneer has all the bid prices, the winning bid is determined by utilizing a winner determination algorithm (Bichler and Kalagnanam 2002; Kalagnanam and Parkes 2004; Ledyard et al. 2002).

Procurement auctions have been used successfully in commercial logistics (Rothkopf and Whinston 2007; Elmaghraby and Keskinocak 2006); however, procurement auction platforms in commercial logistics cannot be easily applied in humanitarian logistics during the aftermath of a disaster. Nevertheless, Trestrail et al. (2009) is one of the few studies that analyze the procurement process from the bidders' perspective and illustrate the remote procurement of the world's largest donor of food aid (i.e., United States Department of Agriculture (USDA)). Bagchi et al. (2011) proposes an optimal auction mechanism for USDA to deter gaming of suppliers and enhance bid preparation process by combining carrier and supplier bids. On the other hand, Falasca and Zobel (2011) present a two-stage stochastic procurement model from the perspective of humanitarian organizations (i.e., auctioneer's perspective). Here, we propose an auction-based procurement framework for humanitarian logistics that utilizes a single coordinating platform with an assumption that the suppliers are acting on humanitarian grounds based on their corporate social responsibility and are trying their best to supply the requirements. The type of auction utilized here is a single round sealed-bid auction. Such a platform with the proposed framework could also be used as a coordination point to overcome the lack of coordination among organizations (Oloruntoba and Gray 2006; Kovacs and Spens 2009; Balçik et al. 2010).

In the proposed auction-based procurement framework, the coordinating platform (CP) is the auctioneer and the suppliers of relief goods are the bidders. This framework is developed to be used during response and recovery operations after the first rush (i.e., 12–72 h) of the disaster onset. The main idea for using auctions in disaster relief procurement is to utilize the inventory of available suppliers more efficiently by introducing special parameters (i.e., priority of items, announcement options, ease of logistics) for humanitarian logistics. The framework aims to satisfy the requirements of beneficiaries with a higher fulfilment using these parameters. The framework consists of three phases: (1) announcement construction, (2) bid construction and submission, and (3) bid evaluation. Figure 6.2 depicts these phases, which correspond to the *appeals management*, the *suppliers' bid quotation*, and the *supplier selection* activities in humanitarian logistics, respectively.

In Fig. 6.2, the announcement construction and bid evaluation phases are managed by the CP, and the bid construction phase is managed by the suppliers. The CP collects the appeals from humanitarian organizations. CPs can be exemplified by Humanitarian Procurement Centers (HPCs) of ECHO. These humanitarian organizations can be exemplified by ECHO partners. ECHO case is used to describe the framework in this chapter, but the model can be applied to other similar entities. The CP accumulates demands from humanitarian organizations and releases announcements based upon predefined criteria. Once an announcement is released, the suppliers evaluate their on-hand inventory quantities and product values. Here, product value is considered to be a function of its sales price, condition, and age. Suppliers then decide on product quantity and mix in their bids. Using a general multidimensional knapsack problem (MDKP), bid quantities and associated item values are maximized by the CP while primarily selecting the suppliers that have easy access to the disaster location since the need of the beneficiaries should be satisfied as soon as possible in a disrupted transportation network.

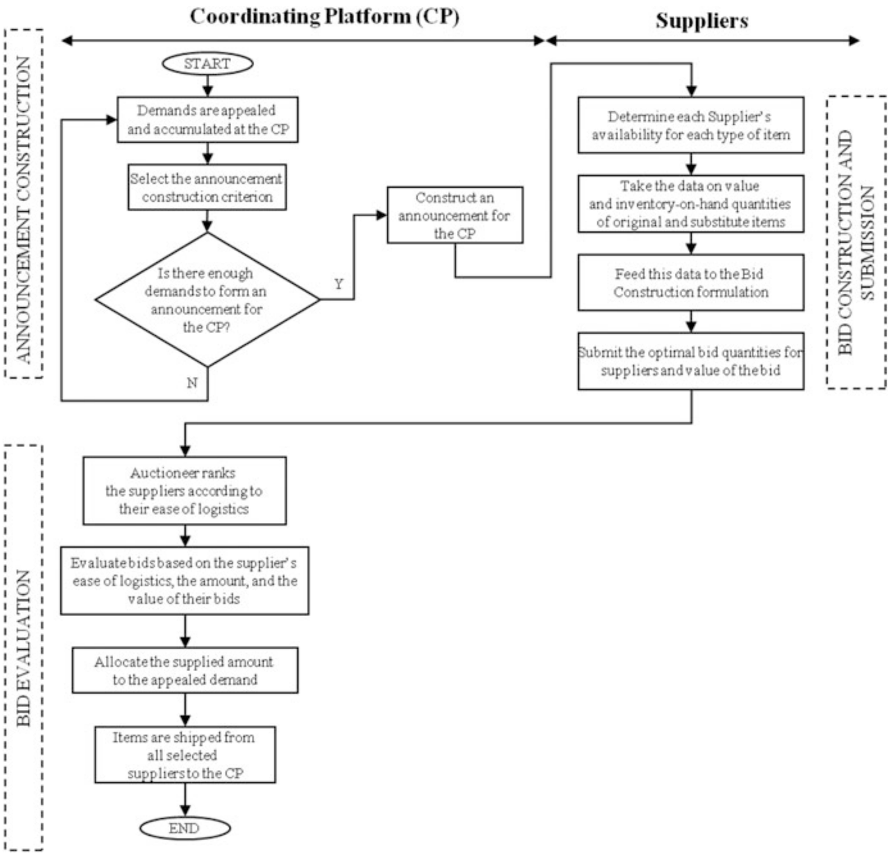

Fig. 6.2 Procurement auction framework for humanitarian logistics

6.3.1 Procurement Auction Parameters

Here, we explore the design parameters of the auction-based procurement framework that address the unique characteristics of the humanitarian logistics. These unique characteristics include irregular and unpredictable demand and supply pattern, flows for specific resources such as kits and shelter, dynamic delivery network structure, limited use of technology and information systems, and a multi-faceted stakeholder environment.

In humanitarian logistics, satisfying the immediate demand with available supply is challenging, because demand in humanitarian logistics is highly irregular and unpredictable with respect to quantity, time, and place. To address this irregularity, *priority of items* parameter is included in the framework. Priority of items is determined by the humanitarian organizations based on the phase of the disaster relief (*time*) and the severity of the disaster location (*place*). The *quantity* dimension is included by accumulating the appeals and releasing an announcement based on a criterion (announcement construction phase in Fig. 6.2). Prioritization of the appeals list is necessary in humanitarian logistics because individual items might have varying urgency. Moreover, since disaster relief atmosphere is known for resource scarcity, not all the items in the appeals list can be satisfied within a certain amount of time. Therefore, priority of items concept is used in this framework. Three levels are used to specify urgent-immediate (first level), the low-priority (second level), and the non-priority items (third level) (Van Wassenhove and Tomasini 2003; Davidson 2006; Chiu and Zheng 2007).

Two types of supply sources are available in humanitarian logistics : cash donations and gifts-in-kind donations. Both supply sources are unpredictable and tend to proliferate after the disaster onset. Gifts-in-kind donations cause extra burden on relief personnel and cash donations require procurement of the appealed amount from the suppliers. However, the local suppliers might become unavailable after the disaster onset and utilization of all available resources is necessary. *Announcement options* are used to address this kind of supply pattern. Here, appeals are publicized with two announcement options: (1) substitution and (2) partial fulfilment. These options are binary parameters and decided by the CP in order to utilize the available supplier inventory efficiently. Substitution option enables suppliers to bid on the item using substitutes even if they do not have the necessary original amount (bid construction phase in Fig. 6.2). Here, we consider that when substitution is allowed, a similar line item can be replaced with the original appealed item. Substitution option can also be used for gifts-in-kind to address the problem of unsolicited donation (i.e., a similar unsolicited line item can be offered instead of the solicited item). The partial fulfilment option gives suppliers the opportunity to bid partially even if they do not have the full required amount. This option relaxes the demand constraint for better utilization of supplier inventories in a scarce resource environment. In typical procurement platforms, partial bidding is not usually allowed. Partial bids are then bundled by the CP to acquire the full appealed amount (bid evaluation phase in Fig. 6.2). The announcement options proposed here may supplement complex auction types such as multi-item auctions (for substitution) and multi-unit auctions (for partial fulfilment).

Regarding the flow type, instead of commercial products in commercial logistics, the framework focuses on relief products such as shelter, food, hygiene, and medical kits. Since a procurement platform is analyzed, we concentrate on mostly consumables and do not address the equipment availability or scheduling of these resources. Priority of items is included to address the characteristics of relief products.

In a disaster relief environment, relief goods, equipment, and personnel need to flow in almost zero lead-time from the origin to the consumption using ad-hoc distribution facilities and network structure. This dynamic delivery network structure is addressed by the *ease of logistics* concept. Ease of logistics is determined by the CP based on the information received from the suppliers around the disaster location. The ease of logistics concept embraces infrastructural and geographical accessibility of the supplier to the destination where items are required. Three levels as an integer from the $[1, 3]$ interval represents the ease of logistics. In the bid evaluation phase, CP prefers the suppliers with higher ease of logistics (i.e., quantity and value is weighted by the ease of logistics parameter in the objective function). Lead time differences of suppliers are assumed to be handled by the ease of logistics concept.

6.3.2 Auction Model

Procurement auctions considered in this model have one auctioneer (i.e., buyer) and multiple bidders (i.e., sellers). The CP is the auctioneer in this model and the suppliers of relief goods are the bidders. Individual demands on the appeals list are collected and accumulated until a threshold is met. The demand up to that threshold are bundled and announced together. It is considered that different disaster relief environment would require different type of demand bundling. Therefore, five different threshold criteria are proposed:

a. A threshold amount for any item type in the accumulated requirements. (Quantity)
b. A certain time period t to elapse since the last announcement. (Time)
c. A total value ($V_T = \sum_j^m R_j \cdot Q_j$) for an announcement with m items; where, R_j is the reserve value of original item j and Q_j is the original amount required for item j. (Value)
d. A threshold priority count for the urgent priority items. (Count Priority)
e. The weighted priority (*WP*) of the accumulated requirements falls into an interval. Interval is defined as ($lp \leq WP < up$) where, lp is the limit for lower priority and up is the limit for upper priority. *WP* is computed by: ($WP = \sum_j^m p_j Q_j / \sum_j^m Q_j$) where p_j is the priority of item j. (Weight Priority)

Each criterion aims at different auction design parameters, which then leads to different number of bundled auctions. Limiting the quantity of items in an auction provides more auctions with smaller amounts that can be used in earlier stages of response and recovery operations. In addition, if the limit is increased, then the system can take advantage of economies of scale and lower the procurement costs, which can be utilized in later stages (i.e., sustainment) of disaster relief operations. In the second criterion, the CP keeps track of demand times and releases all accumulated demands after a certain period. This criterion considers procurements for time-sensitive items (i.e., items with expiration dates). Also, this criterion can also be utilized when a time sensitive decision has to be made. The announcement can be released when a predetermined total value of items is reached in the third criterion. The reserve price (R_j) used in the third criterion can be considered as the previous purchase price or the current market price of a good. Monetary decisions are included in the model with the third criterion. These decisions may become important during sustainment stage after the disaster. The count and the weighted priority criteria (the fourth and the fifth criteria) enable the CP to handle different priorities for different items by bundling them. If there is "enough" urgent demand for items exists in an announcement, it can be announced without waiting any longer to fulfil the immediate requirement.

When an announcement is constructed and announced based on a criterion of CP's choice, it comes with allowed substitution (S_j) or partial fulfilment (P_j) options for demanded items. Here, S_j and P_j are binary parameters where 1 represents allowing the option and 0 represents otherwise. Suppliers then decide whether to use substitute items or not (if allowed) while satisfying the requirements in the bid construction phase. An integer programming formulation is developed to represent the bid construction phase of the model:

Objective Function: $Min \sum_j^m (X_j V_j + Y_j W_j)$

With subject to:

$$X_j + S_j Y_j \geq Q_j - M z_j \quad \forall j \tag{6.1}$$

$$Y_j \leq M S_j \quad \forall j \tag{6.2}$$

$$X_j \leq I_j \quad \forall j \tag{6.3}$$

$$Y_j \leq H_j \quad \forall j \tag{6.4}$$

$$X_j \geq P_j I_j - M(1 - z_j) \quad \forall j \tag{6.5}$$

$$Y_j \geq S_j P_j H_j - M(1 - z_j) \quad \forall j \tag{6.6}$$

$$X_j \geq 0 \text{ and integer} \quad \forall j \tag{6.7}$$

$$Y_j \geq 0 \text{ and integer} \quad \forall j \tag{6.8}$$

The decision variables in this formulation are original (X_j) and substitute (Y_j) item quantities bid by the supplier for the item types (index j) in the bundle. The objective function minimizes the sum-product of item values (V_j, W_j) and bid quantities to use the low-valued items as early as possible in the auction. The value of a relief item is considered to be a function of its sales price, condition, and age. Suppliers are assumed to know the item values in their inventory and are ready to provide the quantity that is allocated by the auctioneer at the same value as they offered for the whole quantity.

A binary inventory availability parameter (z_j) is used to assess the suppliers' inventory on hand. It is calculated by summing the original (I_j) and the substitute (H_j) item counts. This inventory availability parameter is used in the formulation (constraints 5 and 6) to request whatever the suppliers have even if they don't have the required announcement amount (Q_j), where M is a sufficiently large integer. In the formulation, two constraints (1 and 2) handle the demand fulfilment requirements. Two constraints (3 and 4) forbid the supplier from bidding more than the on-hand inventory. The decision variables are positive integers.

In commercial logistics, winner determination is the phase that has been studied the most. In humanitarian logistics, suppliers might be differentiated with additional parameters. For instance, a bidder that is closer to the disaster area but offers substitute items could be more favourable than a distant bidder that offers original items. After the bidders construct their bids, the CP satisfies the requirements by only original items, only substitute items, or a mix of those depending on the bids received. Here, a modified version of the general multidimensional knapsack problem (MDKP) (Akcay et al. 2007) is used.

Objective Function: $Max \sum_i^n \sum_j^m \alpha_i (A_{ij} V_{ij} + B_{ij} W_{ij})$

With subject to:

$$\sum\nolimits_i^n (A_{ij} + B_{ij}) \leq Q_j \qquad \forall j \tag{6.9}$$

$$A_{ij} \leq C_{ij} \qquad \forall i, j \tag{6.10}$$

$$B_{ij} \leq D_{ij} \qquad \forall i, j \tag{6.11}$$

$$A_{ij} \geq 0 \text{ and integer} \qquad \forall i, j \tag{6.12}$$

$$B_{ij} \geq 0 \text{ and integer} \qquad \forall i, j \tag{6.13}$$

The decision variables are the original (A_{ij}) and substitute (B_{ij}) item quantities supplied from each bidder (index i) for the CP. The objective function maximizes the sum-product of item values (V_{ij}, W_{ij}) and bid quantities (C_{ij}, D_{ij}) to receive the newest and the most valuable items possible. Ease of logistics parameter (α_i) is used in the objective function to favour the suppliers that are more conveniently located. In the IP formulation, a knapsack constraint (6.9) makes sure that we have enough bid for the required amount (Q_j). Allocating at most the bid quantities to the suppliers are handled by two constrains, one for original items (6.10), one for substitutes (6.11). Decision variables are positive integers.

6.4 Results

The proposed framework with its formulations in three phases is tested using numerous sets of synthetic data and the system behaviour under different conditions is studied using simulation techniques. The linear programming formulations were solved using CPLEX 10.1™. Different disaster types with different requirements are taken into account. Suppliers with varying inventory on hand quantities and values are used. The ease of logistics parameter is also altered among the suppliers. In the system, the CP needs to determine the announcement construction criteria and the thresholds after the disaster based on the disaster type and characteristics of the relief mission.

In the bid construction phase, suppliers make bid decisions based on substitution and partial fulfilment options determined by the CP as well as their on-hand inventories. In different experiments, it is observed that substitution and partial fulfilment options provide bidders with fewer inventories on hand to give substitute types instead of original types and to partially bid in auctions. It is also illustrated by the experiments that the addition of these options allows less powerful suppliers to bid in procurement auctions. It is also observed that the suppliers make better use of the substitution when it is the single announcement option. The effect of substitution reduces, when the partial fulfilment option is permitted together with substitution.

Partial fulfilment option too enables better usage of supplier inventories. If partial fulfilment is not allowed, powerful suppliers are more likely to be awarded an auction than the less powerful ones. Allocation shares of bidders change, when these announcement options are allowed.

The performance of the procurement auction framework is measured by the fill rate, which is defined by dividing the supplied amount to the required amount. In the bid evaluation phase, experimental results state that using only a partial fulfilment option results in slightly better fill rates than using only a substitution option. The maximum fill rate is reached when substitution and partial fulfilment options are utilized together.

Suppliers are better evaluated with the ease of logistics parameter, which gives importance to the suppliers that have easy access to the disaster location. On the other hand, the ease-of-logistics parameter does not change the fill rate, but the allocation shares of bidders fluctuate significantly because of the ease of logistics parameter.

6.5 Conclusion

Humanitarian logistics is related to control, planning, and management of complex operations in the aftermath of a disaster where relief items are needed both immediately and in the long term. To supply the demand of beneficiaries efficiently, the use of procurement auction-based methods has a prospect to increase. Coordinating platforms (CPs) require effective auction models designed specifically for procurement in humanitarian logistics. This chapter gives an overview of procurement operations in humanitarian logistics and presents a unique procurement auction-based framework for coordinating platforms.

The coordination in a multi-faceted stakeholder environment of disaster relief operations is more difficult than the coordination in commercial logistics. Especially, diverse stakeholder spectrum poses extra challenges on coordination efforts during a disaster relief operation. A single-coordinating platform would help address the coordination issues that are caused by the lack of professionalization due to the mostly voluntary nature of relief operations. Also, more tracking and tracing technology could be used and more operational data could be recorded to help after-the-fact performance analysis. Procurement operations could be used as a means to facilitate coordination among NGOs, suppliers, governments, military, and the United Nations.

Several system level auction parameters specifically designed for humanitarian logistics are presented. Announcement creation is tied to five different methods that could be used in different disaster specific settings. For example, announcements can be created with a lower-interval-level weighted priority criterion during the initial days after a disaster. This will result in having more frequent announcements with higher priority items. Then, in the sustainment phase, the criterion can be changed to the total value for budgetary motives.

Two announcement options are presented, substitution and partial fulfilment. The use of substitution is beneficial both for suppliers and the CP. By this way, the inventory on hand at the suppliers is better utilized. In addition, allowing substitution provides more diverse sets of suppliers, which benefits the CP. Suppliers are allowed to bid less than the announced quantity, which provides suppliers the opportunity to quick inventory turnaround. Options in announcements nearly double the fill rate which is critical in disaster relief performance. In disaster relief operations, substitutions and partial fulfilment options should be permitted to get the highest fill rate. Moreover, the announcement options proposed here may supplement complex auction types such as multi-item auctions (for substitution) and multi-unit auctions (for partial fulfilment).

The value of the items plays a balanced role in the framework, since the bid-construction phase aims to discover the minimum valued original and substitute item type combination, but the bid evaluation phase aims to discover the maximum valued original and substitute item type combination. The use of item value helps suppliers to make use of the old items more effectively in the bid-construction phase and helps the CP to get better-conditioned items in the bid evaluation phase.

Varying quality of original relief supplies from different bidders and substitute items from the same bidder might be a limitation of the proposed framework. To alleviate this limitation, coordinating platforms should explicitly declare the product quality specifications during the announcement phase.

As a future study, the framework should be tested using the data from real disaster relief operations. We believe that the current structure of the ECHO-Humanitarian Procurement Centres (HPCs) allows the introduction of such framework. Moreover, 3PL services such as transportation scheduling, vehicle routing, and warehousing could be included in the supplier selection process using a reverse auction process. Procurement thresholds of HPCs could also be studied in the future and optimized to select the best procurement procedure.

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Chapter 7
A Fuzzy Multicriteria Methodology to Manage Priorities and Resource Assignment in Critical Situations

Mário Simões-Marques and Isabel L. Nunes

7.1 Introduction

Humanitarian Assistance and Disaster Relief (HADR) Logistic problems are at the cross roads of many knowledge domains and involve many actors from Nations, International Organizations, Governmental Organizations, Non-Governmental Organizations, from several civilian and military sectors.

HADR operations require a Comprehensive Approach (CA), i.e., they call for Unity of Effort. The gaps and requirements for an effective implementation of the CA are thoroughly addressed in literature (e.g., UNOCHA 2003; NATO 2010a; USJFCOM 2010; Wendling 2010; Simões-Marques and Nunes 2012a). In a Gap Analysis done by the NATO Allied Commander Transformation the main category gaps for Civil-Military Interaction on what HADR is concerned were identified as being related with situational awareness, communication and information sharing, cultural awareness, education and training, planning and resources (ACT 2010).

Therefore, HADR requires strong Crises Management capabilities and this calls for decision-making support tools. However, decision-making support in the HADR context raises many questions, some of them very hard to solve because they fall on the domain of cultural awareness, policy and willingness to openly cooperate. Other questions, the ones in the technological domain, can be more easily solved, and they relate with issues such as situational awareness, maturity of interaction among entities, or interoperability. The second type of questions is quite important

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since it affects the effectiveness and efficiency of humanitarian and relief support, and contributes decisively to the desired Unity of Effort.

Current technology offers the means (platforms and tools) to develop solutions that can contribute to deal with a substantial part of the problem, but not all of it. In fact, some key issues for the implementation of a CA go far beyond technology and they relate, for instance, with organizational structure, policy, culture, values and will. Williams discusses these issues while addressing the maturity of interaction among organizations for developing his Interaction Magnitude Model (Williams 2010). To define the level of interaction maturity this author proposes the following dimensions:

Organizational structure—where various types of organizational structural features are considered: chain of command, hierarchical divisions and level of centralization;
Communications—the type, structure, and protocol of organizations' communications methods;
Information sharing—regulations governing and constraining information usage, and processes of organizations' information sharing mechanisms;
Decision making and operating procedures—affects the degree of constraints or freedoms, on the level of cooperation possible;
Authority and accountability—the mechanisms that permit allocation of responsibility for actions on a particular individual or department in an inter-organizational cooperation context;
Culture and values—intangible characteristics that underlie the operating basis of an organization in the context of sensemaking;
Planning—ability (including relationship and methods) of military planners or civilian policy makers to agree a goal, and authority to commit resources towards achieving that goal;
Evaluation—key processes, resources, and planning required for evaluation activities.

Considering these dimensions is important to understand the implications that operationalizing HADR may have, particularly because the context in which HADR operations are developed is varied and complex. In fact, some international organizations (e.g., NATO and UN) refer to them as Complex Emergencies (UNOCHA 2003), Complex Operations (NDC 2010) or Complex Contingency Operations (NATO 2010b), since they involve many heterogeneous actors, engaged in stabilization, security, transition and reconstruction operations (also known as SSTRO) which are developed in environments that are characterized by a low to medium level of conflict intensity (USJFCOM 2006, 2007, 2010; DPKO 2008).

This chapter focuses in Emergency Management as an integral part of the HADR operations.

Emergency Management (EM) is a complex process that requires the coordination of different actors, with different cultures, aims and views of the world. The development of decision support systems that support the decision-makers and provide a common picture about a crisis scenario is a big challenge. This paper will discuss some of the requirements for an Emergency Management System (EMS),

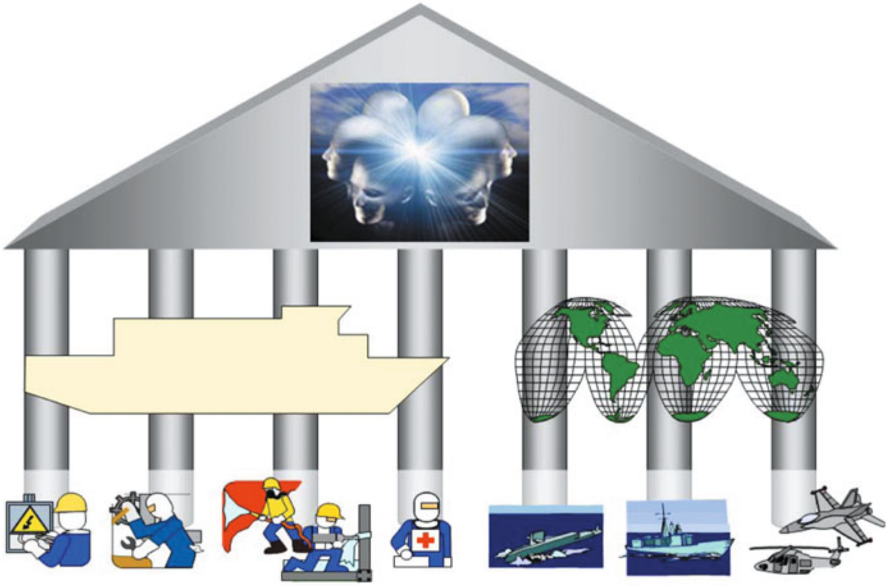

Fig. 7.1 Traditional stovepiped decision processes

and will introduce the SINGRAR model (Simões-Marques 1999) which was used in the implementation of a distributed EMS expert system installed a board of ships and land infrastructures.

