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Two-stage network design in humanitarian logistics.

Seyed Soroush Moeini
University of Louisville

TWO-STAGE NETWORK DESIGN IN HUMANITARIAN LOGISTICS

By

Seyed Soroush Moeini
B.S. in Industrial Engineering, Azad University of Karaj, Karaj, Iran, 2007
M.S. in Industrial Engineering, Sharif University of technology, Tehran, Iran, 2011

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Department of Industrial Engineering
Speed School of Engineering
University of Louisville
Louisville, Kentucky

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A Dissertation Approved on

March 3, 2014

by the Following Dissertation Committee:

Dr. Sunderesh S. Heragu

Dr. Anup Kumar

Dr. Gerald W. Evans

Dr. John S. Usher

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ABSTRACT

TWO-STAGE LOGISTICS NETWORK DESIGN IN HUMANITARIAN OPERATIONS

Seyed Soroush Moeini

March 3, 2014

Natural disasters such as floods and earthquakes can cause multiple deaths, injuries, and severe damage to properties. In order to minimize the impact of such disasters, emergency response plans should be developed well in advance of such events. Moreover, because different organizations such as non-governmental organizations (NGOs), governments, and militaries are involved in emergency response, the development of a coordination scheme is necessary to efficiently organize all the activities and minimize the impact of disasters.

The logistics network design component of emergency management includes determining where to store emergency relief materials, the corresponding quantities and distribution to the affected areas in a cost effective and timely manner. In a two-echelon humanitarian relief chain, relief materials are pre-positioned first in regional rescue

centers (RRCs), supply sources, or they are donated to centers. These materials are then shipped to local rescue centers (LRCs) that distribute these materials locally. Finally, different relief materials will be delivered to demand points (also called affected areas or AAs).

Before the occurrence of a disaster, exact data pertaining to the origin of demand, amount of demand at these points, availability of routes, availability of LRCs, percentage of usable pre-positioned material, and others are not available. Hence, in order to make a location-allocation model for pre-positioning relief material, we can estimate data based on prior events and consequently develop a stochastic model. The outputs of this model are the location and the amount of pre-positioned material at each RRC as well as the distribution of relief materials through LRCs to demand points.

Once the disaster occurs, actual values of the parameters we seek (e.g., demand) will be available. Also, other supply sources such as donation centers and vendors can be taken into account. Hence, using updated data, a new location-allocation plan should be developed and used. It should be mentioned that in the aftermath of the disaster, new parameters such as reliability of routes, ransack probability of routes and priority of singular demand points will be accessible. Therefore, the related model will have multiple objectives.

In this dissertation, we first develop a comprehensive pre-positioning model that minimizes the total cost while considering a time limit for deliveries. The model incorporates shortage, transportation, and holding costs. It also considers limited capacities for each RRC and LRC. Moreover, it has the availability of direct shipments (i.e., shipments can be done from RRCs directly to AAs) and also has service quality. Because this model is in the class of two-stage stochastic facility location problems, it is NP-hard and should be solved heuristically. In order to solve this model, we propose using Lagrangian Heuristic that is based on Lagrangian Relaxation.

Results from the first model are amounts and locations of pre-positioned relief materials as well as their allocation plan for each possible scenario. This information is then used as a part of the input for the second model, where the facility location problem will be formulated using real data. In fact, with pre-positioned items in hand, other supplies sources can be considered as necessary. The resulting multi-objective problem is formulated based on a widely used method called lexicography goal programming. The real-time facility location model of this dissertation is multi-product. It also considers the location problem for LRCs using real-time data. Moreover, it considers the minimization of the total cost as one of the objectives in the model and it has the availability of direct shipments. This model is also NP-hard and is solved using the Lagrangian Heuristic.

One of the contributions of this dissertation is the development of Lagrangian Heuristic method for solving the pre-positioning and the real- time models. Based on the results of Lagrangian Heuristic for the pre-positioning model, almost all the deviations from optimal values are below 5%, which shows that the Heuristics works acceptably for the problem. Also, the execution times are no more than 780 seconds for the largest test instances. Moreover, for the real-time model, though not directly comparable, the solutions are fairly close to optimal and the execution time for the largest test instance is below 660 seconds. Hence, the efficiency of the heuristic for real-time model is satisfactory.

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CHAPTER 1

INTRODUCTION

1.1 Definition of disaster

According to the International Federation of Red Cross [1] **, "**A disaster is a sudden, calamitous event that seriously disrupts the functioning of a community or society and causes human, material, and economic or environmental losses that exceed the community's or society's ability to cope using its own resources". Both natural causes and human activities can create a disaster. There is almost a general agreement that there is a significant difference between "every day emergencies" and "serious disasters" [2]. Routine or everyday emergencies include small fires or car accidents. Such cases are often covered quickly by ambulances, firefighters and other emergency response vehicles. But serious disasters cannot be handled in a short amount of time and requires a long term response. Also, many entities will need to participate in responding to such emergencies.

Disasters can be categorized according to two major factors: the speed of onset and the source that causes the disaster to occur [3]. Table.1 presents some examples for each category:

Table 1 Examples of different categories of disasters

	Natural	**Man-made**
Slow on-set	Drought, Famine	Political crisis
Sudden on-set	Earthquake, Flood	Chemical leak, Terrorist attack

Disasters with sudden on-set require an emergency response.

1.2 Emergency Response

In the United States, emergency management includes four major phases: Mitigation, Preparedness, Response, and Recovery [2, 4, 5].

1. **Mitigation**: This step is ideally done before the disaster. It includes activities that minimize or at least reduce the negative consequences of a disaster (such as injuries or property damage). In fact, in the mitigation stage, activities that minimize the risk to people's lives and properties in case of disasters are investigated. At a microscopic level, it may contain activities such as fastening bookshelves or heaters to walls so that they do not fall in an earthquake. At a macroscopic level, it consists of higher level activities such as identifying appropriate safe areas, designing and constructing buildings differently, locating temporary housing areas during a disaster, and performing engineering studies in the designing process of buildings so that they can withstand natural forces. It should be mentioned that a separate but very important part of mitigation is insurance (for people, properties, and businesses). Other activities related to mitigation stage are as follows:
    - Constructing barriers to deflect disaster forces

- Tax disincentives to locate in disaster prone areas and incentives to construct in safe areas.

2. **Preparedness**: Simply put, this phase pertains to planning, organizing, training, exercising, evaluating and correcting in order to have an efficient coordination of activities that should be undertaken in response to a disaster. This phase involves the development of a DSS (Decision Support System) for the duration of a disaster. It also involves division of work and responsibilities of the emergency activities as well as prepositioning necessary materials such as food, blanket and medical supplies required for responding to a disaster. Generally, major activities that should be done in this phase are as follows:
    - Hiring and training personnel for emergency services
    - Training citizens
    - Education about do's and don'ts during emergency periods
    - Preserving emergency supplies
    - Preparing budget for vehicles and ambulances
    - Developing a DSS and emergency communication system.

3. **Response**: In this phase, the emergency response actions that were developed for specific scenarios predicted in the preparedness phase should be executed subject to the updated information available immediately after the occurrence of a disaster. Time is the most important element of this phase. Moreover, donations

play an important especially in severe disasters such as earthquakes. A list of important activities of the response phase is provided below.

- Continuous update of information related to disaster (e.g. availability of roads, quantity of demand for different relief materials, statistics of affected population, and percentage of usable pre-positioned material)
- Activating the emergency plans
- Evacuating affected areas
- Firefighting equipment
- Performing medical care
- Sheltering
- Fatality management

4. **Recovery**: The response phase starts immediately after the disaster. But recovery involves activities that restore the situation to normalcy. Recovery stage has two steps: short term recovery and long term recovery. Short term recovery overlaps in many areas with the response phase. In fact, in short term recovery, the goal is to return life-support systems to minimum standards. On the other hand, long term recovery is about returning the situation to normalcy or improved status. Re-establishing damaged routes is an example of short term recovery activities while complete re-building a fully damaged building pertains to long term recovery. The following list shows important activities of the recovery phase.
    - Debris clean-up
    - Rebuilding bridges, roads and buildings

- Mental health services
- Financial assistance to people and organizations

The focus of this dissertation is on the preparedness and response stages.

1.3 The prepositioning problem

One of the most important activities in the preparedness stage is the pre-positioning of different relief materials. In case of a war, the pre-positioning problem plays a vital role. In that case, different types of materials such as weapons, tanks, and meals are pre-positioned in order to facilitate the military in taking a quick action (reaction) in case of a war. In humanitarian logistics, the pre-positioned materials are required to cover at least the immediate period of the aftermath of a disaster. After a disaster occurs, the pre-positioned materials will be shipped from regional rescue centers (RRCs) to local rescue centers (LRCs) and then will be delivered to affected areas (AAs). In practice, LRCs help improve the response time. If all the relief materials are shipped directly from RRCs to AAs, there will be too much empty back-haul for transportation vehicles, but when we have LRCs, a set of vehicles can cover a certain route (e.g. from an LRC to an AA) which has less empty back-haul. Moreover, in LRCs, different materials coming from different RRCs can be sorted and packed in order to become ready to be shipped to AAs. If each RRC is designed to store a certain quantity of relief materials, an LRC will be assigned to different RRCs and from there, required materials for each demand point can be grouped together and delivered. Figure 1 shows the material flow between RRCs, LRCs and AAs.

The objective of the problem is to minimize the total cost (including transportation,

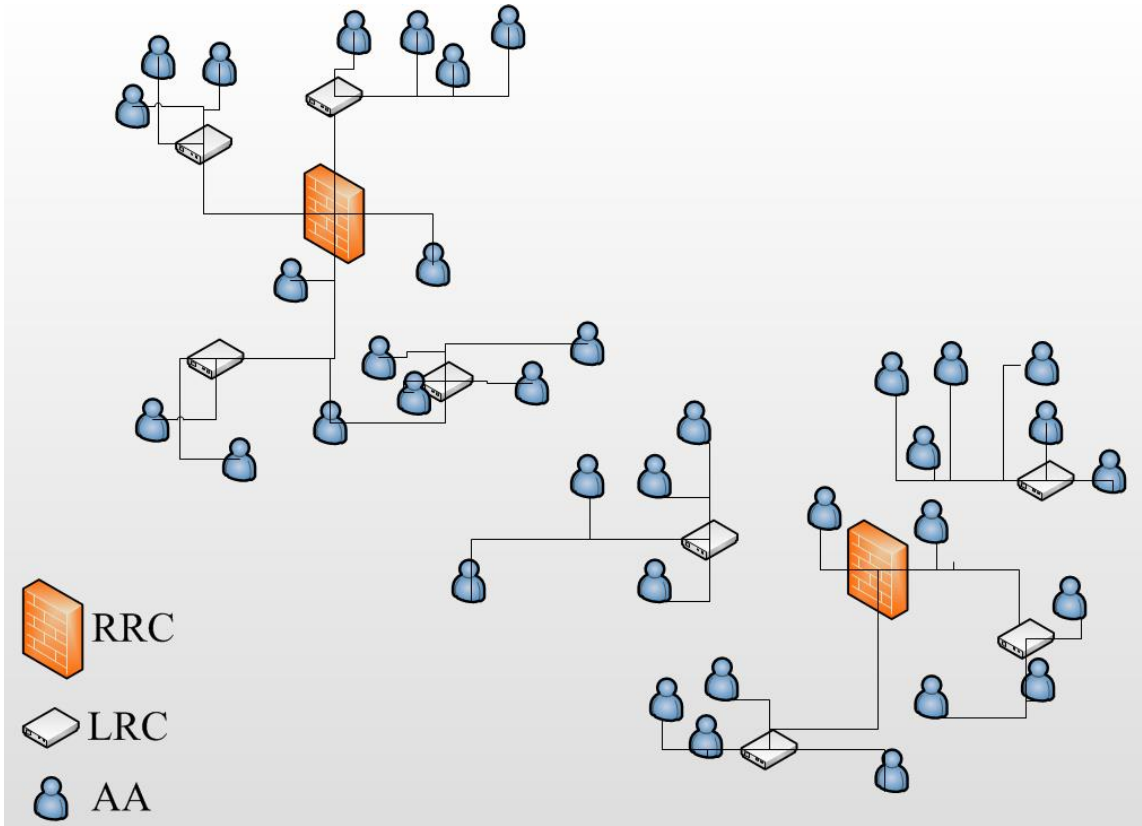


Figure 1. Material flow between supply sources, distribution nodes and affected areas

shortage, and fixed operational costs) subject to meeting delivery constraints. The decisions made include:

1) The set of RRCs to open.
2) The amount of each relief material that should be pre-positioned in opened RRCs
3) The set of LRCs to open under each scenario.
4) Under each scenario, the amount of the material that should flow between RRCs, LRCs and AAs.
5) The set of scenarios to include in the reliable set (i.e., the scenarios for which all the demand must be met)

6) Direct shipments (i.e. direct transportation between RRCs and AAs) if any.

1.4 The real-time facility location problem

The modeling and analysis activities in the preparedness stage are based on possible scenarios and estimations of the real disaster. But when a disaster occurs, the actual values of parameters of the problem will be available. In fact, this is one of the most important activities of the response stage (other important activities of this phase include alerting and warning, protecting, and restoration). After the disaster, data related to following must be updated.

- Exact locations of demand points
- Demand at each demand point
- Availability of routes and roads between the different sets of nodes (RRCs, LRCs and AAs)
- Availability of pre-defined LRCs
- Exact amounts of usable pre-positioned materials
- Reliability of routes (in terms of accessibility and availability)
- Ransack probabilities of routes.

According to the updated data, it is possible that the distribution scheme, obtained from the preparedness stage, is not optimum. Moreover, the amount of usable pre-positioned materials might not be adequate to satisfactorily cover the demand. Thus, other supply sources can be taken into account. In fact, there will be a new facility location problem that has some pre-positioned materials in hand and aims to optimize multiple objectives such as demand satisfaction, cost minimization, and ransack probability minimization. The following decisions will be made in this model:

1) Should donation centers be used?

2) Should we provide more relief items from vendors?

3) According to real-time data, which LRCs should be opened?

4) What is the new distribution plan according to real-time data?

5) Should we have direct shipments?

Figure 2 shows the map of the two-stage network. Pre-positioning model is built up based on estimations of parameters of the disaster (e.g., amount of demand at demand points, travel times, and transportation costs). Values of decision variables of the period before the occurrence of the disaster (e.g., location of the pre-positioning facilities) along with real-time values of all other parameters are inputs of the real-time model. The major output of the real-time model is the complete distribution plan.

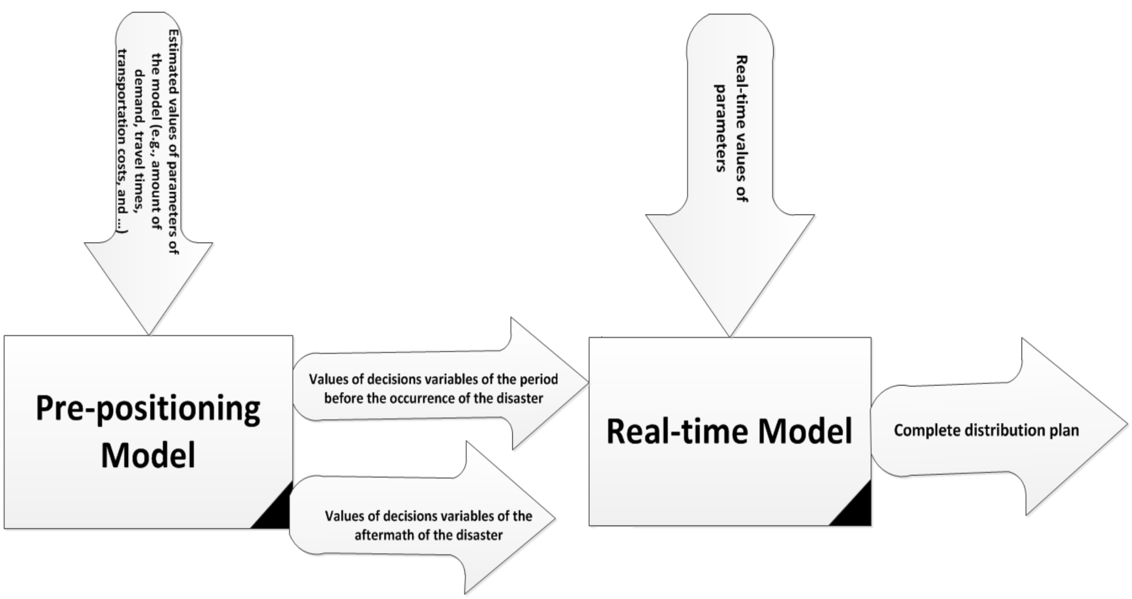


Figure 2. The map of the two-stage network

CHAPTER 2

LITERATURE REVIEW

2.1 Surveys about 4-stage emergency response

The Federal Emergency Management Agency (FEMA) [4] in the US describes the features of each of the four stages while giving guidelines about the important activities that must be done in each. It also presents comprehensive information about the relationship between the four stages. This reference is actually an online course about emergency management.

Altay et al. [2] list some of the most important papers (mainly related to Operations Research and Management Science) done on different aspects and activities of each stage and as conclusion, introduce the fields that require more effort. They also mention that by year 2006, most papers had concentrated on only the mitigation stage. They present a list of valuable resources about disaster operations. The list includes journals, research centers, and data bases.

The Electronic Encyclopedia of Civil Defense and Emergency Management [5] is another source that defines and explains the four stages.

2.2 Literature related to humanitarian logistics and relief chains

Balcik et al. [6], first, list different fields of a relief supply chains that require coordination. Some instances are transportation and relief procurement. Then, they investigate different coordination mechanisms and papers pertaining to each. They also name the NGOs (non-governmental organizations) as well as military and local government as main entities of a relief chain.

Holguín-Veras et al. [7] mention the "decision support tools" as one of major research areas that needs attention and effort. Decision support in emergency management pertains to preparedness and response phases. The preparedness phase is before the occurrence of disaster (pre-disaster). They also investigate the effects of different parameters of the problem in the decision making process. These parameters include the severity of the event (disaster or catastrophe), features of the demand, and the complexities of the required decision support system. They also provide the areas that require more effort.

Heaslip et al. [8] list the stakeholders in the occurrence of a disaster and highlight the importance of coordination between them. They mention that in order to respond effectively to a disaster, NGOs, Logistics Firms, Military agencies and even Citizens should be prepared. They, then, mention the complexities of establishing effective relationships between each group of stakeholders and suggest a method called SADT (System analysis and design technique) as an appropriate solution to analyze such relationships.

Days et al. [9] define the concept of humanitarian and disaster relief supply chain (HDRSC) and its differences with other supply chains. They also provide guidelines on how one should study such a chain.

References [2, 6, 9] were actually surveys and literature review papers about the efforts done on emergency management. Some other papers investigate certain previous disasters.

Gatignon et al. [10] explains how the IFRC (International Federation of the Red Cross) uses a decentralized supply chain for its activities. They investigate different aspects of a decentralized supply chain. And finally, as an assessment of this change, they analyze the effect of that on the earthquake that occurred in Yogyakarta, Indonesia on 2006 and make a comparison between that and some other earthquakes such as the one in Pakistan (2005). They show that using decentralized supply chain leads to better outcome in terms of cost, time and service quality.

Holguín-Veras et al. [11] conduct a comparison between various structures related to humanitarian logistics that was formed in response to the 2010 earthquake in Port-au-Prince, Haiti. The three structures are as follows:

1. Agency Centric Efforts (ACE): Most of the emergency activities are done by an external group.
2. Collaborative Aid Networks (CANs): Activities are performed by entities that are part of both impacted land and other communities (such as religious groups).

3. Partially Integrated Efforts (PIEs): This structure is between the two previous ones. Each side will perform different levels of activities. Note that there are many possibilities.

The study showed that the CAN structure should be considered because solely leaning on ACE is not effective.

Argollo da Costa et al. [12] focus on four large disasters (Indian Ocean 2004, Pakistan 2005, Brazil 2011, and Japan 2011) and study the effect of logistics procedures on the emergency response to each of them. Their paper emphasizes on important activities that should be done in the immediate aftermath of a disaster. They mention that in Japan's earthquake, because activities such as health team training, using professional managers as assessors, and implementing screening systems for medical services helped create the best (among four) response to the disaster.

2.3 Literature related to facility location problem

2.3.1 Taxonomy of facility location problems

The remainder of this chapter reviews literature on quantitative models similar or related to those that are considered in this dissertation. The major models of the dissertation are facility location and allocation models with different assumptions. Hence, we first review the literature of facility location problem.

According to Brandeau et al.[13], facility location problems can be categorized according to three major factors:

1. Objective: Examples are minimizing total travel distance, and maximizing minimum travel time/cost
2. Decision variables: Location of and capacity of facilities
3. Parameters: Deterministic versus probabilistic, and constrained versus unconstrained

Then, according to different combinations of each category, they list 54 different facility location problems. Klose et al. [14] developed a taxonomy and use nine criteria to categorize the facility location problem. Then, according to how each problem is formulated, they list three categories for the problem.

<u>Network Location Models</u>: Nodes are demand points as well as possible locations for facilities. P-median, p-center and set-covering are three major problems of this group. Revelle et al. [15] conducts a comprehensive literature review on papers related to these three problems).

<u>Continuous Location models</u>: The solution space is continuous and an appropriate metric is chosen to calculate distances (e.g. Euclidian and right-angle metrics). Weber problem and multi-source Weber problems pertain to this branch.

<u>Mixed-integer programming models</u>: this type is similar to network models, but the major difference is that here, the distances between nodes (facilities and demand points) are considered as input parameters while in network models, they have different metrics.

Farahani et al. [16] review papers on the multi-objective facility location problem. The categorization here, is based on the decision making approach each paper has used. They present three types of problems: bi-objective problems, *k*-objective problems, and multi-attribute problems. In bi-objective problems, decisions are made according to two objectives whereas in k-objective problem, more than two objectives are considered. The multi attribute problem is solved using techniques such as Analytical Hierarchy Process (AHP). Arabani et al. [17] review literature related to several types of facility location problems.

We now briefly review Network Location Models as well as Continuous Location models.

2.3.1.1 Network Location Models

***P*-median model:**

One the most basic formulations of the facility location literature is the p-median model. It was first developed by Hakimi [18] in 1964. In this model, there is a set of nodes that contain demand points as well as candidate locations for building facilities. The distances between nodes are weighted. The model locates p facilities in way that minimizes the total weighted distance between facilities and their assigned demand points. The mathematical formulation is as follows.

$$min \sum_{j \in J} \sum_{k \in K} w_k d_{kj} x_{kj}$$

Subject to

$$\sum_{j \in J} x_{kj} = 1 \qquad \forall\ k \in K$$

$$x_{kj} - y_j \leq 0 \qquad \forall\ k \in K,\ j \in J$$

$$\sum_{j \in J} y_j = p$$

z and *y* are binary variables

Where k is a set of nodes, j (a subset of k) is set of potential facilities, $w_k d_{kj}$ is the weighted distance between nodes j and k. x_{kj}= 1 if demand point k is assigned to facility j, and y_j = 1 if a facility is located at node j.

Mladenovic et al. [19] review the literature on solution methods for this problem. The various well-known heuristics used are greedy, stingy and composite. Genetic search, simulated annealing and ant colony are mentioned as popular meta heuristics for solving the problem.

Berman et al. [20] have developed a variant of the *p*-median problem. According to this model, not necessarily all, but at least α percent of total demand will be satisfied. This type of approach is called α-reliable modeling which is also used in this dissertation.

_p_-center problem:

This problem was also first addressed in [18] and locates p facilities in a way that maximum distance between facilities and demand points is minimized.

Min r

Subject to

$$r - \sum_{j \in J} \sum_{k \in K} w_k d_{kj} x_{kj} \geq 0 \qquad \forall \ k \in K$$

$$\sum_{j \in J} x_{kj} = 1 \qquad \forall \ k \in K$$

x_{kj} - $y_j \leq 0$ $\forall$ k∈K , j∈J

$$\sum_{j \in J} y_j = p$$

x, *y* are binary variables

There are 2 other problems called "conditional p-median" and "conditional p-center". Both models assumes that there is an existing set of facilities and attempts to locate new facilities with respect to the current ones according to regular *p*-median and *p*-center problems. The first reference that addressed these problems was [21].

Later, Berman et al. [22], used a new formulation for those problems, assuming that each demand point will be served by the closet facility, whether it is an existing or a new one.

Set-covering problem:

The objective of this problem is to locate a minimum number of facilities so that the distance between the locations of facilities and demand points do not exceed a threshold.

$$\boldsymbol{Min} \sum_{j \in J} \boldsymbol{y_j}$$

Subject to

$$\sum_{j \in J} \boldsymbol{a_{kj} \cdot y_j \geq 1} \qquad \forall\ \boldsymbol{k} \in \boldsymbol{K}$$

y_j is a binary variable

Here, $\boldsymbol{a}_{kj}$= 1 if the distance between node k and facility j is no more than a predetermined value.

Farahani et al. [23] have done a comprehensive review of the literature on set covering problem. It also presents all the mathematical formulations related to each paper it reviews.

There is also a two-stage set covering problem (called as hub covering) that was first addressed by Campbell [24]. Supplies are first sent from facilities to distribution nodes (i.e. hubs) and then shipped to demand points. The location of hubs will be determined in a way that covers all the demand.

2.3.1.2 Continuous models:

Weber problem: The original Weber problem locates a facility in a way that the sum of its weighted distances form k demand points (each located at (a_k,b_k) is minimized. The formulation is as follows.

$$\underset{x,y}{\text{Min}} \sum_{k \in K} w_k d_k(x,y) \quad , \quad d_k(x,y) = \sqrt{(x - a_k)^2 + (y - b_k)^2}$$

Multi-source Weber problem: This is an extension of Weber's original problem. Here, the location of p (more than 1) facilities should be determined with the same objective. Also, each demand point should be assigned to only one facility.

$$\underset{x,y}{\text{Min}} \sum_{k \in K} \sum_{j=1}^{p} (w_k d_k(x,y)).\ x_{kj} \quad , \quad d_k(x,y)$$

Subject to

$$\sum_{j \in J} x_{kj} = 1 \; \forall \;\; k \in K$$

x_{kj} is a binary variable

x_{kj} = 1 if the demand of node *j* be assigned to *j*

An interesting variant of Weber problem was developed by Bhattacharya [25] where a multi-objective model was developed so that the minimum distance of facilities is maximized (the closeness of facility is hazardous). This problem also pertains to maximal covering class because one of its objectives is to maximize the number of covered demand points.

2.3.2 Mixed integer programming models

In mixed integer programming models, there is a tradeoff between the fixed cost of opening facilities and variable transportation cost. This type of models themselves can be categorized according to following criteria [14]:

- Single stage (echelon) vs. Multi-stage
- Capacitated vs. Uncapacitated
- Single products vs. Multiproduct
- Single period vs. Multi period (Dynamic models)
- Deterministic vs Stochastic.

Single stage (echelon) vs. multi-stage

The simplest form of mixed integer facility location models is provided below

$$Min \sum_{i \in I} f_i . y_i + \sum_{i \in I} \sum_{k \in K} c_{ik} x_{ik}$$

Subject to

$$\sum_{i \in I} x_{ik} = 1 \qquad \forall \quad k \in K$$

$$x_{ik} \leq y_i \qquad \forall \quad i \in I \quad , \quad k \in K$$

y_i and x_{ik} are binary variables

In this single-stage model, f_i is fixed cost of opening a facility at location i, c_{ik} is unit transportation cost between facility i and demand point k, y_i equals 1 if a facility is opened at location i, and x_{ik} equals 1 if demand of demand point *k* is satisfied by facility i. The first constraint assures that each demand point will be allocated to exactly one facility. The second constraint allows shipments from a facility only if it is opened. If we assume that x_{ik} is non-negative variable, then we will have a mixed-integer linear programming model. c_{ik} is the unit transportation cost between facility i and demand point *k*.

On the other hand, in multi-stage models, the demand of each demand point is not directly shipped from facilities. It is first sent to one or more intermediate nodes and from there to demand points. Depending of the nature of the problem, these nodes can be warehouses, distribution nodes, or even retailers. The most widely used form of multi-stage models is the two-stage model where there is only one set of intermediate nodes. Figure 3 shows the general structure of two-stage models.

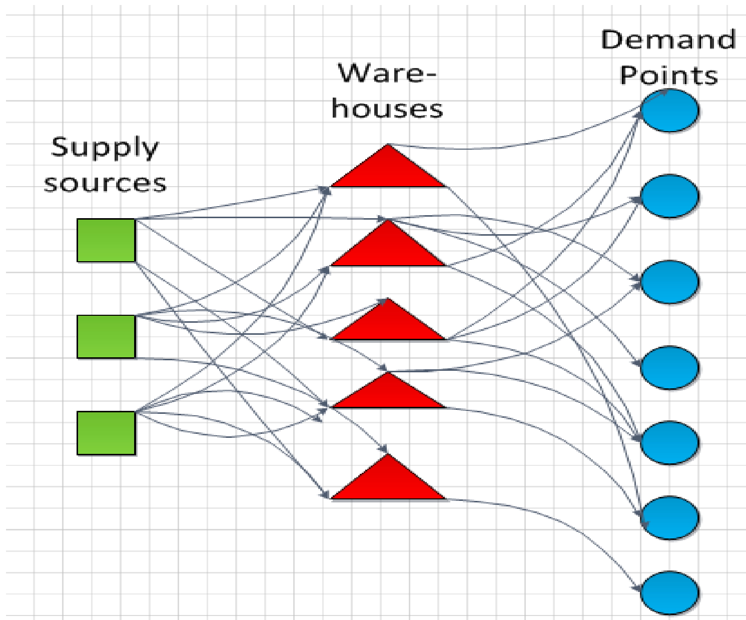


Figure 3. Two-echelon business supply chain

Syarif et al. [26] perform an analysis on such models. There is no single way of modeling this problem, but two general ways of modeling it are transshipment and complete allocation models. In a complete allocation model, each demand point can be satisfied by only one facility via exactly one intermediate node. But in transshipment, this assumption is not considered. The simplest way of formulating the complete allocation problem is as follows.

$$Min \sum_{i \in I} f_i . y_i + \sum_{j \in j} g_j . z_j + \sum_{i \in I} \sum_{j \in J} \sum_{k \in K} c_{ijk} . x_{ijk}$$

Subject to

$$\sum_{i \in I} \sum_{j \in J} x_{ijk} \geq 1 \quad \forall \quad k \in K$$

$$x_{ijk} \leq y_i \qquad \forall \quad i \in I \quad , \quad j \in J \quad , \quad k \in K$$

$$x_{ijk} \leq z_j$$

x_{ijk} , y_i , and z_j are binary variables.

where i is set of facilities, j is set of warehouses, k is set of demand points, f_i and g_j are fixed costs of opening a facility at location i and a warehouse at location j, respectively. x_{ijk} = 1 if the demand point of location k is satisfied by facility i via warehouse j. y_i , z_j equals one if a facility is opened at location i and a warehouse is opened at location j, respectively. The first constraint guarantees that demand is satisfied. The second and third constraints assure that shipments from a facility to a warehouse and then to a demand point can occur only if the corresponding facility and warehouse are open.

Capacitated vs. Uncapacitated

In a typical facility location problem, the facilities are considered to have unlimited supply capacity. But in reality, this assumption rarely holds because the total number of facilities as well as the capacity of each is not unlimited. In two stage problems, the intermediate nodes (such as warehouse) can also have limited capacity. In network models, the arcs (i.e. the links between facilities and demand points) can be capacitated. Ghosh [27] compares three heuristics for the uncapacitated problem in terms of their performance.

Dasci et al.[28] impose capacity limits to the problem in an interesting manner. In fact, instead of assigning a fixed value for facility capacity, they include an increasing function for operational cost of a facility. The model allocates optimal capacity at each facility.

Single products vs. multiproduct

In many cases, more than one product is produced or supplied at a facility. In the simplest case, more than one product is produced in facilities and will be shipped to different demand points. In more realistic models, each facility will incur a certain fixed cost related to each product type, if it desires to produce that product (Barros [29]).

Also, Chandra et al. [30] assumed that each product type is made of different combinations and quantities of different raw materials and consequently, before production, the producers should buy each material type (related to the product types it is going to produce) from raw material vendors first.

Deterministic vs. Stochastic

Models that have complete deterministic inputs (especially parameters) are called deterministic models. In many cases, some of inputs are probabilistic. Such models are called stochastic (or probabilistic models). In most of the stochastic models, demand is considered to be probabilistic. Other parameters such as traveling time between locations and production capacity of facilities can also be probabilistic. If the probability distribution is discrete, the model may be converted to a deterministic facility location problem so that can easily be solved. For instance**,** Lin [31] considers Poisson demand for demand points and converts the problem into a single-source capacitated facility location problem. If the distribution is continuous, then other solving methods become necessary. For example, when they consider, a normally distributed demand, they convert the problem into a mixed integer non-linear model, which is hard to solve.

In a different work, Sambola et al. [32] assume that demand has Bernouli distribution. By using two different strategies (facility outsourcing and customer outsourcing) and considering the expected value of each they convert the stochastic model into a deterministic one.

Single period vs. Multi period (Dynamic models)

Most of the problems that have been studied in the literature consider only one period. In fact, a one-time decision about the location of facility and the allocation of demand points to them is made. But in another group of problems, the planning horizon is longer and each period of the horizon has its own parameters (i.e. demand, capacities, availability and other parameters are different in different periods). These models are similar to inventory models. In many cases, demand of one period can be postponed and satisfied in other periods.

Hinojosa et al. [33] developed a two-stage multi-period facility location problem and permit the opening of facilities in any period. In [34], Thanh et al. [34] mention that facilities can be opened, closed, and even enlarged (in terms of capacity) in different periods.

Canel et al. [35] solve the dynamic problem in three phases. First they identify the facilities to be opened at each period. Then, appropriate combinations of those facilities are generated, and finally, by means of dynamic programming technique, the optimal solution is obtained.

Recently, Romauch [36] developed a stochastic dynamic model and solved it optimally for small-scale problems (almost all dynamic facility location models in the literature are deterministic).

2.3.3 Facility location models related to humanitarian logistics

As mentioned in the first part of this chapter, there are four stages for emergency management. Most facility location problems in humanitarian logistics pertain to the "preparedness" and "response" stages.

Caunhye et al. [37] review optimization models that are used in both pre-disaster and post-disaster activities. This classification (i.e. pre-disaster and post-disaster) is further broken down for different activities or combination of activities. Most available optimization models are for pre-disaster and short-term post-disaster (i.e. response stage). The short term post-disaster response includes activities such as evacuation of affected people, distribution of relief materials, and performing medical care on injured people. Figure 4 shows the framework for emergency operations, before and after a disaster. As can be seen, in pre-disaster period, stock pre-positioning as well as facility location are major challenges. After the occurrence of a disaster, relief distribution among AAs (which can also be a facility location problem) plays an important role. Although evacuation is an important activity in post-disaster response, because it has its own formulation and logic, it will not be reviewed here. A comprehensive definition of that problem can be found in [38]. A sheltering model for people of areas affected by flood events is developed by Konsomsaksakul [39].

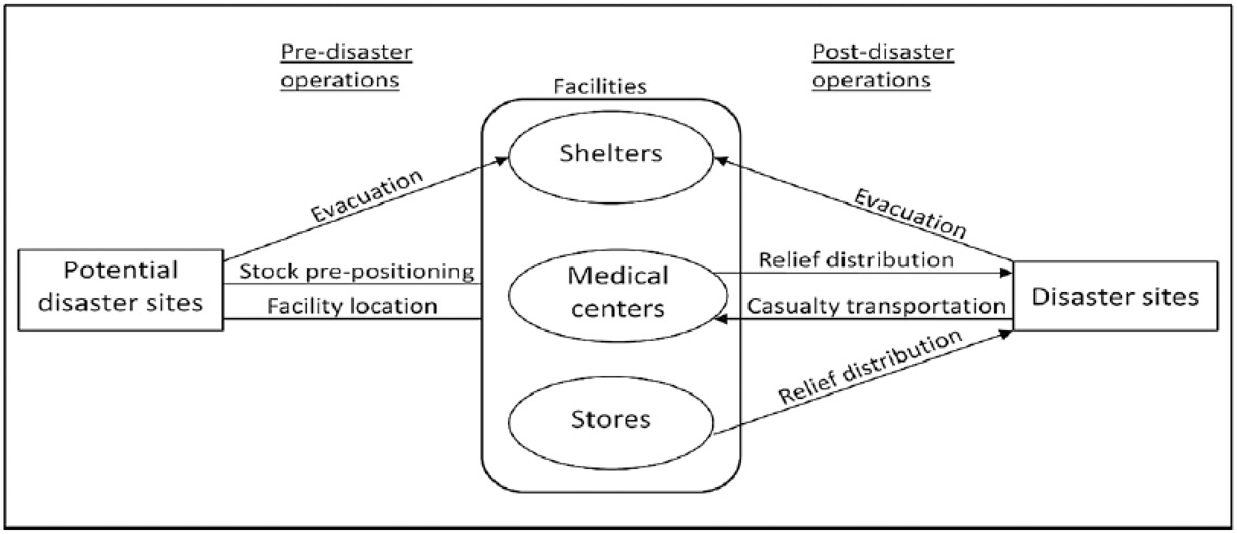


Figure 4. Emergency operations framework

Before reviewing the literature related to pre-positioning and post-disaster facility location problems, we should mention that another important challenge in emergency response is the vehicle routing problem (VRP). The models related to the VRP in emergency response management are surveyed by Ghiani et al. [40]. These models are labeled as "real-time vehicle routing". Yuan et al. [41] developed two models for path selection problem: a single-objective model aiming to minimize total travel time, and a multi-objective that considers not only time minimization, but also path-complexity minimization. Path-complexity is defined as the number of arcs (i.e. links between different nodes, including supply centers, distribution centers, and demand points).

2.3.3.1 Pre-positioning related literature

Lakovou et al. [42] develop a model to determine the location of facilities that are going to preserve equipment that are used in order to clean oceanic areas in case of oil spilling.

The prevention process should be done as fast as possible so that the leaks cannot spread through the oceans or seas. Different spill types as well as different equipment types are considered. The main objective is to minimize the total cost that includes items such as response cost, evacuation cost, and pollution thread cost. Another important objective is the minimization of total travel time (for vehicles that are carrying different equipment).

In Wilhelm et al. [43], a problem similar to that in [42] is considered. The major difference in the assumptions is that there currently exist some storage facilities, each containing a specified amount of the required equipment and items. The presented model locates new facilities or expands the current ones at pre-specified costs.

Another pre-positioning model is introduced by Balcik et al. [44]. There are different scenarios for the level of damage to different AAs (a discrete distribution) and the objective is to minimize the total cost. A novelty of this paper is the assignment of an importance coefficient called "criticality weight" for each relief material defined. By using this concept, relief materials can be prioritized and those with higher importance rise to the top of satisfaction list.

Chang et al. [45] build a decision support tool that can manage the emergency response in case of a flood. The model first considers different rain events. Associated with each rainfall event, there are different affected urban locations. Each location or group of locations is under the responsibility of a certain rescue center. Objectives are minimizing the cost as well as the distance traveled to deliver rescue materials.

Dessouky et al. [46] present an emergency response scheme in order to respond to an anthrax emergency. The facility location problem is formulated as *p*-median and *p*-

center problems. The model also requires that all located facility should be within a certain pre-specified distance from demand points. Then, a VRP is formulated to distribute relief materials to AAs. The problem considers multiple relief materials. It should be mentioned that although the facility location model is deterministic, the vehicle routing part is based on stochastic parameters.

McCall [47] presents a mixed-integer programming model for pre-positioning items such as food, water, mask, and blanket. This model was be used by the United States Navy in case of war in certain countries (e.g. Australia). The model considers budget limitations as well as capacity constraints.

Jia et al. [48] develop a *p*-median, a *p*-center, and a covering model for large-scale emergencies. In those models, there can different levels of damage at each AA and each area is affected by a certain probability.

An optimization model for hurricane is presented by Hormer et al. in [49]. In the paper, the supply centers are called Logistical Staging Areas (LSA). The model assumes there are different facility types and that the AA is divided into multiple neighborhoods, with each neighborhood served by a facility.

Campbell et al. [50] mention that the location of pre-positioned materials should be close enough to the AA so that the relief materials can be delivered in a reasonable amount of time. The location must be at a reasonable distance from the center of the disaster so that the risk of damage to the material is minimized. Hence, the optimal location and amount of pre-positioned materials should be obtained from a trade-off between delivery time and damaging probability. The paper develops a model to optimize the problem.

Akkihal [51] studies the pre-positioning problem. He categorizes the problem as a facility location problem and develops a simple model based on the *p*-median formulation. Yushimito [52] extends the model by considering the reliability of routes. It should be mentioned that the model of [52] was a location-routing model (i.e. a model that solves the location allocation and routing problems in a single model).

Tean [53] was probably the first person to present a broad model for the pre-positioning problem. His main novelty was making the model "scenario-based". In fact, because the prepositioning decisions are done before the occurrence of a disaster, they should be based on a set of some (or all) possible disaster scenarios in terms of factors such as severity of the disaster or the center of the disaster. Then, these scenarios are considered in a model and the location decision is made according to the probability of occurrence of each scenario. He also considers different vehicle types so that the commodities can be transported to several demand points in one route of a vehicle. Tean [53] did not consider costs in his model although he minimizes unmet demand and maximizes the number of survivors. Rawls et al. [54] define a similar, but cost-based model by considering transportation, holding and shortage costs. Their model was single-stage, subject to arc capacities, meaning that between each pair of locations, a limited amount of relief material can be transported. In the solution procedure, the problem was divided into two sub-problems: the first one includes variables that are independent from scenarios (e.g. amount of prepositioning in different locations) and the second sub-problem pertains to scenario-based variables. They diminish the second sub-problem using *L*-shaped methods and then, because the remaining sub-problem is convex, they solve it using approximation-based methods. Duran et .al [55] also developed a mixed-integer programming model in order to minimize the average response time over all the demand points. In fact, they considered a larger weight (priority) for areas with higher amounts of demand.

Alper et al. [56] extend Rawls model by considering two echelons. First, supplies come to distribution nodes, and then they are distributed to different demand points. Their model is capacitated (i.e. distribution nodes have limited capacities). Each distribution node can be assigned to only one supply center and each demand point can be allocated to only one distribution node. The travel time between supply centers and distribution nodes is considered to be negligible. Wang et al. [57] formulated the model according to region division problem. In region division problem, each point (location) can be a supply source as well as an AA. Points are grouped into rescue regions. Through regional division and resource sharing, the groupings can be improved so that the efficiency of rescue (i.e. the cost and time of satisfying the demand of AAs) increases. The first stage of this model is the grouping process while the second stage pertains to distribution of supplies.

Rawls et al. [57] extend their model in [55] twice. First, they add service quality constraints to the model so that at least a certain percentage of scenarios are completely satisfied (in terms of demand). The fully satisfied scenarios are placed in a set called the reliable set. Moreover, for scenarios in the reliable set, there is a maximum value on the shipment distance for the supplies [58]. This enhancement is really helpful because for certain scenarios, a complete satisfaction of the demand might be vital. Rawls et al. [57]

also made the deliveries dynamic so that both the demand and transportation become variable, representing scenarios that are closer to reality [59]. In this new model, the allocation part has two stages. The first stage pertains to the first 72 hours of the aftermath of the disaster, and the second stage, covers the time after that. It should be mentioned that the model can have more than 2 stages. The allocation of the demand to the demand point at each stage can be different.

A new type of pre-positioning logic is presented by Amiri et al. [60], where pre-positioned materials are stored not in supply centers, but in specific AAs. In the aftermath of the disaster, it is possible to transport more supplies to AAs from supply centers. The models attempts to achieve two objectives: 1) Minimizing the total cost including setup, shortage, transportation, and holding costs. 2) Minimizing the maximum shortage in AAs.

2.3.3.2 Post-disaster

Most of the previous mentioned models were pre-positioning models. They were based on the fact that the disaster has not yet occurred. Hence, different scenarios about the type and location of the disaster are estimated and appropriate facility location decisions are made. In all these models, cost minimization is the major objective though some of the models consider maximizing the delivery of relief materials as another objective. But in facility location models related to the aftermath of a disaster, there is only one scenario. Recent models tend to become multi-objective. In fact, other objectives such as maximizing the reliability of chosen routes and minimization of ransack probability of routes are considered. These objectives are hard to predict prior to the occurrence of a disaster (in pre-positioning stage). Now we review some of works done in this area below.

Some papers considered pure inventory control (as well as supply chain management) formulations and models for the problem. Lodree et al. [61], for instance, used the Newsvendor technique to estimate the extra cost caused by disruption in inventory planning for a disaster. Beamon et al. [62] defined an inventory model with all parameters (e.g. lead time and cost of placing order) to minimize the entire cost to the system.

Fredrich et al. [63] exerted a combination of dynamic programming and graph theory to build a model and solved it heuristically.

Other papers have developed OR models for supplying, transporting and distributing supplies for AAs. Each model has its own assumptions, objectives and parameters.

Crarnes et al. [64] is one of earliest papers related to this area. It presents a deterministic single-period allocation model for assigning different equipment to marine environment that have had an oil spill. The problem is modeled via goal programming in which the importance weights of different objectives can be changed by the user. Three years later, that model was upgraded to a multi-period model ([64]).

Haghani et al. [65] develop a single-objective multi-period network model for emergency response. The demand at AAs can be met at different periods. Hence, this model pertains more to the long-term rather than the short-term response. All parameters are deterministic and the objective is to minimize the fixed cost of opening facilities and transportation cost of relief material.

Tzeng et al. [66], first, conduct a comparison between the features of a general distribution system and a relief distribution system. The results show that in relief distribution systems, the objective is maximization of efficiency rather than profit, facilities are temporary, and decisions are urgent and based on available information (compared to general systems where decisions are long term). Then, they develop a model, containing three objectives (i.e. minimization of cost, minimization of total travel time, and maximization of demand satisfaction). The model, also, considers vehicle capacities.

In the model developed by Barbarosoglu et al. [67], there are two stages. First, according to the probability distribution of the demand at the AAs, and the reliability of different arcs (i.e. routes between facilities and demand points), some amount of supplies will be determined to be pre-positioned in open facilities. Then, in the second stage (which is the after-math of the disaster) the amount of usable pre-positioned materials will become known but, the arc capacities and demand values remain probabilistic. In this stage, no further supply is allowed and only the pre-positioned materials can be used. In order to make the second stage feasible for all situations, shortage and excess amounts are allowed, each having its own cost. In summary, the supply decisions are made in the first stage (and a preliminary allocation scheme is also developed), but the actual allocation decisions are made in the second stage.

Rottkemper et al. [68] developed a single-objective allocation model for demand satisfaction after a disaster in multi-period horizon. (In fact, they considered two objectives: minimization of cost and minimization of unsatisfied demand, but because the latter can be defined in the constraints which eliminated the need for multi-objective optimization techniques, one can consider their work as a single objective model). Their model had only one echelon (supply flow from central depot to regional depots as well as between regional depots) although they considered international donations. On the other hand, Ortuno et al. [69] considered multiple objectives such as minimizing travel time, fitting maximum ransack probability and minimum reliability, and minimizing the cost. They also considered different vehicle types, but just one planning period. They, then extended their model by making it two-echelon as well as adding parameters such as arc capacities (flow capacities of the links between depots) [70]. In both [69] and [70], lexicographic goal programming method was used and only a single product was considered.

2.4 Heuristics for Facility Location Problem

Many heuristic and meta-heuristics have been used to solve alternate facility location problems. We review some of them here.

A heuristic concentration (HC) metaheuristic is developed by Rosing et al. [71] to solve the p-median problem. This metaheuristic has two stages. In the first stage, many different fundamental solutions are randomly chosen and tested (this is called 1-opt heuristic) and those that have a better objective function are selected. Then, all the facilities of all solutions are gathered in a set called concentration set or CS. In the second stage, those facilities are located using another heuristic called the 2-opt heuristic.

Tragantalerngsak et al. [72], develop a Lagrangian relaxation heuristic for the complete 2-stage capacitated location problem in which each distribution node can be served by only one facility and each demand point can be served by only one distribution node. Six different lagrangian heuristics are tested. For the same problem, Chen et al [73] develop a hybrid algorithm, consisting of Lagrangian relaxation and ant colony optimization (ACO) algorithm to solve the problem. In fact, two different ACO algorithms are used - one for location and another for allocation. Based on the results presented, it appears that the developed hybrid algorithm performs better than multiple ant colony system (MACS). In fact, the MACS coordinate the solutions of facility location and demand assignment solutions whereas the hybrid algorithm solves them separately.

Escudero et al.[74],by means of lagrangian relaxation, convert the capacitated facility location problem to an uncapacitated problem, and solve the transformed problem using a branch and bound algorithm.

A heuristic developed by Mazzola et al. [75] performs the same procedure on capacitated multi-product facility location problem. For the same problem, Keskin et al. [76] present a solution procedure based on scatter search metaheuristic.

Christiansen et al. [77] mention that solving the capacitated facility location problem using Lagrangian relaxation has the disadvantage that no fractional optimal solution for the master (i.e. capacitated) problem is obtained. Hence, they use a column generation technique to get some information about the primal fractional solution and then solve sub-problems using branch and price algorithm.

For solving capacitated, multi-product, multi-period facility location problems, a two-stage heuristic are developed Canel et al. [78]. First, by using branch and bound, a set of solutions for each period as generated and then, by using dynamic programming techniques, the best sequence of solutions through all periods is selected.

Marić et al. [79] conduct a comparison between the performance of three heuristic methods (i.e. Simulated Annealing, Particle Swarm Optimization and a combination of Variable Neighborhood Search and Reduced Variable Neighborhood Search methods). The results show that the combined method has the best outcomes in terms of time and quality of the solution.

Arostegui et al. [80] conduct a comprehensive comparison between the performance of Genetic Algorithm, Simulated Annealing, and Tabu Search. The comparisons are done separately for capacitated problem, multi-period problem, and multi-product problem. According to the results, Tabu search works best for capacitated as well as multi-period problem, but for multi-product problem, best performance belongs to Genetic Algorithm.

CHAPTER 3
A COMPREHENSIVE PRE-POSITIONING MODEL

3.1 Introduction

As seen in section 2.3.3.1, the two-echelon pre-positioning model is still preliminary and none of the upgrades that have been done on single echelon model has been applied to it. Moreover, the current two-echelon models do not consider supply capacity constraints. In fact, a majority of current papers assume that some number of facilities preserve the supply materials with unlimited capacity until a disaster occurs. But, according to Beamon et al. [44], when a disaster occurs, three main sources will provide the supply: prepositioning facilities, donations, and regular suppliers who often vend supplies. Consequently, considering unlimited supply capacity for pre-positioning facilities is neither practical nor needed. Finally, the current two-echelon model, developed in [56], confines maximum delivery durations only between RRCs (Regional Rescue Centers or suppliers) and LRCs (Local Rescue Centers or local distribution centers) and not to the demand points. Also, it is not a complete transshipment model because each demand point can be allocated only to one distribution node and each distribution node should be assigned to only one supply source. For overwhelming these limitations, we need to define the main decision variable of the system in a way that the total shipping distance for relief materials become observable. Finally, we add the capability of direct shipment (i.e., relief materials can be shipped directly from RRCs to

AAs) to our model to make it more comprehensive. This technique was first used by Sun [81].

Before presenting the full details of the model, we review its mission. In the aftermath of a disaster, there are different types of materials that should be distributed among the people of affected areas and volunteers. Basically, these materials are food, water, medical supplies, digging tools, blankets and other relief items. Because it is very important to take care of affected people in a very short amount of time, such materials should be readily available in the aftermath of the disaster. Therefore, these materials should be pre-positioned in safe places (e.g. RRCs) so that the procurement time becomes zero and the distribution process starts instantly after the occurrence of the disaster. The pre-positioned materials can be shipped to the affected areas either directly or via regional rescue centers (LRCs). The travel time and cost between RRCs, LRCs, and AAs, as well as the amount of demand at AAs for different relief materials are not completely known before the occurrence of the disaster. Hence, the pre-positioning model should give a solution for each possible scenario (of the real disaster) in a way that the average cost over all possible scenarios becomes minimized. The more the pre-positioning materials, the better the demand coverage in the aftermath of the disaster. But, more pre-positioning materials will increase the holding costs. Hence, the optimal solution for this two contradicting objectives should be developed. Figure 1 schematically shows the general picture of the pre-positioning problem. It should be mentioned that in this model, it is assumed that not necessarily all the pre-positioned materials are usable after the occurrence of the disaster, and therefore, for each scenario, a certain percentage of pre-positioned materials will survive the disaster as well as expiration dates are usable. Also, the capacities of LRCs are also scenario-based and probabilistic. This is regarding the fact that candidate facilities for LRCs are chosen from routinely operative and active places such as stadiums, sport centers and schools, because otherwise, new facilities must be built and maintained or a set of existing facilities should remain idle until the occurrence of a disaster, which is very costly. On the other hand, such facilities can be affected by the disaster and consequently, their capacities in the aftermath of the disaster can be affected by the type and severity of the disaster [56].

In the pre-positioning model, there are 3 sets of locations: set of RRCs, set of LRCs and set of AAs. There is a set of relief materials as well. In the model, a subset of locations of RRCs is chosen to hold different relief materials to cover the aftermath of a disaster. After the occurrence of a disaster, these materials will be shipped to AAs, either directly or via LRCs. There is also another set, called set of scenarios. Each scenario is a set of different values for some of the parameters of the model. Theses parameters are called scenario-based parameters and are as follows:

- Capacity of LRCs
- Amount of demand at AAs
- Transportations times between different locations (i.e., RRCs, LRCs, and AAs)
- Fixed cost of opening and operating LRCs
- Transportation costs
- Shortage cost of different relief materials
- Usable percentage of pre-positioned materials

In fact, each scenario is a prediction of the situation of the aftermath of the disaster. For instance, according to a rather severe scenario, amount of demand at AAs is high and usable percentage of pre-positioned materials is low. Each scenario has a certain probability of occurrence. The pre-positioning model is a cost-based model (i.e. the objective is the minimization of the total cost). This model minimizes the "average cost over all the scenarios". In other words, it minimizes the weighted average cost.

3.2 The pre-positioning problem

3.2.1 The pre-positioning model

The comprehensive pre-positioning model is provided below.

Sets

I: set of candidate RRCs

J: set of candidate LRCs

K: set of demand points (AAs)

L: set of relief types

S: set of scenarios

Parameters

p_s: Probability of scenario *s*

v_l: Unit volume of relief item *l*

${q_j}^s$: Capacity of LRC_j under scenario *s*

s_{il}: Capacity of RRC_i for item *l*

${d_{kl}}^s$: Amount of demand at demand point k for relief type l under scenario s

${t1_{ijk}}^s$: Transportation time from RRC_i to demand point k via LRC_j under scenario s

${t2_{ijk}}^s$: Direct transportation time from RRC_i to demand point k

f_i: Fixed cost of opening and operating RRC_i

${g_j}^s$: Fixed cost of opening and operating LRC_j under scenario s

${a_{ijkl}}^s$: Transportation cost for one unit of item l shipped from RRC_i to demand point k via LRC_j under scenario s

${b_{ikl}}^s$: Transportation cost for one unit of item l shipped directly from RRC_i to demand point k under scenario s

h_{il}: Procuring and holding cost for one unit of item l at RRC_i

${c_{kl}}^s$: Unit shortage cost of item l under scenario s at demand point k

${\rho_{il}}^s$: Usable percentage of total pre-positioned amount of item l at RRC_i under scenario s

α : Service quality proportion

t_{max} : Maximum allowed delivery duration

Decision Variables

H_{il}: Amount of item l stored at RRC_i

${X_{ijkl}}^s$: Amount of item l shipped from RRC_i to demand point k via LRC_j under scenario s

${Y_{ikl}}^s$: Amount of item l shipped directly from RRC_i to demand point k under scenario s

${P_{kl}}^s$: Shortage amount of relief item l at demand point k under scenario s

$U_i: \begin{cases} 1 & \text{if } RRC_i \text{ is opened} \\ 0 & \text{Otherwise} \end{cases}$

${M_j}^s: \begin{cases} 1 & \text{if } LRC_j \text{ is opened under scenario } s \\ 0 & \text{Otherwise} \end{cases}$

$B_{ijk}{}^{s}: \begin{cases} 1 & \text{if any relief item is shipped from } RRC_i \text{ to demand point } k \text{ via } LRC_j \text{ under scenario } s \\ 0 & \text{Otherwise} \end{cases}$

$D_{ik}{}^{s}: \begin{cases} 1 & \text{if any relief item is shipped from } RRC_i \text{ directly to demand point } k \text{ scenario } s \\ 0 & \text{Otherwise} \end{cases}$

$\Upsilon^{s}: \begin{cases} 1 & \text{if scenario s is included in reiability set} \\ 0 & \text{Otherwise} \end{cases}$

Objective function:

$$\text{Min} \sum_i f_i . U_i + \sum_j \sum_s p_s . g_j{}^{s} . M_j{}^{s} + \sum_k \sum_l \sum_s p_s . P_{kl}{}^{s} . c_{kl}{}^{s} +$$

$$\sum_i \sum_j \sum_k \sum_l \sum_s p_s . a_{ijkl}{}^{s} . X_{ijkl}{}^{s} + \sum_i \sum_k \sum_l \sum_s p_s . b_{ikl}{}^{s} . Y_{ikl}{}^{s} + \sum_i \sum_l h_{il} . H_{il} \qquad (1)$$

Constraints:

$$d_{kl}{}^{s} - \sum_i \sum_j (X_{ijkl}{}^{s}) - \sum_i (Y_{ikl}{}^{s}) = P_{kl}{}^{s} \qquad \forall\ k, l, s \qquad (2)$$

$$\rho_{il}{}^{s} . H_{il} \geq \sum_j \sum_k (X_{ijkl}{}^{s}) - \sum_k (Y_{ikl}{}^{s}) \qquad \forall\ i, l, s \qquad (3)$$

$$H_{il} \leq s_{il} . U_i \qquad \forall\ i,l \qquad (4)$$

$$\sum_i \sum_k \sum_l X_{ijkl}{}^{s} . v_l \leq q_j{}^{s} . M_j{}^{s} \qquad \forall\ j, s \qquad (5)$$

$$\sum_s p_s . \Upsilon^{s} \geq \alpha \qquad (6)$$

$$P_{kl}{}^{s} \leq d_{kl}{}^{s} . (1 - \Upsilon^{s}) \qquad \forall\ k, l, s \qquad (7)$$

$$\sum_l X_{ijkl}{}^{s} \leq M . B_{ijk}{}^{s} \qquad \forall\ i, j, k, s \qquad (8)$$

$$\sum_l Y_{ikl}{}^{s} \leq M . D_{ik}{}^{s} \qquad \forall\ i, k, s \qquad (9)$$

$$t1_{ijk}{}^{s} . B_{ijk}{}^{s} \leq t_{max} \qquad \forall\ i, j, k, s \qquad (10)$$

$$t2_{ik}{}^{s} . D_{ik}{}^{s} \leq t_{max} \qquad \forall\ i, k, s \qquad (11)$$

The terms, in order of their appearance in objective function (1), are as follows:

- Fixed cost of opening RRCs
- Fixed cost of opening LRCs
- Shortage cost
- Indirect transportation cost
- Direct transportation cost
- Holding cost.