In fact, Navy ships are a good example of small worlds where many actors and systems intertwine performing multiple complementary tasks. Traditionally, coordination was assured based on a hierarchical stovepiped structure, supported by vertical communications, from decision-makers down to executers and back. Hardly these parallel communication/decision processes were performed with sufficient awareness and articulation of each other's objectives. Figure 7.1 illustrates these independent processes as different stovepipes focused on specific technical or operational areas. Usually deconfliction of internal activities and mitigation have to be performed by top level decision-makers, which are the ones that tend to have better awareness of the Command goals and a broader picture about the internal and external contexts.

The increase in number, complexity and interdependency of systems, and the need for quick response forced the evolution of the organization, flattening it and creating the need for horizontal connections. The technological evolution offered also means for providing support to the decision-making process. This can be done via integrated command and control systems of different natures (e.g., tactical, engineering) that fuse data originated in sensors (e.g., radars, engines, flood sensors), process it, present information to users, and eventually allow the remote operation of actuators (e.g., weapons, fuel injectors, pumps).

For the Portuguese Navy the commissioning of the "Vasco da Gama" frigates, in the early 90s, was the turning point in terms of Command and Control (C2) technologies. These ships were equipped with tactical (focused on the external environment) and platform (focused on the internal environment: ship, propulsion and power plant) command and control systems. However, these two main systems were independent and isolated, and the coordination of the needs/constrains of the two user groups was performed based on human processes and voice communications, supported by "aide mémoire" paper boards.

The interaction among the two groups is critical since the internally-focused activities—e.g., engineering, damage control, medical and logistics—support the operability and survivability of the ship, crew and systems, namely the ones that ensure the fighting capabilities (externally-focused). Note that this missing internal C2 component is the EMS of the ship.

Aware of this fact, and unhappy with the manual processes on use, a significant effort was put on finding and developing a base model to support a solution to bridge this gap, and an EMS was developed (Simões-Marques 1999). The implementation of the solution was a slow but steady process that took almost 10 years to become operational. A full scale system was developed and customized for the "Vasco da Gama" class frigates to validate the concept and the project feasibility, and also to evaluate the procedural and organizational impact resulting from the introduction of such system onboard. After a very successful testing and validation period initiated on 2004, all three ships of this class received the system and continuous improvements were implemented, both in terms of features and of usability (Nunes and Simões-Marques 2010; Simões-Marques and Nunes 2012b). In 2009 the EMS entered also in service in the two ships of "Bartolomeu Dias" class (M-class frigates which were acquired from The Netherlands and up-graded) after a quite smooth parameterization period.

Despite the EMS is not presently integrated with the tactical C2 system, a major step on direction of an integrated ship management system was taken. Now top level decision-makers can have a complete picture of the internal and external environments just by looking at two systems' screens that are one next to the other (refer to Fig. 7.2). By inputting basic data about the tactical situation on the EMS it is assured coherence between priorities settled for the internally-focused activities and the externally-focused goals. The EMS outputs highlight the systems' main operation limitations for the defined tactical environment, and supports the resource management to improve resource availability for operations.

The interest in using fuzzy approaches to deal with emergency management problems is growing, despite not necessarily addressing HADR situations or addressing very specific thematics of the emergency management problem. This is evident by the number of references that can be found in recent scientific literature (see for instance, Mendis et al. 2007; Tzeng et al. 2007; Lau et al. 2008; Espinosa-Paredes et al. 2008, Lewis et al. 2009; Adivar and Mert 2010; Sheu 2010; Yan et al. 2010; De Maio et al. 2011; Gong et al. 2012; Wex et al. 2012; Zhao et al. 2012).

The next sections contain a brief description about the emergency management requirements, and a discussion on the main features of the SINGRAR model applied

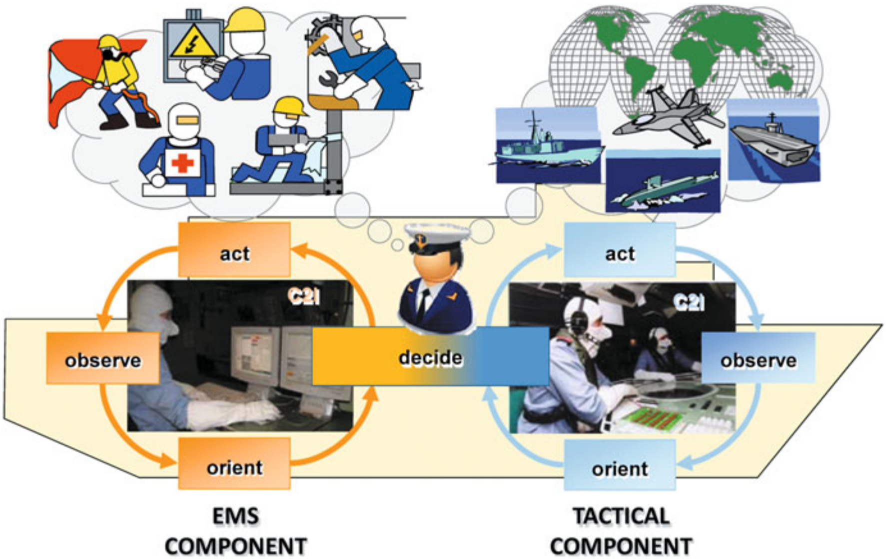

Fig. 7.2 An approach toward the integration of ship's management processes

to the Command and Control of emergency management considering HADR operations, particularly regarding the benefits of the adoption of the FMADM approach in which it lays, and of the use of a distributed environment that is able to provide shared situational awareness through a common operational picture, and uniform and coherent recommendations regarding lines of action/resource assignment, contributing to the desired unity of effort. The chapter also provides an inter-agency scenario for the application of an Emergency Management System and illustrates some of the factors and relations to consider in the resource assignment management process. The chapter ends with some conclusions that synthesize the main ideas.

7.2 Generic Requirements for an Emergency Management System

According to FEMA, Emergency Management must be (FEMA 2007):

Comprehensive—emergency managers consider and take into account all hazards, all phases, all stakeholders and all impacts relevant to disasters.

Progressive—emergency managers anticipate future disasters and take preventive and preparatory measures to build disaster-resistant and disaster-resilient communities.

Risk-driven—emergency managers use sound risk management principles (hazard identification, risk analysis, and impact analysis) in assigning priorities and resources.

Integrated—emergency managers ensure unity of effort among all levels of government and all elements of a community.

Collaborative—emergency managers create and sustain broad and sincere relationships among individuals and organizations to encourage trust, advocate a team atmosphere, build consensus, and facilitate communication.

Coordinated—emergency managers synchronize the activities of all relevant stakeholders to achieve a common purpose.

Flexible—emergency managers use creative and innovative approaches in solving disaster challenges.

Professional—emergency managers value a science and knowledge-based approach; based on education, training, experience, ethical practice, public stewardship and continuous improvement.

Emergency Management aims to provide efficient and effective responses to multiple and often conflicting needs in situations of scarce resources. Emergency Management has to consider several complementary functional elements, such as Supply, Maintenance, Personnel, Health, Transport and Construction. In all these elements the decision-making issues relate to basic questions What, Where, When, Who, Why, How, How Much? These questions become particularly difficult to answer in critical situations, such as disaster relief, where the urgency and impact of the decisions is especially sensitive, and resources are usually very limited (Simões-Marques 2005a).

Briefly, the main goals of an intelligent system for Emergency Management are:

- provide decision support in the management of emergencies;
- ensure a reliable and flexible network, including mobile components, for accessing the emergency management system, serving the needs of the various actors of the decision process, including:
  – compilation of information producing a standardized, integrated and consistent picture on the status of incidents and on the usage of resources for a given area of interest, and
  – dynamic advice to decision-makers regarding alternative courses of action.

To make this possible, it is necessary to develop a set of activities, the preliminary system implementation, which are designed to gather knowledge that is essential to allow this level of decision support (for example, by developing ontologies that allow to categorize and characterize the types of incidents and resources to engage, identify the resources available, and characterize them as to their usefulness to the potential areas of intervention envisaged; refer for instance to (Galton and Worboys 2011). These activities are usually designated by Knowledge Engineering (Turban et al. 2010).

An effective management of resources requires the adoption of multiple criteria for evaluating the degree of adequacy of allocating a given resource to an incident. Some aspects to consider in assessing the suitability of the resources are, for example, skills, proximity, and resources availability to intervene in a specific incident.

The EMS' interface design must consider usability principles (Nielsen 1993). For example, it should be possible to record and represent the incidents, among others, in a graphical format (for instance, georeferenced). Some advantages of this type of representation relate with the easier understanding of visual information and the possibility of presenting information in a more intuitive and synthetic way. For instance, the use of a map to present the location of incidents and means of assistance facilitates the perception if there is a concentration of incidents, how close are the means available and which ones should be allocated.

The EMS should provide advice on courses of action, which must adapt dynamically to the scenario evolution. Obviously the adoption of the advised actions is not mandatory, and the decision-maker has to evaluate and validate system's recommendations. Nevertheless, the use of common robust advice tools in a distributed/shared system ensures predictability and coherence of the decision-making process, which facilitates the linkage between parallel and concurrent decision processes.

Since the system must be scalable and flexible, the area covered by the system must be adapted to the needs of decision-makers. Assuming that the system serves an organization structured based on a hierarchy of emergency operations centers, it is possible to have workstations dedicated to high-level decision-makers, whose scope is broader, and others dedicated to lower-level decision-makers, focused on a more restricted area of intervention. Naturally, the larger the area covered the greater the complexity of the integrated information and lesser the degree of detail that is possible to apprehend. Thus, a general coordination center should be concerned with the overall picture, analyzing where the "hot spots" are and making a macroscopic management of resources, for example, moving available means to places where there is scarcity. On the other hand, a local decision-maker will be concerned to respond to each individual incident, in real time, and making a discrete allocation of resources.

The management system should be flexible so that it can be used regardless of the level of the decision-maker. The information should be available for all levels; however, the amount of detail and how it is presented to each decision-maker should be adjusted to the specific needs. For example, a local decision-maker who struggles with limited resources can expand its field of view to understand what is happening in adjacent areas, allowing directed requests for assistance to those who have resources available.

To make acquisition, integration and dissemination of information possible it is necessary to have operator terminals with mobility features suited to users' roles and having an architecture that supports data transfer using radio communications (e.g., radio, satellite, GSM).

Figure 7.3 shows an example of a distributed architecture for an integrated emergency management hierarchy where user terminals offer different degrees of mobility. The main coordination centers may meet their functional requirements in fixed installations; however, teams on the ground need to have portable terminals which provide greater mobility (e.g., portable computers, tablets or smartphones).

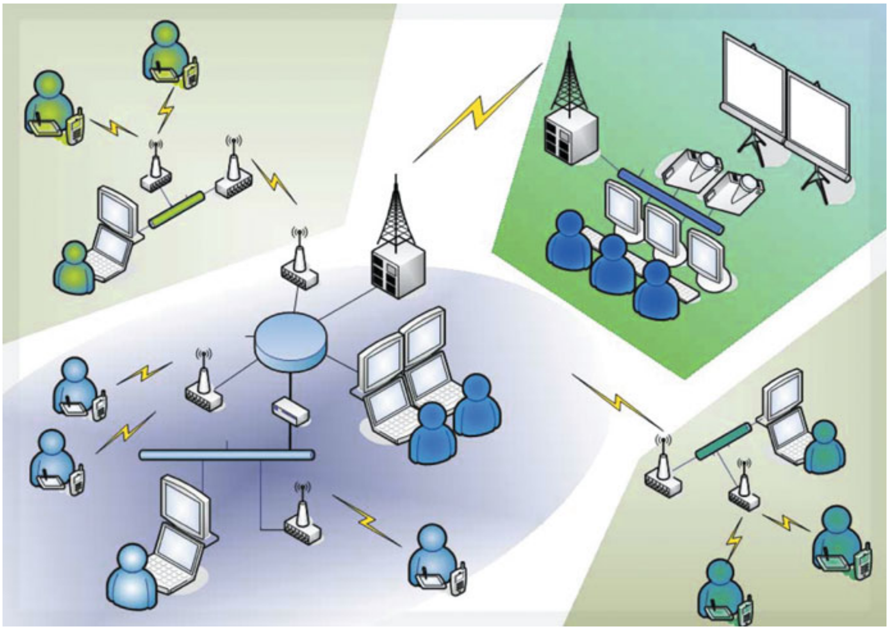

Fig. 7.3 Example of a distributed emergency management integrated system architecture. (Adapted from Simões-Marques 2005a)

7.3 SINGRAR Model

7.3.1 General Characteristics

Unlike what happens in the operational/tactical component of the warfare where several systems are available to assist the decision-making process, there is a lack of similar tools for the command and control of the emergency management activities, namely the ones that provide courses of action advise based on the current operational context.

SINGRAR is an emergency management model that was developed for implementing fuzzy distributed emergency management expert systems. The model was first implemented in an EMS for the Portuguese Navy to assist Command and Control functions related with the emergency management in warships.

SINGRAR is the Portuguese acronym for Integrated System for Priority Management and Resource Assignment.

The system (a) provides a common platform for the compilation of the incident status, (b) includes decision support system features that provide support for managing priorities of alternative courses of action (e.g., equipment repair, damage control) based on the current operational context (e.g., threat assessment), (c) supports the damage control C2 process, (d) acts as an expert system advising actions regarding, for instance, ship's combat system, platform and damage control, and (e) is a platform that federates different databases which are used in conjunction with the knowledge base.

SINGRAR model was implemented in a flexible and scalable expert system shell, which allows the parameterization of the knowledge base according to the characteristics of the Universe of Discourse. For instance, when used on naval applications the ship's characteristics can be configured, thus accommodating virtually any type of ship; when used in shore applications the facilities and processes characteristics can be configured, accommodating virtually any type of infrastructures (e.g., industrial, urban, regional).

Due both to the complexity of the evaluation and advice problems handled by SINGRAR model and to the vagueness of most of the data under consideration, a fuzzy logics (Zadeh 1996) approach was selected for the underlying inference process.

The implemented system uses a distributed architecture and has several advantages over the classical manual procedures. Some of the more relevant advantages are the instantaneous integration of the information compiled at different workstations; the automatic and coherent reaction to data changes; the fault tolerance; the increased survivability of compiled information and decision support capabilities; and the decrease of total time between acknowledging an incident and the triggering of the response, thus improving tempo, information sharing, situational awareness, responsiveness and coordination.

The system provides also means for virtual training of decision-makers and for simulation.

7.3.2 FDSS Model

As previously mentioned there is a lack of command and control intelligent tools to support the emergency management activities. There are strong reasons for the lack of such capabilities. First, any such decision process is extremely complex due to the high number of parameters under consideration. Second, one faces the problem of "explaining" to a machine the meaning of vague concepts usually used in situational characterization, such as the ones implicit in linguistic expressions like "*severe limitations*", "*very degraded*", "*quickly repaired*" or "*very important asset*". Another important problem is the vagueness inherent to the information used by decision support systems, with classifications based in natural language, i.e., in terms of human language. Even if this language is constrained by some formalism, there will be the question of how to handle such statements as "*asset A, which is fundamental to respond to threat X, is degraded*" or "*asset B, which is very important to respond to incident Y, is unavailable*". These problems are further increased if a multi-domain scenario is considered (e.g., security, rescue, health, damage control, supply chain, reconstruction) as the one that characterizes HADR. Classical set theory and Boolean logics present serious limitations to manipulate data that has such ill-defined outlines.

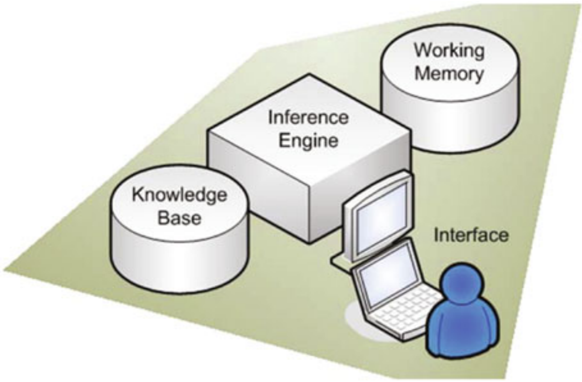

Fig. 7.4 Standalone version of the EMS implementing the SINGRAR model

The complexity of the evaluation problem handled and the vagueness of most of the data under consideration, led to the selection of an approximate reasoning approach in the implementation of the SINGRAR model, which was based on a Fuzzy Multiple Attribute Decision Making (FMADM) model (Chen and Hwang 1992; Zimmermann 2001). The Fuzzy Set Theory (Zadeh 1965) is a generalization of classical set theory that provides a way to incorporate the vagueness inherent to phenomena whose information is highly subjective and supplies a strict mathematical framework that allows its study with some precision and accuracy.

In Box 7.1 are presented some basic concepts of the Fuzzy Set Theory. The first stage of development of the model, concluded in 1999, resulted in the production of a fuzzy decision support system (FDSS) standalone prototype for emergency management which ensured the core functionalities of the system (Simões-Marques 1999; Simões-Marques et al. 2000). Figure 7.4 depicts the architecture of such FDSS.

Box 7.1 Fuzzy Set Theory Basics Fuzzy Set Theory (FST) was formulated by Lotfi Zadeh, based on the conviction that conventional quantitative techniques are not adequate to deal with humanistic systems neither with similar complex systems. Humanistic systems are the ones that deal with problems using an approach comparable to human reasoning; opposite to mechanistic systems, which reduce systems behavior to deterministic laws of mechanics, electromagnetism or thermodynamics.

The fuzziness treated by the FST relates with the semantic interpretation of events, phenomena or statements, i.e., when the vagueness is related with the meaning of a concept. This fuzziness is present in most human activities, particularly the ones involving judgment, evaluation and decision, whenever natural language is used, since the meaning of the words is frequently vague and context dependent.

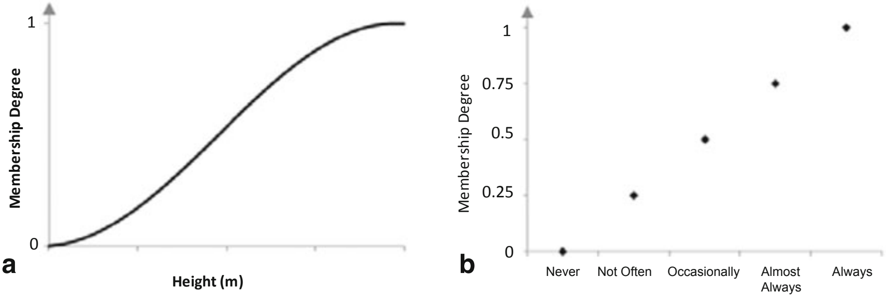

Fig. 7.5 Example of (**a**) a continuous and (**b**) a discrete fuzzy set

FST provides a strict mathematical framework (fuzzy arithmetic and logic) for the study in a precise and accurate way of conceptually vague phenomena. This framework, which also encompasses the concept of linguistic variable, supports approximate reasoning and information extraction and processing in an increasing number of application domains, for instance artificial intelligence, computer science, control engineering, decision theory, expert systems, logic, management, operations research, pattern recognition or robotics.

The basic concept is that a fuzzy set presents a boundary with a gradual contour, by contrast with classical sets, which present a discrete border. In a classical set an element either belongs fully to a set or is not member of that set (i.e., the membership to a classical set is either 1 or 0, meaning true or false). However, in fuzzy sets the membership (μ) of an element may be partial, i.e., it can be considered as satisfying only part of the requirements established to be member of full right of that set, therefore partial degrees of truth are admitted (i.e., the membership degree can vary between 0 and 1, inclusive). Figure 7.5a illustrates one continuous fuzzy set, representing the concept of “high”, while Fig. 7.5b illustrates a discrete fuzzy set (in this case a linguistic variable) representing the concept of “periodicity”.

A membership degree equal to zero means that the element is not member of the set. The closer the value gets to one the bigger is the affinity of the element to the set. A membership degree equal to one means that the element is member of the set.

Fuzzy sets admit a set of basic operations such as union, intersection, complement, product, Cartesian product, concentration and dilation, which allow for the development of a fuzzy arithmetic and logic.

Fuzzy logic is an approximate reasoning process that allows the production of relevant results based on imprecise or vague premises.

From a conceptual point of view, the SINGRAR model lays on a rule based priority management inference process.

Considering a response to incident decision problem context the rules can adopt the following structure:

IF incident impact is high **AND**
incident severity is high
THEN incident response priority is high

Such rule is the final one of an inference chain where, for instance, incident impact (or criticality) assessment is based on rules like the following:

IF human health impact is high **OR**
infrastructures impact is high **OR**
... **OR**
environmental impact is high
THEN incident impact is high

Obviously, due to the high number of foreseeable incident types and to the high complexity of interdependencies, defining crisp/Boolean rules for each relevant combination (of the multidimensional incident impacts and incident severity) would be almost impossible.

The approach used in the SINGRAR model is based on a fuzzy quantification of the degree of truth of each statement in the condition side of the rule, followed by its aggregation by means of fuzzy operators. For example, the conclusion of the first rule can be numerically computed using the following expression, where the result is a measure of the degree of truth of the statement "incident response priority is high":

$$\mu_{priority} = \mu_{impact} \otimes \mu_{severity}$$

where:

$\mu_{priority}$—truth degree of the conclusion "*response priority is high*"
μ_{impact}—truth degree of the condition "*incident impact is high*"
$\mu_{severity}$—truth degree of the condition "*incident severity is high*"
$\otimes$—fuzzy intersection operator (*t-norm*)

Both the condition statements and the conclusion are quantified in the interval [0, 1], where 0 means no priority, no impact or no severity and 1 means the highest priority, impact, or severity. Intermediate values can represent different degrees of priority, impact, or severity. Identically, on the case of the second rule presented the assessment of the degree of truth of the statement "incident impact is high" can be numerically computed, this time using the expression:

$$\mu_{impact} = \mathrm{U}_i \quad \mu_{impfactor\ i}$$

where:

μ_{impact}—truth degree of the conclusion "*incident impact is high*"
$\mu_{impfactor\ i}$—truth degree of the i^{th} condition "*impact* (*factor*$_i$) *is high*"
U_i—fuzzy union operator (*t-conorm*)

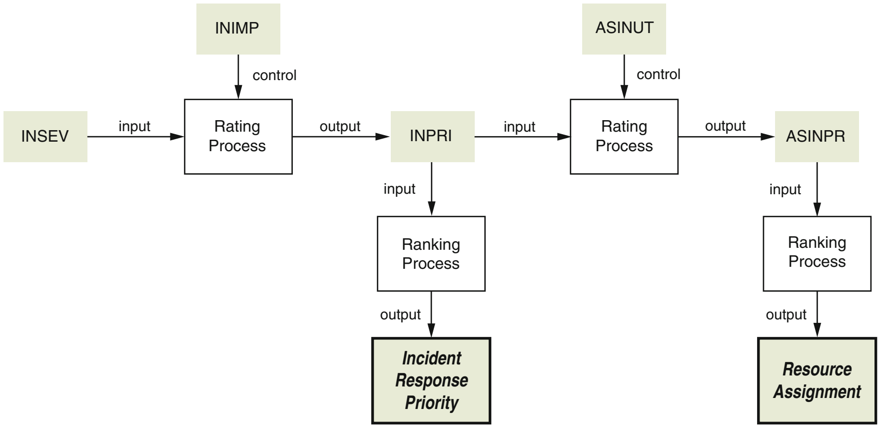

Fig. 7.6 Scheme of the SINGRAR FMADM model. *INPRI* Incident response priority evaluation fuzzy set; *ASINPR* Asset assignment priority to incident evaluation fuzzy set; *INIMP* Aggregated incident impact fuzzy set according to situational context; *ASINUT* Asset to incident utility fuzzy relation; *INSEV* Incident severity fuzzy set

Membership degrees can be obtained either by means of linguistic variables (Zadeh 1975a, b, c) or continuous membership functions. The relation between the antecedent part (IF) and the consequence part (THEN) of the Rules is defined by means of fuzzy relations. Furthermore, the model can increase in sophistication, thus in complexity, by assigning weights to the different decision factors, incorporating their preferences or importance to the decision; and by selecting fuzzy aggregation operators that produce some desired effects, such as synergy of factors. Detailed descriptions of the model can be found on (Simões-Marques 1999; Simões-Marques et al. 2000; Simões-Marques and Pires 2003). These types of issues are also discussed in detail by the authors in the context of risk analysis in (Nunes and Simões-Marques 2012).

As the second rule reveals the evaluation of the criteria can be a rather complex task since the SINGRAR model considers several operational and technical factors related, for instance, with selection and prioritization of a set of tasks the emergency response system is able to perform, taking in to consideration different potential incident scenarios and the characteristics of the Universe with which the EM response system is interacting.

Incident response priority and resource assignment assessment processes both follow a similar approach where a ranking process sorts priority levels evaluated by a rating process. The scheme of the SINGRAR FMADM model combining incident response prioritization and resource assignment processes is depicted in Fig. 7.6.

Another important feature of the Fuzzy methodologies is associated with the fact that Fuzzy Set Theory is a generalization of the Classical Set Theory. This means that the results of other analysis methodologies (e.g., probabilistic, optimization, propagation or stability models) can be integrated in the Fuzzy model.