It should be mentioned that all the terms in the objective function except the holding cost and fixed cost of opening RRC, are scenario-based. The holding and fixed costs of opening RRCs are not scenario-based regarding the fact are incurred before the occurrence of the disaster and the severity of the actual disaster does not affect them: a certain number of RRCs should be opened and a certain amount of different relief materials should be pre-positioned in them, and thus, the related costs are incurred regardless of the disaster. However, transportation costs, shortage costs, and fixed cost of opening LRCs are scenario-based because their values will be known after the occurrence of the disaster. Hence, they all have p_s as coefficient. In fact, the objective function for scenario-based terms acts as a weighted average over all of scenarios. If there is not enough pre-positioned materials in RRCs, we will have more shortage cost. On the other hand, pre-positioning such materials will cause more fixed cost of opening RRCs as well as more holding cost. There is a trade-off between these two sets of costs in the objective function.

Constraints (2) show that under scenario *s*, the shortage amount of item *l* at demand point *k* is the difference between the demand of the demand point *k* and amounts of item *l* transported to demand point *k*. According to constraint (3), under scenario *s*, for each item *l*, the total shipments (direct and indirect) from RRC_i cannot exceed the total amount of usable pre-positioned materials in that RRC. Constraints (4) guarantee that the all pre-positioned items at RRC_i do not exceed its capacity. They also assure that a shipment can start from an RRC only if that RRC is opened. Constraints (5) guarantee that not all LRC need to be opened to be able to accept shipments, but an open LRC cannot store more items than its capacity. Constraint (6) is actually the definition of the reliability set. In fact, if for a certain s, Υ^s=1, then the scenario associated with that s will be reliable (i.e., all the demands of demand points for different items under scenario s are covered). Constraints (7) guarantee that if a scenario is in the reliable set, then all the shortage amounts associated with it are zero. Constraints (8) are complementary constraints for constraints (10). In fact, routes from RRCs to LRCs and then to AAs that are going to be used to ship different items under different scenarios" are identified (using ${B_{ijk}}^s$ binary variables) in (8), and in constraints (10), a maximum delivery time is assigned to those routes. The relationship between constraints (9) and (11) are the same as that between (8) and (10), except for the fact that constraints (9) and (11) are related to direct shipments (i.e., for routes starting from RRCs and directly ending in AAs under different scenarios). It should be mentioned that the combination of constraints (3) and (4) guarantees that shipments are allowed only from opened RRCs: According to constraints (4), different materials can be pre-positioned only in opened RRCs, and according to constraints (3), shipments are possible only from locations with pre-positioned materials. Therefore, it is implicitly guaranteed that only opened RRCs can send shipments.

3.2.2 Experimental Results

According to [56], the second stage of the pre-positioning model (i.e., the scenario-based part) is a two-echelon stochastic facility location problem, which falls under the category of NP-hard problems. Before proving this fact, we run some random experiments to assess the solution time of the problem. In Table 2, a summary of the results from running 23 randomly generated instances of the model in Lingo software is presented. These experiments are conducted in a computer with Microsoft Windows 7 (2009), 2.40 GHz Intel Pentium, and 4 Gb of RAM, and Microsoft windows XP Profession 2002. The table includes data on the number of constraint, number of decision variables, and software running time for each case. It appears that the number of RRCs and number of scenarios are the two key factors that determine the run time values.

Table 2 Lingo software execustion times (in seconds) for 23 random problems

#	I	J	K	L	S	# of Non-negative Variables	# of Binary Variables	# of Constraints	Time
1	2	15	5	3	3	1509	530	1120	35
2	2	15	10	3	3	2994	1010	2170	47
3	2	15	20	3	3	5964	1970	4270	59
4	2	15	40	3	3	11904	3890	8470	95
5	2	15	80	3	3	23784	7730	16870	354
6	2	15	100	3	3	29724	9650	21070	425
7	2	15	150	3	3	44574	14450	31570	853
8	2	30	20	3	3	11364	3815	7915	116
9	2	30	50	3	3	28374	9395	19615	487
10	2	30	80	3	3	45384	14975	31315	1006
11	2	30	20	3	5	18936	6357	13185	324
12	2	30	20	3	10	37866	12712	26367	919

13	2	30	50	3	10	94566	31312	65367	>4000
14	2	30	20	5	3	18940	3815	8167	105
15	2	30	50	5	3	47290	9395	20227	746
16	2	45	20	3	3	16764	5660	11557	247
17	2	45	50	3	3	41874	13940	28657	882
18	2	45	80	3	3	66984	22220	45757	2202
19	4	30	20	3	3	22548	7537	15379	408
20	4	30	50	3	3	56298	18697	38239	1480
21	6	30	50	3	3	84222	27999	56863	> 2700
22	2	0	50	3	3	1374	305	1525	121
23	2	0	500	3	3	13524	3005	15025	3383

According to the Table 2, sets I and S have the highest impact in running times. This can also be verified by observing the variables, parameters and constraints: all the parameters, decision variables, and constraints (except the parameter v_l) contains elements i, s, or both. Therefore, increasing the values of I and S, increases the problem dimensions more, compared to the case where values of other sets increase. In the next section, we prove that the pre-positioning problem is NP-hard.

3.3 Pre-positioning model solving procedure

The main contribution of this dissertation is the development of a heuristic method for solving the pre-positioning problem. Hence, we comprehensively present the details and steps of this heuristic. According to Alper et al. [56], the two-stage facility location problem (TSLP) belongs to the category of NP-hard problems. It should be mentioned that, in general, TSLP is the problem of opening a set of RRCs and a set of capacitated LRCs, and assigning the demand of demand points to the LRCs that are fed by RRCs. In fact, it is proven that single source capacitated facility location problem, which in other words is the second echelon of the prepositioning problem (i.e., opening LRCs and assigning the demand of each AA to them), is NP-hard. Hence, TSLP which includes the single source capacitated facility location problem is also NP-hard.

3.3.1 Model complexity

Theorem 1: The two stage facility location problem is NP-hard.

Proof: The TSLP model of this dissertation belongs to the category of transshipment problems: in a transshipment problem, there are three types of vertices: supply (V_1), demand (V_2), and transit (V_3). The system is a digraph. The set of demand and supply vertices is fixed while the transit vector is permutable (equivalently, the location of transit vertices should be determined). The objective is to minimize the total transportation cost ([82]). The transshipment problem is already proven to be NP-hard ([82,83]). The general form of transshipment problem is as follows:

$$\text{Min z } = \sum_{i\in V_1}\sum_{j\in V_2} a_{ij}x_{ij} + \sum_{j\in V_2}\sum_{k\in V_3} b_{jk}y_{jk} + \sum_{j\in V_2} e_j.U_j$$

s.t

$$\textstyle\sum_{j\in V_2} x_{ij} = c_i \qquad i \in V_1 \qquad (1)$$

$$\textstyle\sum_{i\in V_1} x_{ij} = \sum_{k\in V_3} y_{jk} \qquad j \in V_2 \qquad (2)$$

$$\textstyle\sum_{i\in V_1} x_{ij} \leq M.U_j \qquad j \in V_2 \qquad (3)$$

$$\sum_{j \in V_2} y_{jk} = d_k \qquad k \in V_3 \tag{4}$$

In order to prove that our version of TSLP problem is NP-hard, we need to show that our model can be reduced to the above mentioned model: Considering the pre-positioning model of section 3.1, if we eliminate maximum delivery duration and service quality constraints (i.e, (6-11)) we will have the following model:

$$\text{Min} \sum_i f_i . U_i + \sum_j \sum_s p_s . g_j{}^s . M_j{}^s + \sum_k \sum_l \sum_s p_s . P_{kl}{}^s . c_l{}^s +$$
$$\sum_i \sum_j \sum_k \sum_l \sum_s p_s . a_{ijkl}{}^s . X_{ijkl}{}^s + \sum_i \sum_k \sum_l \sum_s p_s . b_{ikl}{}^s . Y_{ikl}{}^s + \sum_i \sum_l h_{il} . H_{il} \tag{1}$$

Constraints:

$$d_{kl}{}^s - \sum_i \sum_j (X_{ijkl}{}^s) - \sum_i (Y_{ikl}{}^s) = P_{kl}{}^s \qquad \forall\ k, l, s \tag{2}$$

$$\rho_{il}{}^s . H_{il} \geq \sum_j \sum_k (X_{ijkl}{}^s) + \sum_k (Y_{ikl}{}^s) \qquad \forall\ i, l, s \tag{3}$$

$$H_{il} . v_l \leq s_{il} . U_i \qquad \forall\ i,l \tag{4}$$

$$\sum_i \sum_k \sum_l X_{ijkl}{}^s . v_l \leq q_j{}^s . M_j{}^s \qquad \forall\ j, s \tag{5}$$

Now, if we eliminate direct shipment option as well as capacity constraint of RRCs, we will have the following model:

$$\text{Min} \sum_i f_i . U_i + \sum_j \sum_s p_s . g_j{}^s . M_j{}^s + \sum_k \sum_l \sum_s p_s . P_{kl}{}^s . c_l{}^s +$$
$$\sum_i \sum_j \sum_k \sum_l \sum_s p_s . a_{ijkl}{}^s . X_{ijkl}{}^s \tag{1}$$

Constraints:

$$d_{kl}{}^s - \sum_i \sum_j (X_{ijkl}{}^s) = P_{kl}{}^s \qquad \forall\ k, l, s \tag{2}$$

$$\rho_{il}{}^s . H_{il} . U_i \geq \sum_j \sum_k (X_{ijkl}{}^s) \qquad \forall\ i, l, s \tag{3}$$

$$\sum_i \sum_k \sum_l X_{ijkl}{}^s . v_l \leq q_j{}^s . M_j{}^s \qquad \forall\ j, s \tag{5}$$

Then, if we fix the location of RRCs and eliminate the shortage cost and capacity of LRCs, the following model will be obtained:

$$\text{Min} \sum_j \sum_s p_s . g_j{}^s . M_j{}^s + \sum_i \sum_j \sum_k \sum_l \sum_s p_s . a_{ijkl}{}^s . X_{ijkl}{}^s \qquad (1)$$

Constraints:

$$d_{kl}{}^s = \sum_i \sum_j (X_{ijkl}{}^s) \qquad \forall\ k, l, s \qquad (2)$$

$$\rho_{il}{}^s . H_{il} \geq \sum_j \sum_k (X_{ijkl}{}^s) \qquad \forall\ i, l, s \qquad (3)$$

$$\sum_i \sum_k \sum_l X_{ijkl}{}^s \leq M. M_j{}^s \qquad \forall\ j, s \qquad (5)$$

If we exclude the scenario-related indices as well as item-related indices (which will reduce the number of decision variables), the model will be reduced to the following:

$$\text{Min} \sum_j g_j . M_j + \sum_i \sum_j \sum_k a_{ijk} X_{ijk} \qquad (1)$$

Constraints:

$$d_k = \sum_i \sum_j X_{ijk} \qquad \forall\ k \qquad (2)$$

$$\rho_i . H_i = \sum_j \sum_k X_{ijk} \qquad \forall\ i \qquad (3)$$

$$\sum_i \sum_k X_{ijk} \leq M . M_j \qquad \forall\ j \qquad (5)$$

Now if we compare the above model with the classic transshipment model, the only difference is the way we defined the transportation decision variables (i.e., X_{ijk}). In fact, here, instead of x_{ij} and y_{jk} of classic transshipment model, we have X_{ijk} so that we can set a limit on delivery durations. It is obvious that both models lead to the same solution because:

1. $a_{ijk} = a_{ij} + b_{jk}$: unit transportation cost of an item from RRC i to AA k via LRC j is equal to the sum of unit transportation cost from RRC i to LRC j and from LRC j to AA k
2. $\rho_i . H_i = c_i$
3. $\sum_i \sum_j \sum_k X_{ijk} = \sum_i \sum_j x_{ij} = \sum_j \sum_k y_{jk}$: if we sum up constraints (3) in the transshipment model, we obtain $\sum_i \sum_j x_{ij} = \sum_j \sum_k y_{jk}$. Also if we sum up constraints (1) and constraints (4) separately, we will have: $\sum_i \sum_j x_{ij} = \sum_i c_i$ and $\sum_j \sum_k y_{jk} = \sum_k . d_k$. Because the problem should be balanced, we have: $\sum_i c_i = \sum_k d_k$ (i.e. total supply is equal to total demand). Now in the above model, if we sum up constraints (2) and (3) separately, we obtain:

   $\sum_i \sum_j \sum_k X_{ijk} = \sum_k d_k$, $\sum_i \sum_j \sum_k X_{ijk} = \sum_i . \rho_i . H_i = \sum_i c_i$.

   Consequently: $\sum_i \sum_j \sum_k X_{ijk} = \sum_i \sum_j x_{ij} = \sum_j \sum_k y_{jk}$.

By reducing our prepositioning model to the classic transshipment model (which is proven to be NP-hard) we proved that our model is also NP-hard and needs to be solved heuristically for large instances.

3.3.2 Summary of lagrangian relaxation and Sub-gradient optimization

As mentioned in section 2.4, most of the papers in the literature proposed the Langrangian relaxation method to solve the pre-positioning (and in general, the TSLP) problem. In fact, they relax the capacity constraints and solve the resulting problem using other heuristics. Also, by relaxing specific constraints, Alper et.al [56] divided the problem into two sub-problems: in the first sub-problem, the decisions about the location as well as pre-positioning amount are made and in the second sub-problem, the distribution decisions are made.

The solving time of OR problems depends mainly on the number of constraints included in the problem. In many cases, some of the constraints make the solving procedure hard even if the problem is solved heuristically. Relaxing such constraints may improve the solving time and process significantly. In lagrangian relaxation method, such constraints are relaxed and added to the objective function, using lagrangian multipliers. The multipliers are selected in a way that violating their related constraints leads to a worse objective function value. To better clarify the issue, we consider the following example:

Original problem

Min cx

s.t.

$Ax \geq b$

$Bx \geq d$

$x \geq 0$

Suppose we relax the first set of constraints. Using $\sigma_j \in R^+$ as lagrangian multipliers, the relaxed problem will be as follows:

Relaxed problem

Min $cx + \sigma(b - Ax)$

s.t.

$Bx \geq d$

$x \geq 0$

As can be seen, whenever the term "$b - Ax$" becomes positive, the first set of constraints in the original problem is violated. On the other hand, because σ values are non-negative, the objective function value of the relaxed problem will increase, which is not desirable. In other words, the relaxed constraint is added to objective function as a penalty cost. Hence, the relaxed problem, internally will tend to determine x values in a way that "$b - Ax$" becomes non-positive. Solving the relaxed problem will lead to obtaining a lower bound (LB) of the original problem because:

1. We excluded some of the constraints of the original problem. By eliminating the constraints in a mathematical programming problem, the objective function value (OFV) will become better (or at least no worse) than the OFV of the original problem.
2. We added some terms to the objective function. The lagrangian multipliers are non-negative, and "$b - Ax$" terms only give this opportunity to the problem to get a lower OFV.

The best lower bound to the problem is achieved by solving the following problem, called the maximum dual problem [84]:

$$\max_{\sigma \geq 0} \left\{ \begin{array}{c} \textbf{Min}\, cx + \sigma\,(b - Ax) \\ s.t. \\ Bx \geq d \\ x \geq 0 \end{array} \right\}$$

Ideally, the solution of the dual problem will be equal to the solution of the original problem. Otherwise, there will be a difference between the two OFVs, which is referred to as the duality gap. The sub-gradient optimization updates the lagrangian multiplier values in a way that this gap is minimized. The process can be summarized in the following algorithm:

Subgradient optimization formula

Initialize μ ∊ [0,2]

Initialize σ_i

While Z_{UB} - Z_{LB} > α **do**

Solve relaxed problem given σ values and get the *x* and Z_{LB}

Calculate sub-gradients: $G_i = b_i - \sum_j a_{ij} x_j$

Calculate the step size $T = \frac{\mu \, (Z_{UB} - Z_{LB})}{\sum_i {G_i}^2}$

$\sigma_i = \max\,(0\,,\, \sigma_i + T.\, G_i)$

where α is a predetermined value, and Z_{UB} is the OFV of the original problem for a feasible solution. It is advisable to insert a feasible solution into the algorithm. If one considers a superior algorithm for obtaining high-quality feasible solutions, the corresponding Z_{UB} should be inserted into the above algorithm. Moreover, it should be mentioned that the choice of μ value is subjective, but generally it is considered to be equal to 2, and if the algorithm does not yield appropriate solutions, the value will be decreased.

3.3.3 Proposed heuristic method for the pre-positioning problem

The pre-positioning problem has two major parts: the location problem (of RRCs and LRCs), and the distribution problem (of relief materials among AAs). In order to solve the model efficiently, we need to relax some set of constraints in a way that each of the two mentioned parts can be solved separately. By relaxing constraints (3) and (5) we achieve this goal and divide the problem into the following sub problems:

Model 3.1

This is the first sub-problem:

$$Min\ \sum_i f_i . U_i + \sum_i \sum_l (h_{il} - \sum_s \lambda_{il}{}^s . \rho_{il}{}^s)\ H_{il} + \sum_j \sum_s M_j{}^s (\ p_s . g_j{}^s - \sigma_j{}^s . q_j{}^s)$$

s.t.

$$H_{il} . v_l \leq s_{il} . U_i \qquad \forall\ i,l \qquad (4)$$

Model 3.2

This is the second sub-problem:

$$Min \sum_k \sum_l \sum_s p_s . P_{kl}{}^s . c_{kl}{}^s + \sum_i \sum_j \sum_k \sum_l \sum_s (p_s . a_{ijkl}{}^s + \lambda_{il}{}^s + \sigma_j{}^s . v_l)\ X_{ijkl}{}^s + \sum_i \sum_k \sum_l \sum_s (p_s . b_{ikl}{}^s + \lambda_{il}{}^s)\ Y_{ikl}{}^s$$

s.t.

$$d_{kl}{}^s - \sum_i \sum_j (X_{ijkl}{}^s) - \sum_i (Y_{ikl}{}^s) = P_{kl}{}^s \qquad \forall\ k, l, s \qquad (2)$$

$$\sum_s p_s . \Upsilon^s \geq \alpha \qquad (6)$$

$$P_{kl}{}^s \leq d_{kl}{}^s . (1 - \Upsilon^s) \qquad \forall\ k, l, s \qquad (7)$$

$\sum_l X_{ijkl}{}^s \leq M \,.\, B_{ijk}{}^s \qquad \forall \; i, j, k, s \qquad (8)$

$\sum_l Y_{ikl}{}^s \leq M \,.\, D_{ik}{}^s \qquad \forall \; i, k, s \qquad (9)$

$t1_{ijk}{}^s .\, B_{ijk}{}^s \leq t_{max} \qquad \forall \; i, j, k, s \qquad (10)$

$t2_{ik}{}^s .\, D_{ik}{}^s \leq t_{max} \qquad \forall \; i, k, s \qquad (11)$

Theorem 2: Model 3.1 can be solved by inspection.

Model 3.1 can be easily solved using Lingo or CPLEX. Yet it is better to solve it using another analytical method that does not involve matrix manipulation:

1. for all *l*: **if** $(h_{il} - \sum_s \lambda_{il}{}^s . \rho_{il}{}^s) \geq 0$ **then** $H_{il} = 0$

   else $H_{il} = \frac{s_{il}}{v_l}$

2. **if** $\sum_l (h_{il} - \sum_s \lambda_{il}{}^s . \rho_{il}{}^s) H_{il} + f_i < 0$ **then** $U_i = 1$

   else for all *l* : $H_{il} = 0$, $U_i = 0$

<u>Proof</u>: First of all, variables $M_j{}^s$ only exist in objective function (and not in constraints). Because the model is of minimization type, each $M_j{}^s$ will get value of 1 if and only if its objective function coefficient is negative:

for all *j*,*s*: **if** $(p_s . g_j{}^s - \sigma_j{}^s . q_j{}^s) < 0$ **then** $M_j{}^s = 1$

else $M_j{}^s = 0$

Second, after excluding the terms related to the $M_j{}^s$ variables, the problem can be divided into *I* Integer Linear Programming problems (*I* is the number of RRCs). We can generalize the analytical method for solving each of these problems to all others:

for all *i*:

$$Min\ f_i . U_i + \sum_l (h_{il} - \sum_s \lambda_{il}{}^s . \rho_{il}{}^s). H_{il}$$

s.t.

$$H_{il}. v_l \leq s_{il} . U_i \qquad \forall\ l$$

Again, because the problem has a minimization objective, the H_{il} variables will take positive values only if their objective function coefficients are negative. On the other hand, according to the constraints, each H_{il} variable can become positive only if its related binary variable U_i is equal to 1. If U_i =1, then the OFV will be increased by positive value f_i (fixed cost of opening and operating RRC_i). Hence, RRC_i will be opened only if we can make up for its related fixed cost by giving positive values to H_{il} variables. According to the constraints: $H_{il} \leq \frac{s_{il}}{v_l}$, and according to one of the fundamental theorems of mathematical modeling, each H_{il} will take its maximum allowable value if it is a basic variable (i.e., it has positive value). That theorem is as follows: When a decision variable becomes a basic variable, it will take its maximum possible value because all the basic solutions are located on the edges of the feasible region and such edges consist of extreme (yet feasible) values of the related basic variables. Using all the above mentioned arguments, one can develop the following simple heuristic to solve each of the *I* Integer Linear Programming models related to model 3.1:

Algorithm 3.1

3. for all *l*: **if** $(h_{il}$ - $\sum_s \lambda_{il}{}^s . \rho_{il}{}^s) \geq 0$ **then** $H_{il} = 0$

   else $H_{il} = \frac{s_{il}}{v_l}$

4. **if** $\sum_l (h_{il} - \sum_s \lambda_{il}{}^s \cdot \rho_{il}{}^s)\, H_{il} + f_i < 0$ **then** $U_i = 1$

   else for all l : $H_{il} = 0$, $U_i = 0$

The outputs of model 3.1 are as follows:

1. List of opened RRCs
2. List of opened LRCs
3. Amount of pre-positioned relief materials of each type at each RRC

Lagrangian Heuristic Method

Model 3.2 needs to be solved heuristically. Because the proposed Lagrangian Heuristic (LH) method is fairly complicated, we first show the general scheme of the entire heuristic in Figure 5 and then, describe its different stages in the remainder of this chapter.

Algorithm 3.2.1

Model 3.2 has no capacity constraints. Hence, under each scenario, the demand of different relief materials in different AAs should either be completely satisfied (using direct <u>or</u> indirect shipment) or completely backlogged (according to the Theorem 2). The decision will be made by comparing the cost of direct shipment, indirect shipment (using opened RRCs and opened LRCs), and backlogging. The related costs can be viewed in objective function of Model 3.2:

1. Indirect shipment: $p_s . a_{ijkl}{}^s + \lambda_{il}{}^s + \sigma_j{}^s . v_l$

2. Direct shipment: $p_s.b_{ikl}{}^s + \lambda_{il}{}^s$

3. Backlogging: $p_s.\, c_{kl}{}^s = c_1$

4. For each *k* and *l* (under each scenario), we first find the combination of *i* and *j* (out of opened RRCs and LRCs) that minimizes the indirect shipment cost:

5. (i^* , j^*) = arg $\min_{i,j}$ $\{ p_s.a_{ijkl}{}^s + \lambda_{il}{}^s + \sigma_j{}^s.v_l\}$, $p_s.a_{i^*j^*kl}{}^s + \lambda_{i^*l}{}^s + \sigma_{j^*}{}^s.v_l$ $= c_2$

6. Then, we find the *i*, according to which the direct shipment cost is minimized:

7. i^{**} = arg $\min_i$ $\{ p_s.b_{ikl}{}^s + \lambda_{il}{}^s\}$, $p_s.b_{i^{**}kl}{}^s + \lambda_{i^{**}l}{}^s = c_3$

Then, by comparing c_1, c_2, and c_3, we determine the values of $X_{ijkl}{}^s$, $Y_{ikl}{}^s$, and $P_{kl}{}^s$:

1) **if** min $\{c_1, c_2, c_3\} = c_1$, then $P_{kl}{}^s = d_{kl}{}^s$, $X_{ijkl}{}^s = 0 \quad \forall\ i, j$, $Y_{ikl}{}^s = 0 \quad \forall\ i$

2) **if** min $\{c_1, c_2, c_3\} = c_2$, then $P_{kl}{}^s = 0$, $X_{i^*j^*kl}{}^s = d_{kl}{}^s$, $Y_{ikl}{}^s = 0 \quad \forall\ i$

3) **if** min $\{c_1, c_2, c_3\} = c_3$, then $P_{kl}{}^s = 0$, $X_{ijkl}{}^s = 0\ \forall\ i, j$, $Y_{i^{**}kl}{}^s = d_{kl}{}^s$

The process is repeated for all the scenarios.

After that, we check to see if service quality constraints (i.e. constraints (6) and (7)) are satisfied:

if $\sum_k \sum_l P_{kl}{}^s = 0$ then $\Upsilon^s = 1 \quad \forall\ s$

else: $\Upsilon^s = 0$

If $\sum_s p_s.\Upsilon^s \geq \alpha$, then those constraints are satisfied. Otherwise, we need to make more scenarios reliable. This will be an easy task because no capacity constraints are involved:

For each unreliable scenario, we need to obtain the extra cost we should pay to

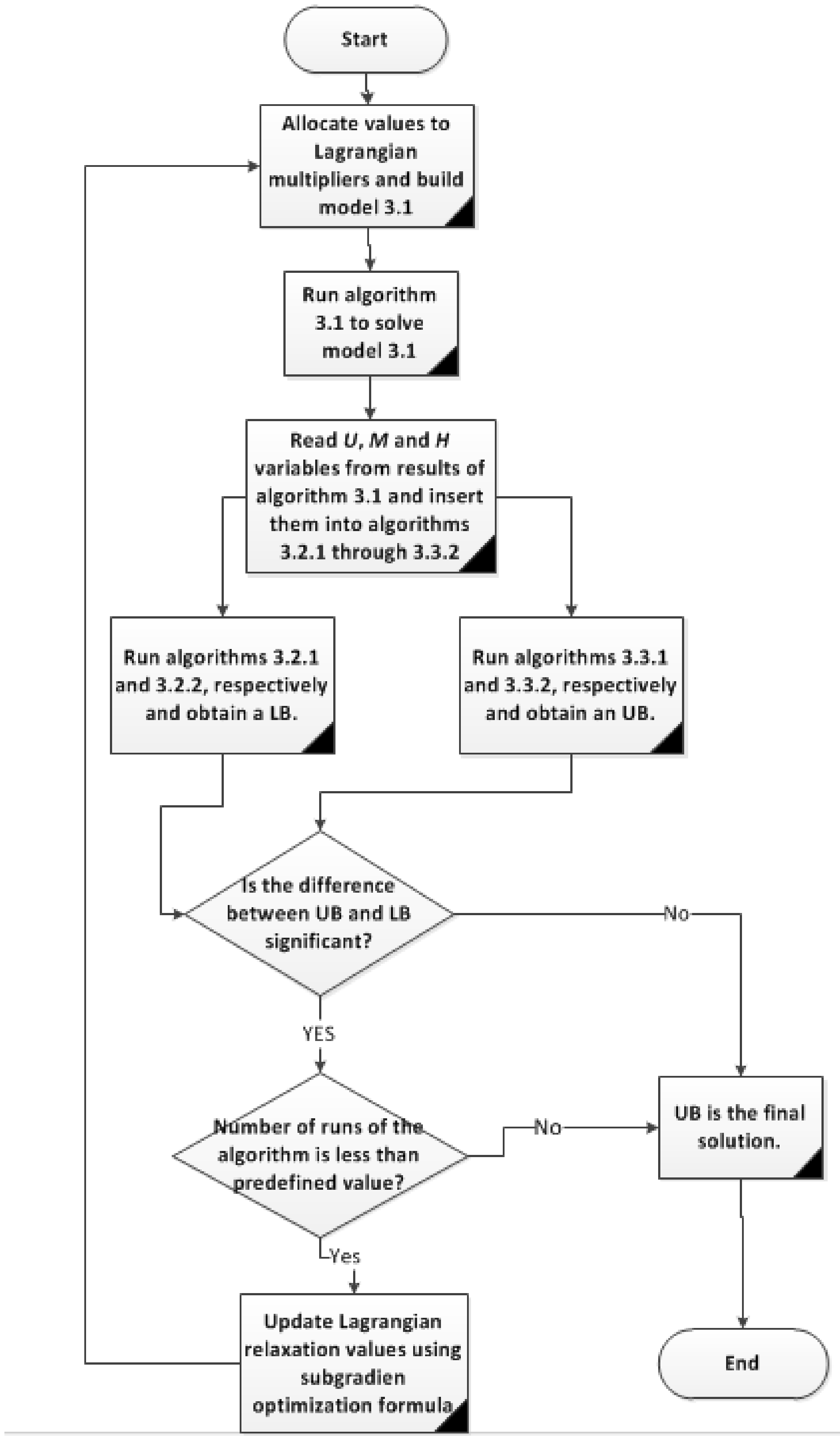


Figure 5. Flow chart of lagrangian heuristic for the pre-positioning model

make it reliable. For unreliable scenarios, there are ${P_{kl}}^s$ values that are not equal to zero. For each of those ${P_{kl}}^s$values (i.e., for each k and l under each scenario) we have previously calculated the minimum indirect and direct shipment costs (i.e. c_2 and c_3, respectively). Now we only need to find the:

$c_4 = \min\{c_2 \text{ and } c_3\}$.

Then, "c_4 - c_1" will be the extra cost of satisfying the related ${d_{kl}}^s$demand. Now, we sum up "c_4 - c_1" values of each unreliable scenario: the total sum will be the cost of making that scenario reliable.

On the other hand, each unreliable scenario has a probability of occurrence (i.e. p_s). Hence, selecting a sub-set of unreliable scenarios in order to satisfy the service quality constraints (after making those scenarios reliable) should not only be based on the cost, but also the probability of that scenario. Hence we need to consider $\frac{p_s}{RC_s}$ as the criteria for choosing such scenarios, where RC_s is the cost of making scenario s reliable. Hence, we rank the scenarios according to the criteria (the larger the criteria, the higher the rank of the scenario), and choose the minimum number of scenarios that satisfies the service quality constraints. It should be mentioned that, some of scenarios are already reliable, and the selection of the sub-set of unreliable scenarios should be such that:

$\sum_s p_s . \Upsilon^s \geq \alpha \quad \forall\, s$

Once all the values of decision variables are determined, we sum up the OFVs of models 3.1 and 3.2, and achieve a supposed LB to the problem.

It should be mentioned that in order to eliminate constraints (8) through (11), we need to make all ${X_{ijkl}}^s$, ${Y_{ikl}}^s$ variables equal to zero before running the above algorithm and make their related shipment costs equal to M. This way, the problem will indirectly forbid the shipments through routes with long delivery times. Also, for scenarios for which $p^s > 1 - \alpha$: ${c_{kl}}^s = M$, because if any of those scenarios are not fully covered, it may violate the service quality constraints.

On the other hand, UB can be obtained in a different algorithm. First, we know that results of Model 3.1 are always feasible (because they are the list of opened RRCs, opened LRCs, and amount of pre-positioned materials). We use these results (simultaneously with procedure of achieving LB) and by using modified "regret-based greedy heuristic", we generate an UB for the problem. The only difference between the process of obtaining UB and LB is the consideration of capacity of LRCs and pre-positioned amounts in RRCs. In fact, the demand of each combination of *k* and *l*, will not necessarily be subjected exclusively to the direct shipment, indirect shipment and backlogging and can become subjected to any combination of these three cases. In order to get a feasible solution, we use the following heuristic, however, before running the heuristic, both of the changes that were mentioned in the above paragraph should be implemented. In other words, the shipping costs for routes with long delivery duration as well as shortage cost of all AAs of scenarios for which $p^s > 1 - \alpha$, must be set to M)).

For all combinations of *k* and *l*, regardless of capacities, we calculate the two minimum cost ways of handling the demand and calculate the difference between them as the regret. The combination of *k* and *l* that has the maximum regret will rise to the top of the list of decision.

Set s = 1;

For all $d_{kl}{}^{s} \neq 0$:

If for any i, l: $H_{il} = 0$, **then**: for all j,k: $a_{ijkl}{}^{s} = M$ and $b_{ikl}{}^{s} = M$

If for any j: $M_j{}^{s} = 0$, **then**: for all i,k,l: $a_{ijkl}{}^{s} = M$

For all k,l,s: (i^{*}, j^{*}), $= \arg\min_{i,j}\{a_{ijkl}{}^{s}\}$

$(i^{**}, j^{**}) = \arg\min_{i,j}\{a_{ijkl}{}^{s} \backslash a_{i^{*}j^{*}kl}{}^{s}\}$

$i' = \arg\min_{i}\{b_{ikl}{}^{s}\}$

$i'' = \arg\min_{i}\{b_{ikl}{}^{s} \backslash b_{i'kl}{}^{s}\}$

$O^{1}{}_{kl}{}^{s} = \text{Min}\ \{ c_l{}^{s}, a_{i^{*}j^{*}kl}{}^{s}, a_{i^{**}j^{**}kl}{}^{s}, b_{i'kl}{}^{s}, b_{i''kl}{}^{s} \}$

$O^{2}{}_{kl}{}^{s} = \text{Min}\ \{(c_l{}^{s}, a_{i^{*}j^{*}kl}{}^{s}, a_{i^{**}j^{**}kl}{}^{s}, b_{i'kl}{}^{s}, b_{i''kl}{}^{s}) \setminus O^{1}{}_{kl}{}^{s}\}$

$R_{kl}{}^{s} = O^{2}{}_{kl}{}^{s} - O^{1}{}_{kl}{}^{s}$

$(k^{*}, l^{*}) = \arg\max_{k,l} R_{kl}{}^{s}$

- If $O^{1}{}_{k^{*}l^{*}}{}^{s} = c_l{}^{s}$ then: $P_{kl}{}^{s} = d_{kl}{}^{s}$, $X_{ijkl}{}^{s} = Y_{ikl}{}^{s} = 0$, $d_{kl}{}^{s} = 0$
- If $O^{1}{}_{k^{*}l^{*}}{}^{s} = a_{ijkl}{}^{s}$, then: $X_{ijkl}{}^{s} = \min\{H_{il}, M_j{}^{s}, d_{kl}{}^{s}\}$, $d_{kl}{}^{s} = d_{kl}{}^{s} - X_{ijkl}{}^{s}$, $H_{il} = H_{il} - X_{ijkl}{}^{s}$, $M_j{}^{s} = M_j{}^{s} - X_{ijkl}{}^{s}$
- If $O^{1}{}_{k^{*}l^{*}}{}^{s} = b_{ikl}{}^{s}$ then: $Y_{ikl}{}^{s} = \min\ \{H_{il}, d_{kl}{}^{s}\}$, $d_{kl}{}^{s} = d_{kl}{}^{s} - Y_{ikl}{}^{s}$, $H_{il} = H_{il} - Y_{ikl}{}^{s}$

We continue until:

$$d_{kl}{}^{s} = 0 \quad \forall \ k, l, s$$

Now we investigate whether or not each scenario is in reliable set:

if $\sum_k \sum_l P_{kl}{}^{s} = 0$ then $\Upsilon^{s} = 1 \quad \forall \ s$

else: $\Upsilon^{s} = 0$

Now we need to check if the service quality constraint is satisfied. In fact, if $\sum_s \Upsilon^s \geq \alpha$ then final solution is obtained. Otherwise we need to place more scenarios in the reliable set so that: $\sum_s \Upsilon^s \geq \alpha$. We define S' as the set of scenarios that are not in the reliable set. In order to derive a feasible solution, we need to re-run the entire algorithm, this time by considering the following steps:

1. For all scenarios that are in reliable set (according to the obtained solution):

   $c_{kl}{}^s = M$

2. Finding a subset of scenarios that are not in reliable set (by using the algorithm 3.2.2) and re-running the algorithm 3.2.1 after making $c_{kl}{}^s = M$ for all scenarios in the subset.

Now we describe the second algorithm:

Algorithm 3.2.2

In each scenario in S', there exists at least one demand that is fully or partially backlogged. There are four reasons for each scenario, not to be in the reliable set:

1. According to the list of opened RRCs, there is not sufficient pre-positioned material in RRCs to be shipped to AA's.
2. According to the list of opened LRCs, there is not enough capacity to ship pre-positioned materials indirectly (i.e., via LRCs) to AAs.
3. Shortage cost is low.
4. Time constraints do not allow shipments to certain AAs (again, according to list of opened RRCs and LRCs).

In order to make the unreliable scenarios reliable, we need to find out which of above four reasons (or their combination) cause the backlogging. If the cause is the RRC capacity, the body of the solution will be drastically affected if we want to make it feasible. This is due to the fact that, first of all, RRC selection belongs to first stage of the problem and also, fixed cost of opening and maintaining RRCs has often the highest contribution OFV and opening a new RRC will likely cause the new solution to have significantly higher OFV than the optimal solution. In this case, the modifications to the solution will be judgmental [75]. But for other cases, it might be possible to satisfy the service quality constraints without drastically changing the solution.

In order to find the reason, we first need to check the capacities. For each scenario in S'(set of unreliable scenarios), if the total backlogged demand exceeds the total remained capacity of all opened RRCs (subject to the percentage of usable relief materials or ${\rho_{il}}^s$ values) that scenario cannot become reliable without opening a new RRC. Then, we need to check the possibility of direct or indirect shipments to the AAs with backlogged demands. Because the fixed cost of opening and maintaining an LRC is much higher than individual shipping costs, it is better to use an opened LRCs as much as possible. Hence, we first check if the remaining capacity of currently opened LRCs is adequate, by comparing the total backlogged demand with total remained capacity. If this capacity is greater than or equal to the backlogged demand, there will be no need to open new LRCs. Otherwise, we need to check the possibility of direct shipments, using the remaining capacity of RRCs and delivery durations. If this is not possible, we should open one or more LRCs in order to cover all the backlogged demands. If there is no new LRC to open, or time constraints do not allow shipments via newly opened LRCs, then the problem does not have a feasible solution, at least regarding the current set of opened RRCs. Details of all algorithms for obtaining LB and UB are as follows:

LB Algorithms

Algorithm 3.2.1

I = set of opened RRCs (based on the results of algorithm 3.1)

J^s = set of opened LRCs under scenario s (based on the results of algorithm 3.1)

K = set of demand points

L = set of relief items

S = set of scenarios

for all s that $p^s > 1 - \alpha$: $c_{kl}{}^s = M$

set s=0;

Step 1) $s = s+1$, k=0;

Step 2) $k = k+1$;

Step 3) $l = l+1$;

Step 4) $C1_{kl}{}^s = c_{kl}{}^s$,

$(i^*, j^*) = \arg\min_{i,j} \{ p_s . a_{ijkl}{}^s + \lambda_{il}{}^s + \sigma_j{}^s . v_l \}$, $C2_{kl}{}^s = p_s . a_{i^* j^* kl}{}^s + \lambda_{i^* l}{}^s + \sigma_{j^*}{}^s . v_l$

$i^{**} = \arg\min_i \{ p_s . b_{ikl}{}^s + \lambda_{il}{}^s \}$, $C3_{kl}{}^s = p_s . b_{i^{**} kl}{}^s + \lambda_{i^{**} l}{}^s$

if min $\{C1_{kl}{}^s, C2_{kl}{}^s, C3_{kl}{}^s\} = C1_{kl}{}^s$, then $P_{kl}{}^s = d_{kl}{}^s$, $X_{ijkl}{}^s = 0 \quad \forall\ i, j$, $Y_{ikl}{}^s = 0$

$\forall\ i$

else if min $\{C1_{kl}{}^s, C2_{kl}{}^s, C3_{kl}{}^s\} = C2_{kl}{}^s$, then $P_{kl}{}^s = 0$, $X_{i^* j^* kl}{}^s = d_{kl}{}^s$, $X_{ijkl}{}^s = 0 \ \forall i \neq i^*$,

$j \neq j^*$, $Y_{ikl}{}^s = 0 \ \forall i$

else if min $\{C1_{kl}{}^s, C2_{kl}{}^s, C3_{kl}{}^s\} = C3_{kl}{}^s$, then $P_{kl}{}^s = 0$, $X_{ijkl}{}^s = 0 \ \forall\ i, j$, $Y_{i^{**} kl}{}^s = d_{kl}{}^s$

if $l < |L|$ go to step 2

else l=0

if k< |K| go to step 2

else if s < |S| go to step 1,

else end.

Algorithm 3.3.2

This is actually the process of satisfying service quality constraints:

$\forall$ s: **if** $\sum_k \sum_l P_{kl}{}^s = 0$ then $\Upsilon^s = 1$.

else: $\Upsilon^s = 0$

if $\sum_s p_s . \Upsilon^s < \alpha$:

S' = set of scenarios for which $\Upsilon^s = 0$ ($s \in S'$)

Initialize $s = 0$

Step 1) Set s=s+1

Step 2) For all k,l: **if** $P_{kl}{}^s > 0$:

if $C2_{kl}{}^s < C3_{kl}{}^s$ then $C4_{kl}{}^s = (C1_{kl}{}^s - C2_{kl}{}^s).\ X_{i^*j^*kl}{}^s$

else $C4_{kl}{}^s = (C1_{kl}{}^s - C3_{kl}{}^s).\ Y_{i^{**}kl}{}^s$

else if s < |S'|: go to step 1

Step 3)$RC_s = \sum_k \sum_l C4_{kl}{}^s$ for all s

Sort s according to $\frac{p_s}{RC_s}$ in a descending order (name the ranks as s'')

Set $s'' = 0$

Step 4) For the unreliable scenarios: $s'' = s''$+1:

While (for all k , l: ${P_{kl}}^s > 0$) **do**

if ${C2_{kl}}^s < {C3_{kl}}^s$ then ${X_{i^*j^*kl}}^s = {d_{kl}}^s$

else ${Y_{i^{**}kl}}^s = {d_{kl}}^s$

Step 5) $\Upsilon^s = 1$

if $\sum_s p_s . \Upsilon^s < \alpha$, then go to step 4.

else end.

UB Algorithms:

Algorithm 3.3.1

I = set of opened RRCs (based on the results of algorithm 3.1)

J^s = set of opened LRCs under scenario s (based on the results of algorithm 3.1)

K = set of demand points

L = set of relief items

S = set of scenarios

For all s that $p^s > 1 - \alpha$: ${c_{kl}}^s = M$

$s = 0;$

Step 1) If $s = |S|$, go to step 4

else Set $s = s + 1$;

Step 2) For all ${d_{kl}}^s \neq 0$:

If for any (i^*, l^*): $H_{i^*l^*} = 0$, then: for all j,k: ${a_{i^*jkl^*}}^s = M$ and ${b_{ikl}}^s = M$

If for any $j*$: $M_j{}^s$ = 0, then: for all i,k,l: $a_{ijkl}{}^s = M$

$O^1{}_{kl}{}^s$ = Min { $c_l{}^s$, $a_{ijkl}{}^s$, $b_{ikl}{}^s$}

$O^2{}_{kl}{}^s$= Min {($c_l{}^s$, $a_{ijkl}{}^s$, $b_{ikl}{}^s$) \ $O^1{}_{kl}{}^s$}

$R_{kl}{}^s = O^2{}_{kl}{}^s - O^1{}_{kl}{}^s$

($k*$, $l*$) = arg max$_{k,l}$ $R_{kl}{}^s$

Step 3)

- **if** $O^1{}_{k^*l^*}{}^s = c_l{}^s$ then: $P_{kl}{}^s = d_{kl}{}^s$, $X_{ijkl}{}^s$= $Y_{ikl}{}^s$= 0, $d_{kl}{}^s$ = 0
- **else if** $O^1{}_{k^*l^*}{}^s$ =$a_{ijkl}{}^s$, then: $X_{ijkl}{}^s$= min{H_{il}, $M_j{}^s$, $d_{kl}{}^s$}, $d_{kl}{}^s$=$d_{kl}{}^s$ - $X_{ijkl}{}^s$, H_{il}= H_{il} - $X_{ijkl}{}^s$, $M_j{}^s$ = $M_j{}^s$ - $X_{ijkl}{}^s$
- **else if** $O^1{}_{k^*l^*}{}^s = b_{ikl}{}^s$ then: $Y_{ikl}{}^s$ = min {H_{il}, $d_{kl}{}^s$}, $d_{kl}{}^s$=$d_{kl}{}^s$ - $Y_{ikl}{}^s$, H_{il}= H_{il} - $Y_{ikl}{}^s$

If for any k,l: $d_{kl}{}^s \neq 0$, go to step 2. Otherwise go to step 1.

Algorithm 3.3.2

This is actually the process of satisfying service quality constraints:

$\forall$ s: **if** $\sum_k \sum_l P_{kl}{}^s$ = 0 then Υ^s = 1.

else: Υ^s = 0

if $\sum_s p_s . \Upsilon^s < \alpha$:

S' = set of scenarios for which Υ^s = 0 (s∈S')

s =0

$R1_i^s$ = Remaining capacity of RRC_i under scenario s

for all i,s: $\rho'{}_{il}{}^s$ = max $_l${$\rho_{il}{}^s$}

Step 1) Do while s ≤ $|S'|$

Set s = s +1

if $\sum_k \sum_l P_{kl}{}^s > \sum_{i\epsilon I}(\rho'_{il}{}^s . R1_i^s)$ then exclude s

else $s \in S'''$ (S''' is the set of unreliable scenarios that potentially can become reliable)

Step 2) **For** all $s \in S'''$ (separately):

J'^s = set of unopened LRCs

$j \in J'^s$

$j = 0$

while $j < |J'^s|$ ***do***

$M_j{}^s = 1$

for all $d_{kl}{}^s \neq 0$:

If for any (i*, l*): $H_{i^*l^*} = 0$, then: for all j,k: $a_{i^*jkl^*}{}^s = M$ and $b_{ikl}{}^s = M$

If for any j*: $M_j{}^s = 0$, then: for all i,k,l: $a_{ijkl}{}^s = M$

$O1_{kl}{}^s$ = Min $\{ a_{ijkl}{}^s,\ b_{ikl}{}^s\}$

$O2_{kl}{}^s$= Min $\{(a_{ijkl}{}^s,\ b_{ikl}{}^s) \setminus O1_{kl}{}^s\}$

$R_{kl}{}^s = O2_{kl}{}^s - O1_{kl}{}^s$

(k* , l*) = arg max$_{k,l}$ $R_{kl}{}^s$

- **If** $O1_{k^*l^*}{}^s = a_{ijkl}{}^s$, then: $X_{ijkl}{}^s = \min\{H_{il}, M_j{}^s, d_{kl}{}^s\}$, $d_{kl}{}^s = d_{kl}{}^s - X_{ijkl}{}^s$, $H_{il} = H_{il} - X_{ijkl}{}^s$, $M_j{}^s = M_j{}^s - X_{ijkl}{}^s$
- **If** $O1_{k^*l^*}{}^s = b_{ikl}{}^s$ then: $Y_{ikl}{}^s = \min\{H_{il}, d_{kl}{}^s\}$, $d_{kl}{}^s = d_{kl}{}^s - Y_{ikl}{}^s$, $H_{il} = H_{il} - Y_{ikl}{}^s$

co_j = total extra cost of satisfying s while opening new LRC j

sort co_j in ascending order (ranks are called j').

if there are multiple j's that have feasible solution, the one with the minimum cost will be chosen to make the s reliable.

else $M_j{}^s = 1$ for first two j's in the ranking. Repeat the do-while loop.

If no feasible solution exists:

$M_j{}^s = 1$ for the first three js in the ranking Repeat the do-while loop.

else related co_j will be equal to RC_s

Step 4) Sort s according to $\frac{p_s}{RC_s}$ in a descending order (name the ranks as s'')

Set $s'' = 0$

While $\sum_s p_s . \Upsilon^s < \alpha$:

$s'' = s'' + 1$;

$s'' \in$ reliable set

Step5) Re-run algorithm 3.3.1 while considering $c_{kl}{}^s = M$, for all scenarios in the reliable set.

The efficiency of the proposed LH method as well as experimental results is presented in chapter 5 of this dissertation.

CHAPTER 4
THE REAL-TIME FACILITY LOCATION PROBLEM

4.1 Introduction

This chapter, first of all, will be the continuation of the prepositioning problem that was fully discussed in chapter 3. In fact in the pre-positioning model, decisions for locations of supply centers (RRCs) as well as the amount of different relief materials at each RRC would have been made. Now, we are in the aftermath of the disaster and those supplies should be transported and distributed. Emergency coordinator department decides about the details of relief materials distribution. Finally, according to such decisions, RRCs starts the distribution process as supply sources. Different relief materials will either be shipped to AAs directly from RRCs or indirectly via LRCs (this way, LRCs play the role of intermediate distribution nodes where relief materials are received, sorted, packed and stored in order to be ready for final shipment to the AAs). Figure 6 shows multi-stage logistic network of the problem.

While making the distribution decisions, there might be a need for more supplies (than what is already pre-positioned) because the exact amount of required supplies was not clear before the occurrence of the disaster, and also, the demand amounts at demand points might be different than initial estimations. Hence, two more supply sources

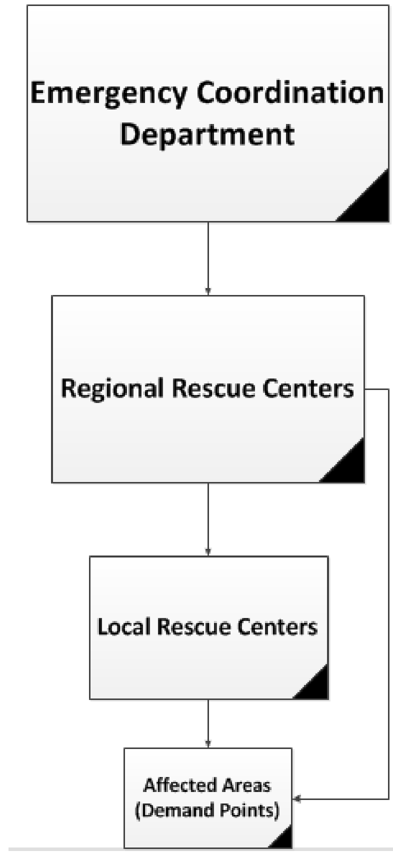


Figure 6. Multi-stage logistics network of the real-time model

(donations and vendors) can be considered [44]. Using real-time data (e.g. demand at AAs), the real-time model will be a location-allocation model with some inventory already in hand. The basis of the work will be the model of [70]. Two major upgrades will be considered: first, the model will be multi-product (instead of single product) and second, the model will be location-allocation (instead of a sole allocation model). Generally, there are the four sets of inputs for this new model:

1. **Outputs of pre-positioning model**: As mentioned before, locations and pre-positioned amounts of various relief materials are the major outputs of the pre-positioning model. In fact, one can look at the pre-positioned materials as "in-hand" inventory for the real-time facility location model.

2. **Updated data related to parameters of the pre-positioning problem**: Several parameters such as demand values, shortage costs and transportation costs were used in the pre-positioning model. Here, we need to upgrade these values because the disaster has already occurred and they are available. However, some of thr parameters of the pre-positioning model will not be used in the new model (e.g. holding costs).
3. **Data related to new supply sources:** Donation centers and vendors are main additional supply sources. Their capacity as well as locations can be inputs of the new model.
4. **Data related to new parameters:** These parameters were mentioned in section 1.4. Some examples are the reliability of routes and ransack probability of routes.

While the pre-positioning model tries to develop a preliminary plan for allocation of relief materials to AAs based on predictions about the quality and quantity of the disaster (that were incorporated into the pre-positioning model using the concept of scenarios), the real-time model uses real-time data to plan the final allocation scheme. The locations of RRCs are already known and there is a set of opened LRCs related to each scenario. Because in reality, none of the scenarios can be the same as the actual disaster, the ultimate location of LRCs should be determined in the real-time model. Hence, this model is a location-allocation model.

Another major difference between the real-time model compared to the pre-positioning model is that the real-time model is multi-objective. Although the pre-positioning model also has objectives other than cost minimization (e.g., setting a maximum delivery duration), because such objectives were not truly optimized, the pre-positioning model cannot be categorized as a multi-objective model. A list of considered objectives in the real-time model will be mentioned and described later in this chapter.

After the occurrence of the disaster it is possible that the amount of pre-positioned relief materials is not adequate to cover the entire real-time demand at AAs. Thus, other supply sources should be added to the model. The donated relief materials usually take some time to be gathered and are used in the recovery stage, but vendors are readily available [44]. The locations of vendors are known and also, there is no fixed cost related to opening or operating such facilities. Therefore, there is no location problem of RRCs in the real-time model and only the location of LRCs should be determined.

There are common objectives related to the real-time facility location problem, extracted from different studies. Yet, there are different criteria, suggested for measuring each of them. The list of such objectives is as follows:

1. **Minimization of time:** As mentioned before, time is the most important element in the aftermath of a disaster (especially in the response stage). By minimizing the delivery duration of distributing relief materials, the severity of the negative effects of the disaster can be significantly reduced. Two major measurements are suggested in the literature for assessing the element of time: maximum arrival time, and total travelling time of relief materials. The first one basically focuses on the latest arrival time of shipments to AAs while the latter focuses on the entire delivery process. Minimization of maximum arrival time will fit a maximum value for every single delivery duration to AAs while minimization of total travel time does not consider single deliveries and only focus on the total time. Hence,

in the latter, it is possible that for some of the AAs, delivery duration is much longer than that of the other AAs.

2. **Minimization of ransack probability of routes:** In the aftermath of a disaster, there usually are groups of thieves that try to rob the relief materials while they are being delivered to AAs. Even normal people may steal the supplies from vehicles in the aftermath of a severe disaster because of the huge mental pressure and immediate need to vital materials [12]. Estimation techniques of ransack probabilities of different routes are beyond the scope of this dissertation. It is worthwhile to mention that data related to magnitude of population of districts, economical status of the population and structural type of routes (i.e. streets, highways, and roads) are some of the factors that are considered in such estimation techniques. There are two criteria suggested for measuring the ransack probability of the system: maximum ransack probability in the distribution system and overall security (or equivalently, overall ransack probability).

3. **Maximization of reliability of routes:** While ransack probability pertains to the relief materials, reliability is directly related to the availability of routes between different nodes (i.e. RRCs, LRCs, and AAs) in terms of infrastructure status. Reliability as an objective is more appropriate in the aftermath of a disasters such as floods and earth quakes because such disasters can have significant impact on infrastructure. Different factors (other than the severity of disaster) such as the age of infrastructure, durability of used materials in building the infrastructure, and type of route (i.e. road, street, and highway) should be considered in the estimation of reliability of routes. Moreover, tools such as Google map can also

be used to investigate the reliability of routes in the aftermath of the disaster. Similar to time and ransack probability, there are two measurements for reliability: Minimum reliability of routes and overall system reliability.

4. **Maximization of demand satisfaction:** As mentioned in the pre-positioning model, having shortage in AAs has severe consequences (e.g. death of injured people). Therefore, the distribution plan should be developed in a way that maximizes the total served demand. If the supply sources are considered to have unlimited supply capacity (or at least have total supply capacity that is not less than the total demand), the total served demand should be considered equal to the total demand. Otherwise, maximization of the total served demand should be considered.

Also, there are a few objectives that are suggested specifically in some of the studies:

5. **Cost minimization:** Although cost minimization should not be considered a highly important objective in humanitarian relief chains, in many cases, there are budget limits that naturally prevent the system from being developed in an ideal manner (in terms of other objectives). Limiting the cost to a budgeted amount minimization of the total system cost are two types of optimization, suggested in the literature.