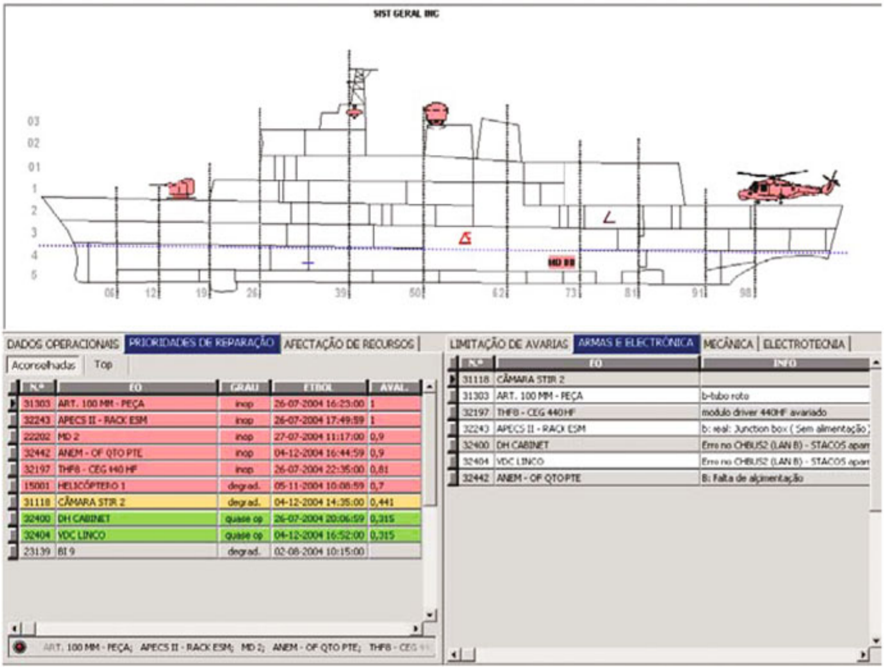

Fig. 7.7 Expert system screen used in support of top level decision-making

7.3.3 Distributed Expert System

The subsequent phase of the model implementation was the development of an expert system (Kandel 1992; Turban and Aronson 2000) shell that allows the parameterization of the knowledge base according to different ship classes' characteristics thus accommodating virtually any type of ship.

Such expert system uses a distributed architecture based on a Local Area Network that supports data transfer between workstations placed for instance on critical decision centers onboard the ship. Further to advising on priority and resource assignment new features were added on this version improving SINGRAR capabilities (e.g., advice, explanation about the presented recommendations, and damage control C2). An example of screen used by top level decision-makers is illustrated in Fig. 7.7.

The distributed architecture has several advantages over the classical manual system (voice communications and board recordings) such as:

- instantaneous integration of the information compiled at different workstations;
- automatic and consistent reaction to data changes;
- increased survivability of the compiled information and of the decision support capabilities in case of failures;

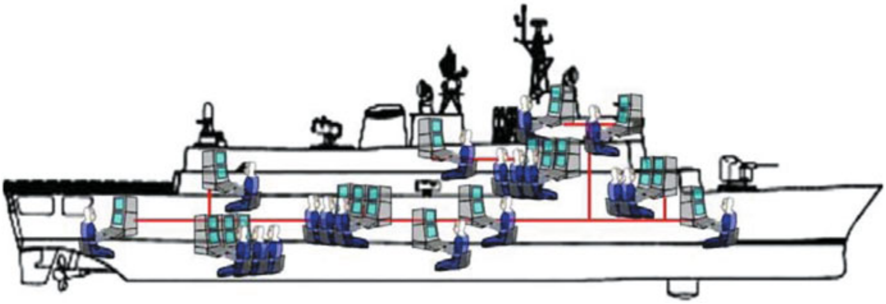

Fig. 7.8 Example of distributed system configuration

- reduced human workload on command and control activities;
- reduced human error;
- decrease of the time lag between acknowledging a fault and the triggering of the repair process;
- broadcast of advice on recommended courses of action, and prediction of operational impact resulting from damage;
- alternative means of communication.

Figure 7.8 illustrates a typical EMS configuration to use onboard warships, manned when the ship activates Emergency Stations.

The three main decision centers (Operations Room, Weapons Engineering center, and Machine Control Room) have a large number of workstations that are permanently manned and coordinate all EM activities. Damage control organization has three coordination cells also permanently manned. Several other workstations provide access to the EMS for data input, status monitoring or action advice. These workstations, not permanently manned, are located for instance on equipment compartments, medical centers, and backup command centers. The initial configuration for the distributed system used a Client-Server architecture. However since this solution is not totally reliable and the EMS is most needed when it is more probable that equipment fails, namely Servers and LANs, a new approach to ensure EMS survivability was pursued. Basically every workstation is able to operate independently from others; nevertheless the workstations actively look for others and try to cluster in a federation that can share data related with the situational status. If the data transfer infrastructure is working properly the behavior of the system is identical to a centralized system. In case of failure the system still survives, with one or several groups of workstations sharing information, or with stand-alone workstations where the information is updated manually based on voice communications.

Implementing this approach presented some challenges, like the detection and management of the integration of newcomers to a group of workstations or the exclusion of "missing" partners; or the fusion of data from different sources in order to provide a unique and coherent situational picture. Since these actions should be as transparent to users as possible, a multi-agent component (Jennings and Wooldridge 1998;

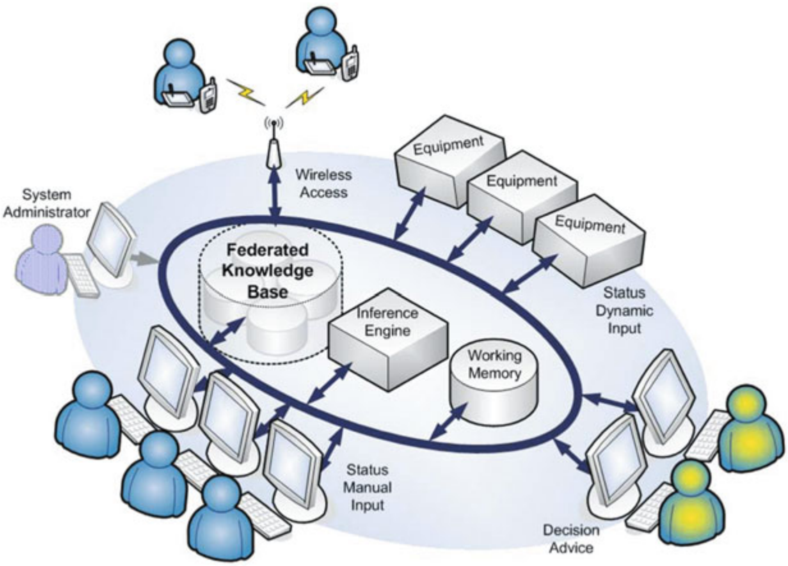

Fig. 7.9 EMS depicted as a virtual centralized system. (Adapted from Simões-Marques 2005b)

Sycara 1998; Jennings and Lespérance 2000), was implemented and tested on the EMS. The agents operate autonomously:

- monitoring and responding to evolutions in network partnerships;
- synchronizing data contents on distributed databases.

Using this approach the EMS is able to operate with intermittent connections and still consolidate a common picture.

Figure 7.9 presents a view of the EMS depicted as a virtual centralized system. Some promising tests were also performed to try the use of wireless technologies to automatically feed inputs to the system (e.g., personnel monitoring using RFID).

7.4 Model Generalization

As it was unveiled in the latter sections, accommodating C2 requirements for different users operating onboard a ship is a challenging task. Nevertheless, no matters how big a ship is, the amount of knowledge associated to her is finite, i.e., the Universe of Discourse for EM decision-making purposes is quite "dominable". Despite experienced professionals can even dispense decision support tools as assistants for many daily tasks, these systems are a major asset and provide competitive advantage for training and simulation, and mostly for real live management of complex and high stress situations, where humans tend to fail their judgments (a matter commonly discussed as decision making under bounded rationality (Simon 1955).

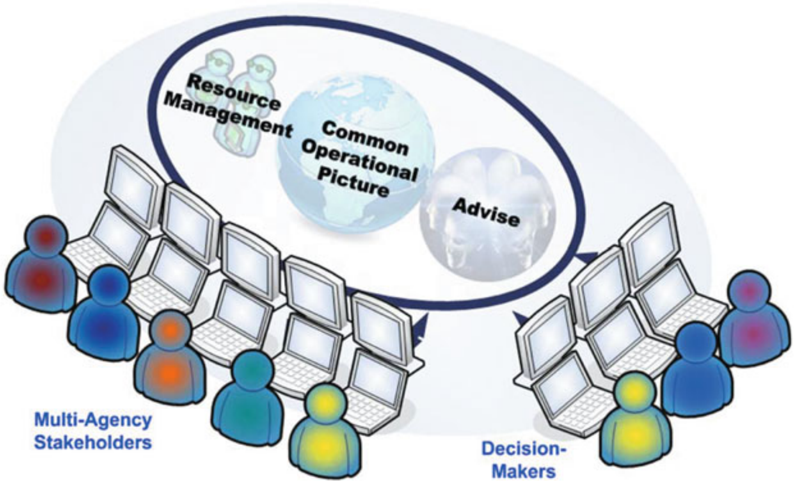

Fig. 7.10 A view of a generalization of the SINGRAR model to complex emergency management in an inter-agency environment

The need for support and exchange of information increases dramatically whenever one operates on an unknown area, even if performing a task for which training was received. The same is true for the operations' commanders/coordinators that need to have a clear picture about incidents and assigned resources.

Complex scenarios like man-made disasters (e.g., oil spills, industrial incidents) or natural disasters (e.g., floods), catastrophic accidents (e.g., earthquakes) or military operations other than war on remote areas (e.g., Non-combatant Evacuation Operations on underdeveloped countries) may be given as examples where this need becomes evident. The picture compilation and resource coordination calls for an emergency management infrastructure that supports all C2 activities (Simões-Marques 2005b). This operational scenario reflects the generalization of the SINGRAR model in order to integrate and support more levels of decision in an inter-agency environment (Fig. 7.10).

Besides the development of feasible models there are obviously many other issues related with technology (e.g., interoperability of systems and data models), organizations (security, culture and procedures) and, not least, with policy that are a challenge to the successful implementation of large scale decision support systems.

7.5 Inter-agency Coordination Scenario

This section illustrates a scenario where the model described above could be used in benefit of Emergency Management process. The following scenario, despite fictitious, is realistic since it places actual events in similar industries existing in a different geographic location.

Fig. 7.11 Scenario of a complex emergency management situation requiring inter-agency coordination

An incident in the demolition of a large structure near the perimeter of petrochemical facilities resulted in its collapse over a pipeline causing an explosion followed by a large fire in a fuel reservoir. The facilities are in the banks of a river, opposite to one of the countries' largest cities and very close to another large urban area. Despite these urban areas are in no immediate danger, a strong response force is required because some main infrastructures and services are being affected by the heavy smoke plume. Thus, local Emergency Management Coordination center took control of the situation. In complement of the petrochemical company's and of the local fire department response resources, the port authority was also engaged, and maritime fire fighting capabilities were mobilized, consisting of a couple of tugs equipped with high capacity water cannons, and other means to control a potential spill of pollutants. The port authority also restricted the navigation of the shuttle ferries that cross the river and of commercial traffic entering and leaving the harbor. The accident occurred at the basis of a cliff where a bridge reaches the margin. This bridge is the main road and railway infrastructure connecting the south and the north of the country. The heavy smoke caused some road accidents, forcing the traffic authorities to close the highway. The train circulation was also forced to stop. The final approach corridor to one of runways of the local international airport is above the affected area. Air traffic control was contacted and air traffic was rearranged to prevent low altitude flights over the risky area. The dense plume of smoke is spreading in the top of the adjacent cliff, heavily affecting the air quality. Population in the area had to be evacuated, particularly an existing hospital. This required the activation of civil protection lodging plans and the call of Armed Forces to provide transportation and other logistic support. Figure 7.11 depicts the geographical context of the described EM scenario.

An example of the application of SINGRAR model to assess the priority of the incident response is presented in Box 7.2.

Box 7.2 Application of SINGRAR Model to Emergency Management For maintaining the example simple, it will be assumed that the evaluation of the attributes considered is done based on the linguistic variables *severity* and *impact*, defined as discrete fuzzy sets:

$$\begin{aligned} severity &= \frac{1}{high} + \frac{0.7}{medium} + \frac{0.35}{low} + \frac{0}{irrelevant} \\ impact &= \frac{1}{high} + \frac{0.75}{quite\ high} + \frac{0.5}{medium} + \frac{0.25}{low} + \frac{0}{irrelevant} \end{aligned}$$

It is also assumed that the impact factors considered for the "*petrochemical factory incident*" are only the ones presented in Table 7.1, that were classified as shown.

The first step is to aggregate these individual assessments in a single incident impact degree (refer to INIMP in Fig. 7.6). This aggregation requires the selection of a fuzzy union operator. The most basic fuzzy union operator is the *max* function, which will be used in this example; therefore, considering the membership degrees associated to each linguistic variable:

$$\mu_{impact} = U_i\, \mu_{impfact\, i} = \max\left(0.5, 0.75, 0.5\right) = 0.75$$

For the incident Rating Process it is required the input regarding the incident severity. It will be assumed that it was classified as "*high*" using the *severity* linguistic variable.

The aggregation of the severity with the impact requires the selection of a fuzzy intersection operator. Considering its characteristics the *product* function presents an adequate behavior for this aggregation; therefore the incident priority is rated using the following formula:

$$\mu_{priority} = \mu_{impact} \otimes \mu_{severity} = 0.75 \times 1 = 0.75$$

This incident priority is then compared against other incidents that concur in time with this one. Table 7.2 illustrates a scenario where this incident is the second in terms of response priority, considering that the "*wild fire*" incident has a higher priority.

As mentioned, the model can be refined using weights for the factors, which can improve the discrimination of the rating process. For this example it is assumed that the weights shown in Table 7.3 were defined based on the following linguistic variable:

$$importance = \frac{1}{high} + \frac{0.95}{medium} + \frac{0.9}{low}$$

Table 7.1 Linguistic classification of Incident on the different impact factors

	Impact factor		
	Human health	Infrastructure	Environment
Linguistic classification	Medium	Quite high	Medium

Table 7.2 Example of a list of incident priorities

Incident	Rating	Ranking
Wild fire	1	1st
Petrochemical Factory	0.75	2nd
Highway traffic accident	0.56	3rd

Table 7.3 Linguistic classification of the weights of the different impact factors

	Impact factor		
	Human health	Infrastructure	Environment
Importance	High	Medium	High

The rating process would then be affected by the weights ($\omega_{impfact\ i}$) as follows:

$$\mu_{priority} = \mu_{impact} \otimes \mu_{severity} = U_i(\omega_{impfact\ i} \times \mu_{impfact\ i}) \otimes \mu_{severity}$$
$$= \max(1 \times 0.5, 0.95 \times 0.75, 1 \times 0.5) \times 1 = 0.71$$

Whenever possible the application of the FMADM model to the decision-support in a specific context requires the previous parameterization of the Knowledge Base to the geographical and organizational reality and of the Inference Engine to the business rules applicable in such context. This improves the accuracy of the advice provided by the expert system. Nevertheless the basic framework to adopt in emergency management is quite generic. Figure 7.12 illustrates just a small portion of such framework, which reflects fuzzy relations that can be used to assess the utility of the assets to assign in an incident such as the one described in the above scenario (refer to ASINUT in the FMADM model presented in Fig. 7.6). The fuzzy relations are expressed by arrows connecting attributes for the different categories with a μ symbol, which conveys the strength of the relation (a fuzzy value).

The diagram illustrates some relevant relationships between Responders and Incident Types, considering factors such as Incident Impact Type, Geographical Context or Response Coordination. The completeness of the model depends on the amount of attributes considered in these relations. On the other hand the accuracy of the advice depends on how well the Knowledge Base relations reflect real world relationships.

The inter-agential nature of the scenario is obvious and the model also reflects this fact, since the response coordination involves several entities that should cooperate to improve the effectiveness and efficiency of their collective effort. This goal can be achieved if all entities share a common operational picture that allows gaining situational awareness (as presented in Fig. 7.10), and can anticipate the courses of action of other stakeholders in the process. The use of common Emergency Management System is undoubtedly a step in that direction.

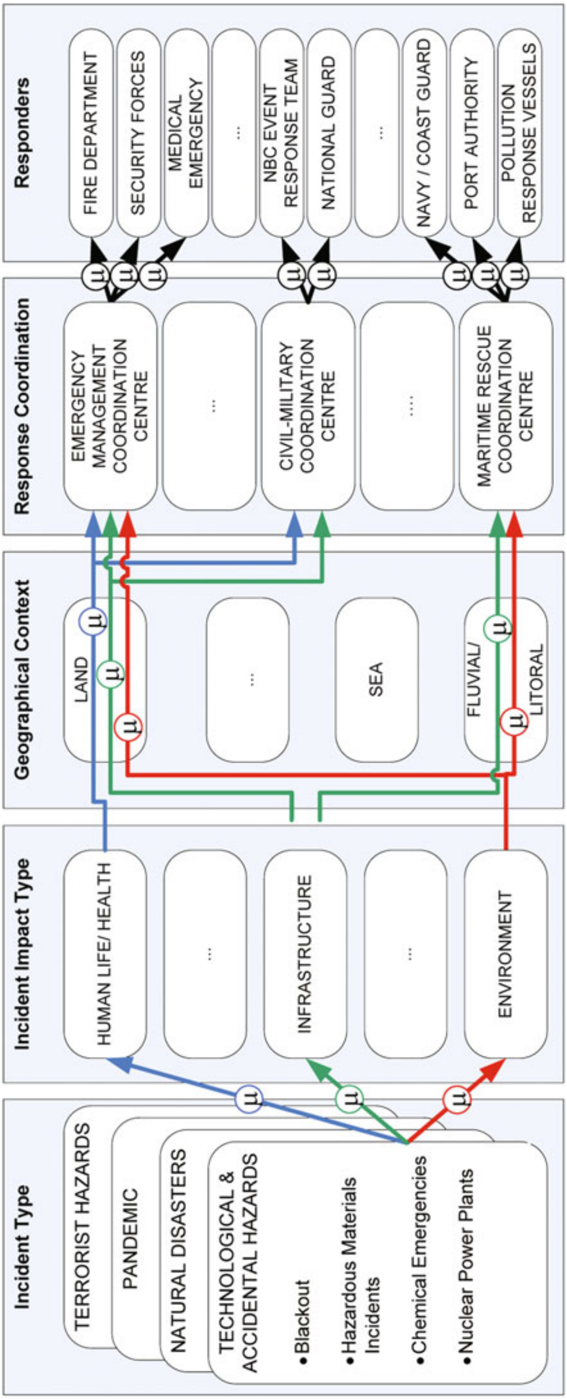

Fig. 7.12 Examples of fuzzy relations analyzed to support the emergency management inter-agency process

7.6 Conclusions

Two types of interventions performed under the scope of civilian crises management are Humanitarian Assistance and Disaster Relief operations. Effective Humanitarian Assistance and Disaster Relief operations ask for unity of effort of a variety of International Community actors. To reach the desired unity of effort some requirements are essential. Information sharing is one which is critical to gain situational awareness allowing the identification of (1) what assistance is required and where, and (2) which actors are engaged in the process and what support they can offer. Once there is some level of understanding about the situation, decisions have to be made regarding the more effective distribution of assistance according to the needs. One goal of the decision-making process is setting intervention and support priorities. A second one is leveling the resources, avoiding both excesses and deficits. Multi-Attribute Decision Making (MADM) methodologies can help dealing with this type of problems. However most of the information available in critical situations is vague or imprecise. Fuzzy Logics provides a coherent mathematical framework to deal with uncertainty and imprecision. Thus, the use of Fuzzy MADM (FMADM) methodologies may be an adequate approach to help managing priorities and allocating finite amounts of resources. Decision support systems (DSS) are computer-based information systems that support decision-making activities. The use of a distributed DSS that operates based on a FMADM can be particularly useful in assisting the needs of a community of actors that want to share information and coordinate their humanitarian and relief efforts and resources in an effective way.

This chapter presented the application of the SINGRAR model to support emergency management operations, namely humanitarian and disaster relief operations. The model was developed to dynamically manage priorities based on situational parameters and select the most adequate resources to assign considering emergency situations. SINGRAR model was implemented in a customizable distributed expert system shell that was developed to be scalable and adaptable to different scenarios. The first implementation of the model addressed the management of critical incidents resulting from combat/emergency on board of navy ships, of different classes. Another example of solution developed addressed the management of emergency in complex infrastructures, such as industrial facilities.

The chapter offers a brief description of the emergency management requirements, and a discussion on the main features of the SINGRAR model applied to the Command and Control of emergency management considering the context of HADR operations, particularly regarding the benefits of the adoption of the FMADM approach in which it lays, and of the use of a distributed environment that is able to provide shared situational awareness through a common operational picture, and uniform and coherent recommendations regarding lines of action/resource assignment, contributing to the desired unity of effort. An EMS based on the SINGRAR model also contributes to a high maturity interaction among organizations, offering an information sharing platform that supports collaborative decision-making.

Despite the first applications of the model were for dealing with small worlds (ships and land infrastructures) the results obtained were very robust. The implementation of the SINGRAR model to support of HADR operations is the natural evolution. In many issues the generalization of the model is just a matter of scale. Nevertheless there are still big challenges to face, for instance in order to perform the knowledge engineering activities related with feeding the system Knowledge Base. The inter-agency scenario presented in Sect. 7.5 illustrates both a small scale yet complex incident where an EMS is useful and some of the relationships that can be considered to support the decision process, contributing to a coordinated, effective and efficient Emergency response.

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Chapter 8
Logistics for Decision Support—An Application in Cases of Natural Disasters

Christian Tesch and Uwe Clausen

8.1 Situation

Road transport networks are usually modeled as nodes and edges. Many scientific contributions in the field of disaster logistics focus here on the edges in terms of tour planning and transportation network planning. Doing this, logistic processes of disaster relief is often regarded on a higher level (Kovács and Spens 2007; Özdamar et al. 2004).

However, the basis of any planning of transportation networks also results in the performance of the involved transshipment nodes (Hale and Moberg 2005). Further contributions on capacity calculation and performance evaluation of handling facilities exist more in form of site location planning issues, where the choice of nodes to be built in disaster areas is examined as mathematical problem.

The lack of leaving out node resources like doors, forklifttrucks, areas and staff in mathematical models may end up in node overflows and supply bottlenecks (Balcik and Beamon 2008; Hale and Moberg 2005). The solution approach of this paper offers the possibility to be combined with several simulation and mathematical models. For example, externally generated delivery schedules of vehicles with given shipment information can be used as input data of incoming trucks at one node.

Intra-transport routes are determined by fixed assignments of outbound relations to door, where the goods have to be moved to reach their destinations in the transportation network. In literature only few approaches optimizing LTL processes exist and are focusing only on the improvement of one of these activities (e.g., Bartholdi and Gue 2000; Braysy and Gendreau 2005; Chmielewski et al. 2009; Ghiani et al. 2003; Laporte et al. 2000; Savelsbergh and Sol 1998; Tsui and Chang 1992).

To narrow the wide field of applications in cases of natural disasters it is necessary to focus on the specific situation. Considering a natural disaster which destroyed a

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working infrastructure, many people became homeless. There is the need of a quick supply of relief goods and special medicaments. In detail, regarding relief goods characteristics is important for our work. Relief goods often have to be transshipped near to the area of the natural disaster. Therefore, problems like few resources and various handling devices have to be considered. Especially varying amounts of packages, weights, sizes and arrival times produce difficulties for planning the transshipment. Very important is a quick handling of vital important shipments like medicaments and food.

Because of these characteristics, the handling must always be planed ad-hoc near to the disaster area and potentially known concepts of relief goods supply have to be implemented in a couple of days. Therefore, it is possible to learn from existing solutions of logistics research. The following aims express the requirements of the optimization:

- Increasing cargo handling
- Minimization of handling distances
- Minimization of truck waiting time
- Prioritized trucks with time sensitive shipments
- Overview of resources and capacity usages
- Fast possibility to react in case of changes
- Fast calculation of an optimized discharge queue

Supporting the decisions of relief goods handling the great question is: At which time should which arriving truck be discharged at which place?

8.2 Transferring the Problem

Considering the pictured situation of relief goods handling a transfer needs to take place to a suitable logistic concept. All relevant actors and influential factors of the transshipment process are taken into account. The best suitable logistic cargo handling concept is shown in Fig. 8.1.

We decided the concept of LTL transshipment to compare to relief goods handling. Doing this, it is possible to discover close similarities of packages, vehicles, handling devices and characteristics of the arrival forecasting. In addition the comparison of facility properties in Fig. 8.2 shows the possible transfer to handling areas in regions near to a disaster.

Transferring the decisions of piece goods handling to cases of natural disasters we analyze in detail the process of the entire transshipment. The first decision is which vehicle should be unloaded first, at the time if more than one vehicle is reaching the terminal or more than one vehicle are waiting to be unloaded. By approaching the cut-off time (the latest arrival time for trucks so that shipments can enter the network on the same day) it is more likely that several vehicles are arriving simultaneously. Thereafter, the assignment of vehicles to inbound doors and with that intra-terminal transport decisions have to be made.