6. **Fairness of distribution:** In case for some reason, the total demand cannot be served, demand satisfaction percentage (i.e. the ratio of total served demand to the total demand) for some of the demand points will be greater than others. In this case, it is suggested that the total supply is distributed to AAs in an equitable

manner so that such ratio is equal for all AAs. This can be obtained by minimizing the maximum ratio of satisfied demand for all of AAs.

Appropriate objectives should be chosen and inserted into the model. It should be mentioned that considering too many objectives in the model can significantly reduce the efficiency of the model in terms of both the accuracy and the solving process.

Contributions

The real-time model is formulated as a mixed integer programming model. There are two major contributions in the model:

- **Multi-product consideration:** Because we are formulating the problem as a mixed integer model, we can add another dimension to the currently developed model (i.e., network-based model) for different relief materials. Consequently, this model is closer to reality.
- **Location-allocation:** Unlike models that might just be allocation models, our model is a location-allocation model. As mentioned before, the location of RRCs is already known, but the optimal location of LRCs is to be. Therefore, because the second echelon of the problem is location-allocation, the overall model is location-allocation as well. Unlike network model, our model will be NP-hard and should be solved.
- **Consideration of fixed and variable costs:** Although cost minimization may not be a very important objective in life and death, in reality, there are always budget limits that cause reconsiderations in the humanitarian operations. Most of the papers in the literature assume a limited to cover the transportation costs. In [70],

this budget is used to recover some of the possibly damaged routes. In our model, the fixed cost of opening and operating the LRCs are also considered.

- **Availability of direct shipments:** Just as direct shipments were possible in the pre-positioning model, we also allow this possibility for the real-time model. According to this feature, different relief materials can be shipped directly from RRCs to AAs. This feature is useful for cases where the distances from certain AAs to certain RRCs are very short and it is more beneficial to ship directly rather than using LRCs for such routes.

In [69], a Humanitarian Aid Distribution System (HADS) is developed in order to optimize the allocation of a single relief material type to affected areas. This system is more of a vehicle routing problem. In [70], HADS is evolved and converted into an allocation problem and the new system is called RecHADS. That model is the basis for the real-time model of this dissertation. In RecHADS, objectives such as minimization of ransack probability, maximization of total served demand and maximization of reliability of routes are considered and mathematical model is developed. It is then solved using the Lexicographical optimization method. This method is proven to work effectively in this area [69,70].

4.2 The real-time facility location model definition

Many of the parameters of the real-time model are similar to those of pre-positioning model though the dimensions are different because the real-time model is not scenario-based. The details of the real-time model are as follows:

Sets

I: set of RRCs

J: set of LRCs

K: set of demand points (AAs)

L: set of material types

Parameters

v_l: Unit volume of relief item *l*

q_j: Capacity of LRC_j

s_{il}: Supply amount of item *l* at RRC_i

d_{kl}: Amount of demand at demand point *k* for relief item *l* under scenario *s*

$t1_{ij}$: Transportation time from RRC_i to LRC_j

$t2_{jk}$: Transportation time from LRC_j to demand point *k*

$t3_{ik}$: Direct transportation time from RRC_i to demand point *k*

$r1_{ij}$: Reliability of route between RRC_i and LRC_j

$r2_{jk}$: Reliability of route between LRC_j to demand point *k*

$r3_{ik}$: Reliability of direct route between RRC_i to demand point *k*

$p1_{ij}$: Ransack probability of route between RRC_i and LRC_j

$p2_{jk}$: Ransack probability of route between LRC_j and demand point *k*

$p3_{ik}$: Ransack probability of direct route between RRC_i and demand point *k*

g_j: Fixed cost of opening and operating LRC_j under scenario *s*

a_{ijl}: Transportation cost for one unit of item *l* shipped from RRC_i to LRC_j

b_{jkl}: Transportation cost for one unit of item *l* shipped from LRC_j to demand point *k*

c_{ikl}: Transportation cost for one unit of item *l* shipped directly from RRC_i to demand point *k*

w_l: Coefficient of importance of satisfaction of demand of material type *l*

Decision variables

X_{ijl}: Amount of item *l* shipped from RRC_i to LRC_j

Y_{jkl}: Amount of item *l* shipped from LRC_j to demand point *k*

Z_{ikl}: Amount of item *l* shipped directly from RRC_i to demand point *k*

$AT1_j$: Maximum Arrival time of shipments to LRC_j

$AT2_k$: Maximum Arrival time of shipments to demand point *k*

$$M_j : \begin{cases} 1 & \text{if } LRC_j \text{ is opened} \\ 0 & \text{otherwise} \end{cases}$$

$$B1_{ij} : \begin{cases} 1 & \text{if any relief item is shipped from } RRC_i \text{ to } LRC_j \\ 0 & \text{otherwise} \end{cases}$$

$$B2_{jk} : \begin{cases} 1 & \text{if any relief item is shipped from } LRC_j \text{ to demand point } k \\ 0 & \text{otherwise} \end{cases}$$

$$B3_{ik} : \begin{cases} 1 & \text{if any relief item is shipped from } RRC_i \text{ directly to demand point } k \\ 0 & \text{otherwise} \end{cases}$$

An important part of our model accounts for vendors and donation centers as new supply sources. In fact, when the total demand exceeds total supply, decision makers utilize capacity from all sources. Vendors are usually readily available while donations centers take some time to setup and become available [44]. In order to insert these two supply sources to the model, one should add the purchase cost of supplies to corresponding a_{ijl} and c_{ikl} parameters, where i is the vendor indicator. Note that the purchase cost is added to transportation cost. For instance, if purchase cost of item *l* from vendor *i* is equal to p units, then:

$$\forall\, j,k:\ a'_{ijl} = a_{ijl} + p \quad , \quad c'_{ikl} = c_{ikl} + p$$

where a'_{ijl} and c'_{ikl} are updated transportation costs. This means that, if any shipments are done from vendor i, an extra cost is added to the model. On the other hand, if we assume that relief items of donation centers have zero purchase cost, they will take time to become available. In this case, we need to add the preparation time of relief items in donations centers to all the related $t1_{ij}$ and $t3_{ik}$ values. For instance, if preparation time of relief items in donation center *i* is equal to w, then:

$$\forall\, j,k:\ t1'_{ij} = t1_{ij} + w \quad , \quad t3'_{ik} = t3_{ik} + w$$

where $t1'_{ij}$ and $t3'_{ik}$ are updated transportation times.

List of attributes

SD: satisfied demand

TT: total travel time	U1
MA: maximum arrival time	U2
CO: total cost	U3
GR: global reliability	U4
GS: global security	U5

Each attribute has its own constraints and objective function. Also there are some general constraints in the model. All the constraints and their explanations are as provided below:

Supply constraint: As mentioned before, the pre-positioning facilities have limited capacity. Also, donation centers and vendors can also have their own supply capacities. Total shipment from each supply facility (both direct and indirect shipments) cannot exceed its capacity:

$$\sum_j X_{ijl} + \sum_k Z_{ikl} \leq s_{il} \qquad \forall \ i,l \tag{1}$$

Constraints (1) guarantee that sum of all the direct and indirect shipments of a relief material from a RRC cannot exceed the supply capacity of that RRC for that relief material.

LRC capacity constraint: LRCs have limited capacity:

$$\sum_i \sum_l X_{ijl} \,.\, v_l \ \leq q_j \ .\ M_j \qquad \forall \ j \tag{2}$$

Constraints (2) guarantee that no shipments via an LRC are possible unless that LRC is opened. They also guarantee that total shipments via each LRC cannot exceed that LRC's capacity.

Flow conservation constraint: In indirect shipments, all the flow that goes into an LRC should leave that LRC and arrive at AAs:

$$\sum_i X_{ijl} = \sum_k Y_{jkl} \qquad \forall \ j, \ l \tag{3}$$

Shipment indication constraints: In order to build up constraints for most of the objectives, we need to keep track of the used routes. Hence, a set of constraints should be defined in order to identify the used routes via binary variables:

$$\sum_l X_{ijl} \leq \text{M}.\, B1_{ij} \qquad \forall i,\ j \qquad (4)$$

$$\sum_l Y_{jkl} \leq \text{M}.\, B2_{jk} \qquad \forall j, k \qquad (5)$$

$$\sum_l Z_{ijl} \leq \text{M}.\, B3_{ik} \qquad \forall i, k \qquad (6)$$

Constraints (4-6) guarantee that no shipments of any type are allowed unless their related indicator variables take the value of 1.

Now we define the constraints related to different attributes:

1) ***Demand satisfaction***: Obviously, the main objective of the problem is to deliver different relief materials to AAs. Shortage, in this case, may lead to severely negative consequences such as death of people. Hence, maximization of satisfied demand is considered. If we know that total supply capacity exceeds the total demand, we may make the total shipments equal to the total demand. But in general, total shipment is less than or equal to the total demand:

$$\sum_j Y_{ijl} + \sum_i Z_{ikl} \leq d_{kl} \qquad \forall\ k, l \qquad (7)$$

And the satisfied demand can be measured as:

$$SD_l = \sum_j \sum_k Y_{jkl} + \sum_i \sum_k Z_{ikl} \qquad \forall\ l \qquad (8)$$

2) ***Total shipment time***: this attribute is suggested in [69] and is of great importance because as mentioned before, time is the most important element of the Response stage of emergency management.

$$TT \geq \sum_i \sum_j \sum_l (X_{ijl} \ . t1_{ij}) + \sum_j \sum_k \sum_l (Y_{jkl} \ . t2_{jk}) + \sum_i \sum_k \sum_l (Z_{ikl} \ . t3_{ik}) \qquad (9)$$

In constraints (9) total travel time of all relief materials are calculated.

3) ***Maximum arrival time***: The process of distribution of relief materials starts in a point of time and finishes in another. It is important to minimize the full distribution time (the time that final latest load is delivered):

$$AT1_j \geq t1_{ij} - M.(1 - B1_{ij}) \qquad \forall\ i, j \qquad (10)$$

$$AT2_k \geq AT1_j + t2_{jk} - M.(1 - B2_{jk}) \qquad \forall\ j, k \qquad (11)$$

$$AT2_k \geq t3_{ik} - M.(1 - B3_{ik}) \qquad \forall\ i, k \qquad (12)$$

$$MA \geq AT2_k \qquad \forall\ k \qquad (13)$$

In constraints (10), the maximum arrival (visit) time of shipments (indirect) at each LRC is calculated. In constraints (11), the maximum arrival time of indirect shipment to each AA is calculated. In constraints (12), maximum arrival time of direct shipment to each AA is recorded. It should be mentioned that in constraints (10-12), M is a value greater than or equal to the longest related travel time. For instance, in constraints (9), M is greater than or equal to the maximum travel time between RRCs and LRCs (i.e. $M = \max_{i,j}\{t1_{ij}\}$). If any shipment is made from any RRC to LRC_j, then $B1_{ij}$ will be equal to 1 and the maximum arrival time at LRC_j (i.e., $AT1_j$) will be greater than or equal to

$t1_{ij}$. Otherwise, $AT1_j$will be greater than or equal to “M - $t1_{ij}$” which is a non-positive value. Therefore, $AT1_j$ will eventually be equal to the greatest $t1_{ij}$ value among all used routes between RRCs and LRCs. Constraints (13) record the maximum value of all the arrival times at all the AAs.

4) ***Total cost***: Although cost is not a very important attribute in life and death situation, in many cases, the budget limits must be considered. In our model, total cost include fixed cost of opening and operating LRCs as well as transportation costs:

$$CO = \sum_i \sum_j \sum_l a_{ijl}.X_{ijl} + \sum_j \sum_k \sum_l b_{jkl}.Y_{jkl} + \sum_i \sum_k \sum_l c_{ikl}.Z_{ikl} + \sum_j g_j.M_j \quad (14)$$

Constraint (14) records the total cost of the solution.

5) ***Global reliability:*** As mentioned before, each route may be damaged during or after a disaster. Therefore, each route has a reliability value. The global reliability criterion refers to the case in which, all the shipments are successfully and safely done (meaning that damaged routes cause no delay in the delivery process). Logically, this criteria is calculated by multiplying the $r1_{ij}$, $r2_{jk}$, and $r3_{ik}$ values of all used routes:

$$\prod_{i,j|B1_{ij}=1} r1_{ij} \,.\, \prod_{j,k|B2_{jk}=1} r2_{jk} \,.\, \prod_{i,k|B3_{ik}=1} r3_{ik}$$

Because we wish to use linear programming, we linearize such a measurement by considering the logarithm of reliability values [69,70]:

$$GR = \sum_i \sum_j \log(r1_{ij}).\, B1_{ij} + \sum_j \sum_k \log(r2_{jk}).\, B2_{jk} + \sum_i \sum_k \log(r3_{ik}).\, B3_{ik} \quad (15)$$

Constraint (15) calculates the global reliability criterion.

6) ***Global security:*** Similar to global reliability, global security refers to the case where all the shipments are securely made without any ransack. As mentioned before, $p1_{ij}$, $p2_{jk}$, and $p3_{ik}$ are ransack probabilities for routes between RRCs and LRCS, LRC and AAs, and RRCs and AAs, respectively. Hence, the probability of finishing those routes securely are $q1_{ij}$ = 1 - $q1_{ij}$, $p2_{jk}$ = 1 - $p2_{jk}$, and $q3_{ik}$ = 1 - $p3_{ik}$, respectively. And the global security will be obtained from the following:

$$\prod_{i,j|B1_{ij}=1} q1_{ij} \cdot \prod_{j,k|B2_{jk}=1} q2_{jk} \cdot \prod_{i,k|B3_{ik}=1} q3_{ik}$$

We need to linearize such a measurement by considering the logarithm of security values:

$$\text{GS} = \sum_i \sum_j \log(1 - p1_{ij}).\, B1_{ij} + \sum_j \sum_k \log(1 - p2_{jk}).\, B2_{jk} + \sum_i \sum_k \log(1 - p3_{ik}).\, B3_{ik} \quad (16)$$

Constraint (16) records the newly defined global security value. It should be mentioned that in GR and GS formulas, it is assumed that all the routes are independent in terms of reliability and ransack probability. This may not be true in reality, but in order to keep the problem in the category of OR models, such simplifying assumption is considered in the literature.

Thus far, all the possible constraints are defined and one can separately optimize the problem according to each criteria. Because we prefer to consider all the objectives at the same time, a multi-objective technique is applied to fully formulate and solve the problem. In similar problems in literature, the Lexicographic goal programming is used and is proven to work effectively [69,70].

4.3 Lexicographic goal programming

Among different goal programming techniques, lexicographic method is the most widely used method [86] (It is fully in [86]). The following section discusses that method:

When there are multiple objectives in an OR model, a solution will lead to different values for each of those objectives. If one solves the model optimally for every single objective, the best possible value (optimal) for each objective will be achieved and obviously, no other solution can give a better value to that objective. Hence, any solution will cause deviation from optimal value for at least one of the objectives. The negative impact of deviations on the final outcome may not be equal for each of the objectives. In other words, if there are two objectives, for example, time and cost, deviation from optimal value for cost may not be as important as that of time.

There are three major goal programming techniques:

- Lexicographic goal programming
- Weighted goal programming
- Chebyshev goal programming

In lexicographic optimization, the decision maker assigns priority levels to different objectives. For instance, in a bi-level lexicographic optimization model, in the first level, a model is solved while only considering "time" as the objective and recording the OFV. Then, in the second level, a new model for optimizing both the time and the cost is developed, while considering a maximum limit for deviation from optimal value for objective "time" by adding a constraint (e.g., $Z_t - t \leq q$, where Z_t is the value for "time" obtained from a solution, t is the minimum possible value for "time", and q is the maximum desirable deviation). In fact, in this example, a higher priority is given to the "time". It should be mentioned that in each of the levels, different criteria for the relationship between objectives can be considered. For instance, in the previous example, it is possible to minimize the sum of deviations of both the objectives, by assigning a higher priority to "time" (e.g. "minimizing $w_1.q_1 + w_2.q_2$", where q_1 is the deviation from optimal "time" value, q_2 is the deviation from optimal "cost" value, w_1 is the coefficient of importance of "time" and w_2 is the coefficient of importance of "cost" and $w_1 > w_2$).

In general, if there are I priority levels and J objectives, the lexicographic optimization is shown as:

Lex Min c = $[g_1(\vec{n}, \vec{p}), g_2(\vec{n}, \vec{p}), \ldots, g_I(\vec{n}, \vec{p})]$

s.t.

$Z_j + n_j - p_j = b_j \quad , \quad j = 1$ to J

$p_j, n_j \geq 0 \quad , \quad j = 1$ to J

where $\vec{n}$ and $\vec{p}$ are vectors of negative deviations (under-achievements) and positive deviation (over achievements) of each of the J objectives, Z_j is achieved value of objective j, each g_i is a function of those deviations, b_j is a predetermined target for objective j. In each lexicographic level, one of the g_i functions are optimized (starting from $i = 1$).

A Weighted Goal Programming model is obtained by replacing the objective function of lexicographic method with the following:

Min c = $\sum_j (w1_j^l.n_j + w2_j^l.p_j)$, where $w1_j^l$ and $w2_j^l$ are normalized relative importance coefficient of minimization of n_j and p_j, respectively. As can be seen, trade-offs between deviations are directly possible.

A major variant of goal programming is Chebyshev goal programming that is based on minimax logic of Chebyshev. In fact, it aims to minimize the maximum deviation of any objective as opposed to the sum of all the deviations (of all the objectives). This deviation (distance) is usually shown as L_∞. Unlike the lexicographic method that prioritizes some of the objectives over some others, and unlike weighted goal programing that minimizes the achievement function, the Chebyshev method tries to achieve a more balanced solution. The mathematical formulation of Chebyshev method is as follows:

Min c = L

s.t.

$w1_j^l . n_j + w2_j^l . p_j \leq L$, $j = 1$ to J

$Z_j + n_j - p_j = b_j$, $j = 1$ to J

$p_j, n_j \geq 0$, $j = 1$ to J

It should be mentioned that in all of the above three methods, there are subjective importance weights (preferential weights), but the difference between the methods is the fact that these weights appear in the constraints for lexicographic and Chebyshev methods while for the weighted method, they appear in the objective function.

The approach of this dissertation for solving the multi-objective model is similar to that of [70]. The method is based on lexicograophic method (i.e., prioritizing some of the goals over some others). However, in some of the lexicographic levels, the logics of Chebyshev and Weighted methods are used.

4.4 The real-time model formulation and solving procedure

In this section we completely formulate the model, assess its complexity, and present the solving procedure. The model has three levels. Each level has a separate formulation, complexity and solving procedure. Hence, each level is formulated, assessed and solved separately in the content of the dissertation.

4.4.1 Lexicographic level #1: maximization of satisfied demand (SD)

The most important purpose of humanitarian logistics is the distribution of relief materials among people of affected areas. Therefore, the most important objective among all of the six previously mentioned objectives is the SD. Consequently, the first level of the lexicographic optimization is dedicated to maximization of SD.

As mentioned in the beginning of this chapter, if the total demand of AAs exceeds the total pre-positioned materials, one can benefit from other supply sources such as vendors or donation centers. Yet, for a general case, it is possible that the total demand exceeds total supply and not all the demand can be satisfied. For our model, mathematically, it will be very easy to achieve this goal. The following model is used:

Model 4.1

Max $\sum_l w_l . SD_l$

$s.t.$

$\sum_j X_{ijl} + \sum_k Z_{ikl} \leq s_{il} \quad \forall\ i,l \qquad (1)$

$\sum_i \sum_l X_{ijl} . v_l \leq q_j . M_j \quad \forall\ j \qquad (2)$

$\sum_i X_{ijl} = \sum_k Y_{jkl} \quad \forall\ j, l \qquad (3)$

$\sum_j Y_{ijl} + \sum_i Z_{ikl} \leq d_{kl} \quad \forall\ k, l \qquad (7)$

One can measure the satisfied demand as follows:

$SD_l = \sum_j \sum_k Y_{jkl} + \sum_i \sum_k Z_{ikl} \quad \forall\ l \qquad (8)$

In the objective function, total weighted demand satisfaction is calculated. Hence, the priority of using capacities (supply capacities and LRC capacities) is on the items with larger $w_l$value. The above model is actually not a location-allocation model because the binary variables M_j do not exist in the objective function. Hence, the solving method is free to open all the LRCs. The resulting model is a simple LP model and can be solved with commercial software. Basically, this model has multiple optimal solutions since any combination of indirect and direct shipments that can maximize the total demand satisfaction without violating capacity constraints is optimal. The determination of final solution will be done in the other lexicographic levels.

After obtaining the maximum possible shipments for each relief material (i.e., $SD^*{}_l$ values in other lexicographic levels), we add the following constraint so that maximum possible demand is always satisfied:

$SD^*{}_l = \sum_j \sum_k Y_{jkl} + \sum_i \sum_k Z_{ikl} \quad \forall\ l \qquad (17)$

4.4.2 Lexicographic level #2: Chebyshev goal programming model

In this level, we formulate the problem based on Chebyshev goal programming method. As mentioned in the previous section, Chebyshev method minimizes the maximum distance from the ideal (best) value for all of the attributes. Therefore, we need to first obtain the best and worst values for each of the attributes:

An arbitrary solution gives a value to each of the attributes. In other words, a plan for distributing the relief materials, regardless of being feasible or not, has a total distribution time (TT), total cost (CO), global security (GS) and so on. Therefore, when optimizing one of the attributes, the resulting solution gives values to other attributes as well:

- Best value of an attribute is obtained by solely optimizing its related objective function. For instance, solution for the model that minimizes the total cost, gives the best value for attribute CO.
- Worst value of an objective is equal to the minimum of all obtained values for that attribute while optimizing other objectives one at a time.

In order to find the best and worst values for each of the attributes, we need to run the model for all the attributes, one at a time. As mentioned before, attribute SD is already considered. Hence, we need to run the model 5 times for other attributes. Each time, the objective function of the model optimizes one of the attributes and records the value of the other attributes for the resulting solution. As a result, a $5^x 5$ matrix is obtained:

$a^{a'}$ is the value of attribute a obtained as a result of optimizing attribute a'. Because we have already considered attribute SD, a and a' will be a member of the following set:

a , a' ∊ {TT,MA,CO,GR,GS}. The $a^{a'}$ values are obtained from solving the following model:

Model 4.2

Minimizing (or maximizing) a

s.t.

$\sum_j X_{ijl} + \sum_k Z_{ikl} \le s_{il}$ $\forall$ i,l (1)

$\sum_i \sum_l X_{ijl} \cdot v_l \le q_j \cdot M_j$ $\forall$ j (2)

$\sum_i X_{ijl} = \sum_k Y_{jkl}$ $\forall$ j, l (3)

$SD^*{}_l = \sum_j \sum_k Y_{jkl} + \sum_i \sum_k Z_{ikl}$ $\forall$ l (17)

$TT \ge \sum_i \sum_j \sum_l (X_{ijl} \cdot t1_{ij}) + \sum_j \sum_k \sum_l (Y_{jkl} \cdot t2_{jk}) + \sum_i \sum_k \sum_l (Z_{ikl} \cdot t3_{ik})$ (9)

$AT1_j \ge t1_{ij} - M.(1 - B1_{ij})$ $\forall$ i, j (10)

$AT2_k \ge AT1_j + t2_{jk} - M.(1 - B2_{jk})$ $\forall$ j, k (11)

$AT2_k \ge t3_{ik} - M.(1 - B3_{ik})$ $\forall$ i, k (12)

$MA \ge AT2_k$ $\forall$ k (13)

$CO = \sum_i \sum_j \sum_l a_{ijl} \cdot X_{ijl} + \sum_j \sum_k \sum_l b_{jkl} \cdot Y_{jkl} + \sum_i \sum_k \sum_l c_{ikl} \cdot Z_{ikl} + \sum_j g_j \cdot M_j$ (14)

$GR = \sum_i \sum_j \log(r1_{ij}) \cdot B1_{ij} + \sum_j \sum_k \log(r2_{jk}) \cdot B2_{jk} + \sum_i \sum_k \log(r3_{ik}) \cdot B3_{ik}$ (15)

$GS = \sum_i \sum_j \log(1 - p1_{ij}) \cdot B1_{ij} + \sum_j \sum_k \log(1 - p2_{jk}) \cdot B2_{jk} + \sum_i \sum_k \log(1 - p3_{ik}) \cdot B3_{ik}$ (16)

In the above model, each time an attribute is optimized, the values of the other attributes are recorded as decision variables. Also, fundamental constraints such as capacity constraints are considered. Moreover, constraints (17) that maximize the demand satisfaction are a part of the model. After solving the model for all the attributes, the resulting matrix, called pay-off matrix (*P* matrix), and is as follows:

$$P = \begin{bmatrix} TT^{TT} & MA^{TT} & CO^{TT} & GR^{TT} & GS^{TT} \\ TT^{MA} & MA^{MA} & CO^{MA} & GR^{MA} & GS^{MA} \\ TT^{CO} & MA^{CO} & CO^{CO} & GR^{CO} & GS^{CO} \\ TT^{GR} & MA^{GR} & CO^{GR} & GR^{GR} & GS^{GR} \\ TT^{GS} & MA^{GS} & CO^{GS} & GR^{GS} & GS^{GS} \end{bmatrix}$$

The above model is not difficult to solve for TT, MA, GR, and GS as long as the number of relief items is low (this is usually the case) because for those attributes, the location problem does not apply and the solution procedure is free to open all the LRCs. If we do not consider multiple items, the resulting problem will have [*I* + *2J* + *K* + *I.J* + *J.K* + *I.K* + 4] constraints, [*J* + *K* + *I.J* + *J.K* + *I.K* + 5] non-negative and [*J* + *I.J* + *J.K* + *I.K*] binary variables. This is proven not to be NP-Hard in [70] because its solving time is not polynomial. But for attribute CO, the model is a location-allocation one. As mentioned in chapter 3, a capacitated location-allocation model is NP-hard and should be solved heuristically. Since this model is similar to that of pre-positioning, we use the same heuristic (lagrangian heuristic) to solve it: Constraints (2) should be relaxed to make the model solving relatively easy. Because there are total of *J* constraints, we need *J* lagrangian multipliers. By doing so, the resulting problem is as follows:

Model 4.3.1

Min CO + $\sum_j(\lambda_j(\sum_i \sum_l(X_{ijl}.v_l) - q_j.M_j))$

s.t.

supply capacity constraints of model 4.2 (1)

flow balance constraints of model 4.2 (3)

attribute-related constraints of model 4.2 (9-16)

flow-maximization constraint (17)

It should be mentioned that constraints (9-16) are only considered (in the above model) in order to record the value of four other attributes and in practice, they have no impact on the final solution. The above model generates a LB for the problem. In the solution of LB, values of M_j variables are known. If we call the set of opened LRCs (i.e. j | M_j = 1) as J', we can run the optimization model for CO, in order to get an UB for the problem:

Model 4.3.2

Min CO

s.t.

supply capacity constraints of model 4.2 (1)

LRC capacities constraints of model 4.2 (2)

flow balance constraints of model 4.2 (3) *attribute-related constraints of model 4.2* (9-16)

flow-maximization constraint of model 4.3.1 (17)

$M_j = 1$ *for* $j \in J'$

The above model is equivalent to a two-stage transportation problem, which is an LP problem (as mentioned previously, constraints (9-16) only record the values for other attributes and have no impact on the solution) and can be solved using any OR programming software. After obtaining an LB and an UB, one can use subgradient optimization formula (described in chapter 3) to upgrade the lagrangian multipliers and run the LB and UB models again, until either the difference between LB and UB becomes non-significant or the computation time to run the LB and UB models exceeds a predetermined value. At the end of the heuristic, the solution that belongs to the best obtained UB is the final solution. The obtained values for 5 attributes are inserted into the third row of pay-off matrix.

After obtaining the above matrix, we need to find the best and worst values of each column. The best values are obviously the TT^{TT}, MA^{MA}, CO^{CO}, GR^{GR}, and $GS^{GS}$for attributes TT, MA, CO, GR, and GS, respectively. In general, for attribute a:

$a_{best} = a^{a}$

For TT, MA, and CO, the worst values are the maximum vales in their related column because we want the values of these three attributes to be minimized:

$TT_{worst} = \min \{TT^{TT}, TT^{MA}, TT^{CO}, TT^{GR}, TT^{GS}\}$

MA_{worst} = min $\{MA^{TT}, MA^{MA}, MA^{CO}, MA^{GR}, MA^{GS}\}$

CO_{worst} = min $\{CO^{TT}, CO^{MA}, CO^{CO}, CO^{GR}, CO^{GS}\}$

But, for GR and GS, because we try to maximize them, their worst values are equal to the minimum values of their related columns:

GR_{worst} = max $\{GR^{TT}, GR^{MA}, GR^{CO}, GR^{GR}, GR^{GS}\}$

GS_{worst} = max $\{GS^{TT}, GS^{MA}, GS^{CO}, GS^{GR}, GS^{GS}\}$

For simplicity, from this point forward, we use a_b and a_w instead of a_{best} and a_{worst}, respectively.