Fig. 8.1 Enumeration of influential process factors to relief goods handling

	Piece goods		Relief goods
Packages	1 kg up to 3000 kg	➢	Medicaments up to machines
Shipments	Time-sensitive	➢	Vital important shipments
Vehicles	"Van" up to truck, airplane	➢	Car up to trailer train
Arrival forcasting	Ca. 40 % of Pick-up orders are unknown at tour start	➢	Damaged/ destroyed routes
	Rush-hour traffic		Robbery
Handling devices	Handcart up to fork lift truck	➢	"Hands" up to crane

Fig. 8.2 Transfer of handling facility properties

	Piece goods		Relief goods
Facility	Gates	➢	Gates/storage areas
Handling areas	Buffer areas	➢	Earth/floor

Small and medium-sized LTL-agencies as well as large cargo carriers detected the opportunities in the coordinated control of sequences in the yard, resources and processes in the forwarding terminals. As a result of this, control centers are already implemented in several terminals. Mostly there is a monitor, an inner and an external camera system and a radio telephone system. Although the actual solutions are considered in practice to be very progressive, the lack of a central database and a software-based planning methodology are crucial disadvantages. The dispatcher must obtain the information he requires of the situation on the yard and the forwarding agency through various media. Especially in peak hours of operation, it can lead to congestion and lack of information. The lack of a standardized planning methodology currently leads to solutions that are only able to visualize the status quo of the system. This raises the question whether a support of the dispatcher through intelligent planning makes sense because of the highly complex planning task. Although some work integrate intra logistical aspects in combination with the dimension of time and the models are very practical, they require long calculation times. Additionally, the developed algorithms lack dynamic aspects (e.g., late arrival) and are completely inflexible.

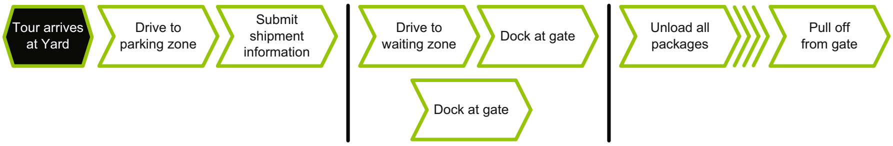

Fig. 8.3 The process chain of the relevant yard movements in the discharge

8.3 Solution Approach

An efficient transport has a positive effect on the utilization of resources (e.g., buffer areas, forklift trucks). The objective is to maximize the throughput of a terminal within a fixed time-period. If possible the waiting time for vehicles shall be minimized as long waiting times result in high times of unproductiveness for the trucks and congested yards.

In our test data we have a cross-docking terminal with 14 unloading gates with each 1 buffer area and more than 80 loading areas. Within the graphical layout all transshipment distances can be computed. In this terminal 25 fork lift trucks are operating. The algorithm has to handle 213 tours and more than 4,000 units, which have to be moved within 6 h. All required intra-terminal operations are reproduced in the software according to their respective execution times in the real terminal. To calculate the optimized unloading sequence, specifically adapted heuristics are developed and tested. As decisive reasons are cited here as follows: Heuristics are fast because they have mostly solutions in polynomial computation time and the quality of the determined solution for many practical applications is sufficiently high. Very advantageous for practical use is the property that the development of heuristics is also very easy to understand and therefore a transfer or integration with other applications is quite possible. The chain of yard management can be considered starting with the arrival of the vehicles at the barrier on the yard. To complete basic shipment information, the detailed information must be submitted by the truck driver at the detection point (Arnold 2008). The driver then receives a ticket with a serial number indicating the position in the unloading sequence. If time-sensitive items are on the vehicle, the driver gets a red card, which allows him a right of way at a next free unloading gate. Once he has docked at a gate, he opens the vehicle and automatically unloads all loaded packages into a buffer zone behind the unloading bays. Next he locks the car and pulls the vehicle off from the gate (Fig. 8.3).

The connection of the sub-processes between discharge and transshipment takes place in the buffer zone, where the transfer of packages from the driver to the forwarding agency happens. Subsequently, an employee can take the package with an appropriate transfer resource to the loading area to drop it there. The return trip to the buffer zone closes the process chain of each package handling. The existing transfer resource fleet consists mainly of forklifts. The further loading of the tours has usually no effect on the discharge or handling processes and is therefore not considered (Fig. 8.4).

Fig. 8.4 The chain of internal cargo handling

8.3.1 Door Assignment

The control of the yard consists mainly of sequencing the unloading gates. The algorithms developed for this purpose are based on the principle of scheduling, which makes it possible to combine a variety of resources in an overall plan (Conway et al. 2003; Maravelias and Sung 2009; Zäpfel and Braune 2005). As all identified resources, unloading gates, transfer resource and buffer areas are used, each of the abstract buffer spaces is seen as one resource. Because of the afterwards discharge of the tours, the calculation and optimization of the yard and hall usage is directly dependent on the arrival times of the tours. Consequently, a recalculation of the unloading sequence must be performed every time when a change occurs concerning the tour arrival list. Other changes such as the breakdown of a forklift, defect of an unloading gate or delay in the discharge can also make a recalculation necessary. The resulting non-functional requirements of the algorithm were derived as follows:

- Fast calculation of optimized unloading sequence to allow an operation in operational use
- Rapid response options for any plan deviation
- Inclusion of all relevant actors that are needed for unloading and transshipment
- User-oriented input possibility of static data and calculation parameters

Hence, the overall objective is to achieve a more efficient handling of shipments. Specifically for the handling this means that the same handling work should be done with fewer resources in less time. The following sub-goals round off the overall objective.

- Minimizing movement ways of internal resources
- Shortening the periods of tours in the yard
- Preferred unloading of time sensitive shipments

8.3.2 Input Data

To take into account all factors that affect the entire handling process, first all the necessary input data is divided into static and dynamic data. The group of static data includes parameters that are changed more than once daily. The group of dynamic data consists mainly of the tour arrival list. This data can expand, decrease or change at any time during the day. The following data of the yard and the hall are required:

- Internal areas (position, size, destination relation(s))
- Gates (position in the hall, provided for discharge)
- Internal network of paths
- Cargo handling equipment fleet (count, velocity, shunting time)
- Process times in the yard (parking, docking/undocking, opening/closing, unloading a package)

To allow a user-friendly entry, Microsoft Visio drawing is used for modeling. Herein is modeled the layout of the forwarding hall with all gates, areas and ways to scale.

Figure 8.5 represents a LTL terminal layout. The network of paths is generated in the form of purple (route in both directions) or gray (one way) arrows. The driving time to the loading area plays an important role in the calculation of the transfer duration of one package. Every shortest path starting from each buffer area corresponds to the problem of multiple "single-source shortest path problem". In this case a path is searched in a given graph with weighted edges from one source node to all other nodes. The way is short, if it has the lowest weight. Transferred to the handling hall, this means that our problem must be solved twice as often as there are buffer zones for the unloading. Applied to the test scenario of the terminal, 492 shortest paths are calculated. The chosen algorithm of Dijkstra calculates an exact solution in polynomial time (Ottmann and Widmayer 1990; Schulz et al. 1999). A recalculation of the distances needs to be done only if the internal infrastructure changes. The results of the distance calculations are then transferred to a database.

The group of dynamic data is actually a list of tours and includes all information of the vehicles and the associated shipments. For each shipment the number of packages, the weight per package, the relation, the outgoing tour and the program type is stored. The dynamics of this data is reflected in several factors. While the number of tours remains generally constant over the day, the predicted arrival times may change very frequently.

8.3.3 Calculation of the Unloading Sequence

The calculation and optimization of the sequence was developed and tested with several heuristics Morlock and Neumann (2004). Overall, the following well-known and new scheduling methods were implemented.

- FCFS ("First Come, First Serve"): All incoming vehicles will be added according to their arrival at the next free gate to the unloading schedule. This procedure is used only as a comparison heuristic.
- FCFS with priority: This approach also serves as a comparison, but reflects the current unloading strategy in the examined forwarding agency. As an extension of the FCFS heuristic tours, where time sensitive shipments are preferred.

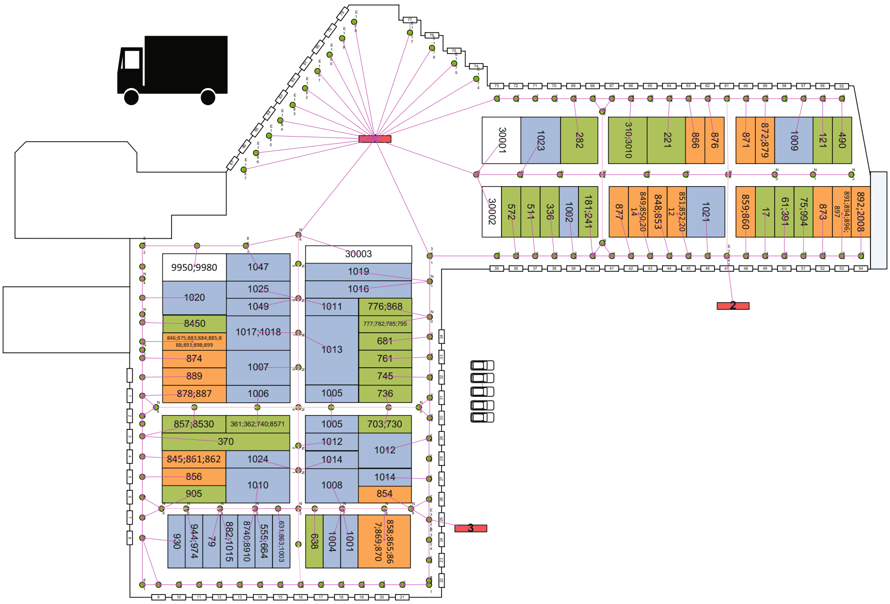

Fig. 8.5 Input of parameters of a LTL terminal

- Shortest movement: It calculates a route-optimal unloading plan for all tours. The plan will be created by adding the tours, where their packages have the shortest internal ways. Since this strategy does not consider queuing in front of the zones, the worst case is that all tours would be unloaded in the same zone.
- Longest movement: With this method, the upper limit for shipment cost is calculated. It is the opposite of the shortest movement and is used only for comparison.
- Distance-Time-optimized: This unloading plan takes advantage of the short internal ways and the waiting time of already docked tours. So, it avoids an uneven distribution of tours to the unloading zones.

The basic idea of this planning is to include every single tour with all their packages in the planning of each unloading area and then to determine the discharge end of the tour. The unloading zone in which the tour has the earliest discharge end, is foreseen for the discharge of this tour. This approach considers the following two cases of possible situations:

Case 1: The internal movements is not a bottleneck, and the discharge can begin in each zone at the same time. Thus, the tour is always discharged in those unloading area at the earliest, which causes the shortest movements ways. For these cases, the discharge has minimum movement ways, see heuristics *Shortest movements*.

Case 2: Is valid in all other situations. This means that the zone with the shortest movements ways must not be at the same time the zone with the earliest discharge of the tour. By an earlier discharge start one zone with longer ways can reach an earlier discharge end than the zone with the shortest ways.

This procedure selects accordingly the best zone for the shortest movements, but also takes into account the current situation in the unloading zones and ensures that no tour is scheduled in a zone that already has a high utilization. Basically, the order of the planning is based on the FCFS principle, so that still the "fair" distribution of waiting times for the drivers is guaranteed.

Distance-time-optimized with priority: While in the previous method the distance-time problem is already treated, this variant also takes care of the preferred discharge of tours. The integration of the priorities in the optimization is done by selecting the tour at the beginning of the calculation. First, the time of the next available free gate is determined and the amount of tours (*TYard*) is searched, which are at that time waiting at the yard and could be discharged. If at least one tour of *TYard* contains time-sensitive shipments, the tour is scheduled for discharge, whose time-sensitive shipments have the earliest departure time. If in *TYard* no tours with time-sensitive shipments are available, a priority is skipped and the further planning will continue similar to the previous strategy. As identified above, the calculation of movements has to be considered down to each individual package. In the following Fig. 8.6 a schematically scheduling of one tour with four packages is shown. For simplicity there is only one buffer space and one lift truck.

The calculation of the discharge duration of the tour begins from the arrival at the gate 74 and can only end when its last item is placed in the buffer. The duration of a package in the buffer ends with the beginning of the movement of a forklift. The forklift is released as soon as he has moved the fourth package and has returned back to the unloading area. In this example, it can be seen how the internal movements affect the discharge duration of the tours in spite of the buffer between.

8.3.4 Output Data

Various visualization and many performance indicators are created that provide information about the expected yard and facility usage.

Gate schedule To represent the gate-occupation of the unloading zones, a Gantt chart is used, see Fig. 8.7.

In the first column, all the discharge gates of a zone are displayed and marked with their respective gate numbers. The duration of each tour discharge is visualized as a horizontal light green bar. A dark red bar represents a tour with at least one time-sensitive shipment. The vertical line before the unloading start represents the arrival of the tour at the yard. As additional information, the arrival time, the number of shipments, the number of packages, the beginning and the end of the discharge are visualized.

Buffer Schedule The occupation of the buffer spaces of one unloading area is also displayed as a Gantt chart. The buffer space is mapped one line and the residence

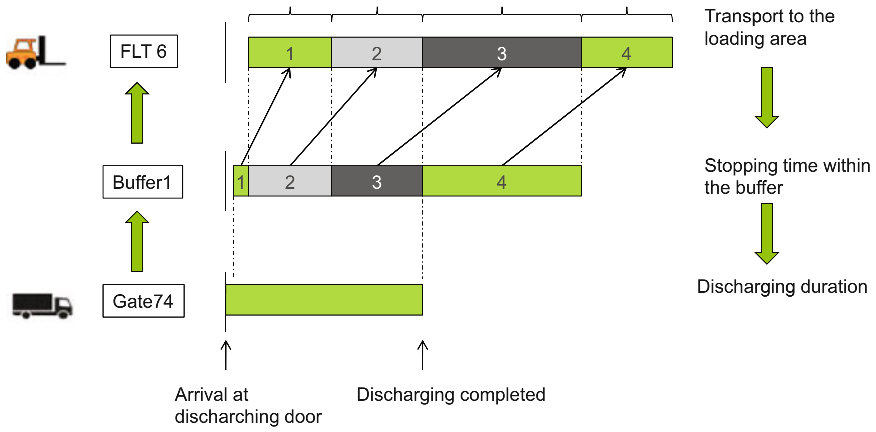

Fig. 8.6 Illustrative example of scheduling one tour with four packages

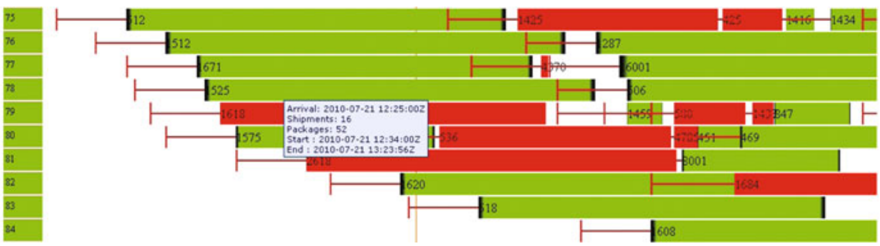

Fig. 8.7 A gate schedule for 10 gates as a Gantt chart

of a package on a buffer space is shown as an horizontal bar. Red bars represent packages of time-sensitive shipments.

Movements resources schedule Similar to the representation of the occupancy of the buffer, each package is shown as a bar in the movements resources plan.

Area occupancy based on package weights, a graphic displays a further overview of the resources of the hall, which gives information about the filling progress. In Fig. 8.8 target areas of the forwarding hall are shown.

The overview has been intentionally connected to the hall structure, so that individual areas which are spatially connected with each other can be considered individually. This allows also strategic arrangements of areas afterwards. Various decisions for area arrangement and sizing are supported by this.

Performance indicators In addition to detailed evaluations of each unloading area, internal movements and time-sensitive shipments, various performance indicators are calculated, which can be used to make detailed comparisons.

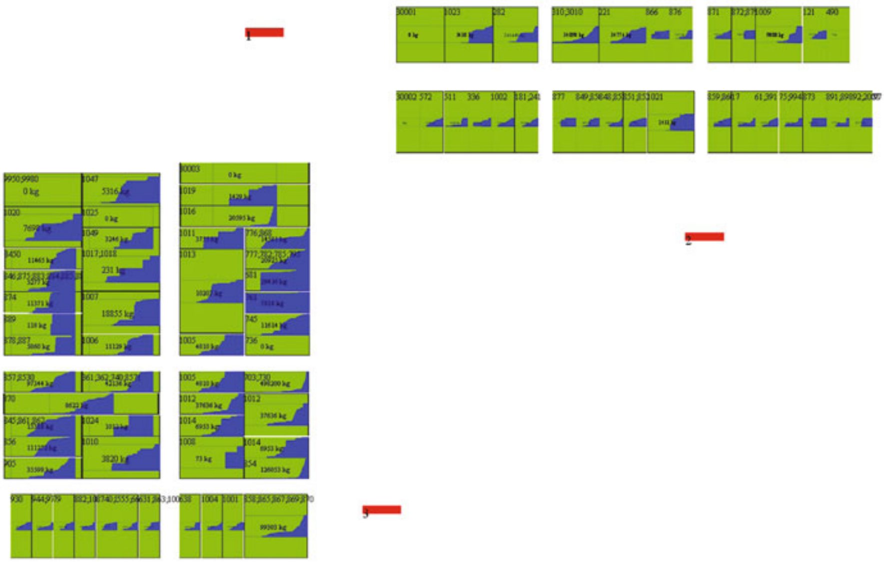

Fig. 8.8 Illustrative example of the relative area utilization

Strategy	Total distance [km]	Total discharge end [hh:mm:ss]	Total waiting time of ts-tours [h]	Avg. discharge duration [hh:mm:ss]
FCFS	350	20:09:28	52:01	0:25:41
FCFS (+prio.) (=actual strategy)	*370*	*20:11:27*	*18:46*	*0:25:26*
Shortest movements	**299 (opt.)**	(>23:59:59)	(600)	(3:06:09)
Longest movement	524 (pes.)	(>23:59:59)	(3372)	(5:57:11)
Distance-time-optimized	332	20:10:27	50:00	0:25:30
Distance-time-optimized (+prio.)	337	**20:04:20**	**18:22**	**0:24:38**

Fig. 8.9 Comparison of the main performance indicators of developed discharge heuristics

8.4 Conclusion

In this study different scheduling heuristics have been developed to solve the complex problem of gate assignment in polynomial time. One is planning unloading slots for the trucks, one is scheduling the buffering of the shipment units, and one schedules the required resources. This enables computing a solution for all tours and allowing the quick integration of additional tours. Especially the computation of the unloading times is crucial and, depending on the terminal, challenging.

To determine the quality of the optimized yard management and utilization of the hall, the heuristics above are used for comparison. In direct comparison, the main performance indicators *total distance traveled*, *total discharge end*, *total waiting time of tours* and *average discharge duration* are compared. In Fig. 8.9 it can be seen that the heuristic *Distance-Time-optimized with priority* is with 337 km distance only 14 % above the optimum (strategy *Shortest movements*) and well below the pessimum (strategy *Longest movement*).

Compared to the current behavior (strategy *FCFS with priority*), the performance indicators of the optimized strategy *distance-time-optimized with priority* show the best results, which demonstrates the potential of the gate-assignment strategies and a confirmation of the developed solutions.

8.5 Outlook

The process of relief goods handling in case of natural disasters can be supported by the shown methods. The possibility to profit from logistics research represents an advantage to prepare for natural catastrophes. Therefore, we transferred the results of logistics research to relief goods handling. The similarities of the LTL handling process and the LTL shipment characteristics demonstrate possibilities to transfer further logistic concepts to humanitarian and relief logistics. Furthermore it is planned to evaluate the results of the unloading sequence with detailed simulation runs. For this purpose, the aim is to expand the current simulation model, so that possible strategies can deal with more than one unloading zone (Neumann et al. 2006; Neumann 2007).

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Chapter 9
A Multi-agent Based Framework for Vehicle Routing in Relief Delivery Systems

A. S. Xanthopoulos and D. E. Koulouriotis

9.1 Introduction

The past decade has witnessed numerous large disasters such as the 2010 earthquake in Haiti, the 2004 tsunami in the Indian Ocean and the 2005 Katrina hurricane. Entire populations were left in need of urgent assistance due to catastrophic events. In this type of situations, the delivery of relief supplies in the early stages of the disaster is of crucial importance but it is highly complicated due to the inherent uncertainty of the post-disaster environment.

An important factor that hinders the humanitarian efforts is the uncertainty regarding the demand of supplies in affected locations. Due to the magnitude of the disaster most past data and statistics that could be used to predict the demand are rendered obsolete. However, situation assessment can be a time-consuming process and as a consequence the delivery of supplies often needs to commence before all the necessary data have been gathered. This dictates the need for the development of fast and efficient methods for coordinating the relief delivery operations that react rapidly to incoming information and operate on a minimal set of theoretical assumptions. Another source of uncertainty is the occurrence of unexpected events and situations that alter the travel times needed to dispense the supplies in an unpredictable way.

In this chapter, we model the uncertainty in demand and travel times encountered in real-life situations with the use of a dynamic vehicle routing problem (DVRP) formulation (Liao and Hu 2011; Lorini et al. 2011; Branchini et al. 2009). A multi-agent system is proposed for obtaining approximate yet qualitative solutions to it. The proposed system consists of a two-level hierarchy and two types of agents; the fleet manager agent and the vehicle agents. The fleet manager agent initiates auctions where the vehicle agents bid for new orders and implements a randomized reallocation strategy for exchanging orders among vehicles in order to generate more efficient routes. The vehicle agents compute bids with the use of an insertion heuristic

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augmented by a localized random search procedure and de-commit to previously undertaken tasks according to a binary tournament selection technique. In order to evaluate the proposed architecture, discrete-event simulation was used. The behavior of the proposed approach was compared to that of a centralized, on-line heuristic solution approach in a series of simulation experiments.

The remainder of this chapter is organized as follows. In Sect. 9.2 we present a brief review of related agent-based methods for vehicle routing problems. The formal description of the dynamic vehicle problem is given in Sect. 9.3. In Sect. 9.4 and its sub-sections the proposed approach is presented. In Sect. 9.5 the heuristic on-line procedure that was compared to the proposed approach is described. The results from the computer simulations are presented in Sect. 9.6. Section 9.7 contains the concluding remarks of this chapter along with some guidelines for future research.

9.2 Related Work

The administration of relief delivery operations following catastrophic events is characterized by a number of distinctive traits, to name a few, incomplete information regarding the needs of the affected locations and the extent of damage in the infrastructure, collaboration of multiple and diverse parties (non-governmental organizations, international organizations, armed forces etc.) and rapid response to probably remote locations around the globe. Nevertheless, numerous problems that need to be resolved in relief operations, namely, resource allocation (Arora et al. 2010), transportation scheduling of containers (Hu 2011), vehicle route construction for commodity dispatching to distribution centers (Yi and Kumar 2007) coordination mechanisms for supply chains (Balcik et al. 2010) and field vehicle fleet management (Martinez et al. 2011), are common, although customized, to issues pertaining to more standardized frameworks.

In this paper, the problem of vehicle routing /dispatching to deliver humanitarian aid is addressed. In the past few years there has been a surge in the literature pertaining to agent-based solution approaches to vehicle routing problems. The reasons for this phenomenon can be attributed primarily to the established belief that multi-agent architectures are inherently well-suited for vehicle routing problems due to their decentralized nature. Moreover, they are expected to outperform centralized optimization methods in large scale problems with high degree of uncertainty.

Selected applications of multi-agent system (MAS) technology to vehicle routing problems are cited hereafter: (Barbucha 2012; Bohnlein et al. 2011; Bayakasoglu and Kaplanoglu 2011; Teo et al. 2012; Adler et al. 2005; Claes et al. 2011). Most existing multi-agent systems use insertion heuristics to implement an initial assignment of jobs to vehicles and then employ an iterative stochastic or deterministic technique such as *b*-cyclic *k*-transfers (Thompson and Psaraftis 1993), string exchanges (Laporte et al. 2000) and random reallocations to improve the solution (Dorer and Calisti 2005; Mahr et al. 2010; Fischer et al. 1995; Kohout and Kutluhan 1999). Although simple heuristics have been frequently argued to perform better than optimization methods in highly dynamic environments, agents have been also combined with exact optimizers such as branch-and-bound (Mes et al. 2007; Persson et al. 2005). Another characterizing feature of multi-agent systems is the existence and type of a hierarchical structure within the system. At one end lies the completely 'horizontal' system where there is no agent hierarchy at all (Bürckert et al. 2000) whereas at the other end we have firm hierarchies where high level agents have complete information of other agents and coordinate them (Leong and Liu 2006).

Despite the increasing volume of publications on multi-agent architectures for vehicle routing problems, to the best of the authors' knowledge, the relief operations domain has not been dealt with explicitly. The dynamic vehicle routing problem investigated in this work models, at a certain level of abstraction, characterizing aspects of vehicle fleet management in humanitarian operations namely, uncertainty in demand volume and travel times as well as re-routing and re-allocation decisions among vehicles in response to continuously arriving information. A novel point of the proposed approach is the hybridization of the vehicle agents with a custom randomized local search procedure to aid to task de-commitment decisions. Finally, the agent-based system is compared to an adaptation of a classical routing heuristic to the dynamic vehicle routing framework.

9.3 Problem Description

Let $G = (V, E)$ be a complete graph, where $V = \{0, 1, 2, \dots, n\}$ is the set of nodes and $E = \{(i, j) | i, j \in V, i \neq j\}$ denotes the edge set. Node 0 symbolizes the depot, whereas nodes $1, 2, \dots, n$ represent the affected locations. Initially, the depot holds a homogeneous fleet of vehicles with capacity $C \in \mathrm{N}$. Each edge (i, j) is associated to the time $d(i, j) \in \mathrm{N}$ for travelling from location i to location j. For simplicity, the terms 'travelling time' and 'distance' will be used interchangeably in the text to describe the quantity $d(i, j)$. The implicit assumption is made that a vehicle needs one time unit to travel one distance unit. We assume that the problem is symmetric, i.e. $d(i, j) = d(j, i)$.

The fleet of vehicles is used to transport a single type of commodities to the affected locations. An order o is defined as the pair (i, q_i), $i = \{1, 2, \dots, n\}$ where i is the requesting node and q_i the needed quantity. All orders are assumed to be initially unknown. Information regarding the demand of the nodes arrives dynamically to the system. The time intervals between successive order arrivals follow a continuous probability distribution. The quantity q_i is the realization of a discrete random variable Q_i. Moreover, the actual time needed for a vehicle v to traverse edge (i, j) is $\hat{d}_v(i, j) = d(i, j) + \omega$, where ω is also a realization of a discrete, random variable used to model the unexpected disruptions that might occur during the journey.

Due to the turbulent post-disaster environment the distribution of the inter-arrival times as well as the probability distributions of Q_i and ω are assumed to be unknown. As a consequence there is no capability for planning; the aim here is the quick and effective reaction to the continuous flow of incoming information. Note that the proposed solution method does not depend on any assumptions regarding the underlying processes of the problem formulation, an attribute which aids to its practical significance.

The goal of the relief operations is to minimize the expression given in (1) under the following constraints: (i) vehicle capacity C (integer), (ii) the demand of all nodes must be satisfied, (iii) each node is visited only once, (iv) each vehicle route starts and finishes at the depot. When a vehicle returns to the depot its cargo is replenished up to capacity. The fleet size is assumed to be infinite. However, the number of currently deployed vehicles is dynamic (please refer to Sects. 9.4.2 and 9.5).

$$\min \sum_{i=1}^{n} T_i \tag{9.1}$$

Where T_i symbolizes the time at which pending demand of node i is met, or equivalently, the 'completion' time for node i.

9.4 Agent-Based Approach

An agent is a piece of software that implements an entity endowed with some degree of autonomy. The fundamental elements that a generic agent is comprised of are: (i) a task that the agent tries to accomplish, (ii) an agent-environment interface with which the agent is able to perceive the status of its environment, where the environment can include self-monitoring aspects, e.g. location of the agent, and the status of other autonomous agents, (iii) an instruction set that determines the behavior of the agent in different situations. The behavior of the agent may consist of elementary actions such as 'turn left' and 'increase speed', communication actions (make some information available to some agent or agents), or actions that modify its internal state, i.e. revision of its goal. The behavior of a prototypical agent is typically determined by simple if-then rules, decision trees and heuristic policies, however it is also possible to equip an agent with meta-heuristic or optimization tools to aid its decision-making process.

Any set of properly defined, interrelated and interacting agents forms a multi-agent system (MAS). MASs are inherently suitable for modeling complex, dynamic systems such as social systems, Internet applications etc. Another fruitful direction of research is the application of MASs to hard optimization problems where the optimal solution cannot be found within a reasonable computation time. This type of problems are typically dealt with meta-heuristics such as genetic algorithms, simulated annealing etc. where all relevant data or solving the problem are available to a single, central processing element, which tries to address the problem in its whole, that is without decomposing it to smaller parts. The rationale for applying MASs to hard optimization problems is that the decomposition of the original problem into smaller building blocks and the synthesis of the locally optimal solutions found by the autonomous agents might lead to an overall (globally) optimal solution with significant savings in time and effort.

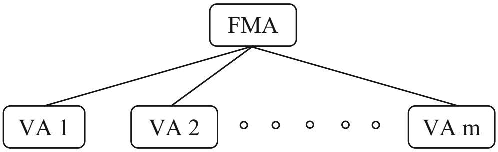


Fig. 9.1 Hierarchy of proposed MAS

9.4.1 Hierarchy of Proposed MAS and Agent Types

The MAS that was developed for approximately solving the dynamic routing problem addressed in this paper consists of a two-level hierarchy and two types of agents. At the top level of the hierarchy lies the fleet manager agent (FMA), whereas the bottom level is occupied by the vehicle agents (VA). The hierarchy of the proposed MAS is shown in Fig. 9.1. Sections 9.4.2–9.4.3.1 are devoted to the detailed description of the two types of agents.

9.4.2 Fleet Manager Agent

In the proposed MAS architecture, there is a single FMA. Its prime responsibilities are: (a) the provision of an interface between the environment and the vehicle agents, (b) the high-level management of the fleet of vehicles as described in the remainder of this section. At every time point, the FMA is aware of the number of the currently deployed VAs and has the ability to deploy an additional vehicle agent. However, and in order to maintain information localization, the FMA agent is unaware of the current state of the VAs, meaning their cargo and their planned route. The practice of breaking down the inference mechanism to multiple processing modules that work in parallel offers significant advantages regarding the robustness of the system in the sense that it would still be able to operate at the event of failure in one or more of its components. In addition to the above the modular design improves the scalability of the system.

The FMA observes the occurrence of a new demand arrival and consequently initiates an auction to assign the order to a vehicle. Only vehicles that can satisfy the demand in full are permitted to bid at the auction, and if the FMA receives no bids in some auction, it deploys an additional vehicle from the depot with the task to satisfy the unassigned demand. Note that there exists the possibility that the deployment of a vehicle from the depot could be a preferable decision in terms of minimizing the objective function despite the fact that one or more vehicles en route might be able to satisfy a newly arrived order.

A vehicle agent whose planned quantity for allocation has reached its capacity is prohibited from bidding in forthcoming auctions. Nonetheless, it is possible that the replacement of a node in the current route of the vehicle by a newly arrived order would yield a more 'profitable' route. This situation is commonly known as the 'eager-bidder' problem (Mahr et al. 2010). To alleviate this problem, the FMA implements

Table 9.1 Information available to FMA and admissible actions

	Fleet manager agent—FMA
Data	Number of currently deployed vehicles
	Data pertaining to a newly arrived order; once the order is assigned to a vehicle all the relevant information is lost to the FMA
	Set of vehicle bids for a specific order in some auction
	Internal clock structure for triggering order reallocation events
Functions	Initiate an auction
	Assign an order to a vehicle
	Deploy a new vehicle and assign an order to it
	Initiate a reallocation epoch

a randomized reallocation strategy according to which an order assigned to some vehicle is selected randomly at stochastic time intervals. That order is removed from the relevant VA's route and an auction is initiated where all allowed trucks are invited to bid.

Concluding this section, we summarize the functions performed by the FMA as well as the information that it is available to it in Table 9.1.

9.4.2.1 Auction Mechanism and Randomized Reallocation Strategy

The procedure for assigning a new order to a vehicle agent is a single-shot, closed-bid auction. In this type of auction, the participants can submit an offer only one time, i.e. they cannot improve their offer subsequently, and are unaware of the offers of other participants. Let $o = (i, q_i)$ be a new order which is announced to the FMA, where i the requesting node, and q_i the needed quantity of items. The FMA forwards the order to the set of VAs and requests bids. The VAs which can satisfy the order in full, while taking into consideration the quantities needed for the planned stops of their route, respond with a bid b_j:

$$b_j(o) = (v_j, c_j^*(o)) \tag{9.2}$$

where b_j symbolizes the bid of VA v_j, and $c_j^*(o)$ the minimum cost for inserting o into the current route of v_j. The calculation of $c_j^*(o)$ is described in Sect. 9.4.3.1.

After the bids have been calculated by the VAs, the FMA receives a set of bids B:

$$B = \{(v_1, c_1^*(o)), \ldots, (v_j, c_j^*(o))\}, j \leq m \tag{9.3}$$

where m is the number of currently active vehicle agents. It is possible that no vehicle can bid for order $o(B = \varnothing)$ and in that case the FMA deploys a new VA v_{m+1} with the goal of satisfying order o and returning to the depot immediately after that. If the set of bids B is not empty, the FMA assigns order o to the agent with the lowest bid $b_{\min}$:

$$b_{\min} = (v_{\min}, c_{\min}^*(o)) \in B \text{ with } \forall b_j = (v_j, c_j^*(o)) \in B : c_j^*(o) \geq c_{\min}^*(o) \tag{9.4}$$

Table 9.2 Information available to VA and admissible actions

	Vehicle agent—VA
Data	Announced order by the FMA
	Current location
	Current route
	Cargo
	Capacity
	Distance matrix
Functions	Execute route
	Calculate bids in auctions
	Re-route
	Select orders to reject from current route in reallocation rounds

The randomized reallocation strategy facilitates the use of information that has been made available recently in the process of vehicle re-routing and the enhancement of existing routes by order exchange among the VAs. To implement it, the FMA maintains a variable t_d which amounts to the time that is remaining for the occurrence of the next reallocation event. At time 0, t_d is initialized with a number drawn from the exponential distribution with mean m_d. The value of t_d decreases linearly with time and when it reaches 0, a reallocation event is triggered and t_d is reset with the use of another random number. In a reallocation event the FMA selects a vehicle agent from the subset of agents that have more than two planned stops in their route with equal probability. The selected VA is requested to give up an order that belongs to its goal and then this order is announced by the FMA similarly to the case of a new order arrival. The smaller the value of parameter m_d is, the more frequently reallocation events take place, and as a consequent, the more frequently routes are updated in order to utilize newly acquired information. However, decreasing the value of m_d beyond some point increases significantly the computational overhead. Intuitively, there is a 'soft spot' that balances the trade-off between increased computational cost and enhanced route-planning that depends on the parameters of the underlying problem instance.

9.4.3 Vehicle Agent

The fleet of vehicles is represented by a set of VAs. VAs are cooperative, meaning that they do not withhold information from other agents nor do they dispense misleading information in order to maximize their local profits at the expense of other agents. The information that is available to a VA and the functions performed by it are presented in Table 9.2. The goal of the VA is the route that it has to follow and the planned allocations in each stop of the trip. The last element of a route is always the depot where the vehicle returns to replenish its cargo up to capacity. The VA remains to the depot until it wins an order in a subsequent auction. The distance matrix is available to the VAs so that they can calculate the cost function for biding in auctions however;

note that the elements of the distance matrix are merely the expected distances since actual travel times are subjected to random perturbations.

Note that the term 'expected' refers to distances as they would be provided by, e.g. a geographical map. In a realistic situation these distances would probably not be accurate due to numerous unforeseen factors, but they are used since there is no better estimate of the actual distances according to the problem description is Sect. 9.3. The task of computing the minimum cost for inserting a new node in the route of a VA consists of solving an instance of the travelling salesman problem (TSP). Because of the computational complexity of the TSP and the fact that decisions must be made in real-time, the VAs calculate bids with the use of a fast insertion heuristic and a localized random search procedure. The bid calculation mechanism is described in Sect. 9.4.3.1.

When a new order is assigned to a VA, the agent inserts this order to the position in the current route that yields the minimum insertion cost, as computed in the bid calculation process. Finally, when asked by the FMA to give up an order in a reallocation epoch, the VA employs a binary tournament selection to pick an order from its current route. The details of the binary tournament selection are given in Sect. 9.4.3.1.

9.4.3.1 Bid Calculation

The primary objective of the fleet of vehicles is to deliver supplies to affected locations as quickly as possible, and this is reflected by the choice of the objective function which is to minimize the sum of arrival times (see Sect. 9.3).

In the discrete-event simulation environment that was implemented to test the proposed agent-based approach, no events, e.g. order arrival, vehicle arrival at a node, can occur simultaneously. As a result, two cases are identified regarding the state of a VA at the initiation of an auction: (i) the vehicle returns to the depot or is located at the depot and has no planned route, (ii) the vehicle is on its way to an affected location.

In the first case, the bid for inserting the new order $o = (i, q_i)$ in the route of the vehicle is $d_{0,i}$, i.e. the expected travel time from the depot to node i. In the second case, an insertion heuristic which is described in Table 9.3 is used to evaluate all possible insertions of order o to the current route. Note that the algorithm checks every possible insertion between the first and the last element of the current route. This is because a route must necessarily end at the depot in addition to the fact that the vehicle is already en route to the first node of the current route and it is not permitted to return back to the previously visited node. The insertion cost computation in line 3 of the algorithm is the difference between the cost of the modified route $f(r')$ and the original route $f(r)$.

$$c = f(r') - f(r) \tag{9.5}$$

Table 9.3 Insertion heuristic

Procedure 1. Insertion heuristic
INPUT r: initial route k: elements in r o: new order
1: $c^* = +\infty$ 2: FOR $i = 2$ TO $i = k$ 3:   temporarily insert o to r in front of the i – th element of the sequence 4:   compute insertion cost c 5:   IF $c < c^*$ 6: $c^* \leftarrow c$ 7: $i^* \leftarrow i$ 8:   END IF 9: END FOR
RETURN the best insertion position i^* and the best insertion cost c^*

We define the cost of a route r to be the sum of the arrival times to all nodes that belong to that route, if the arrival time to the first node of the route is arbitrarily set to 0.

$$f(r) = (k_r - 1)d_{[1],[2]} + \ldots + (k_r - i)d_{[i],[i+1]} + \ldots + d_{[k_r-1],[k_r]} \tag{9.6}$$

where k_r is the number of elements in route r and $d_{[i],[i+1]}$ represents the travelling time between nodes located at the i-th and $(i+1)$-th positions of the route.

In order to obtain the optimal modified route r^*, a complete enumeration of all $(k_r + 1)!$ possible permutations need to be conducted, a prohibitive task in this real-time framework. In order to enhance the solution found by the insertion heuristic the VA employs a light-weight stochastic improvement procedure which is outlined in Table 9.4. In line 6 of the algorithm $o_{[1]}$ and $o_{[k]}$ refer to the orders located at the first and k-th position of the route, respectively. The cost functions f are computed according to Eq. (9.6). Procedure 2 generates *MaxIter* random permutations of the current solution that belong to the neighborhood defined by parameter n. Finally, the bid for inserting the new order $o = (i, q_i)$ in the route r of vehicle v is computed as shown in Eq. (9.7):

$$f_v^*(r \oplus o) - f_v(r) = c_v^*(o) \tag{9.7}$$

where r symbolizes its original route, $f_v(r)$ the cost of executing the route as it is, and $f_v^*(r \oplus o)$ the minimum cost for executing the modified route which includes order o.

When requested by the FMA to remove an order in a reallocation epoch, the VA employs a binary tournament selection to pick an order from its current route. According to this technique, the VA selects two orders from its current goal at random

Table 9.4 Localized random search

Procedure 2. Localized random search
INPUT r: initial solution (route) n: neighborhood parameter *MaxIter*: maximum iterations

compute the cost f of the initial solution r
$r_{cur} \leftarrow r$
$r^* \leftarrow r$
$f^* \leftarrow f$
WHILE $j < MaxIter$
    select n elements other than $o_{[1]}$ and $o_{[k]}$ of r_{cur} at random
    temporarily remove the selected elements from the sequence
    re-insert randomly the selected elements to r_{cur} between $o_{[1]}$ and $o_{[k]}$
    compute the cost f_{cur} of current solution r_{cur}
    IF $f_{cur} < f^*$
        $f^* \leftarrow f_{cur}$
        $r^* \leftarrow r_{cur}$
    END IF
      $j \leftarrow j+1$
END WHILE

RETURN the best sequence of orders r^* and the best cost f^*

with equal probability. Then the cost or profit of removing these two orders is computed using Eqs. (9.5) and (9.6) and procedure 2. The order that yields the minimum cost is selected to be removed from the current route of the vehicle.

9.5 On-line Constructive Heuristic

The proposed MAS is compared to an on-line, centralized, heuristic routing procedure which will be referred to as H for short. Both approaches make use of the order insertion paradigm to calculate cost functions however, they are inherently different in two ways: (i) H gathers all available information in a single, central processing element whereas in the agent-based approach all data is dispersed among the various agents of the MAS, (ii) both approaches attempt to solve a static 'snapshot' of the problem at the occurrence of a new order arrival but the agent-based approach does so at a local level (agent level), (iii) the agent-based approach makes use of a stochastic reallocation strategy that modifies at random time intervals the previously planned routes of vehicles the with the aim to generate improved routes by utilizing information regarding new order arrivals.

Table 9.5 Centralized insertion heuristic

Procedure 3. Heuristic H

INPUT
set of unassigned nodes V'
set of routes R; all m routes are initially empty

```
1. WHILE V' ≠ ∅
2.     c' ← +∞
3.     FOR ∀ i ∈ V'
4.         FOR ∀ r ∈ R
5.             FOR ∀(j−1, j) ∈ r
6.                 IF Feasible(i, j) AND Cost(i, j) < c'
7.                     r' ← r
8.                     j' ← j
9.                     i' ← i
10.                    c' ← Cost(i, j)
11.                END IF
12.            END FOR
13.        END FOR
14.    END FOR
15.    Insert(i', j')
16.    V' ← V' \ i'
17.    Update (R)
18. END WHILE
```

H is a minor adaptation of the classic insertion heuristic of Solomon (Laporte et al. 2000) to the objective of minimizing cumulative arrival time and it is outlined in Table 9.5.

When a new order arrives to the system, the set of unassigned nodes V' is populated with all nodes that their demand has been revealed except from those that the vehicles are already en route. Initially there are m empty routes, one route for each currently deployed vehicle. An empty route has two elements, the current destination of the vehicle and the depot. Procedure 3 incrementally builds multiple routes in parallel, by inserting an unassigned vertex i' into a partial route r' in every iteration of the WHILE loop. The heuristic checks the feasibility and cost of inserting a candidate node in all possible routes and positions, and selects the feasible insertion that yields the minimum cost. The feasibility of inserting i into route r is estimated by operator *Feasible*() which returns true if $q + q_r \leq g$, where q is the estimated demand for vertex i, q_r is the quantity that is planned to be allocated in route r, and g the vehicle cargo. Operator *Cost*() computes the cost of inserting node i between nodes $j-1$ and j of route r, according to Eqs. (9.5) and (9.6) in Sect. 9.4.3.1. The selected node i' is positioned between nodes $(j-1)'$ and j' of route r'; this operation is represented by operator *Insert*() in line 15 of the algorithm. Operator *Update*() is responsible for updating the data structures that store the generated routes. If no feasible insertion can be found in some iteration of the algorithm, a new vehicle is deployed.

9.6 Computational Experience

The two dynamic vehicle routing approaches were tested in randomly generated problem instances with 20, 50 and 100 nodes. For each problem size 30 independent instances were constructed. All instances shared the same set of parameters specifically: the mean times between order arrivals were exponentially distributed with mean $\mu = 10$. Demands Q_i followed the discrete uniform distribution with support set [10, 20]. The elements of the distance matrix were drawn from the discrete, uniform distribution $U(10, 50)$. The travelling time perturbation parameter ω was selected to be $\omega \sim U(-5, 5)$. The capacity C of all vehicles was set to be equal to 100. Regarding the parameters of the proposed MAS, the times between successive reallocation epochs were exponentially distributed with mean $m_d = 10$, whereas the parameters of the localized random search procedure in the bid calculation module of the VAs (refer to Sect. 9.4.3.1 for details) were set to $n = 2$ and $MaxIter = 15$, respectively.

The two dynamic vehicle routing approaches are compared in terms of the primary objective, i.e. minimization of the sum of arrival times. The results of the 3 (levels for number of nodes) $\times$ 2 (routing methods) $\times$ 30 (instances for each combination) = 180 problem instances are presented in Table 9.6. Regarding the 20-node problem configuration the proposed approach outperforms the centralized heuristic in 22 out of a total of 30 instances.

This situation is reversed for the problems with 50 nodes where the heuristic routing method prevails in 18 instances. Finally, for the 100-node experiments the MAS exhibits superior performance in the majority of problem instances, i.e. 20. The analysis and interpretation of the results is continued by applying ANOVA techniques to the data set. In order to determine whether to use parametric or non-parametric tests, the samples are tested at the 5 % significance level for normality and homogeneity of variances with the Lilliefors and the Levene test, respectively. Here, the term 'sample' refers to the 30 measurements of the objective function associated to a combination of instance size and routing method. All samples are found to be approximately normal but a limited number of samples violate the equality of variances assumption. However, the F statistic is known to be robust against violations of the latter assumption and scatterplots of the variances against the means indicated that there is no evident correlation between these two quantities. For these reasons parametric statistics were used.

Three separate one-way analyses of variance were conducted, one for each problem size, where the defining characteristic of the samples is the type of routing mechanism. In both cases, the null hypothesis is that samples are drawn from populations with the same mean and a low p-value casts doubt on the validity of the hypothesis. The three ANOVA tables are presented compactly in Table 9.7.

The first column of the ANOVA table contains the sources of the variability of the data, where "groups" and "error" correspond to variability between and within groups, respectively. The next two columns present the sum of squares and degrees of freedom associated with each source. The last two columns of the ANOVA table

Table 9.6 Objective function measurements

Instance number	20 nodes Heuristic	20 nodes MAS	50 nodes Heuristic	50 nodes MAS	100 nodes Heuristic	100 nodes MAS
1	5739	5546	16110	16373	59997	59297
2	5418	5883	15989	16309	60590	58297
3	5884	5922	16526	16158	60844	58942
4	5926	5890	15398	16173	61827	60292
5	5553	6070	16273	16384	59363	59602
6	6161	5877	16450	16092	59601	59893
7	6161	6039	16388	16455	61064	60226
8	5842	5297	16330	16410	60050	58418
9	5937	5663	16125	16118	59346	59289
10	5897	5621	16367	16235	60551	59253
11	5803	5172	16326	16042	61430	59068
12	6040	5749	16013	15829	60830	59562
13	5699	5342	15967	16498	61717	60566
14	6419	6108	15998	16182	60685	59646
15	5816	5420	15549	16360	61651	60393
16	5881	5833	16021	16340	60086	59258
17	6129	5738	16155	16296	59518	59673
18	5867	5384	16230	16080	60177	59207
19	5827	4997	16659	16092	61172	60015
20	5635	5651	15977	16212	59534	59521
21	5928	5356	16347	16042	60778	59952
22	5504	5860	16414	16069	59900	60063
23	6037	5827	16468	16600	60718	59623
24	6274	6194	15733	16303	59546	60194
25	5672	5853	16191	16035	60388	61031
26	6075	5470	16200	16282	58904	59979
27	6178	5787	15727	16054	59977	59662
28	5437	5357	15828	16008	60655	60208
29	5477	5664	16521	16236	60099	59702
30	6000	5655	16060	16491	61205	59016
Mean	5874	5674	16145	16225	60407	59662
Std. error	49.8	50	45	44	126	127

Table 9.7 ANOVA tables

	Source	SS	df	F	p-value
20 nodes	Groups	598210.5	1	8.05	0.0063
	Error	4309260.3	58		
50 nodes	Groups	97727.6	1	1.63	0.2071
	Error	3482187.9	58		
100 nodes	Groups	8328540	1	17.39	0.0001
	Error	27773100	58		

contain the F-statistic and the p-value of the hypothesis test. The p-values of the analyses for the problem configurations with 20 and 100 nodes approximate 0 and

Fig. 9.2 The mean of the objective function value measurements for the problems with 20 nodes associated to the heuristic routing procedure minus that of the MAS is estimated to be 199.7 and a 95 % confidence interval for the true difference is [58.8231, 340.5800]

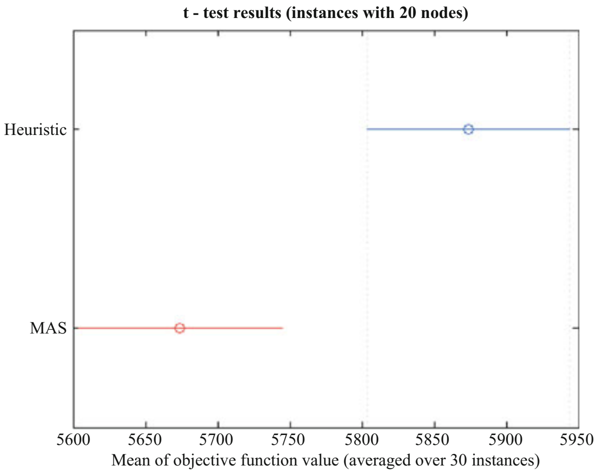
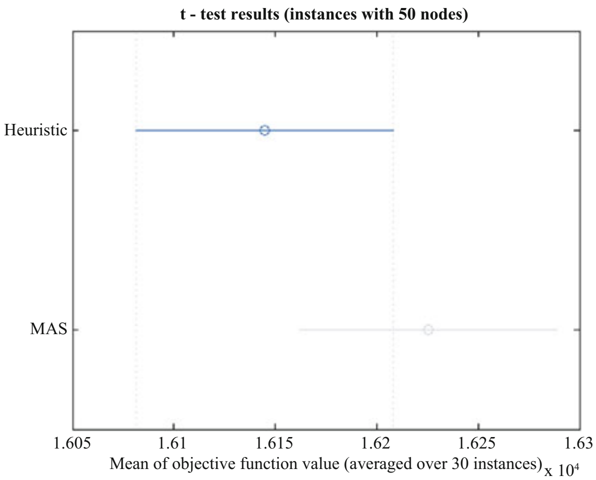


Fig. 9.3 The mean of the objective function value measurements for the problems with 50 nodes associated to the heuristic routing procedure minus that of the MAS is estimated to be − 80.71 and a 95 % confidence interval for the true difference is [−207.3562, 45.9229]



so the null hypotheses are rejected in both cases. However, for the 50-node problems the relatively high *p*-value of the ANOVA test implies that the there is no statistically significant difference between the two means.