In [70], in order to minimize the maximum distance of attributes from their best values, a decision making technique, called Compromise Programming is used. In this technique, the following function that is called distance function is minimized:

$$d(a,t,\beta) = \left[\sum_{a \in Att} (\beta_a \frac{a_{best} - Z_a}{a_{best} - a_{worst}})^t\right]^{1/t},$$

where Z_a is the current value of attribute a, β_a is the importance weight assigned to attribute a, and t is the order of the norm. The distance function is normalized because we divide the distance between current value and best value of each attribute by the distance between best and worst values of that attribute. By doing so, the ratios become comparable and consequently, one can sum them up. It is also assumed that the importance weights are normalized (i.e. $\sum_{a \in Att} (\beta_a) = 1$). The choice of norm (i.e. the value of t) is subjective, but as mentioned before, because we are using the Chebyshev method, we apply the Chebyshev norm which makes the t equal to infinity:

$d(a,\infty,\beta) = \max_{a \in Att} \left\{ \beta_a \left| \frac{a_{best} - Z_a}{a_{best} - a_{worst}} \right| \right\}$

We call the value, obtained from above function, D_∞. In order to insert the D_∞ into our model, we need to add the following constraints:

$$D_\infty \geq \beta_a \frac{a_{best} - Z_a}{a_{best} - a_{worst}} \;, \qquad \forall\ a \in Att \tag{18}$$

$$D_\infty \geq 0 \tag{19}$$

Constraints (18) guarantee that D_∞ is greater than or equal to each of the deviation ratios. Now we can write down the second lexicographic optimization model:

Model 4.4

$D_\infty^* = \text{Min } D_\infty$

s.t.

$$\sum_j X_{ijl} + \sum_k Z_{ikl} \leq s_{il} \qquad \forall\ i,l \tag{1}$$

$$\sum_i \sum_l X_{ijl} \,.\, v_l \leq q_j \,.\, M_j \qquad \forall\ j \tag{2}$$

$$\sum_i X_{ijl} = \sum_k Y_{jkl} \qquad \forall\ j, l \tag{3}$$

$$SD^*_l = \sum_j \sum_k Y_{jkl} + \sum_i \sum_k Z_{ikl} \qquad \forall\ l \tag{17}$$

$$\text{TT} \geq \sum_i \sum_j \sum_l (X_{ijl} \,.\, t1_{ij}) + \sum_j \sum_k \sum_l (Y_{jkl} \,.\, t2_{jk}) + \sum_i \sum_k \sum_l (Z_{ikl} \,.\, t3_{ik}) \tag{9}$$

$$AT1_j \geq t1_{ij} - \text{M.}(1 - B1_{ij}) \qquad \forall\ i, j \tag{10}$$

$$AT2_k \geq AT1_j + t2_{jk} - \text{M.}(1 - B2_{jk}) \qquad \forall\ j, k \tag{11}$$

$AT2_k \geq t3_{ik} -$ M.(1 - $B3_{ik}$) $\forall\ i, k$ (12)

MA $\geq AT2_k$ $\forall\ k$ (13)

CO = $\sum_i \sum_j \sum_l a_{ijl}.X_{ijl} + \sum_j \sum_k \sum_l b_{jkl}.Y_{jkl} + \sum_i \sum_k \sum_l c_{ikl}.Z_{ikl} + \sum_j g_j.M_j$ (14)

GR = $\sum_i \sum_j \log(r1_{ij}).B1_{ij} + \sum_j \sum_k \log(r2_{jk}).B2_{jk} + \sum_i \sum_k \log(r3_{ik}).B3_{ik}$ (15)

GS = $\sum_i \sum_j \log(1 - p1_{ij}).B1_{ij} + \sum_j \sum_k \log(1 - p2_{jk}).B2_{jk} + \sum_i \sum_k \log(1 - p3_{ik}).B3_{ik}$ (16)

$D_\infty \geq \beta_a \frac{a_{best} - Z_a}{a_{best} - a_{worst}}$, $\forall\ a \in Att$ (18)

$D_\infty \geq 0$ (19)

In this model, the maximum weighted normalized distance of all attributes from their ideal values is minimized. Because this model can be reduced into a capacitated facility location problem, it is NP-hard and should be solved heuristically. Again, if we relax constraints (2), the location part of the problem will be eliminated. This way, we will have [*I* + *J* + *K* + *I.J* + *J.K* + *I.K* + 10] constraints, [*J* + *K* + *I.J* + *J.K* + *I.K* + 5] non-negative and [*I.J* + *J.K* + *I.K*] binary variables. This model can be solved using MIP solvers such as CPlex [70]. If we use lagrangian heuristic to do so, the result will be a LB to model 4.4, and similar to heuristic for minimizing CO, one can use the list of opened LRCs and run the following model to obtain an UB. The LB and UB models are as follows:

Model 4.5.1

LB model:

Min $D_\infty + \sum_j (\lambda_j (\sum_i \sum_l (X_{ijl}.v_l) - q_j.M_j))$

s.t.

supply capacity constraints of model 4.2 (1)

flow balance constraints of model 4.2 (3)

attribute-related constraints of model 4.2 (9-16)

flow-maximization constraint of model 4.3.1 (17)

Chebyshev distance constraints of model 4.4 (18,19)

Model 4.5.2

UB model:

D^*_∞ = Min D_∞

s.t.

supply capacity constraints of model 4.2 (1)

LRC capacities constraints of model 4.2 (2)

flow balance constraints of model 4.2 (3)

attribute-related constraints of model 4.2 (9-16)

flow-maximization constraint of model 4.3.1 (17)

Chebyshev distance constraints of model 4.4 (18,19)

$M_j = 1$ *for* j $\in J'$

After running the LB and UB models, one can use subgradient optimization formula to upgrade the lagrangian multipliers and run the LB and UB models again, until either the difference between LB and UB becomes non-significant or the computation time of LB and UB models exceeds a predetermined value. The major output of the heuristic is the value of D^*_∞ which is used as an input for the lexicographic optimization model#3.

4.4.3 Lexicographic level #3: norm one distance minimization

In the second lexicographic level, we forced the optimal OFV (i.e., D^*_∞) to be non-negative according to constraint (19). This was because otherwise, if we wanted D_∞ to be greater than or equal to all normalized deviations, negative deviations could make the entire problem infeasible (i.e., if one of the deviations is negative, all other deviations are also negative). In third lexicographic level we consider a criterion, according to which the negative deviations are allowed in order to eliminate this bias. This criterion is the norm-one distance. According to the compromise programming technique that was discussed in the 4.4.2, the norm one distance formula is as follows:

$$d(a,1,\beta) = \left[\sum_{a \in Att} (\beta_a \frac{a_{best} - Z_a}{a_{best} - a_{worst}})\right]$$

In this formula, the sum of all normalized distances from ideal values for all the attributes is considered. In the lexicographic level#2, we guaranteed that the normalized distance from best value for each off attributes is less than or equal to D^*_∞. Now, in the third optimization level, by fixing the minimized maximum distance we try to minimize the sum of all distances. In order to fix the D^*_∞, we need to add the following constraint to the new model:

$$D^*_\infty \geq \beta_a \frac{a_{best} - Z_a}{a_{best} - a_{worst}} \tag{20}$$

According to constraints (20), the normalized distances from best value for all the attributes should be less than or equal to D^*_∞ . In order to minimize the sum of normalized distances, the following constraint is also added to the problem:

$$D_1 = \sum_{a \in Att} (\beta_a \frac{a_{best} - Z_a}{a_{best} - a_{worst}}) \tag{21}$$

Constraint (21) records the sum of normalized distances. Now we can finalize the third level model:

Model 4.6

$D_1^* = \text{Min } D_1$

s.t.

$$\sum_j X_{ijl} + \sum_k Z_{ikl} \leq s_{il} \quad \forall\ i,l \tag{1}$$

$$\sum_i \sum_l X_{ijl} . v_l \leq q_j . M_j \quad \forall\ j \tag{2}$$

$$\sum_i X_{ijl} = \sum_k Y_{jkl} \quad \forall\ j, l \tag{3}$$

$$SD^*_l = \sum_j \sum_k Y_{jkl} + \sum_i \sum_k Z_{ikl} \quad \forall\ l \tag{17}$$

$$TT \geq \sum_i \sum_j \sum_l (X_{ijl} . t1_{ij}) + \sum_j \sum_k \sum_l (Y_{jkl} . t2_{jk}) + \sum_i \sum_k \sum_l (Z_{ikl} . t3_{ik}) \tag{9}$$

$$AT1_j \geq t1_{ij} - \text{M.}(1 - B1_{ij}) \qquad \forall\ i, j \qquad (10)$$

$$AT2_k \geq AT1_j + t2_{jk} - \text{M.}(1 - B2_{jk}) \qquad \forall\ j, k \qquad (11)$$

$$AT2_k \geq t3_{ik} - \text{M.}(1 - B3_{ik}) \qquad \forall\ i, k \qquad (12)$$

$$\text{MA} \geq AT2_k \qquad \forall\ k \qquad (13)$$

$$\text{CO} = \sum_i \sum_j \sum_l a_{ijl}.X_{ijl} + \sum_j \sum_k \sum_l b_{jkl}.Y_{jkl} + \sum_i \sum_k \sum_l c_{ikl}.Z_{ikl} + \sum_j g_j.M_j \qquad (14)$$

$$\text{GR} = \sum_i \sum_j \log(r1_{ij}).B1_{ij} + \sum_j \sum_k \log(r2_{jk}).B2_{jk} + \sum_i \sum_k \log(r3_{ik}).B3_{ik} \qquad (15)$$

$$\text{GS} = \sum_i \sum_j \log(1 - p1_{ij}).B1_{ij} + \sum_j \sum_k \log(1 - p2_{jk}).B2_{jk} + \sum_i \sum_k \log(1 - p3_{ik}).B3_{ik} \quad (16)$$

$$D^*_\infty \geq \beta_a \frac{a_{best} - Z_a}{a_{best} - a_{worst}} \qquad \forall\ a \in Att \qquad (20)$$

$$D_1 = \sum_{a \in Att} (\beta_a \frac{a_{best} - Z_a}{a_{best} - a_{worst}}) \qquad (21)$$

In above model, the sum of normalized weighted distance of all attributes from their best value is minimized while the maximum weighted normalized distance of all attributes from their ideal values is fixed. Because this model can be reduced into a capacitated facility location problem, it is NP-hard and is solved heuristically. Again, if we relax constraints (2), the location part of the problem will be eliminated. We will have $[I + J + K + I.J + J.K + I.K + 10]$ constraints, $[J + K + I.J + J.K + I.K + 5]$ non-negative and $[I.J + J.K + I.K]$ binary variables. This model can be solved using MIP solvers such as CPlex [70]. If we use lagrangian heuristic to do so, the result will be a LB to the lexicographic model#2, and similar to heuristic for minimizing CO, one can use the list of opened LRCs and run the following model to obtain an UB. The LB and UB models are as follows:

Model 4.7.1

LB model:

Min $D_1 + \sum_j(\lambda_j(\sum_i \sum_l(X_{ijl}.v_l) - q_j.M_j))$

s.t.

supply capacity constraints of model 4.2 (1)

flow balance constraints of model 4.2 (3)

attribute-related constraints of model 4.2 (9-16)

flow-maximization constraint of model 4.3.1 (17)

fixed Chebyshev distance constraints of model 4.4 (19)

Norm one distance of model 4.6 (21)

Model 4.7.2

UB model:

$D^*{}_1$ = Min D_1

s.t.

supply capacity constraints of model 4.2 (1)

LRC capacities constraints of model 4.2 (2)

flow balance constraints of model 4.2 (3)

attribute-related constraints of model 4.2 (9-16)

flow-maximization constraint of model 4.3.1 (17)

fixed Chebyshev distance constraints of model 4.4 (19)

Norm one distance of model 4.6 (21)

$M_j = 1$ *for* $j \in J'$

After running the LB and UB models, one can use subgradient optimization formula to upgrade the lagrangian multipliers and run the LB and UB models again, until either the difference between LB and UB becomes non-significant or computation time to run the LB and UB models exceeds a predetermined value. The solution of the lexicographic level#3 is the final solution of the real-time facility location model. Figure 7 schematically shows the overall solution algorithm. It should be mentioned that this algorithm is developed for a case where number of relief items is a small value (e.g. 3, 4 or 5). Otherwise, for large instances, model 4-2 will become NP-Hard for all the attributes and should be solved using a separate heuristic.

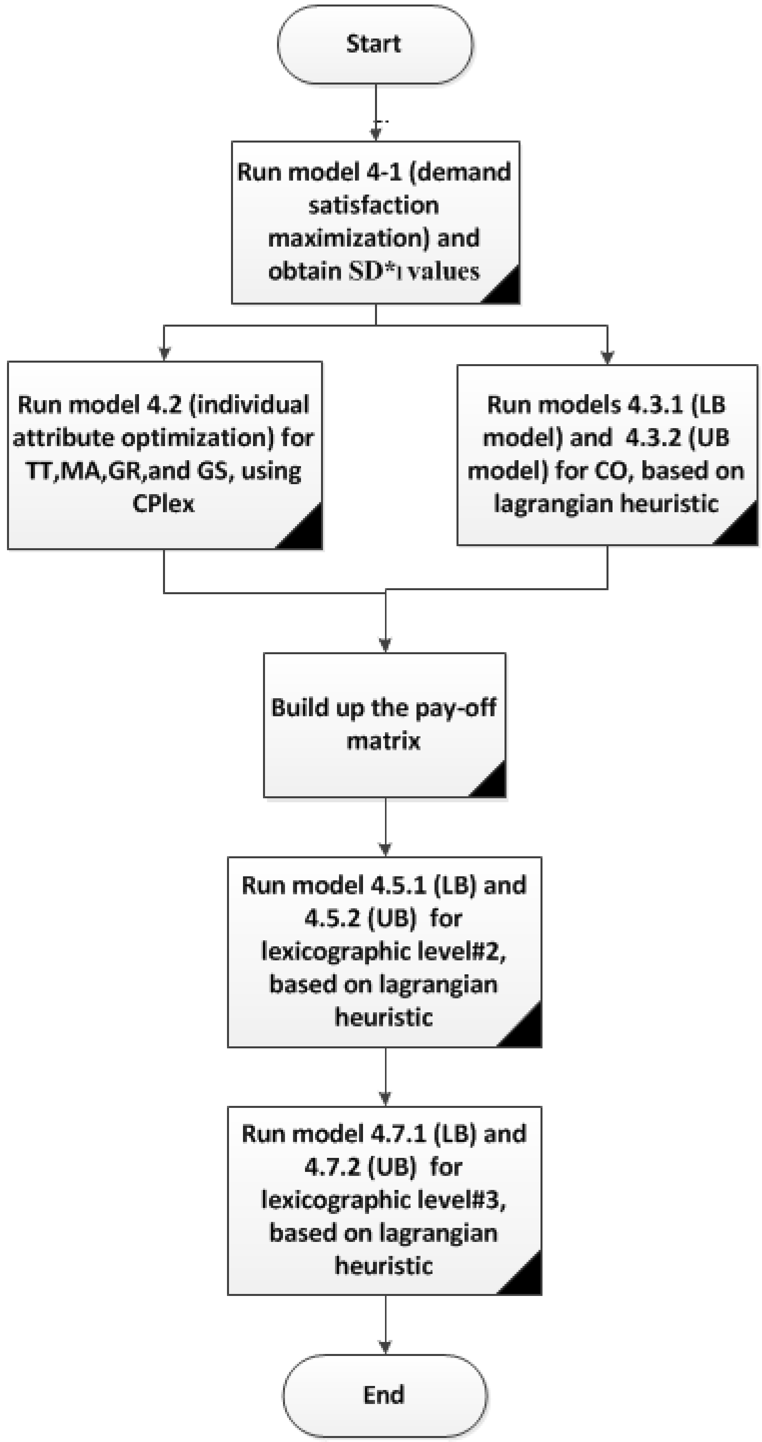


Figure 7. Flow chart of heuristic method of real-time facility location model

CHAPTER 5
EXPERIMENTS AND ANALYSES

In this chapter, we perform comprehensive analysis of the pre-positioning as well as real-time models and their related heuristics in order to both prove the efficiency of the heuristics and obtain a better idea about the two-stage network problem. Figure 8, shows the inputs and outputs of the two-stage network.

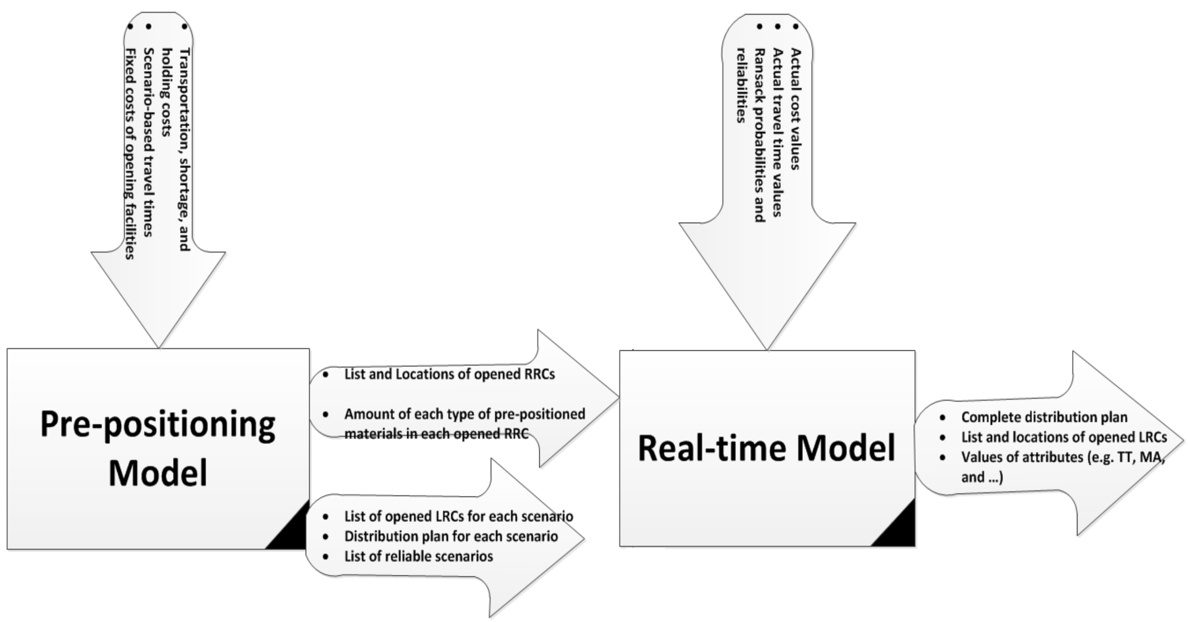


Figure 8. Inputs and outputs of the two-stage logistics network

A list of opened RRCs as well as amount of different pre-positioned materials in each of them is decided in the pre-positioning model. These are used as the inputs of the second stage of the network, which is the real-time facility location model. There are other inputs such as real-time costs and travel times as well as new parameters such as ransack probabilities of the routes. As a result of solving the real-time model, the final distribution plan, i.e., the flow of materials between RRCs, LRCs, and AAs, is determined.

5.1 Experimental results of the pre-positioning model

5.1.1 Design of the experiments

The pre-positioning model has several sets of constraints, e.g. delivery durations and service quality. Hence, in many cases, the actual problem is infeasible. For instance, if the total capacity of RRCs is low compared to the total demand, and reliability value α is relatively high (e.g., over 90%), then the problem is likely to be infeasible. In order to generate the instances, we use the procedure that is presented in Alper et al. [56]. In order to have a better understanding of the difference between scenarios and their effect on ${d_{kl}}^{s}$ values, a new factor, called θ^s, is presented. It shows the intensity of each scenario. Minimum intensity is equal to 1. Therefore, for instance, if $\theta^s = 2$, it means that the intensity of earth quack under scenario s is twice as big as that under scenario with minimum intensity. θ^s values affect many aspects of scenarios:

- The occurrence probability of each scenario is proportional to θ^s (the larger the θ^s the lower the occurrence probability of scenario s)
- The ${a_{ijkl}}^{s}$, ${b_{ikl}}^{s}$, ${t1_{ijk}}^{s}$, and ${t2_{ijk}}^{s}$ values depend on both the θ^s and actual distances between RRCs, LRCs, and AAs (the larger the θ^s, the higher the transportation time as well as transportation cost). This means that both the transportation costs and delivery durations are larger for more intense scenarios.

- The amounts of demand in AAs are assumed to be directly proportional to θ^s variables. For more intense scenarios, demand values are considered to be larger.

Two sets of scenarios, each including four scenarios, are considered. In the first set, all scenarios have equal severities. In the second set, θ^s are as follows: (1.0, 1.1, 1.3, 1.8). Hence, for the first set, probabilities are all equal to 0.25 and for the second set, the vector of the p_s values is as follows: (0.4, 0.25, 0.25, 0.1). Number of RRCs, LRCs and AAs are chosen from {5, 10}, {10, 20, 40} and {50, 75, 100, 200, 400, 600, 800}, respectively. The locations of the above points are randomly generated on a 2-dimensional surface that has length and width of 100 units. f_i and ${g_j}^s$ values are chosen randomly between [60'000, 140'000] and [6'000, 12'000] intervals, respectively. Only one item is considered. Also, in order to generate demand values, using the regression analysis performed by Sengezer et al. [85], we consider that ${d_{kl}}^s = \pi^s . {d'_{kl}}^s$, where ${d'_{kl}}^s$is the demand of the scenario with lowest intensity (it is considered to be randomly chosen from interval [5, 12]) and π^s is a coefficient related to scenario s: π^s = (1.0, 2.25, 4.0, 6.25). Also, we further categorize the test instances as low-cap and high-cap. In a low-cap set, the ratio of the weighted average demand (averaged over all scenarios are based on their occurrence probabilities) to total capacity of RRCs is randomly chosen from interval [1.01, 1.05], while in high-cap set, the ratio is chosen randomly from interval [0.55, 0.7]. In fact, in high-cap scenario, there is extra capacity that gives the solution more flexibility. Finally, in order to observe the effect of different α values on the model, we add two more categories to the experiment. In the first category, α = 0.25, which is a relatively low value, and in the second category, α = 0.75, which is high. It should be mentioned that the α value has a direct relationship with the shortage cost values (i.e., ${c_{kl}}^s$). If ${c_{kl}}^s$ are considered to be very high, then the heuristic will tend to solve the problem in a way that α becomes almost equal to 1, which makes the experiment biased. Hence, we need to consider lower values for the ${c_{kl}}^s$ parameter (compared to the shipment cost) so that a trade-off between shipping cost and shortage cost becomes meaningful. The ${c_{kl}}^s$ values are chosen randomly from interval [8,12] when is multiplied by the maximum transportation cost value. In fact, the occurrence probability of each scenario is proportional to θ^s.

5.1.2 Results of the experiments

A summary of the results are shown in four tables 3 through 6. Table 3 and Table 4 summarize the results of high-capacity sets with equal and unequal severities, respectively. Table 5 and Table 6 summarize the results of low-capacity sets with equal and unequal severities, respectively.

Table 3 Results of high-cap test instances with equal severities

#	dimensions (RRC-LRC-AA)	alpha	# of opened RRC	# of opened LRC	reliability	OFV (Heuristic)	Cplex (Optimal)	% of Deviation
1	5-10-50	0.25	4	13	0.25	529354	517618	2.267
2	5-10-50	0.75	5	16	1	539700	524085	2.979
3	5-10-75	0.25	5	14	0.25	579339	562736	2.950
4	5-10-75	0.75	5	15	0.75	587478	562752	4.412
5	5-10-100	0.25	4	12	0.25	609142	588537	3.501
6	5-10-100	0.75	5	18	0.75	609301	588711	3.497
7	5-20-100	0.25	4	26	0.25	581407	571644	1.707
8	5-20-100	0.75	4	35	0.75	581963	571803	1.776

9	5-20-200	0.25	4	35	0.25	619758	601583	3.021
10	5-20-200	0.75	4	32	0.75	689801	669302	3.062
11	5-40-100	0.25	4	60	0.25	601736	584286	2.986
12	5-40-100	0.75	4	58	0.75	619634	584375	6.033
13	5-40-200	0.25	4	53	0.25	675466	663715	1.770
14	5-40-200	0.75	4	61	0.75	666483	664557	0.289
15	5-40-400	0.25	4	11	0.25	800661	792665	1.008
16	5-40-400	0.75	4	12	0.75	800716	792737	1.006
17	5-40-600	0.25	5	58	0.25	1024811	977091	4.883
18	5-40-600	0.75	4	58	0.75	1032326	977091	5.653
19	5-40-800	0.25	4	53	0.25	1110648	1074175	3.395
20	5-40-800	0.75	4	58	0.75	1104043	1074175	2.780
21	10-40-200	0.25	7	63	0.25	952391	926739	2.767
22	10-40-200	0.75	8	61	0.75	989466	958371	3.244
23	10-40-400	0.25	7	19	0.25	1084613	1060633	2.260
24	10-40-400	0.75	9	65	1	1089372	1060633	2.709
25	10-40-600	0.25	7	20	0.25	1199450	1185735	1.156
26	10-40-600	0.75	8	23	0.75	1202182	1185749	1.385
27	10-40-800	0.25	8	30	0.5	1348094	1315421	2.483
28	10-40-800	0.75	10	50	1	1363675	1315421	3.668

Table 4 Results of high-cap test instances with unequal severities

#	dimensions (RRC-LRC-AA)	alpha	# of opened RRC	# of opened LRC	reliability	OFV (Heuristic)	Cplex (Optimal)	% of Deviation
29	5-10-50	0.25	4	4	0.4	552557	533518	3.568
30	5-10-50	0.75	5	17	0.9	557541	533694	4.507
31	5-10-75	0.25	4	12	0.5	582752	563389	3.436
32	5-10-75	0.75	4	10	0.9	588305	563409	4.418
33	5-10-100	0.25	5	10	1	602616	598996	0.604
34	5-10-100	0.75	4	17	0.9	603236	599103	0.689
35	5-20-100	0.25	5	8	0.25	575706	571710	0.698

36	5-20-100	0.75	5	7	0.9	577313	571813	0.961
37	5-20-200	0.25	5	31	0.6	659207	655987	0.490
38	5-20-200	0.75	4	22	0.9	665531	656083	1.440
39	5-40-100	0.25	5	29	0.4	599693	586050	2.327
40	5-40-100	0.75	5	32	0.9	599976	586123	2.363
41	5-40-200	0.25	4	67	0.4	674928	673045	0.279
42	5-40-200	0.75	4	46	0.9	675281	673843	0.213
43	5-40-400	0.25	4	14	0.4	834515	813681	2.560
44	5-40-400	0.75	5	15	0.9	861730	813876	5.879
45	5-40-600	0.25	4	24	0.4	1030466	1005245	2.508
46	5-40-600	0.75	5	21	0.9	1049677	1006541	4.285
47	5-40-800	0.25	5	31	0.4	1155176	1107286	4.324
48	5-40-800	0.75	5	21	0.9	1164010	1107286	5.122
49	10-40-200	0.25	8	14	0.65	941883	932589	0.996
50	10-40-200	0.75	7	58	0.75	998343	967111	3.229
51	10-40-400	0.25	10	40	0.9	1097539	1074270	2.166
52	10-40-400	0.75	10	48	0.9	1102988	1074335	2.667
53	10-40-600	0.25	8	30	0.5	1232984	1208332	2.040
54	10-40-600	0.75	9	49	0.9	1254529	1208332	3.823
55	10-40-800	0.25	9	54	0.65	1365556	1342932	1.684
56	10-40-800	0.75	9	60	0.9	1378043	1342932	2.614

Table 5 Results of low-cap test instances with equal severities

#	dimensions (RRC-LRC-AA)	alpha	# of opened RRC	# of opened LRC	reliability	OFV (Heuristic)	Cplex (Optimal)	% of Deviation
57	5-10-50	0.25	5	4	0.5	664775	661062	0.561
58	5-10-50	0.75	infeasible					
59	5-10-75	0.25	5	13	0.25	695274	680736	2.135
60	5-10-75	0.75	Infeasible					
61	5-10-100	0.25	5	16	0.25	711045	698662	1.772
62	5-10-100	0.75	infeasible					

63	5-20-100	0.25	5	21	0.5	724951	707878	2.411
64	5-20-100	0.75	infeasible					
65	5-20-200	0.25	5	19	0.25	797425	784407	1.659
66	5-20-200	0.75	infeasible					
67	5-40-100	0.25	5	23	0.25	745060	712216	4.611
68	5-40-100	0.75	5	infeasible				
69	5-40-200	0.25	5	20	0.25	824258	796241	3.518
70	5-40-200	0.75	infeasible					
71	5-40-400	0.25	5	11	0.25	931355	924653	0.724
72	5-40-400	0.75	infeasible					
73	5-40-600	0.25	5	48	0.25	1131006	1080522	4.672
74	5-40-600	0.75	infeasible					
75	5-40-800	0.25	5	14	0.25	1223230	1206340	1.400
76	5-40-800	0.75	infeasible					
77	10-40-200	0.25	10	49	0.25	1354799	1333786	1.575
78	10-40-200	0.75	infeasible					
79	10-40-400	0.25	10	42	0.25	1511248	1472230	2.650
80	10-40-400	0.75	10	50	0.75	1522329	1472230	3.402
81	10-40-600	0.25	10	37	0.5	1632259	1602331	1.867
82	10-40-600	0.75	infeasible					
83	10-40-800	0.25	10	10	0.5	1795256	1728975	3.833
84	10-40-800	0.75	infeasible					

Table 6 Results of low-cap test instances with unequal severities

#	dimensions (RRC-LRC-AA)	alpha	# of opened RRC	# of opened LRC	reliability	OFV (Heuristic)	Cplex (Optimal)	% of Deviation
85	5-10-50	0.25	5	14	0.35	672343	667137	0.780
86	5-10-50	0.75	infeasible					
87	5-10-75	0.25	5	6	0.25	701773	693063	1.256
88	5-10-75	0.75	infeasible					
89	5-10-100	0.25	5	3	0.25	722517	717518	0.696
90	5-10-100	0.75	infeasible					
91	5-20-100	0.25	5	16	0.25	736807	702541	4.877

92	5-20-100	0.75	infeasible					
93	5-20-200	0.25	5	9	0.4	809015	791278	2.241
94	5-20-200	0.75	infeasible					
95	5-40-100	0.25	5	37	0.65	714244	713621	0.087
96	5-40-100	0.75	infeasible					
97	5-40-200	0.25	5	28	0.4	831585	801157	3.798
98	5-40-200	0.75	infeasible					
99	5-40-400	0.25	5	7	0.25	1006202	972578	3.457
100	5-40-400	0.75	infeasible					
101	5-40-600	0.25	5	32	0.4	1152449	1110927	3.737
102	5-40-600	0.75	infeasible					
103	5-40-800	0.25	5	8	0.25	1283925	1228252	4.532
104	5-40-800	0.75	infeasible					
105	10-40-200	0.25	10	61	0.6	1364422	1337157	2.039
106	10-40-200	0.75	infeasible					
107	10-40-400	0.25	10	4	0.4	1520252	1485269	2.355
108	10-40-400	0.75	10	8	0.75	1532541	1485439	3.170
109	10-40-600	0.25	10	9	0.4	1647418	1620546	1.658
110	10-40-600	0.75	infeasible					
111	10-40-800	0.25	10	12	0.4	1800041	1749449	2.891
112	10-40-800	0.75	inf					

In Table 5 and Table 6 all the instances except for instances #80 and #108 for which α is set equal to 0.75, are infeasible. When potential supply is almost equal to total demand and not all the supplies are available after the disaster, at least some of the scenarios will not be reliable, i.e., their demand cannot be fully satisfied, which makes the model infeasible. We eliminate the infeasible instances in the analysis of the data.