The three ANOVA tests were followed up by an equal number of *t*-tests (Tukey least significant difference procedure). The results from these tests are presented graphically in Figs. 9.2–9.4, where the estimated means along with comparison intervals are displayed in the corresponding graphs. Two means are significantly different if their intervals are disjoint, whereas the opposite holds if their intervals overlap.

The implications of this analysis is that the superiority of the proposed approach over the heuristic method in terms of minimizing the objective function is statistically

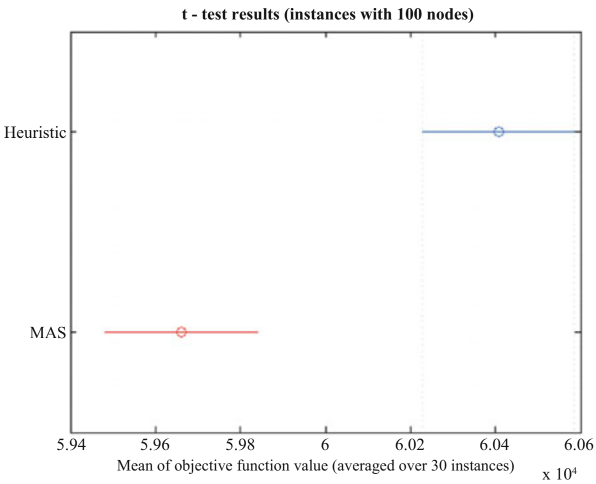


Fig. 9.4 The mean of the objective function value measurements for the problems with 100 nodes associated to the heuristic routing procedure minus that of the MAS is estimated to be 745.1 and a 95 % confidence interval for the true difference is [387.5, 1028]

significant for the problem configurations with 20 and 100 nodes, whereas for the problem instances with 50 nodes, the difference between the performance of the compared techniques is not significant statistically.

9.7 Conclusions

In this chapter, a dynamic vehicle routing problem that models the relief distribution operations in a post-disaster environment was examined. An agent-based framework for approximately solving the problem was developed. Within the proposed framework, the vehicles have the ability to dynamically re-route, bid for new tasks and de-commit to previously undertaken tasks to take advantage of the continuous flow of incoming information. The proposed architecture was compared to a centralized, on-line routing algorithm in randomly generated instances of the problem using simulation. The proposed MAS was found to outperform in a statistically significant manner the on-line algorithm in the 20 and 100 node problem configurations and exhibit a performance analogous to that of the competing routing method in the 50 node problems. The authors are currently working on testing the proposed approach in more extensive test beds and further refining it by incorporating more sophisticated reasoning mechanisms to the agents.

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Chapter 10
Modeling Facility Locations for Relief Logistics in Indonesia

Ratih Dyah Kusumastuti, Sigit S. Wibowo and Rizqiah Insanita

10.1 Introduction

Indonesia has been stricken by disasters in the last decade. According to National Agency for Disaster Management (BNPB), there were 729 disasters affecting around 5 million people in 2010 (BNPB 2011). A few major disasters that happened in Indonesia were the Tsunami in Aceh in 2004, earthquake in Yogyakarta in 2006 and earthquakes in southern Java and West Sumatera provinces in 2009, the eruptions of Mount Merapi and Tsunami in Mentawai in 2010. Apart from Tsunami and earthquake, many areas in Indonesia are also hit by landslide, flood, forest fire and drought.

Most areas in Indonesia are disaster-prone because the country is located at the meeting point of three tectonic layers, namely the Australian layer in the southern part, the Euro-Asia layer in the western part and the Pacific Ocean layer in the eastern part (Rachmat 2006), see Fig. 10.1. Because of its location, disasters are very likely to happen in the country, but their exact time and locations are very difficult to foresee.

After the Aceh Tsunami in 2004, organizations such as governmental ministries and agencies, and non-governmental organizations (NGOs) in Indonesia have become interested and involved in disaster management. Disaster is defined as a serious disruption of the functioning of a community or a society involving widespread human, material, economic or environmental losses and impacts, which exceeds the ability of the affected community or society to cope using its own resources (UN/ISDR 2009). Disaster is usually classified based on the cause, namely natural and technological disasters.

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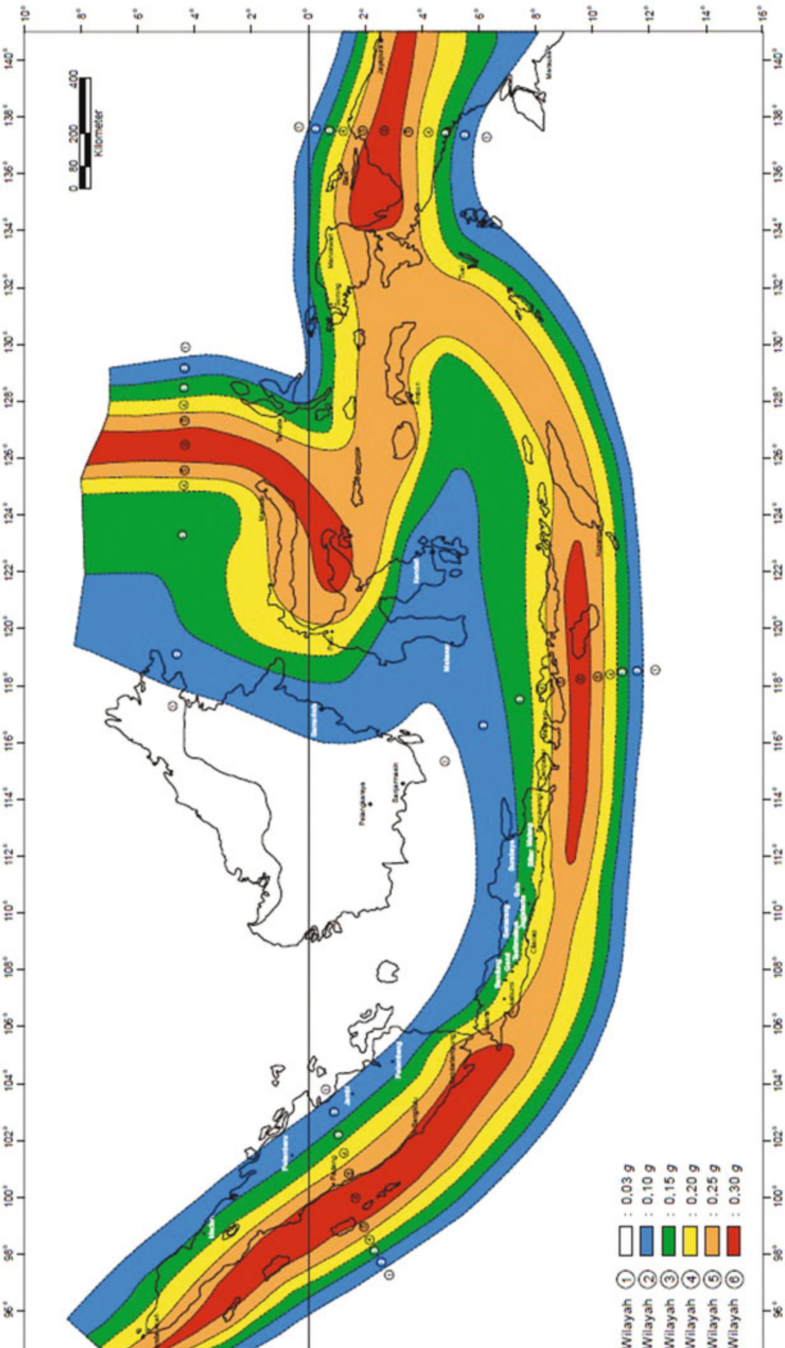

Fig. 10.1 Areas in Indonesia which are prone to earthquake. (Source: Ministry of Public Works 2002)

There are four stages of disaster management cycle: mitigation, preparedness, response and rehabilitation (Tomasini and Van Wassenhove 2009). Mitigation deals with the proactive social component of emergencies. Preparedness denotes implementing the response mechanisms to counter factors that the society has not been able to mitigate. Response comprises the provision of assistance or intervention during or immediately after a disaster took place to meet the life preservation and basic subsistence needs of the affected people. Rehabilitation consists of decisions and actions taken after a disaster took place which aim at restoring or improving the pre-disaster living conditions of the affected community, while encouraging and facilitating essential adjustments to reduce the disaster risk.

Effective logistics management is one of the critical success factors in a disaster management (Moe and Pathranakul 2006). Relief logistics, also known as humanitarian or emergency logistics, is defined as a process of planning, managing and controlling the efficient flows of relief, information, and services from the points of origin to the points of destination to meet the urgent needs of the affected people under emergency conditions (Sheu 2007a). Logistics is crucial in relief operation, because it accounts for eighty percent of the operational cost (Van Wassenhove 2006).

Concerning Indonesia cases where multi organizations are involved, Kusumastuti et al. (2010) conducted surveys regarding disaster survivors' expectations on relief logistics response in Jakarta (based on their experience during the Jakarta flood in 2007) and Yogyakarta (based on their experience during the Yogyakarta earthquake in 2006). We found that there are some gaps between survivors' expectation and the actual response time, indicating that there is room for improvement for better relief logistics response. Therefore the purpose of this study is twofold. Firstly, the purpose is to analyze how organizations in Indonesia (governmental ministries and NGOs) in setting up their relief logistics network. The second purpose is to develop models to determine locations for relief logistics facilities during the response stage of disaster management cycles that are suitable for geographically dispersed countries such as Indonesia.

In this study, information regarding relief logistics network in Indonesia is obtained through interviews and focus group discussions with representatives from organizations that are involved in disaster management in Indonesia (Ministry of Social Welfare, Ministry of Health, The National Agency for Disaster Management, the Indonesia Red Cross, and Several NGOs), and from published articles.

The rest of this paper is organized as follows. Section 10.2 provides relevant literature pertaining to relief logistics. Section 10.3 explains relief logistics structures owned by organizations involved in managing disaster in Indonesia. Section 10.4 describes the modeling process to determine locations for relief logistics facility during the response stage. Lastly, conclusion of the findings is presented in Sect. 10.5.

10.2 Literature Review

A logistics system aims to deliver the proper supplies, in the right condition, at the quantity required, and at the places and time they are needed (Bowersox et al. 2002). Relief logistics includes the movement of goods and equipment, the relocation of

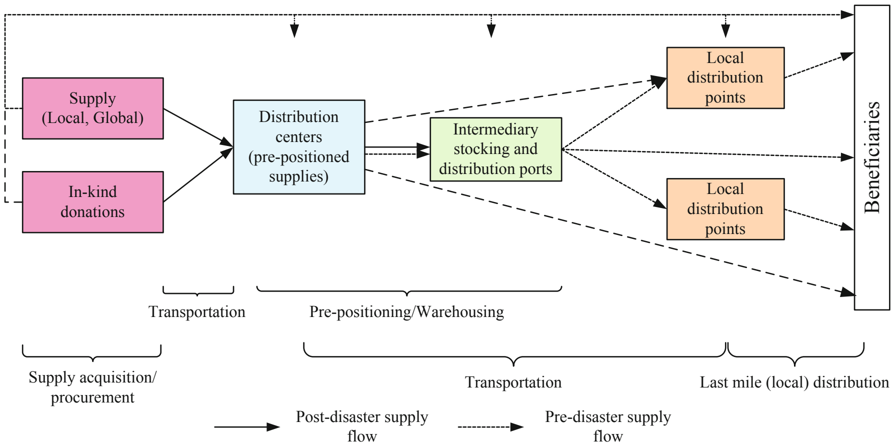

Fig. 10.2 Relief logistics network structure. (Balcik et al. 2009)

disaster-affected people, transfer of casualties and the movement of relief workers (Stephenson 1993).

Relief logistics is different from commercial logistics because it has several unique characteristics (Tomasini and Van Wassenhove 2009). Its objectives are ambiguous, it deals with limited resources and operates in a politicized environment with high degree of uncertainty and urgency.

Challenges in relief logistics management include the timeline of relief supply and distribution is hardly controllable, resource management remains challenging, and accurate, real-time demand information is required but almost inaccessible (Sheu 2007a).

Since a quite number of organizations are usually involved in relief operation, coordination poses certain challenge to the local authority. Several factors affecting coordination in relief logistics operation include the number and diversity of actors, donor expectation and funding structure, competition for funding and the effects of media, unpredictability, resource scarcity/oversupply, and the cost of coordination (Balcik et al. 2010).

The performance of relief logistics operations can be measured according to three metric types (Beamon and Balcik 2008): namely resources (level of efficiency), output (level of effectiveness) and flexibility (response to a changing environment).

According to Tomasini and Wassenhove (2009), relief logistics is involved in the preparedness and response stages. The typical network structure of relief logistics is depicted in Fig. 10.2. The pre-disaster relief chain (preparedness stage) includes procurement and stock prepositioning while the post-disaster operations (response stage) focus primarily on procurement and transportation. The supplies can be purchased locally or globally (Balcik et al. 2010). Relief supplies can also be acquired through donations, though sometimes it may cause congestions in relief chain.

Other literatures in relief logistics focused on developing quantitative models for relief operations activities, such as determining locations and allocations of relief facilities and determining vehicle routing for relief supplies distribution. Altay and Green (2006) discussed operational research/management science literatures in disaster operations management. Recently, Caunhye et al. (2012) studied literatures concerning optimization models in emergency logistics. The models can broadly be classified into facility location, relief distribution, and casualty transportation. Some of the models are as follows.

Church and ReVelle (1974) proposed maximal covering location problem (MCLP) method which aimed to locate a fixed number of facilities in order to maximize the population covered within a certain service distance.

Kongsomsaksakul et al. (2005) developed a location-allocation model to determine shelter in flood evacuation planning. The shelter location problem was posed as a Stackelberg game, consisting of the leader (authority) determining the shelter location to minimize the total evacuation time and follower (evacuees) choosing the destination (shelter) and route to evacuate. The problem was formulated as a bi-level programming. The upper level problem was a location problem that models the authority's decision. A combined distribution and assignment model was developed to model the evacuees' decision as the lower level problem, and the model was solved using genetic algorithm.

Dekle et al. (2005) used covering location model in a two-stage approach to find the disaster recovery center (DRC) locations for the area of Florida County. In the first stage, the approach would give three ideal DRC locations which must be within 20 miles from each residence. In the second stage, the 20-mile requirement was relaxed, and locations which were close to the first stage locations and satisfied other evaluation criteria were identified. Criteria used to decide the feasibility of a location were: at least 2,000 square feet of floor space, it had access for the disabled, it had heating and air conditioning, phone and fax lines, restroom facilities, adequate parking, and it was not in a flood plain.

Chang et al. (2007) proposed a decision making tool that can be used in planning for flood emergency logistics. The problem was formulated as two stochastic programming for models that allow for the determination of a rescue resource distribution system for urban flood disasters, including the structure of the rescue organization, the location of rescue resource storehouse, the allocation of rescue resources within capacity restriction, and the distribution of rescue resources.

Sheu (2007b) developed a hybrid fuzzy clustering optimization approach for the operation of emergency logistics co-distribution responding to the urgent relief demand in the crucial rescue period. The author proposed a three-layer emergency logistics co-distribution conceptual framework which consists of two recursive mechanisms, namely disaster-affected area grouping and relief co-distribution.

Tzheng et al. (2007) developed a relief-distribution model using fuzzy multi-objective programming for designing the relief delivery systems. The objective functions were minimizing the total cost, minimizing the total travel time, and maximizing the minimal satisfaction during the planning period.

Yi and Kumar (2007) proposed a meta-heuristic of ant colony optimization (ACO) for solving the logistics problem arising in disaster relief activities. The logistics planning involved dispatching commodities to distribution center in the affected areas and evacuating the wounded people to medical centers. The proposed method decomposed the original emergency logistics problem into two phases of decision making: vehicle routing constructions and multi-commodity dispatch.

Balcik and Beamon (2008) proposed a variant of maximal covering location model to determine the number and location of distribution centers and the amount of relief inventory to stock therein to maximize the benefits provided to affected people. Balcik et al. (2008) developed a model to determine the delivery schedules/routes for each vehicle throughout the planning horizons. Jotshi et al. (2009) developed a robust methodology for dispatching and routing emergency vehicle in the post-disaster environment with the support of “data fusion”.

Lee et al. (2009) proposed a decision support system for public health infrastructure during emergency response, including the model for resource allocations and model to determine the locations of the point of dispensing (POD).

Sheu (2010) proposed a dynamic relief-demand management model for emergency logistics operations under imperfect information conditions that consists of three steps, namely: data fusion for relief demand forecasting in multiple areas, fuzzy clustering to classify affected area into groups, and multicriteria decision making to rank the order of priority of groups.

Widener and Horner (2010) proposed a type of hierarchical capacitated-median model for hurricane disaster relief good distribution. Lastly, Hu (2011) modeled the system of container multimodal transportation emergency relief as an affinity network inspired by the immune system. An integer linear programming model was proposed to build the path selection for container supply chain in the context of emergency relief.

10.3 Relief Logistics Network Structures in Indonesia: A Comparison

Governmental administration in Indonesia consists of four levels: province, district, sub-district and village. Most organizations in Indonesia follow this structure, and larger size organizations usually have representatives at the provincial and district levels.

Several organizations are involved in managing disaster in Indonesia; they are namely The National Agency for Disaster Management (BNPB), the Indonesian Army (TNI) and governmental ministries (Ministry of Social Welfare, Ministry of Health, Ministry of Public Works), The Indonesia Red Cross (PMI) and several Non-Governmental Organizations (NGOs).

BNPB serves as the policy maker of disaster management in Indonesia and the coordinator in the event of major disaster, whereas TNI provides resources (i.e. people, transportation vehicles and equipment) especially during the response and rehabilitation stages. Ministry of Health (Kemkes) usually handles the health aspect of the disaster (such as providing medical service and allocating medicine supplies), while Ministry of Social Welfare (Kemsos) involves in allocating relief supplies to the affected people, and Ministry of Public Works involves in clearing the affected area and also in rehabilitating the infrastructure, especially transportation infrastructure. PMI is focusing on providing first aid to save the victims' lives, and distributing the relief supplies directly to the victims. NGOs, on the other hand, are involved in distributing relief supplies (directly or indirectly) to the victims. Sometimes, both PMI and NGOs are also involved in the rehabilitation stage.

10.3.1 The National Agency for Disaster Management (BNPB)

BNPB has permanent facilities to keep stocks of relief supplies. It has a central warehouse located in the country's capital city, Jakarta. BNPB is also setting up 12 technical operational units (UPT) in the regional level with attached warehouses (BNPB 2008). These locations are determined based on the following criteria:

- The location is at or near the capital city of the province
- It can cover several provinces that are prone to disasters
- The location is within a disaster-safe area
- It can be accessed and reachable by land, sea, and air transportations.

In the event of a disaster, BNPB may also setup temporary distribution points at the affected area based on requests from the local authorities. Criteria used to select the locations are easy access from/to locations and whether they are located at the disaster-safe zone.

10.3.2 Ministry of Health

The Ministry of Health has a unit called Centre for Health Crisis Management (PPKK Kemkes) that specifically handles the health aspect of disaster management. PPKK has regional level subsidiaries located in nine cities (PPKK Kemkes 2011). PPKK has medical supplies at those cities. The locations of these regional stocking points are determined based on local human resources, supporting facilities and whether or not the city has a teaching hospital. When a disaster strikes, locations of relief supplies distribution points at the affected areas are determined by local authorities based on distance to affected areas and distance to refugee shelter locations. PPKK also provides mobile units to monitor the victims' conditions.

10.3.3 Ministry of Social Welfare

Relief logistics network under the Ministry of Social Welfare consists of permanent facilities that are hierarchical in nature, according to the government administration structure. Their national level warehouses (central warehouses) are located at Bekasi (the suburban city of Jakarta), where they keep relief supplies such as tents and preserved food.

At the provincial level, the Ministry of Social Welfare has 33 warehouses located at the capital city of all provinces in Indonesia, attached to the Division of Social Welfare of the province. These warehouses are managed by the provinces' offices but replenished by the central warehouses. At the district level, on the other hand, permanent warehouses are only established in certain districts (which are prone to disasters). Decisions regarding setting-up warehouses in the district level are made by the local authorities. At this level, the warehouse is usually attached to the Sub Division of Social Welfare of the district. The warehouses are managed by the districts' offices but replenished by provincial warehouses.

In the event of a disaster, Ministry of Social Welfare also sets up temporary distribution points at the affected areas. Locations of these facilities are determined based on input from the local authorities, which criteria include easy access from/to locations and whether they are located in the disaster-safe zone.

10.3.4 The Indonesian Red Cross (PMI)

In the case of the Indonesian Red Cross (PMI), the logistics network consists of central, regional, and emergency-response warehouses. PMI has two central warehouses located at Banten province (to cover the western part of Indonesia) and at the city of Surabaya (to cover the eastern part of Indonesia). Each central warehouse is stocked with family kits, and its function is to replenish the regional and emergency-response warehouses in its covering area. The regional warehouses are located at Bali, Makassar, Manado, Aceh and Padang. The central and regional warehouses are managed directly by the PMI headquarter and their locations are determined based on the covering area. The emergency-response warehouses on the other hand, are located at and managed by PMI branches in all provinces.

In the event of a disaster, PMI also sets up temporary distribution points at the affected area. The locations of these temporary distribution points are determined based on input from local authorities and assessment results. The objective is to minimize distance between distribution points and locations of victims. PMI never kept food supplies in all of its warehouses. In the event of disaster, PMI usually procures food supplies locally to avoid transportation difficulties. Locations of national/regional level facilities of PMI and other organizations are depicted in Fig. 10.3.

10.3.5 Non-Governmental Organizations (NGOs)

NGOs usually do not own permanent logistics facilities. In the event of a disaster, they either set up their own temporary facilities or cooperate with local partners.

Fig. 10.3 Locations of national/regional facilities of BNPB, Ministry of Health (Kemkes), Ministry of Social Welfare (Kemsos), and Indonesian Red Cross (PMI)

They may also act as local partner for international NGOs. Decision criteria used to set up a temporary facility include:

- Degree of disaster (number of victims, damaged building and residential houses, and damaged infrastructure)
- Relief duration
- Available budget and future budget commitment
- Preparedness of the local partner
- Security in the affected areas
- Access to the affected areas.

If NGOs do decide to set up temporary facilities at the site, the criteria used are namely distance to the affected area, capacity of the potential facility, and security issues in the area.

10.3.6 Comparisons of Relief Logistics Network Structures

Comparing the above relief logistics network, it can be concluded that most organizations, have their own relief logistics networks, which consist of permanent and temporary facilities. Permanent facilities are set up at the national, regional, provincial, and district levels, while temporary facilities are set up at the affected area.

Different criteria are used to decide permanent facility locations. For BNPB, as the main coordinator of relief operation, the agency may distribute bulky relief supplies, so the criteria that they use to determine future locations of regional warehouses are the nearest distance to the provinces' capitals and easy transportation access.

For the Ministry of Health, as it focuses on the health aspect, criteria used to determine the locations of regional and sub-regional warehouses are local human resources and availability of the supporting facilities and teaching or university hospitals. PMI uses coverage area as the criterion to determine the permanent facilities, so that they can cover as much area as possible and distribute relief supplies directly to the disaster victims in an effective and efficient manner. The Ministry of Social Welfare is responsible for welfare of all citizens. This ministry use government offices in provincial or district levels as permanent facilities so that they can distribute the relief supplies easily.

Regarding temporary facilities at the affected area, minimizing costs has never been considered as the objective function as fast delivery of the relief items is the main concern to minimize human suffering. Budget is thought more as a constraint in the relief operation.

We can conclude that even though the government of Indonesia has already established BNPB as the policy maker in disaster management and the main operation coordinator in the event of major disaster, it is still difficult to coordinate all organizations involved in the relief operation, especially in terms of logistics. Each organization tends to operate on its own using their own relief logistics facilities, without or may be with little coordination with other organizations that can lead to oversupply/undersupply of relief goods at the affected areas.

As most organizations have already setup their permanent facilities in the national/regional and provincial levels (preparedness stage), we think it is more urgent to develop a model to determine temporary facility locations during the response stage. In practice, temporary facilities are usually set up based on the judgment of local authority. Although in the event of a disaster, these locations must be determined promptly, making the decision solely based on the judgment of local authorities may not result in an optimal relief logistics network structure that can lead to uneven distribution of relief goods in the affected area.

10.4 Developing Models for Locating Facilities During Response Time

10.4.1 Modeling Approach

We propose a relief logistics network as depicted in Fig. 10.4. The proposed network involves two stages of the disaster management cycle, namely preparedness and response stages. It consists of four echelons in accordance with government administration levels, e.g. national, provincial, district and village levels facilities, so that it will be able to quickly respond to a disaster. Logistics facilities (e.g. warehouse) for national and provincial levels are proposed to be permanent, whereas facilities for district and village levels are set up when the disaster occurs. By setting-up permanent facilities at the national and provincial levels, the response time will be shorter,

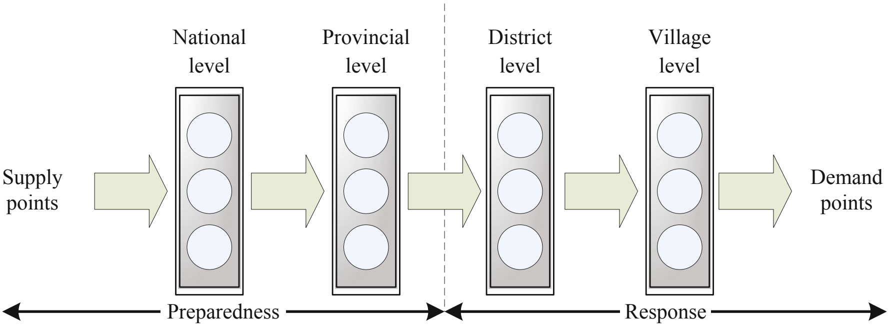

Fig. 10.4 The proposed relief logistics network

which is equal to the delivery time between provincial and village level facilities at the affected area.

At the preparedness stage of disaster management cycle, locations of national and provincial level facilities should be determined based on the delivery cost and time. These facilities are used to stock up the relief supplies during normal time, therefore both delivery cost and time should be considered. Decision criteria that can be used to determine a disaster-prone province are its historical disaster records (severity, frequency, and type of disaster events). Also at this stage, based on these data, the list of potential locations for the district and village level facilities must be known. The criteria that can be used to select the potential locations are transportation access to the potential locations, and the security of the area.

At the response stage, the exact locations of relief logistics facilities at district and village levels are determined. In this study, we focus on developing models to determine temporary relief logistics facility locations during this stage. The proposed modeling approach for the response stage consists of two models with bottom-up approach. The models are developed based on the decision making process that usually happened at the event of a disaster. Each institution usually sends their team to assess the disaster impacts and they usually work with the local authority to choose the locations for relief logistics facilities at the village level. Thereafter, by considering the locations of village level facilities, they will determine the locations for relief logistics facilities at the district level (if they have not had it yet).

Therefore, the objective of the first model is to determine a set of facilities at village level (in the affected area). The proposed model is a slight modification of maximal covering location problem or MCLP (Church and ReVelle 1974) with the objective function of maximizing the number of affected people covered by facilities for certain periods of time. The problem of the model is to determine a set of facilities locations within the available budget, but still ensuring that traveling time from demand points (assumed to be the locations of the victim shelters) to the facility locations are less than the pre-determined service time. Traveling time is considered instead of distance because in the post-disaster period, distance can be short but traveling time can take longer due to damages in transportation infrastructure. The solution of the first model along with other data becomes the input of the second model.

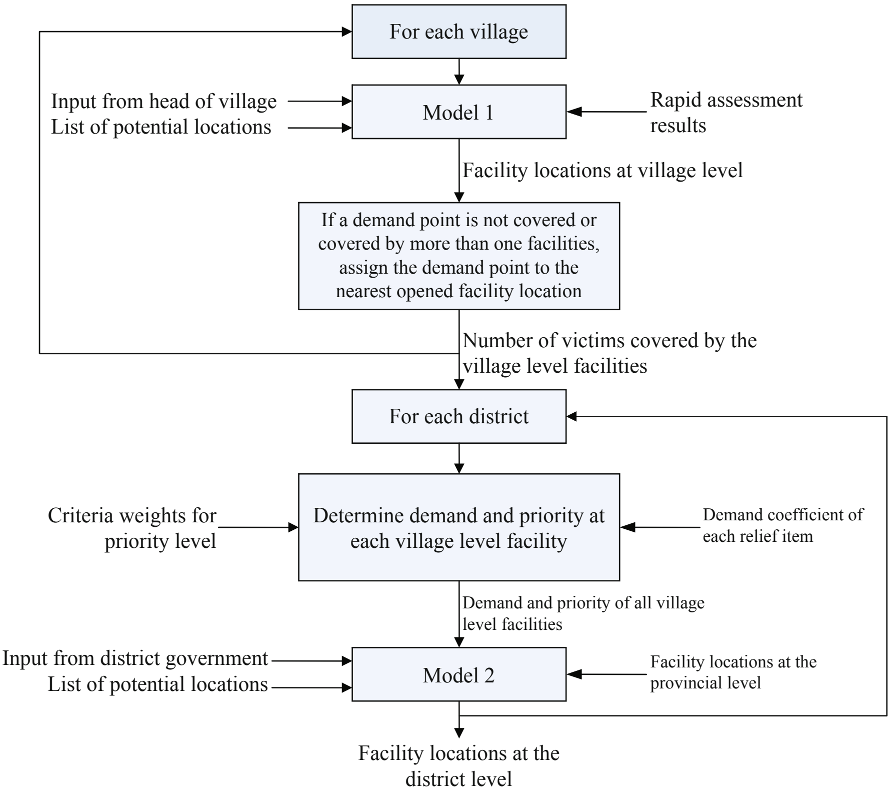

Fig. 10.5 The modeling approach

The second model is formulated as a mixed integer programming (MIP) model and it is used to determine the relief logistics facilities at the district level with minimizing the sum of relief supplies delivery time from provincial level to village level facilities. Balances of flows, capacity at each potential location and the available budget become the constraints. Priority of each facility at the village is also considered and determined based on the severity of the disaster impact.

For each village, the locations of relief logistics facilities are determined using Model 1. Input to this model include list of potential locations, information from the head of village and rapid assessment results. If a demand point is not covered by the facility or it is covered by more than one facilities, it will be assigned to the nearest opened facility. For each district, the locations of village level facilities in a district along with criteria weights for priority level of each village and demand coefficient of each relief item are then used to determine the demand and priority level at each village level facility. Thereafter, Model 2 is solved to determine the facility locations at the district level. Input to Model 2 include demand and priority level at each village level facility, information from district government, list of potential locations of district level, and the facility locations of provincial level facilities. The procedure is depicted in Fig. 10.5.

10.4.2 Model Formulations

The models are developed based on the following assumptions:

1. Victims are concentrated at several refugee shelters, and all the locations are known.
2. Transportation modes that can be used from provincial to district level facilities and from district to village level facilities are known. The traveling/delivery time considered in the model is the shortest traveling/delivery time using the available transportation modes.
3. Priority level at each facility at the village level is determined based on:
   a. Fraction of victims relative to the village population,
   b. Fraction of damaged building (including houses), and
   c. Fraction of damaged transportation infrastructure.

10.4.2.1 Model 1

The notations for Model 1 are presented below:

I = Set of demand points (locations of victim shelters) in a village
J = Set of potential locations for village level facilities
T = Time periods
T_{Max} = The maximum service time. If the travelling time from a demand point to a village level facility location is longer than T_{Max}, uncovered by the facility
$X_j = \begin{cases} 1, & \text{if a facility is allocated to facility location } j \\ 0, & \text{otherwise} \end{cases}$
$Y_i = \begin{cases} 1, & \text{if a demand point } i \text{ is covered by a facility} \\ 0, & \text{otherwise} \end{cases}$
TS_{ij} = The shortest traveling time from demand point i to facility location j
A_i = Expected number of victims at demand point i, where $A_i = \sum_t a_{it}$
a_{ij} = Expected number of victims at demand point i and period t
BV = The available budget to build relief logistics facilities in a village
FV_j = Fixed cost to open a village level facility at potential location j
VF = The maximum number of facilities that can be opened in a village
A_i = $\{j \in J | TS_{ij} \leq T_{Max}\}$, set of facility locations that are eligible to serve demand point i.

As discussed in Sect. 10.4.1, Model 1 is a slightly modified MCLP model and the formulations are as follows:

$$\max \sum_{i \in I} Y_i A_i \tag{10.1}$$

subject to

$$\sum_{j \in E_i} X_j \geq Y_i, \quad \forall i \in I \tag{10.2}$$

$$\sum_{j \in J} X_j FV_j \leq BV \tag{10.3}$$

$$X_j = \{0,1\}, \quad \forall j \in J \tag{10.4}$$

$$Y_i = \{0,1\}, \quad \forall i \in I. \tag{10.5}$$

The objective function (Formulation 1) of the model is to maximize the expected number of victims that can be covered by village level facilities during the considered periods of time. Constraint (10.2) ensures that a demand point can only be covered by a potential location if the traveling time between the potential location and demand point is less than the maximum service time T_{Max}. Constraint (10.3), on the other hand, is related to budget constraint that limits the number of facilities that can be opened in a village. If budget information is unavailable, the constraint can be replaced by the following constraint:

$$\sum_{j \in J} X_j \leq VF. \tag{10.6}$$

The model finds a set of facilities that will maximize the expected number of victims that can be covered within the maximum service time and the available budget. If in the model solutions there exist demand points that are not covered by the facilities (because the traveling time to all potential locations are longer than T_{Max}), then the respective demand point is allocated to the nearest opened facility location. Therefore, the number of victims covered by each opened facility (A'_{gt}) will be known. In Model 2, this information is used to determine demand from each village level facility for each relief item. Furthermore, the output of Model 1 will also determine traveling time and delivery cost from potential locations of district level to village level facilities that are required in Model 2.

10.4.2.2 Model 2

The second model is a location/allocation model and formulated using MIP. The objective of the model is to determine a set of district level facilities within the available budget that minimizes the sum of relief good delivery time from provincial level to village level facilities. Constraints for this model include balances of flows between facilities, capacity limitations at the district level facilities, and the budget limit. The notations for Model 2 are presented below.

G = Set of village level facilities
K = Set of potential locations for district level facilities
L = Set of provincial level facilities
N = Set of relief items

$$Z_k = \begin{cases} 1, & \text{if a district level facility is allocated to potential location } k \\ 0, & \text{otherwise} \end{cases}$$

D_{ngt} = The expected demand for relief item n at the village level facility g in period t, which is a result of multiplication between expected number of victims covered by facility g in period t with a coefficient (U_n) that represents the quantity of relief item n needed by each victim, or:

$$D_{ngt} = A'_{gt}U_n. \tag{10.7}$$

C_{nk} = Capacity for relief item n at potential location k
P_g = Priority level of facility g, the values is between 0 and 1. The lower the value of Pg, the higher the priority will be. Priority of the village is a determined based on the fraction of the victim relative to the population, fraction of damaged building (including houses), and fraction of damaged transportation infrastructure
BD = The available budget to establish district level facilities and deliver relief items from provincial level to village level facilities during the considered period of times
FD_k = Fixed cost to open district level facilities at potential location k
TD_{lk} = The shortest delivery time from provincial level facility l to district level facility k
TV_{kg} = The shortest delivery time from district level facility k to village level facility g
SD_{nlk} = Delivery cost per unit for relief item n from provincial level facility l to district level facility k
SV_{nkg} = Delivery cost per unit for relief item n from district level facility k to village level facility g
S_{nlt} = Supply of relief item n from provincial level facility l in period t
QD_{nlkt} = Quantity of relief item n shipped from provincial level facility l to district level facility k in period t
QV_{nkgt} = Quantity of relief item n shipped from district level facility k to village level facility g in period t
M = Set of criteria that determine the priority level
PC_{gm} = Value of priority criterion m of village level facility g
W_m = Weight of priority criterion m

The model formulations are as follows:

$$\min \sum_{k\in K} Z_k \left(\sum_{l\in L} TD_{lk} + \sum_{g\in G} P_g TV_{kg} \right) \tag{10.8}$$

subject to

$$S_{nlt} = \sum_{k\in K} QD_{nlkt}, \quad \forall n \in N, \forall l \in L, \forall t \in T. \tag{10.9}$$

$$\sum_{l\in L} QD_{nlkt} = \sum_{g\in G} QV_{nkgt}, \quad \forall n \in N, \forall k \in K, \forall t \in T. \tag{10.10}$$

$$\sum_{l \in L} QV_{nkgt} = D_{ngt}, \quad \forall n \in N, \forall g \in G, \forall t \in T. \tag{10.11}$$

$$\sum_{k \in K} QD_{nlkt} \le Z_k C_{nk}, \quad \forall n \in N, \forall k \in K, \forall t \in T. \tag{10.12}$$

$$BD \ge \sum_{k \in K} Z_k FD_k + \sum_{t \in T} \sum_{n \in N} \left(\sum_{l \in L} \sum_{k \in K} SD_{nlk} QD_{nlkt} + \sum_{k \in K} \sum_{g \in G} SV_{nkg} QV_{nkgt} \right). \tag{10.13}$$

$$Z_k = \{0,1\}, \quad \forall k \in K. \tag{10.14}$$

$$S_{nlt}, QD_{nlkt}, QV_{nkgt} \ge 0, \quad \forall n \in N, \forall l \in L, \forall k \in K, \forall g \in G, \quad \forall t \in T. \tag{10.15}$$

The objective function of the second model (Formulation 10.8) is to minimize the total delivery time from provincial to village level facilities. The objective function also includes priority level of the village based on the severity of the disaster impact. The higher the priority level, the shorter delivery time between district and village level facilities should be.

Constraints (10.9)–(10.11) represent the balances of flows in each facility. Constraint (10.12) indicates the capacity limit at the potential district level facilities, whereas Constraint (10.13) represents the limited budget to open district level facilities and deliver relief items from provincial to village level facilities. Constraints (10.14) and (10.15), on the other hand, indicate restrictions in the decision variables.

Priority level of a village level facility is determined using the following formula:

$$P_g = \sum_{m \in M} W_m PC_{gm}. \tag{10.16}$$

Weight of each priority criterion of each village level facility is determined using nine-scale pair-wise comparisons from Analytic Hierarchy Process (Saaty 1980). It is assumed that the pair-wise comparison is performed based on the judgment of one person (the decision maker at the organization that owns the relief logistics facilities).

10.4.2.3 Model Application

The proposed model is applied to analyze relief logistics network owned by Ministry of Social Welfare during the 2007 Jakarta flood. In the district of East Jakarta, the flood affected 45 urban villages, especially in the sub-district of Jatinegara which is located near the Ciliwung River and the Cipinang creeks.

Ministry of Social Welfare has a provincial level facility in Jakarta province which is attached to the Division of Social Welfare, whereas in the district of East Jakarta,

Table 10.1 Refugees at urban village of Kampung Melayu (base case scenario)

No.	Refugee shelters	Number of refugees									Duration[a]	
		02-Feb	03-Feb	04-Feb	05-Feb	06-Feb	07-Feb	08-Feb	09-Feb	10-Feb	KM1	KM11
1	KM1	378	1,134	1,750	2,367	2,367	2,367	2,367	2,059	2,059	0	15
2	KM2	78	231	492	492	492	492	492	328	328	5	15
3	KM3	30	89	138	176	176	176	176	175	175	5	15
4	KM4	23	69	108	137	137	137	137	136	136	5	15
5	KM5	29	85	132	168	168	168	168	167	167	5	15
6	KM6	125	375	398	497	497	497	497	497	497	5	15
7	KM7	151	453	709	905	905	905	905	898	898	5	15
8	KM8	9	26	40	51	51	51	51	51	51	5	15
9	KM9	21	63	98	125	125	125	125	124	124	5	15
10	KM10	23	68	106	135	135	135	135	134	134	5	15
	Total	867	2,593	3,971	5,053	5,053	5,053	5,053	4,569	4,569		

[a] Traveling time to potential locations for village level facilities (minutes)

the ministry has a district level facility that is attached to the Sub-Division of Social Welfare. The ministry setup temporary facilities in the village and district levels during the response stage of the flood disaster. For this case study, Model 1 and Model 2 are solved using optimization software AIMMS 3.8.

(a) Base Case Scenario for Model 1

In this case study, Model 1 is used to determine the facility location at the urban village of Kampung Melayu, whereas Model 2 is used to determine the facility location at the district of East Jakarta. The time periods considered are from 2 to 10 February 2007. Based on our interview with representative from the Ministry of Social Welfare, the maximum service time is determined at 15 min and for easier coordination, they would only open one facility at the village level. It is assumed that fixed cost to open a facility in the urban village is Rp. 5 million, and 10 refugee shelters (KM1-KM10) and 2 potential locations (KM1 AND KM11) are considered. The data used for Model 1 is presented in Table 10.1.

The model is solved, and the results indicate that KM1 is chosen as the location (see Fig. 10.6). As both locations are eligible for village level facility, the model choose the first eligible location, in this case is KM1 which is consistent with decision that was taken by the Ministry of Social Welfare during the disaster.

(b) Modified Problem for Model 1

In order to demonstrate the applicability of the model, we modify the problem where three potential locations (KM1, KM6, AND KM11) are considered, the maximum service time is 10 min, and the traveling time between the refugee shelters and the potential locations are modified as presented in Table 10.2. It is also assumed that the fixed costs to open facilities at KMI, KM6, and KM11 are similar, which is Rp. 5 million, while the available budget for opening the village level facilities is set at Rp. 10 million.

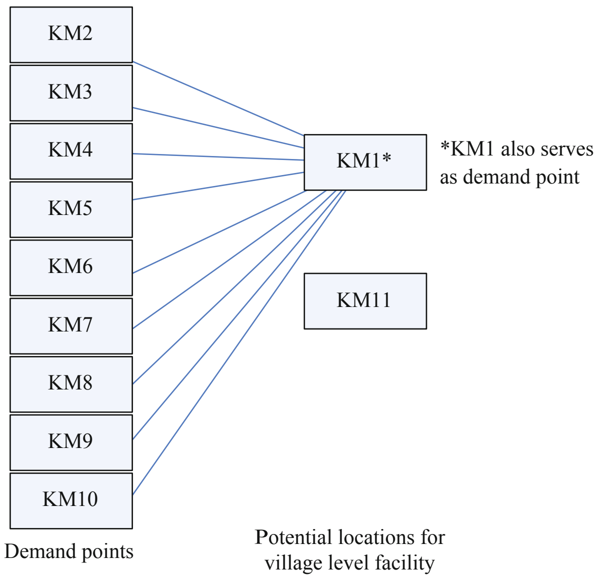

Fig. 10.6 Solution of Model 1 for urban village of Kampung Melayu (base case scenario)

Table 10.2 Travelling time for modified problem

No.	Refugee shelters	Duration[a]		
		KM1	KM6	KM11
1	KM1	0	15	15
2	KM2	5	15	15
3	KM3	5	15	10
4	KM4	5	15	10
5	KM5	5	10	10
6	KM6	5	0	10
7	KM7	15	5	10
8	KM8	15	5	15
9	KM9	15	5	15
10	KM10	15	5	15

[a] Traveling time to potential locations for village level facilities (minutes)

The model is solved, and the result indicates that KM1 and KM6 are chosen. With the budget of Rp. 10 million, two facilities that cover all the demand points can be opened. However, demand points KM5 and KM6 are covered by both locations (KM1 and KM6), and therefore KM5 and KM6 are assigned to nearest opened facility location which are KM1 and KM6 respectively. The resulted network is depicted in Fig. 10.7.

(c) Application of Model 2

Model 2 is then used to determine the district level facility in East Jakarta. We consider 7 urban villages in two sub-districts, and two potential locations for district

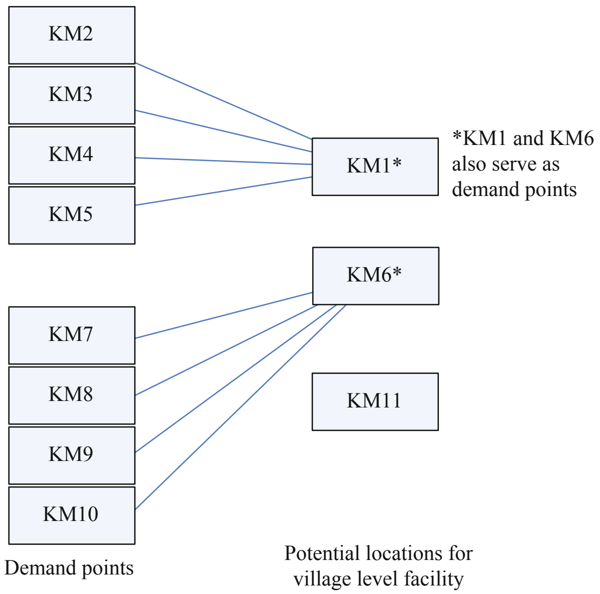

Fig. 10.7 Solution of Model 1 (modified problem)

level facilities, namely a former cinema called Nusantara (BN) and the Sub-Division of Social and Welfare in East Jakarta (SDW-JT). For this case study, we consider that there is only one facility in each urban village (KM1, CBU, CBS, CM, CW, CI and BK).

Time periods considered in the model are from 2 to 10 February 2010 (daily), and it is assumed that trucks are used to deliver relief goods from provincial level to village level facilities. Delivery cost is approximated using the published rate of a logistics company, and it is assumed that the delivery quantity from provincial level to district level facilities is 1000 kg, whereas the delivery quantity from district level to village level facilities is 100 kg. The relief goods considered are rice, instant noodle, and preserved food. The amount of each relief item needed by the victim is assumed based on guidance for disaster advocates from WALHI Yogyakarta (2008) and interview with representative from Ministry of Social Welfare.

Delivery cost from Provincial level facilities to potential locations for district level facilities is assumed at Rp. 2,500 per kg, while the cost from potential locations for district level facilities to each village level facility is assumed to be Rp. 3,000 per kg. Furthermore it is assumed that the available budget for the relief operation for these urban villages is Rp. 2 billion (approximately US$ 210,000).

To determine the priority level of the village level facility, it is assumed that fraction of victims relative to the village population is weakly more important than fraction of damaged buildings, and weakly more important than fraction of damaged transportation infrastructure. Fraction of damaged buildings, on the other hand is considered to be as important as fraction of damaged transportation infrastructure. The remaining data used for Model 2 are presented in Table 10.3–10.7.

Table 10.3 Amount of relief items per person per day

Item No.	Relief Item	U_n (In kg/person/day)
1	Rice	0.4
2	Instant noodle	0.095 (1 package)
3	Preserved food	0.2

The model is solved, and the results indicate that BN is chosen as district level facility and the cost is around Rp. 1.2 billion (see Fig. 10.8). The solution has been verified and consistent with the location which was chosen by the local authority during the flood disaster.

10.5 Conclusions

Many organizations are involved in disaster management in Indonesia. The government has established BNPB as the policy maker and the main coordinator in the event of major disaster. However, coordination of relief operations still face problems like long response time and unequal distribution of relief goods to the affected area. Therefore, there should be a cooperation agreement between all organizations involved so that all the permanent facilities owned by each organization can be shared during relief operation, especially in the event of disaster with severe impacts.

Table 10.4 Potential locations data

Potential locations[a]	Duration[b]	Capacity (kg)			Fixed cost[c]
		Item 1	Item 2	Item 3	
SDW-JT	90	25,000	5,000	15,000	10,000,000
BN	60	25,000	5,000	15,000	10,000,000

[a] Potential locations for district level facility
[b] Traveling time to provincial level facility (minutes)
[c] Fixed cost to open the facility (in Rupiah)

Table 10.5 Travelling time and delivery data. (District: East Jakarta)

No.	Village level facilities	Duration[a]	
		SDW-JT	BN
1	KM1	40	20
2	CBU	35	35
3	CBS	30	40
4	CM	25	45
5	CW	90	30
6	CI	70	50
7	BK	100	60

[a] Traveling time to district level facility (in minutes)

Table 10.6 Village data: flood impact

Urban village	Sub-district	Village level locations	Flood impacts		
			1[a]	2[b]	3[c]
Kp. Melayu	Jatinegara	KM1	0.222	0.1044	0.1
Cipinang Besar Utara	Jatinegara	CBU	0.564	0.0002	0.0
Cipinang Besar Selatan	Jatinegara	CBS	0.228	0.0083	0.0
Cipinang Muara	Jatinegara	CM	0.276	0.0	0.05
Cawang	Kramat Jati	CW	0.052	0.0097	0.0
Cililitan	Kramat Jati	CI	0.007	0.0016	0.1
Bale Kambang	Kramat Jati	BK	0.054	0.0115	0.05

[a] Fraction of victims to population
[b] Fraction of damaged building
[c] Fraction of damaged transportation infrastructure

Table 10.7 Village data: number of refugees

Urban village	Number of refugees								
	02-Feb	03-Feb	04-Feb	05-Feb	06-Feb	07-Feb	08-Feb	09-Feb	10-Feb
Kp. Melayu	867	2593	3971	5053	5053	5053	5053	4569	4569
Cipinang Besar Utara	22101	22101	22101	22101	21696	9248	5097	5097	3957
Cipinang Besar Selatan	5474	5474	5474	5474	5374	2291	1263	1263	981
Cipinang Muara	16394	16394	16394	16394	16094	6860	3781	3781	2935
Cawang	1655	1655	1655	1655	1625	693	382	382	297
Cililitan	320	320	320	320	315	135	75	75	59
Bale Kambang	1148	1148	1148	1148	1127	481	266	266	207

Based on the observation of the existing relief logistics network owned by the abovementioned organizations, we proposed a modeling approach to determine relief logistics facilities. The proposed logistics network involves two stages of the disaster management cycle (preparedness and response stages). At the preparedness stage, based on the disaster history, the national and provincial level facilities should be established and potential locations for the district and village level facilities should also be determined. At the response stage, the district and village level facilities should be opened. We proposed two models for the response stage. The first model is used to decide the facility locations at the village level, whereby the second model is used to determine the facility locations at the district level.

We applied the models to determine temporary facility locations of district and village level facilities in the district of East Jakarta during the 2007 Jakarta flood. The results show that the locations chosen by the models are consistent with the locations chosen during the actual event.