In Table 3, the deviations of the heuristic solutions from the optimal solutions have a mean of 2.88% and a standard deviation of 1.34%. In Table 4, the deviation has a mean of 2.497% while its standard deviation is 1.587%. For the data in table 5, the average deviation is 2.453% while the standard deviation of deviations is 1.297%. Finally, for table 6, mean of the deviation is 2.505% and standard deviation is 1.44%. All the deviations are significantly below 5% and often below 3%). Also, there is no significant difference between mean deviations of Tables 4 through 6, but the mean of Table 5 is a little more than that in the other three tables. It appears that the lagrangian heuristic works better for instances with unequal severities.

5.1.3 Analysis of the experimental results

In this section we perform several analyses on the results of the experiments in order to investigate the role and the effect of parameters of the model on the solutions and OFVs.

5.1.3.1 Cost increase for different alpha values

Figures 9 and 10 show the cost increase as the result of increasing the α values. The even instances of the experiment have $\alpha = 0.25$ while for the odd instances, $\alpha = 0.75$. Each even instance has the same dimensions and parameters as the odd instances. When solving one of the odd instances, the solution has a reliability value. If this reliability value is greater than or equal to 0.75, then the solution is also optimal for the next even instance. Otherwise, the solution will change in order for the model to reach the reliability value of 0.75. Because there is no solution better than the optimal solution, the OFV of even instances are always greater than or equal to the OFV of their previous immediate instance. Figures 9 and 10, show this difference (increasing percentage) for even instances compared to their previous immediate instance for high-cap sets with equal and unequal severities, respectively. Only instances #10, #22, and #50 have significantly higher cost than their immediate previous instance. In fact, because we only minimize the cost, it is possible that by increasing the cost of the final solution by a short amount, a significant improvement in reliability value occurs. In other words, two solutions with very slight difference in total cost may have significant difference in their reliability values. Therefore, for practical cases, sensitivity analysis of the reliability over total cost should be considered.

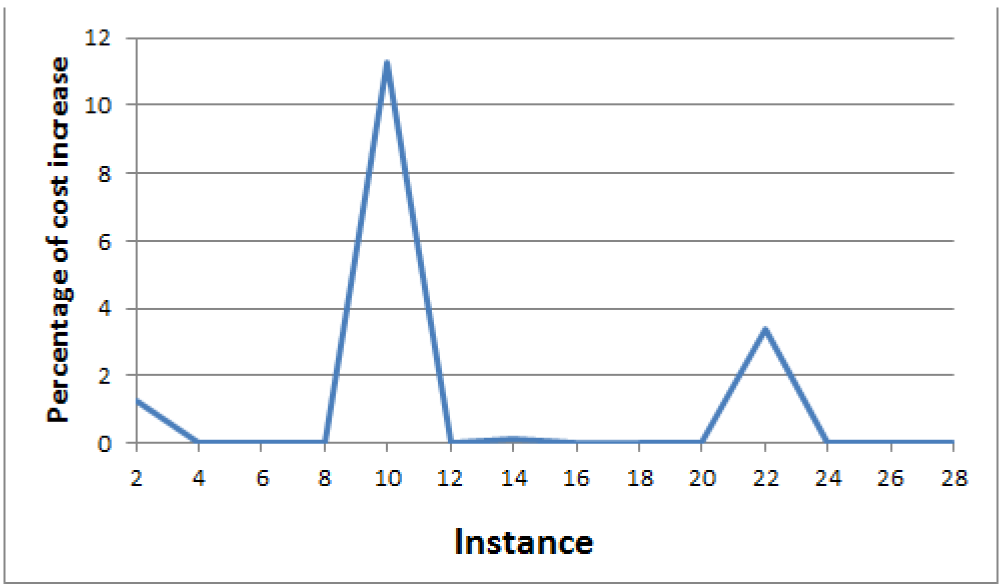


Figure 9. Percentage of cost increase for instances with $\alpha = 0.75$ compared to instances with $\alpha = 0.25$ for high-cap set and equal severities

5.1.3.2 Deviation for different α values

In order investigate the effect of α value on the deviation of OFV of LH from optimal OFV, we compare such deviations for two α values for instances with equal dimension.

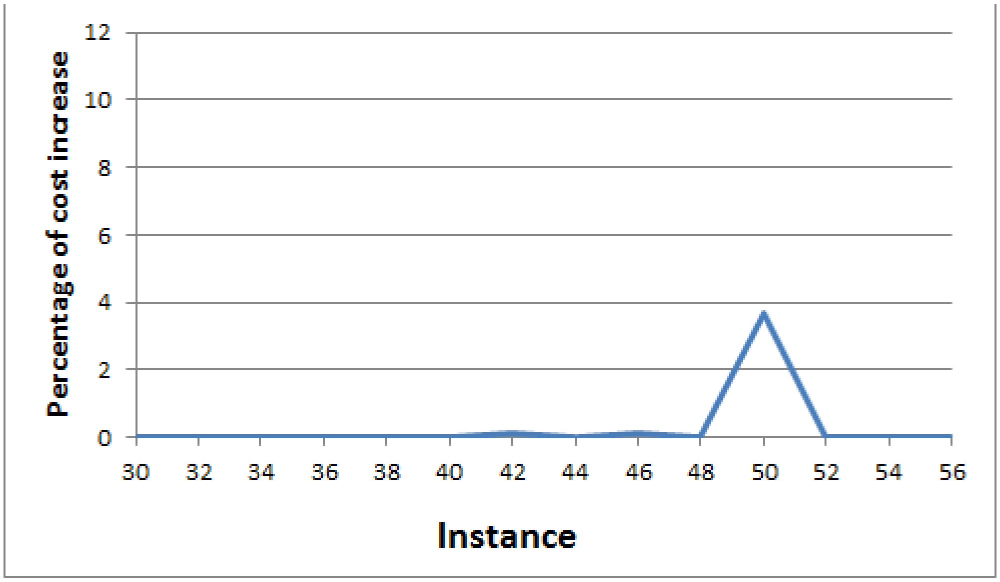


Figure 10. Percentage of cost increase for instances with $\alpha = 0.75$ compared to instances with $\alpha = 0.25$ for high-cap set and unequal severities

Figure 11 shows such a comparison for set of scenarios related to Table 3 while Figure 12 shows this comparison for instances related to Table 4. Except for instances #13,14 and #19,20, the cost deviation percentage for $\alpha = 0.75$ dominates that of $\alpha = 0.25$. This is reasonable because when $\alpha = 0.75$, there is less flexibility in the solving procedure due to the smaller feasible region, which makes the problem harder to solve. Therefore, the percentage of deviation increases. Yet, there is no significant relationship between the dimension of the instance and the deviation percentage.

5.1.3.3 Number of opened LRCs

When the value of α is increased from 0.25 to 0.75, the amount of shipments will not be reduced. New shipments are done directly or indirectly. In order to verify the effect of increasing α value on the number of opened LRCs (indirect shipments), we compare the

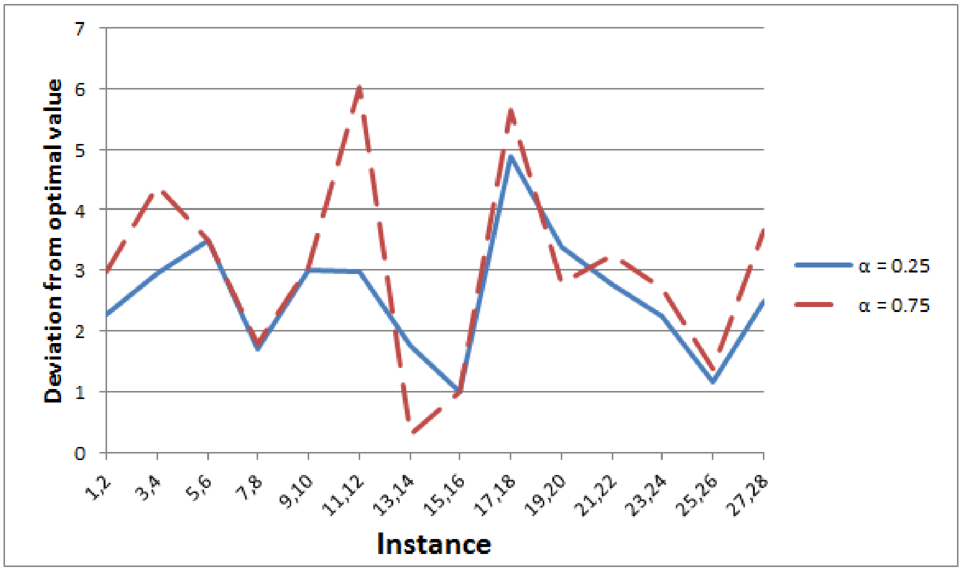


Figure 11. Deviation of OFVs of LH method from optimal OFVs for high-cap set instances with equal severities

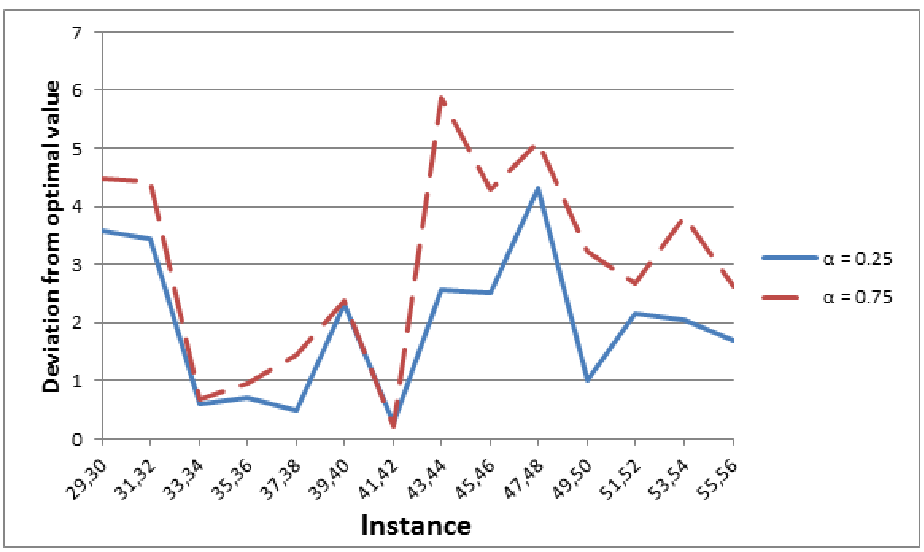


Figure 12. Deviation of OFVs of LH method from optimal OFVs for high-cap set instances with unequal severities

diagrams related to $\alpha = 0.25$ *and* $\alpha = 0.75$ in Figures 13 and 14 (for high-cap scenarios for equal and equal severities, respectively). In Figure 13, the diagram for $\alpha = 0.75$ dominates the one of $\alpha = 0.25$, meaning that the model opens more (or at least equal number) LRCs when α = 0.75. But in Figure 14, for some of the instances, number of opened LRCs for α = 0.25 are greater than that of α = 0.75. This means that for those instances, direct shipments are considered more often and the details of the solution have changed significantly. The same analysis can be done about the number of opened RRCs.

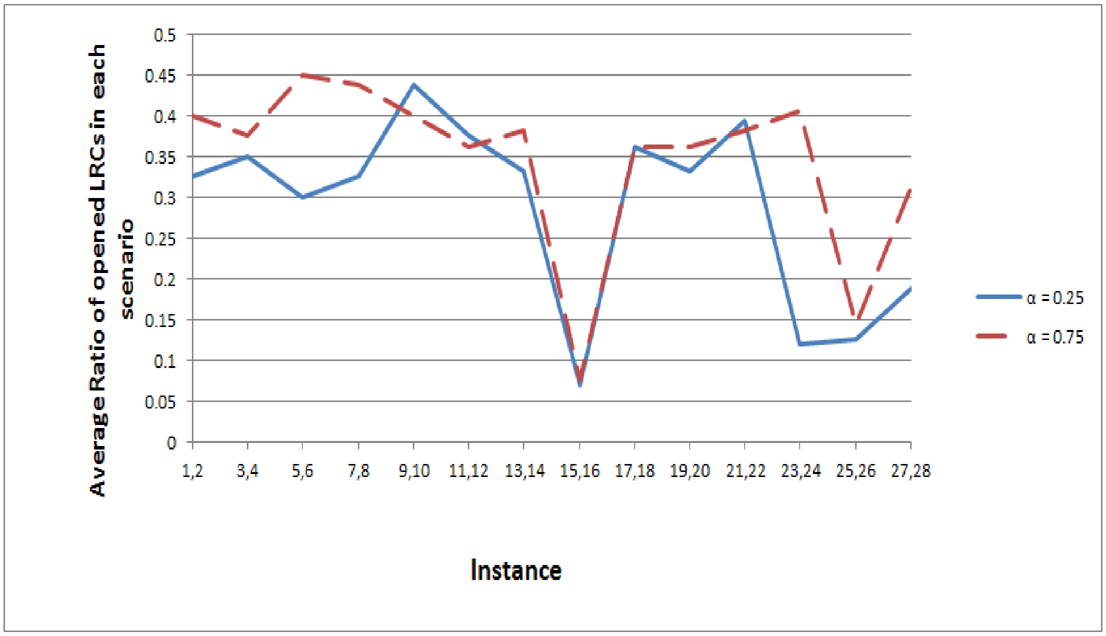


Figure 13. Ratio of opened LRCs for α = 0.25 and α = 0.25 of high-cap set instances with equal severities

5.1.3.4 Ratio of opened RRCs:

We are also interested in observing the effect of instance dimensions on the ratio of opened RRCs (i.e. number of opened RRCs divided by total number of RRCs). Figure 15 shows this ratio for high-cap set instances with equal severities while Figure 16 shows

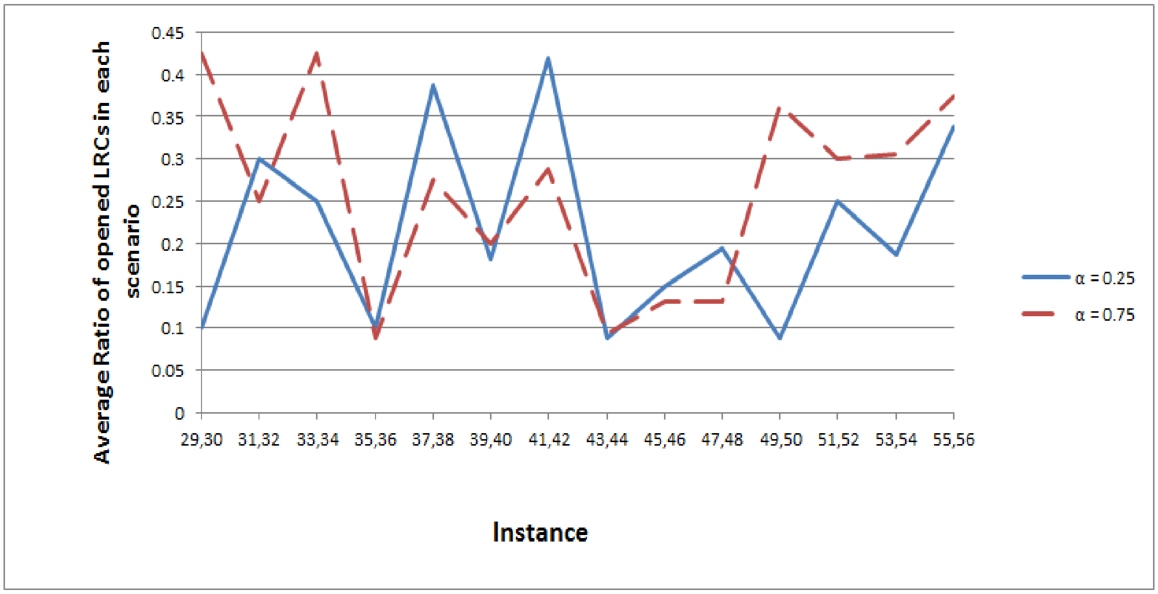


Figure 14. Ratio of opened LRCs for α = 0.25 and α = 0.25 of high-cap set instances with unequal severities

this ratio for high-cap set instances with unequal severities. In Figure 15, only in instance#1, number of opened RRCs for α = 0.25 is more than that of α = 0.75. For other instances, the diagram of related to α = 0.75 dominates that of α = 0.25. But in Figure 16, for some of the instances, α = 0.25 dominates α = 0.75 while for some other instances, α = 0.75 dominates α = 0.25. Aggregately, it can be concluded that when the probabilities of the scenarios are equal (first figure), the results are more balanced and predictable while for the case where scenarios have different probabilities (second figure), the system becomes more complicated and patterns are not predictable. Also, as can be seen in Tables 5 and 6, all RRCs are opened for each instance (either 5 or 10 existing RRCs). This is due to the fact that the RRC capacities are not flexible compared to the total demand and the heuristic is forced to open all the RRCs and use their supplies to be able to cover α percent of the demand.

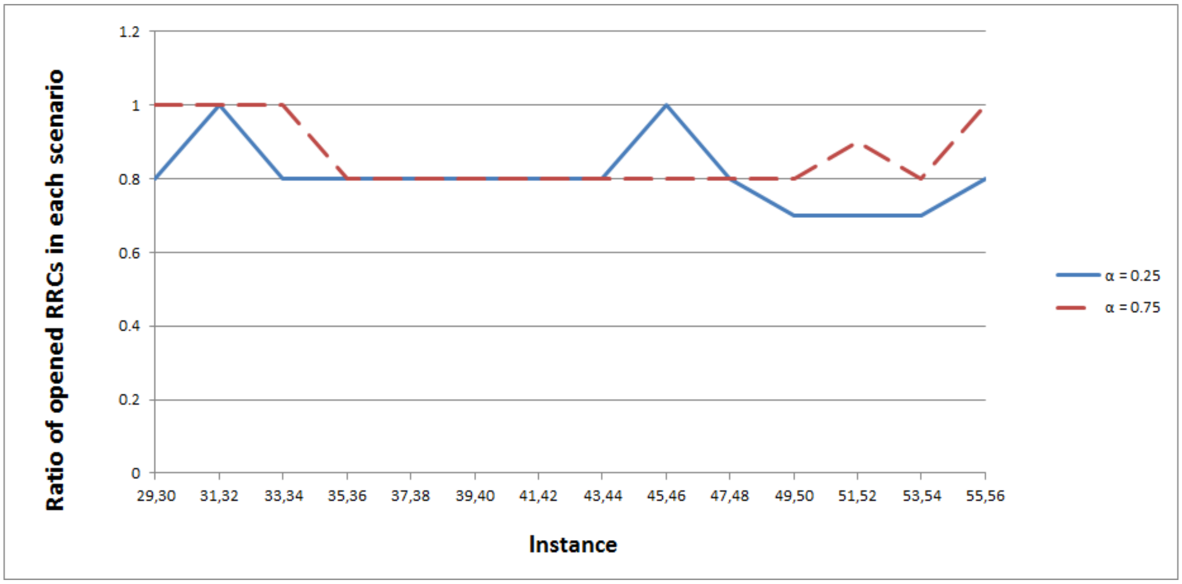


Figure 15. Ratio of opened RRCs for α = 0.25 and α = 0.25 of high-cap set instances with equal severities

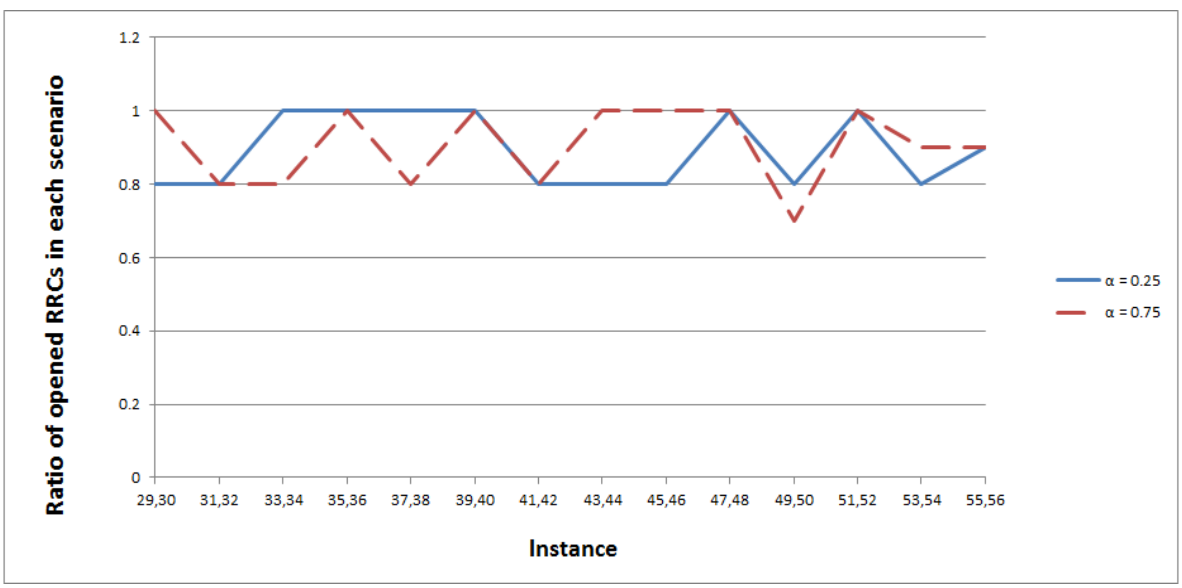


Figure 16. Ratio of opened RRCs for α = 0.25 and α = 0.25 of high-cap set instances with unequal severities

Other types of analysis, based on different criteria, can be done on the data. Unfortunately there are no similar comprehensive models to compare the results of our model with. Even, the data that is used in [56] are generated based on the fact that shortage cost is extremely high which automatically leads to reliability of 1 for most of the cases. Solving our pre-positioning model using other heuristics or meta heuristics and conducting comparisons with our results can be an opportunity for future studies.

5.1.3.5 Effect of number of scenarios

As mentioned in section 3.2.2, number of scenarios has significant effect on execution time. Hence, for experiment with more scenarios involved, it may not be possible to obtain the optimal solution (using Cplex) in a reasonable amount of time. Yet, we run an experiment with the same design, this time using 20 scenarios with equal severities. Also, all α values are considered to be equal to 0.5. The maximum execution time for Cplex is considered to be 12 hours, which was sufficient for considered instances. Figure 17 shows the deviations of OFVs of LH method from optimal OFVs (obtained by Cplex). As can be seen, all the deviations except for instance #8 are below 5% with the average of 4.312% and standard deviation of 0.642. This means that the LH works effectively for experiments with up to 20 scenarios. It should be mentioned that average deviation is significantly more than the experiments with only 4 scenarios which is reasonable.

5.2 Experiments and analysis of the real-time model

5.2.1 Design of the experiments

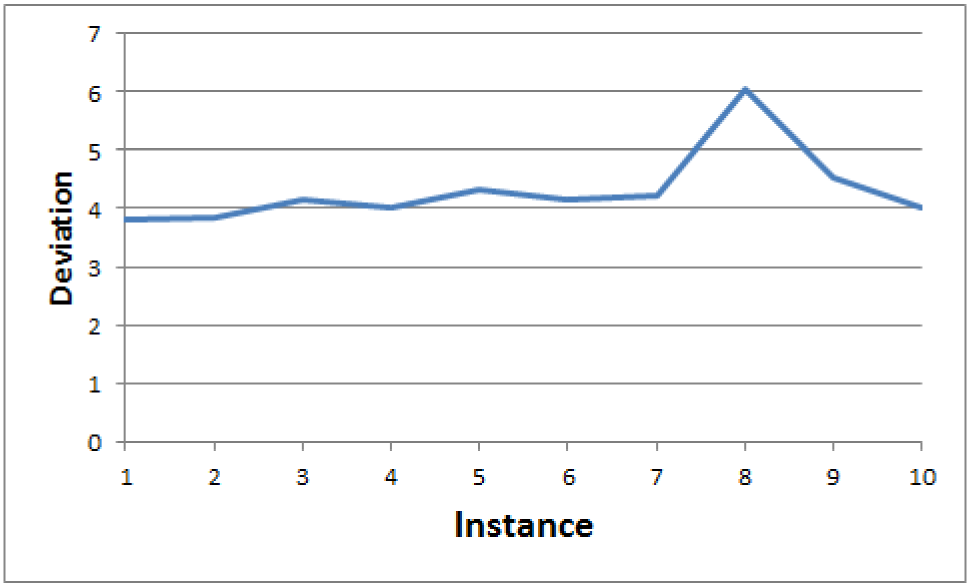


Figure 17. Deviation of OFVs of LH method from optimal OFVs for experiment set with 20 scenarios

After solving the pre-positioning model, we use part of its outputs as inputs of the real-time facility location model. In [70], a similar real-time model (sole-allocation model without heuristic methods) is applied to the 2010 Haiti earth quack and is proven to work effectively. The experiment had a maximum of 347 constraints, 321 non-negative and, 42 binary variables. Our model can be solved in a reasonable amount of time for small or medium size data. But we have developed a heuristic in order to be able to solve the model for large instances as well. In order to prove the efficiency of the heuristic, we design a set of experiments. Because the current model is the continuation of the pre-positioning model, we will use the same experiments that we used for pre-positioning model. It should only be considered that here, there is no longer the set of scenarios, and some of decision variables such as U_i variables do not exist anymore. Also, new parameters such as ransack probability of routes and reliability of routes are added. In the next paragraph, details of the experiments are explained.