The proposed models are a part of the effort to develop a decision support system for disaster management in Indonesia. The models are developed to assist each organization in designing their relief logistics network during response time. The dynamics of collaboration between organizations has not yet been considered in the model, and therefore the model may be modified to consider the collaboration, such as logistics facility sharing between organizations.

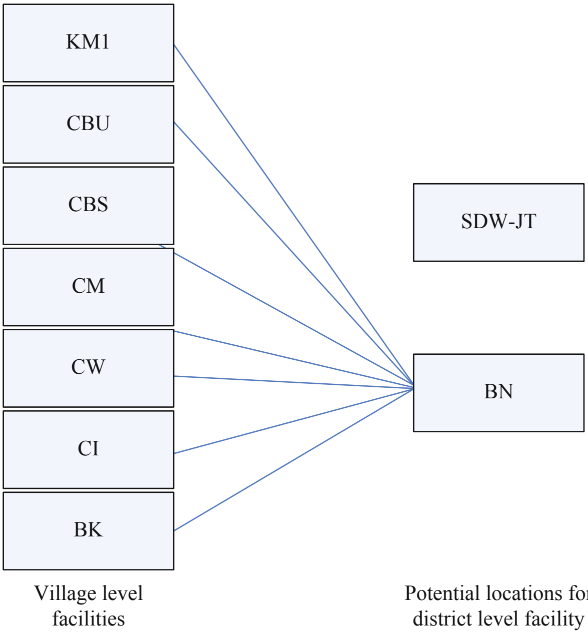

Fig. 10.8 Solution of Model 2 for district of East Jakarta

In order to complete the decision support system, a model to determine the locations of the relief logistics facilities at the preparedness stage should be developed. Furthermore, a model that evaluates the preparedness of an area towards disaster may also be developed to help local authority developing the public policy and building the required infrastructure for the disaster management in the area.

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Chapter 11
Humanitarian Logistics in the Great Tohoku Disasters 2011

Eiichi Taniguchi and Russell G. Thompson

11.1 Introduction

Humanitarian logistics plays a vital role in supplying emergency goods such as water, food and daily commodities to help persons impacted from disasters. This chapter presents details of the humanitarian logistics systems implemented following the Great Tohoku Disasters, "the 2011 off the Pacific coast of Tohoku Earthquake" and subsequent tsunami on 11th March 2011. The magnitude of earthquake was 9.0 which was the largest earthquake in the modern history of Japan. The earthquake hit the northeast part of Japan, which is called the Tohoku region (Fig. 11.1). The number of fatalities from the earthquake and tsunami was 15,870 and with 2,814 persons missing and 6,114 persons injured (as of 26 September 2012, National Police Agency, Japan). The tsunami rather than the earthquake itself affected most persons. In coastal areas the run-up height of the tsunami was between 30 and 40 m and this destroyed a range of infrastructure including roads, railways, airports, seaports as well as a number of houses, schools, factories and offices. In some cities most of the urban area was destroyed by the gigantic tsunami. The total loss in monetary terms was estimated to be 16.9 trillion Japanese yen (about US$219 billion) according to the Cabinet Office, Government of Japan (2011). At the peak, approximately 440,000 persons were displaced to refuge centres due to the severe damage to many residences. For these displaced people, humanitarian logistics was required to supply goods for living including water, food, blankets, fuel, and other daily commodities as well as medical and health care services (Holguin-Veras et al. 2012).

Regarding humanitarian logistics, a number of optimisation models have been proposed and applied in disaster situations (Caunhye 2012). Tzeng et al. (2007) developed a multi-objective model for relief distribution for displaced people. Their

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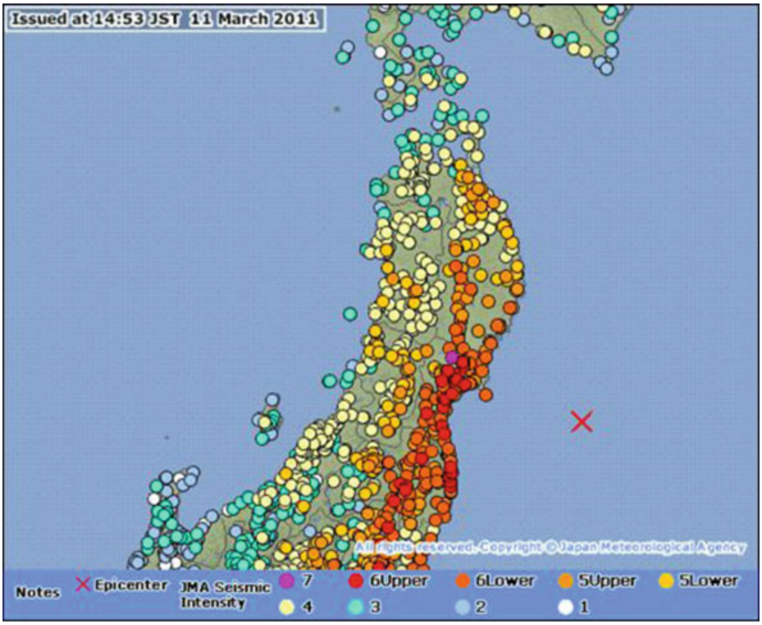


Fig. 11.1 Seismic intensity at Northern Japan due to the 2011 off the Pacific coast of Tohoku Earthquake. (Japan Meteorological Agency)

model aimed to minimise the sum of total cost, total travel time and satisfaction. The total cost and travel time are costs which are often taken into account in commercial logistics, whereas the satisfaction of displaced people is the cost of deprivation which is unique to humanitarian logistics. They applied the model in the case of an earthquake in Taiwan in 1999. Yi and Ozdamar (2007) presented an integrated location-distribution model for coordinating logistics support and evacuation operations in disaster response activities. Huang et al. (2012) presented vehicle routing and supply allocation model and discussed the equity, efficiency and efficacy of relief distribution of emergency goods.

This chapter presents a multi-objective optimisation model of the distribution of relief supplies to displaced persons in disasters. The model considers the objectives of the penalty of total shortage of supply as well as fuel consumption. These terms are most critical for the distribution of emergency goods for relief after disasters. The model was applied to the case of Ishinomaki city (see Fig. 11.1) following the Tohoku disasters 2011 to examine if the model could represent the real situation of disaster relief. The population of Ishinomaki city was 160,826 before the disaster according to the population census in October 2010 and the number of fatalities in Tohoku disaster 2011 was 3,417 and 535 people were unaccounted for. A total of 22,357 houses completely collapsed and 11,021 houses were severely damaged and 20,364 houses were partially damaged (as of 6 April 2012, Miyagi Prefecture).

11.2 Modelling Distribution of Emergency Relief Goods

A multi-objective Vehicle Routing and scheduling Problem (VRP) model is presented in this section to represent the situation where the relief supplies cannot fully satisfy the demands of displaced persons in refuge centres after the earthquake. The model incorporates two objective functions: (1) the penalty of total shortage of supply and (2) the fuel consumption. The penalty of total shortage of supply is defined as the product of the difference in supplies and demands of goods by the priority rates of delivery. Fuel consumption is also important, since in reality a lack of fuel for vehicles generated is a very critical problem associated with the operation of vehicles after disasters. The model aims to minimise the penalty of total shortage of supply and fuel consumption. The vehicle routing and scheduling problem has been formulated (Okabayashi et al. 2011) and is presented in equations (11.1)–(11.10), where:

$$\text{Minimise} \left\{ \sum_{i \in N} p_i(d_i - q_i), \sum_{k \in K} \sum_{(i,j) \in A} c_{ij} x_{ijk} / E_k \right\} \tag{11.1}$$

Subject to

$$\sum_{k \in K} \sum_{j \in V} x_{ijk} = 1 \quad \forall i \in N, \tag{11.2}$$

$$\sum_{j \in V} x_{0jk} = 1 \quad \forall k \in K, \tag{11.3}$$

$$\sum_{i \in V} x_{ihk} - \sum_{j \in V} x_{hjk} = 0 \quad \forall h \in N, \forall k \in K, \tag{11.4}$$

$$\sum_{i \in V} x_{i,n+1,k} = 1 \quad \forall k \in K, \tag{11.5}$$

$$\sum_{i \in S} \sum_{j \in V \setminus S} x_{ij} \geq 1 \quad \forall S \subset V, (S \neq \phi, S \neq V), \tag{11.6}$$

$$\sum_{i \in N} q_i \sum_{j \in V} x_{ijk} \leq Q \quad \forall k \in K, \tag{11.7}$$

$$\sum_{i \in N} q_i \leq T \tag{11.8}$$

$$q_{\min} \leq q_i \leq d_i \quad \forall i \in N, \tag{11.9}$$

$$x_{ijk} = \{0,1\} \quad \forall i, j \in N, \forall k \in K, \tag{11.10}$$

Where,

i, j, h, n	Number of refuge centre, 0 and n + 1 means the depot
N	Set of refuge centres
p_i	Priority rate per unit supply at refuge centre *i*
d_i, q_i	Demand and supply at refuge centre *i*
K, k	Set of delivery trucks and number of truck
A	Set of arcs
c_{ij}	Distance between refuge centre *i* and *j* (km)
x_{ijk}	= 1, if a vehicle *k* passes the arc (*i, j*) and = 0 otherwise
E_k	Fuel efficiency of delivery truck *k* (km/L)
V	Set of refuge centres and depot
S	Subset of *V*
Q	Capacity of delivery truck
T	Total supply at the depot
$q_{\min}$	Minimum supplies to refuge centre

Here, the decision variables are q_i: amount of delivered goods and variable x_{ijk}: = 1, if a vehicle *k* passes the arc (*i, j*) and = 0 otherwise. Constraints (11.2)–(11.6) are related to delivery trucks visiting refuge centres. Constraint (11.7) relates to the capacity of vehicles. Constraint (11.8) indicates that sum of supplies cannot exceed the total supplies at a depot. Constraint (11.9) means that the supply is between minimum supplies and demand at refuge centres. Constraint (11.10) represents the integer condition of variable.

Since the problem described above is a NP-hard combinatorial problem, Elitist Non-Dominated Sorting Genetic Algorithms (NSGA-II) were applied as a solution procedure (Deb et al. 2000). The NSGA-II provides a useful method for solving multi-objective optimisation problems in terms of the accuracy and variability of solutions.

11.3 Case Studies

11.3.1 General

The model described in the previous section was applied to problems associated with the distribution of emergency relief goods in Ishinomaki city which was severely damaged by the tsunami in the Tohoku disasters. Details of the road network where vehicles could pass on 31st March 2011 provided by Ishinomaki city was used in the case studies. Two cases were investigated: (1) Case 1; using real data on the number of displaced persons in refuge centres, (2) Case 2; assuming that the entire population in Ishinomaki city was affected and 50 % of the population was displaced to refuge centres. Figure 11.2 shows the location of refuge centres in the central area of Ishinomaki city.

Table 11.1 indicates the number of refuge centres, displaced persons, total demand and total supply on 21st March 2011 and 11th April 2011. Only the total demand and

Fig. 11.2 Location of refuge centres in the central area of Ishinomaki city

Table 11.1 Number of refuge centres, displaced people, total demands and total supplies. (Source: Ishinomaki city)

Date	Number of refuge centres	Number of displaced persons	Total demand (pieces)	Total supply (pieces)
21st March	110	41,922	125,766	48,514
11th April	152	30,930	92,790	74,570

supply of rice balls ("onigiri" in Japanese) and bread were considered in these applications. The total demand was estimated as three times as the number of displaced persons. We understand that the total supply was only 38.5 % on 21st March (10 days after the earthquake) and 80.4 % on 11th April (one month after the earthquake).

The parameters of NSGA-II were set as follows based on preliminary studies: number of individuals = 16, number of generations = 30, crossover rate = 0.8 and mutation rate = 0.2.

11.3.2 Case 1

The purpose of applications in Case 1 was to determine how many trucks with what capacity were needed as well as how many depots were required for the distribution of emergency relief goods. The results of optimisation were compared with those of the real operation. Data at 21st March (10 days after the earthquake) was used. We assumed three types of trucks, namely the capacity of trucks is 1, 4 and 10 t were used. The location of depots was assumed to be three potential points as shown in Fig. 11.3. The sports park was actually used by Japan Self Defence Forces (JSDF) and private freight carriers who were in charge of relief distribution operations just after the earthquake. The market also used after the sports park was closed in September 2011. The hotel grounds is a hypothetical location, which was not used in the real operation. The clustering of delivering goods for each depot is shown in Fig. 11.3 which was determined based on the real operation of vehicle dispatching by JSDF.

Fig. 11.3 Three potential locations of depots

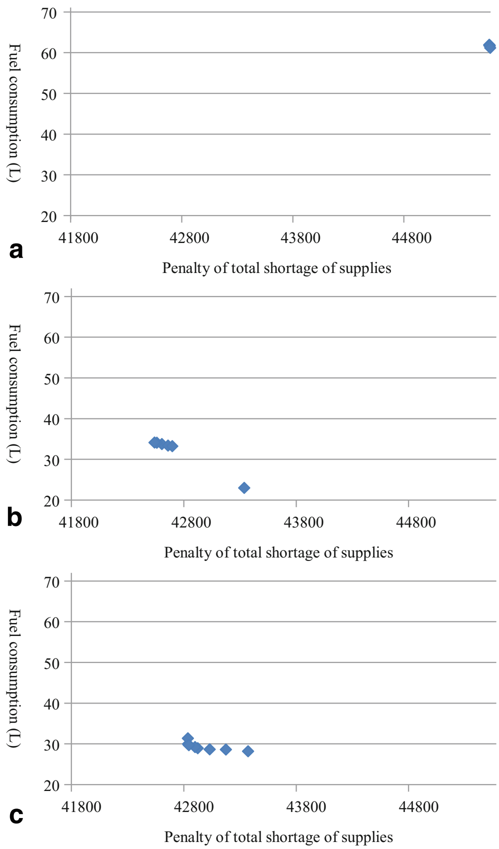


Fig. 11.4 Pareto fronts of optimisation results. **a** 1 ton truck. **b** 4 ton truck. **c** 10 ton truck

Figure 11.4 illustrates the Pareto fronts of the multi-objective optimisation. Here, multiple solutions are given in the calculations. As we can emphasize the penalty of total supply shortage rather than fuel consumption in humanitarian logistics, the minimum point of the total shortage of supplies can be taken as the representative value of the optimisation. Figure 11.5 shows the effect of truck size. It indicates

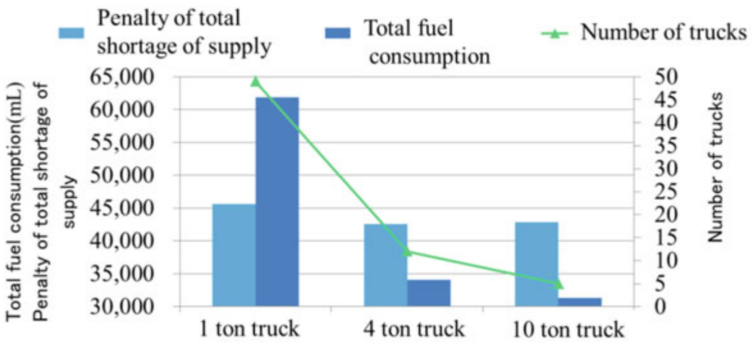


Fig. 11.5 Effect of truck size

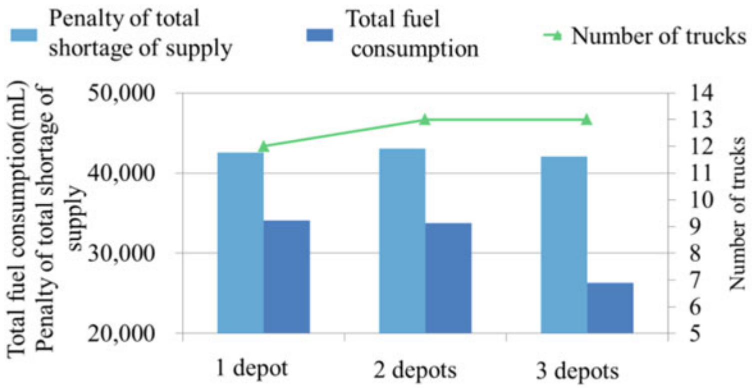


Fig. 11.6 Effects of the number of depots

that the number of trucks and total fuel consumption decreased with increased truck capacity. However, the penalty of total supply shortage became lowest when 4 t trucks were used. In the real situation, 4 t trucks were used for distribution operations by JSDF and private freight carriers. Therefore, this contributed to minimise the penalty of total shortage of supplies. The optimal number of trucks in case where 4 t trucks were used was 12, whereas in the real situation it was 20. As the real operation was not optimised, the optimisation model suggests that some improvement is possible for reducing the number of trucks.

The effect of the number of depots is shown in Fig. 11.6. Three cases were tested: one depot; sports park, two depots; sports park and market, three depots; sports park, market, and hotel grounds, and only 4 t trucks were used based on the previous optimisation results. The results indicate that the penalty of total shortage of supply does not substantially change with the change of number of depots. Total fuel consumption was minimum in the case of three depots and the number of trucks was minimum in case of one depot. The case of three depots was very helpful to reduce the

Fig. 11.7 Results in the case of delivering emergency goods proportional to the number of displaced persons in each refuge centre (Case 2-0)

distance travelled and resulted in the substantial reduction in fuel consumption. Note that the construction costs of depot were not taken into account in the calculation, since there are almost no costs for setting up depots in emergency cases.

11.3.3 Case 2

The case 2 assumes that the entire population of Ishinomaki city was affected by tsunami and 50 % of them were displaced to refuge centres. The road network is the same as in Case 1. The purpose of Case 2 is to obtain basic knowledge on preplanning of distribution of emergency relief goods. Three cases were conducted:

Case 2-0: Emergency goods were delivered proportional to the number of displaced persons in each refuge centre
Case 2-1: Emergency goods were delivered based on the priority rate p_i
Case 2-2: Emergency goods were delivered for four days changing the priority rate p_i

Figure 11.7 shows the results for the case of delivering emergency goods proportional to the number of displaced persons in each refuge centre (Case 2-0). The sufficiency rate which is defined as the percentage of delivered goods to demand was 44.2 % in all refuge centres. This case ensures that all the refuge centres can receive the same amount of goods per displaced person. But the average sufficiency rate of 44.2 % was low.

We examined the effects of introducing priority rate p_i in delivering emergency goods to hospitals and old people's homes $p_i = 1.2$ and to other refuge centres $p_i = 1.0$ in Case 2-1 (Fig 11.8). In this case, the sufficiency rate of refuge centres with higher priority rate increased to 80–100 % but that of refuge centres with

Fig. 11.8 Results in case of delivering emergency goods based on the priority rate (Case 2-1)

Table 11.2 Change of priority rate depending on the sufficient rate of current day

Sufficient rate of current day (%)	Priority rate for ordinary refuge centres	Priority rate for hospitals and old people's homes
0–20	1.2	1.2
20–40	1.1	1.2
40–60	1.0	1.2
60–80	0.9	1.2
80–100	0.8	1.2

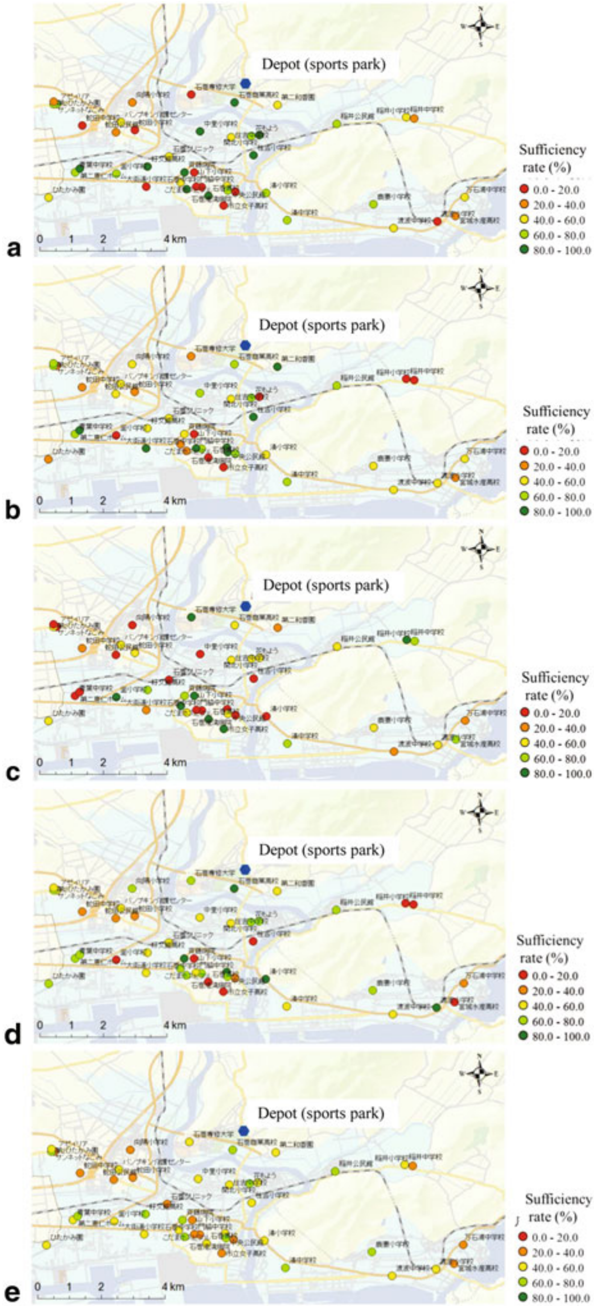
lower priority rate decreased to 0–20 %. As the discrepancy of sufficiency rate among refuge centres is not acceptable, we consider the optimisation in multiple periods in the next case, Case 2-2.

In Case 2-2 we consider four days and change the priority rate depending on the sufficiency rate of current day as shown in Table 11.2. For example, if the sufficient rate of current day is less than 20 %, then the priority rate for next day will be 1.2.

Figure 11.9 illustrates the change of sufficiency rate for 4 days and total of 4 days. This indicates that the sufficiency rate can be improved by changing the priority rate. In Fig. 11.9e the overall sufficiency rate for 4 days is relatively higher compared with Case 2-1 and no refuge centre has a sufficiency rate less than 20 %. Figure 11.10 demonstrates that the overall sufficiency rate for hospitals and old people's homes in Case 2-2 was improved compared with Case 2-0 * 4 days and that of ordinary refuge centres remains almost with the same sufficiency rate. Therefore, the multiple optimisation in Case 2-2 ensures the improvement of overall sufficiency rate during the 4 days.

Figure 11.11 presents a comparison of total fuel consumption between Case 2-2 and Case 2-0 * 4 days. Total fuel consumption in Case 2-2 was reduced by 23 % compared with Case 2-0 * 4 days. This indicates that optimising the delivering emergency goods by considering the penalty of total shortage of supply can also contribute to reduce total fuel consumption for 4 days.

Fig. 11.9 Results in the case of delivering emergency goods for 4 days changing the priority rate (Case 2-2). **a** Day 1. **b** Day 2. **c** Day 3. **d** Day 4. **e** Total of 4 days



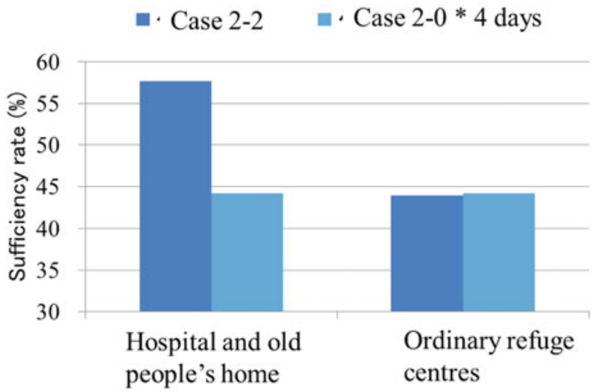


Fig. 11.10 Overall sufficiency rate in Case 2-2 and Case 2-0 * 4 days

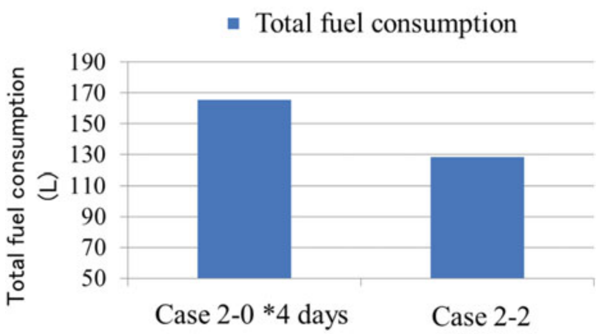


Fig. 11.11 Total fuel consumption in Case 2-2 and Case 2-0 * 4 days

11.4 Conclusions

The Great Tohoku disasters were of an unprecedented scale in Japan and provided enormous challenges for humanitarian logistics. The wide geographic area impacted consisted of many remote townships where populations with a large number of aged persons lived and difficulties servicing the needs of displaced persons was compounded by the lack of electricity and communication systems immediately following the disasters.

This chapter presented a multi-objective vehicle routing and scheduling problem model for delivering emergency goods to refuge centres that was applied in cases of Ishinomaki city which were affected by the Tohoku disasters. The results showed the model can be used for optimising the delivery system in the case of emergency in which the demands of displaced people exceed supplies. The optimisation model allowed the required number of trucks, the location of depots as well as the priority of delivery in hospitals and old people's homes in pre-planning of disaster mitigation to be investigated.

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