First, we mention the mutual parameters: Number of RRCs, LRCs and AAs are chosen from {5, 10}, {10, 20, 40} and {50, 75, 100, 200, 400, 600, 800} respectively. The locations of the above points are randomly generated between a planar surface with length and width of [0,100]. g_j values are chosen randomly between [60'000, 140'000] and [6'000, 12'000]. Then, we assume that there are three relief items (e.g. food, blanket, and medical supplies). Because there are no more scenarios, we assume that the occurred disaster has a medium severity, and the amount demand for items 1, 2, and 3 are randomly chosen from the interval [5,10], [10,20], and [40,60], respectively. The ratio of the total demand to the total capacity of RRCs (for each item) is randomly chosen from the interval [0.55,0.7]. The indirect transportation costs are considered to be distance based. For direct shipment, because separate transportation vehicles should be assigned, which induces extra cost, they are randomly chosen from the interval [200,750]. Reliability values are randomly chosen from the interval [0.63, 0.98] and ransack probabilities are chosen from the interval [0.8,0.98].

5.2.2 Results of the experiments

Table 7 shows the optimal and heuristic values for 14 test instances. The comparisons over the results of LH and optimal values for the real-time model is different from that of pre-positioning model due to the fact that in the objective function of different lexicographic levels of real-time mode, there can be different parameters. These parameters are the best and worst values for different objectives. Recalling from the heuristic, in the calculations of the trade-off matrix, we use the LH method to obtain the values of the row related to attribute CO. These values can affect the final worst and best values of all the attributes. In fact, when we solve model 4.2 for attribute CO optimally, we obtain the minimum cost. But, when we solve it heuristically (using models 4.3.1 and 4.3.2), there will be deviation, not only from the cost, but also from other attributes. These deviations will affect the values of trade-off matrix and because these values are parameters of lexicographic models level 2 and 3, the optimal solutions and heuristic solutions of these two methods are not directly comparable. In other words, for a single model, any heuristic method will lead to a solution which is never better than the optimum. But in the real-time model, because there is not necessarily a single model, the heuristic results and optimal results do not necessarily have that relationship. We can only compare the values of attribute CO obtained optimally and heuristically, which will be discussed later.

Table 7 Summary of results of LH and Cplex for real-time model

Instance #	# of RRC	# of LRC	# of AA	# of opened LRC	ratio of opened LRC	Cplex HADS 2	Cplex HADS 3	LH HADS 2	LH HADS 3
1	5	10	50	5	0.5	0.0297	0.11556	0.03	0.118
2	5	10	75	7	0.7	0.0306	0.11906	0.0315	0.122
3	5	10	100	4	0.4	0.0249	0.09310	0.0249	0.094
4	5	20	100	8	0.4	0.0271	0.07753	0.0283	0.0812
5	5	20	200	10	0.5	0.0268	0.07654	0.0272	0.0734
6	5	40	100	13	0.325	0.0239	0.06783	0.0238	0.0451
7	5	40	200	15	0.375	0.0253	0.06820	0.0247	0.0428
8	5	40	400	18	0.45	0.0257	0.04744	0.0263	0.0468
9	5	40	600	17	0.425	0.0256	0.05964	0.0263	0.0539
10	5	40	800	18	0.45	0.0249	0.07798	0.0257	0.0529
11	10	40	200	14	0.35	0.0258	0.05445	0.0278	0.0529

12	10	40	400	18	0.45	0.0263	0.05967	0.0263	0.0509
13	10	40	600	21	0.525	0.0259	0.05859	0.0261	0.0451
14	10	40	800	26	0.65	0.0265	0.03888	0.0268	0.0404

In Table 7, the first four columns show the instance number and dimensions. Column five shows the number of opened LRCs in the optimal solution. Column six shows the number of opened LRCs divided by total number of LRCs Columns seven and eight shows the optimal values for lexicographic models of levels number 2 and 3, respectively. Column nine shows the OFV value obtained from LH method for lexicographic level number 2, and column ten shows OFV values obtained from LH method for lexicographic level number 3. In Table 8, best and worst values of attributes obtained in lexicographic level#1 are shown. Also, in Table 9, values of attributes obtained from LH as well as Cplex are shown. This table also shows the number of opened LRCs at each instance. The rest of this chapter contains different analysis on the data obtained from running the experiments.

Table 8 Best and worst values of attributes obtained from Cplex in lexicographic level#1

Instance #	**Solution type**	**TT**	**MA**	**CO**	**GR**	**GS**
1	Best	277151	86	470543.6	-1.79028	-1.06632
	Worst	439805	160	1426787	-81	-40
2	Best	413951	91	570623.8	-2.51249	-1.58824
	Worst	663475	160	2150744	-118	-59
3	Best	551145	91	461039.9	-3.318	-2.09086
	Worst	780944	160	1482581	-156	-78
4	Best	550180	88	920980.5	-3.13703	-1.94639

	Worst	903993	160	2952261	-263	-131
5	Best	1096308	88	1698384	-5.69888	-3.64731
	Worst	1807441	160	5879333	-514	-256
6	Best	548310	87	1024027	-3.06946	-1.90968
	Worst	880195	160	2903745	-475	-236
7	Best	1094142	89	1784876	-5.29496	-3.6401
	Worst	1736096	160	5752543	-929	-459
8	Best	2201707	85	3319030	-9.43951	-6.1612
	Worst	3529817	160	11412335	-1828	-905
9	Best	3311968	88	4848360	-13.3753	-8.9586
	Worst	5255355	160	17169512	-2726	-1351
10	Best	4407319	89	6370062	-17.1196	-11.5379
	Worst	7101291	160	22490736	-3630	-1797
11	Best	1063338	84	1767502	-4.69873	-3.17749
	Worst	1772108	160	6069337	-1049	-519
12	Best	2128548	86	3281403	-8.61496	-5.88134
	Worst	3467031	160	12561601	-2046	-1015
13	Best	3202278	88	4798297	-12.3817	-8.50604
	Worst	5298785	160	18625647	-3042	-1509
14	Best	4269813	88	11201723	-28.7363	-17.2213
	Worst	5280626	160	25299695	-4050	-2005

Table 9 Values of attributes obtained from Cplex and LH in lexicographic level#3

Instance #	Solution	# of opened LRCs	% of opened LRCs	TT	MA	CO	GR	GS
1	Opt.	5	50	293258.3	93	754675.8	-9.027	-4.715
	LH	6	60	292518.6	93	773433.6	-9.433	-4.978
2	Opt.	7	70	439435.3	97	1054780	-14.52	-7.400
	LH	7	70	438569.4	97	1093750	-13.34	-6.988
3	Opt.	4	40	570219.5	96	715439.8	-14.69	-7.346
	LH	6	60	570266.6	96	723311	-14.87	-7.654

4	Opt.	8	40	582259	92	703475.5	-19.92	-9.170
	LH	8	40	551376.7	95	704568	-18.99	-8.265
5	Opt.	10	50	1159831	92	2818794	-37.23	-18.78
	LH	8	40	1162705	92	2858978	-34.28	-17.31
6	Opt.	13	32.5	574722.5	92	1472810	-22.08	-10.44
	LH	16	40	574802.5	87	1494923	-20.89	-10.37
7	Opt.	15	37.5	1148336	92	2789737	-42.52	-20.60
	LH.	18	45	1150457	90	2816309	-39.29	-19.62
8	Opt.	18	45	2315703	87	5403170	-64.03	-31.91
	LH	21	52.5	2316251	87	5491474	-59.96	-28.37
9	Opt.	17	42.5	3477804	91	8002571	-113.5	-55.91
	LH	25	62.5	3438987	91	8178315	-112.2	-55.28
10	Opt.	18	45	4630919	90	10384105	-142.5	-70.39
	LH	29	72.5	4630078	90	10556308	-142.3	-70.16
11	Opt.	14	35	1124302	88	2877559	-45.97	-22.03
	LH	22	55	1126010	87	2992279	-41.68	-20.13
12	Opt.	18	45	2245993	89	5724273	-88.53	-42.35
	LH	27	67.5	2247096	87	5757479	-87.06	-41.92
13	Opt.	21	52.5	3383247	89	8379001	-127.1	-62.53
	LH	29	72.5	3384198	89	8464194	-114.9	-56.18
14	Opt.	26	65	4423467	91	12846358	-166.2	-81.36
	LH	40	100	4406482	89	13511382	-158.3	-77.76

5.2.3 Analysis of the experimental results

In this section we perform several analyses on the results of the experiments in order to both assess the efficiency of heuristic method and investigate the role and the effect of some of the model parameters on the solutions and the OFVs.

5.2.3.1 Efficiency of heuristic for attribute CO

The only direct comparison of solutions can be done over optimal and heuristic solutions of attribute CO. Figure 18 shows the deviation of best value for attribute CO obtained from LH (in HADS3) from that of Cplex software. All the deviations are below 5%. And there is no pattern in the diagram, meaning that the instance dimensions is independent from the amount of deviation.

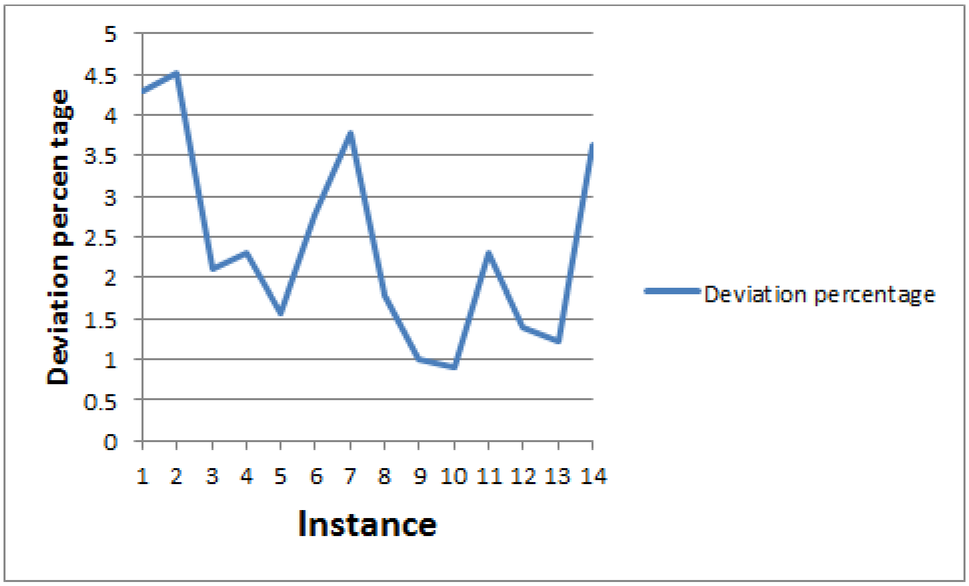


Figure 18. Deviations (in percent) of attribute CO values obtained from LH method from optimal values

5.2.3.2 Efficiency of calculations of trade-off matrix arrays

As can be seen, the percentage of deviation of obtained total cost from the heuristic method compared to optimal cost does not have any trend for different instances and it fluctuates between 1% and 4.5%. Therefore, it can be concluded that the LH works reasonably well for the attribute CO.

As mentioned before, it is not possible to directly compare the results of the second and the third lexicographic levels of LH and Cplex. But, different analysis can be conducted. In the experiments of this dissertation, the heuristical results of the trade-off matrix for attribute CO affect two values of the final best and worst vectors of attributes: the best CO and the worst TT. In fact, for the LH, because it is a heuristic, the best CO is always greater than that of Cplex. Also, the worst TT of the LH is often less than that of Cplex. This looks reasonable because there is always a trade-off between time and cost, and a solution with higher cost is likely to have lower time. First, we compare the values for each attribute obtained from two methods in lexicographic level#3.

Figures 19 shows the deviations of TT attribute values obtained by LH method from that of Cplex. Also, Figure 20 shows the TT values obtained from the two methods. For most of the instances, the results are fairly close, but for some instances such as #4 and #9, the LH results in significantly better solutions. This is due to the fact that the best TT value from trade-off matrix is equal for both methods while the worst TT value is higher for Cplex compared to LH (as mentioned before). Therefore, the LH is more likely to get a better value for attribute TT. Now, if we plot the deviations for attribute CO, based on same analysis we would expect better values from Cplex than LH:

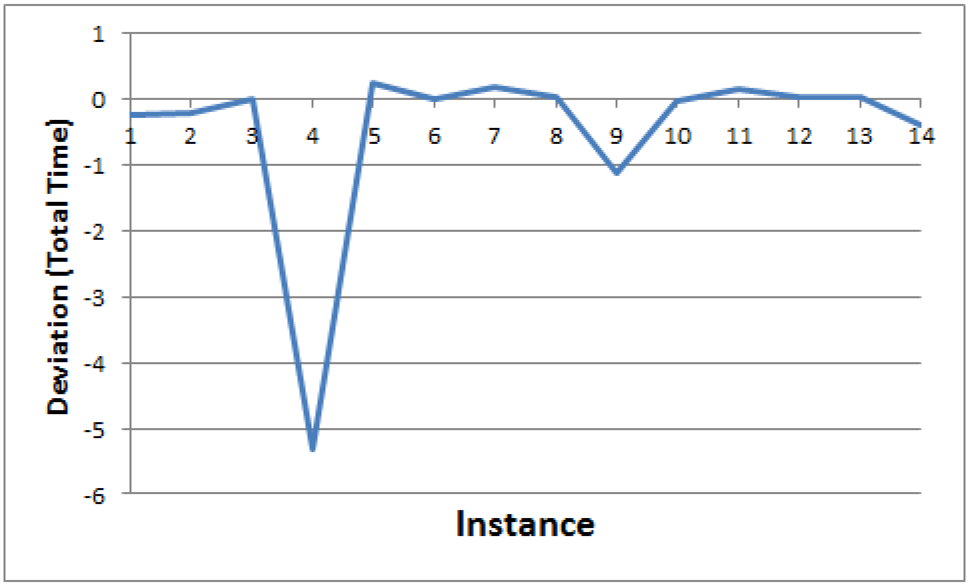


Figure 19. Deviations (in percent) of TT attribute values obtained from LH method from Cplex results

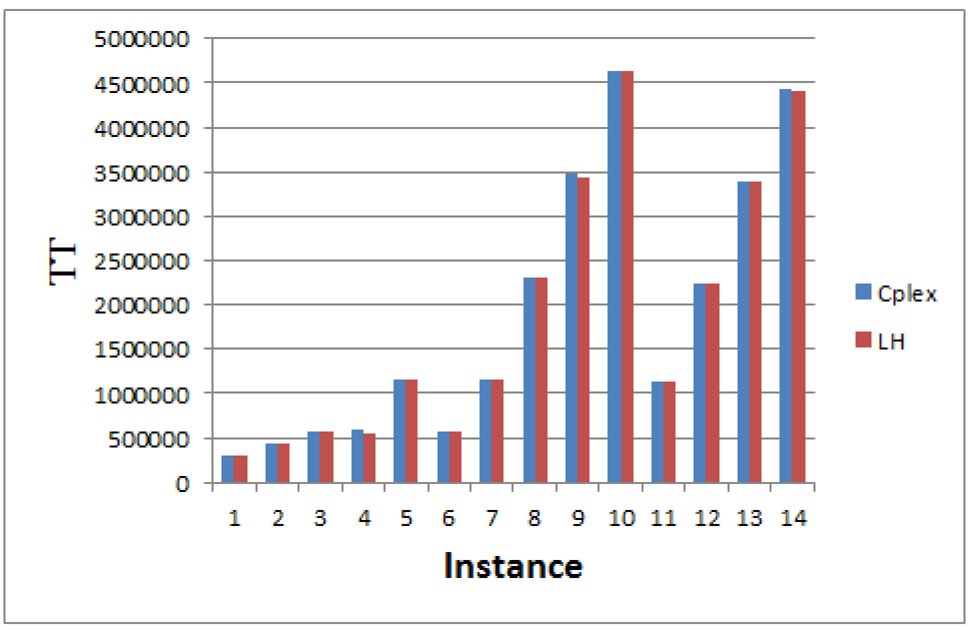


Figure 20. Comparisons of TT attribute values obtained from LH method and Cplex

Figures 21 shows the deviations of CO attribute values obtained by LH method from that of Cplex. Also, Figure 22 shows the CO values obtained from the two methods. As expected, all the deviations are positive, meaning that all optimal CO values are better than values that are obtained from LH although they are not directly comparable.

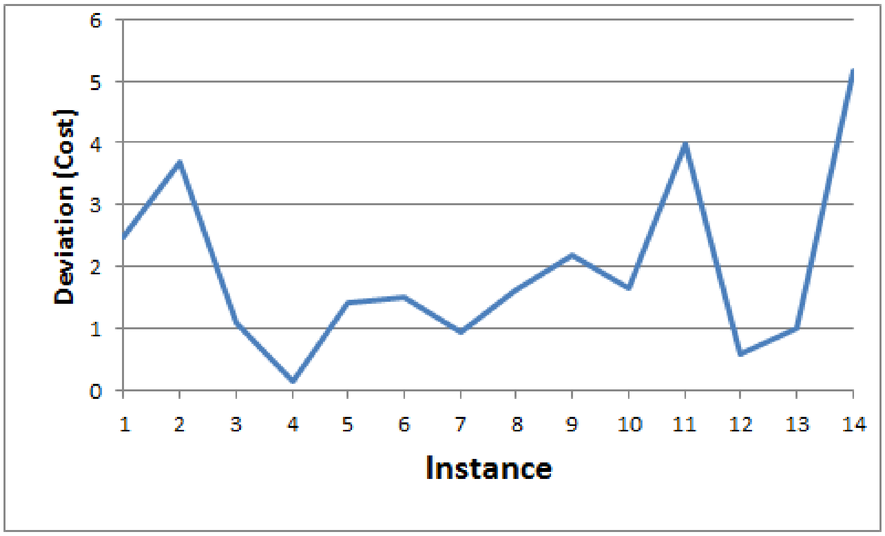


Figure 21. Deviations of CO attribute values obtained from LH method from Cplex results

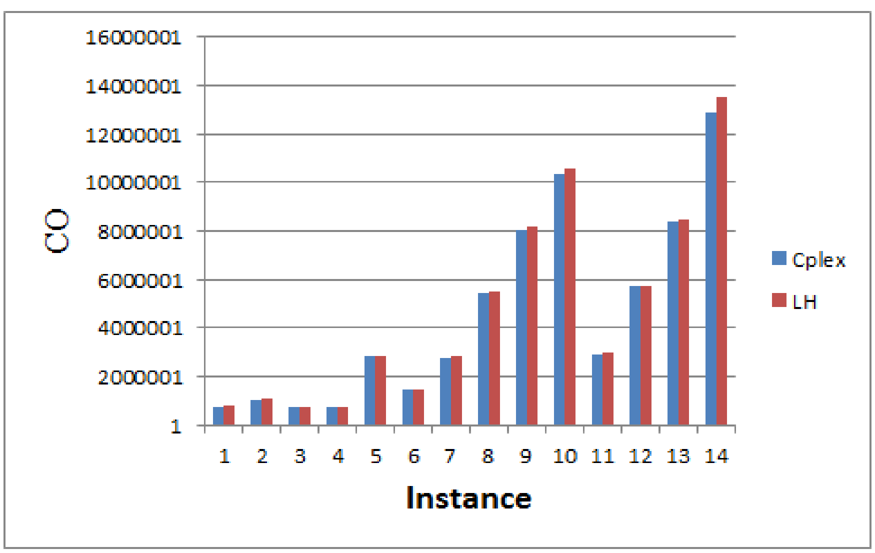


Figure 22. Comparisons of CO attribute values obtained from LH method and Cplex

Same analysis can be done for attribute MA. Figures 23 shows the deviations of MA attribute values obtained by LH method from that of Cplex. Also, Figure 24 shows the MA values obtained from the two methods. For many of the instances, MA values are equal while for some others, either method can work well. Now we plot the deviations of LH method from Cplex, for attribute GR. It should be mentioned that because all GR values are negative, in order to calculate the deviations, we need to divide the difference between results of Cplex and LH by the absolute result of Cplex.

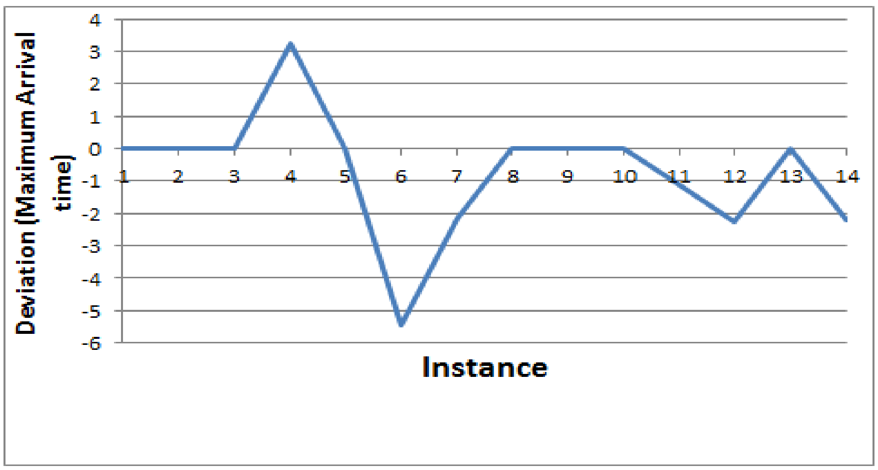


Figure 23. Deviations of MA attribute values obtained from LH method from Cplex

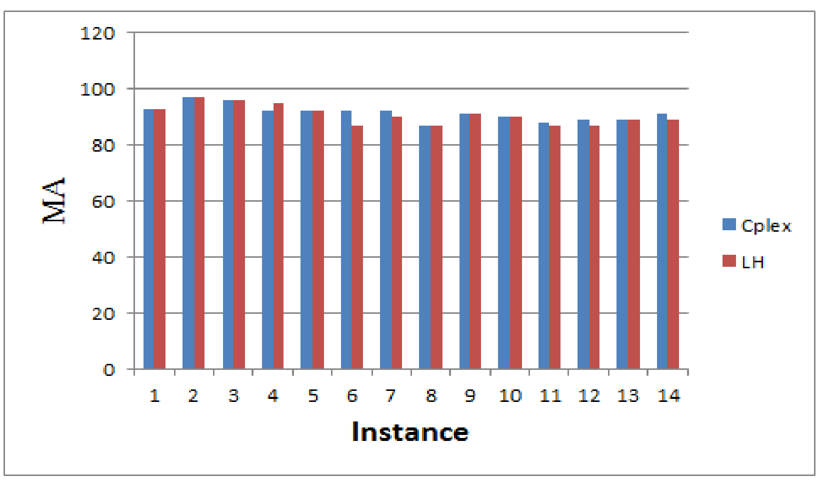


Figure 24. Comparisons of MA attribute values obtained from LH method and Cplex

Figures 25 shows the deviations of GR attribute values obtained by LH method from that of Cplex. Also, Figure 25 shows the GR values obtained from the two methods. As can be seen, except for first instance, the LH values are non-negative, meaning that the solutions of LH have higher GR value.

Same fact can be concluded from the chart related to attribute GS. Figures 27 shows the deviations of GS attribute values obtained by LH method from that of Cplex.

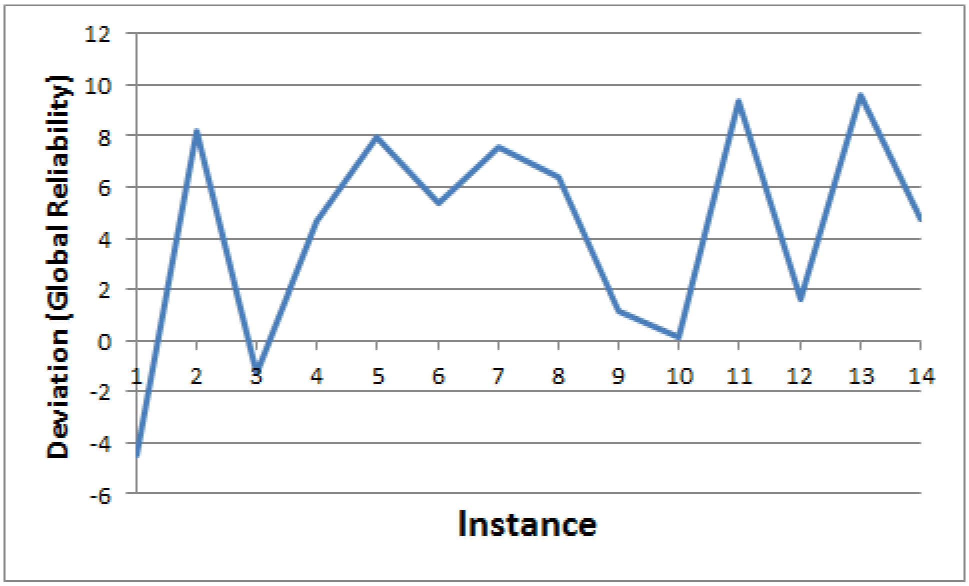
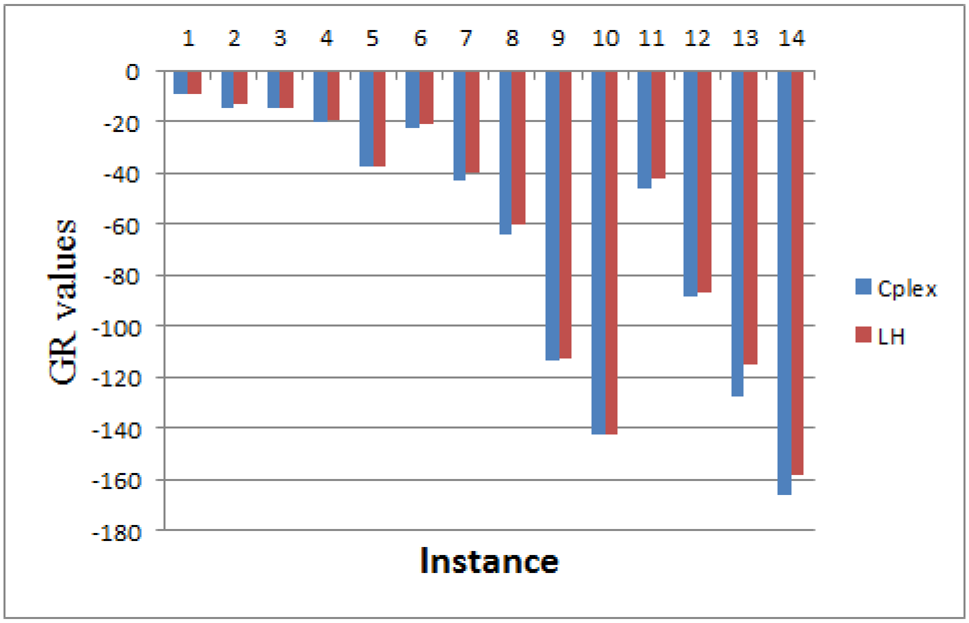
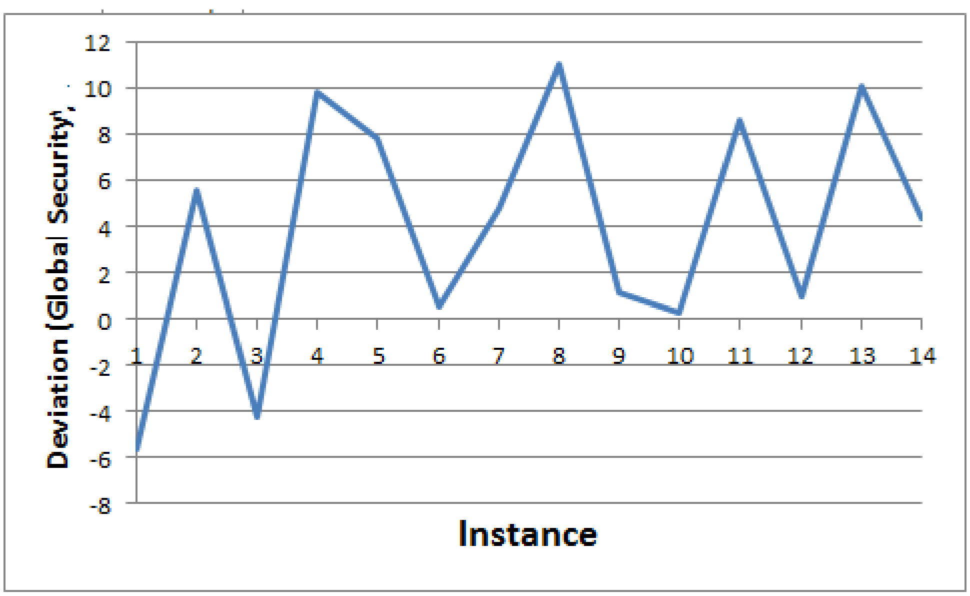


Figure 25. Deviations of GR attribute values obtained from LH method from Cplex results

Also, Figure 28 shows the GS values obtained from the two methods. As can be seen, except for first instance, the LH values are non-negative, meaning that the solutions of LH have higher GR value.



<u>Figure 26.</u> Comparisons of GR attribute values obtained from LH method and Cplex



<u>Figure 27.</u> Deviations of GS attribute values obtained from LH method from Cplex results

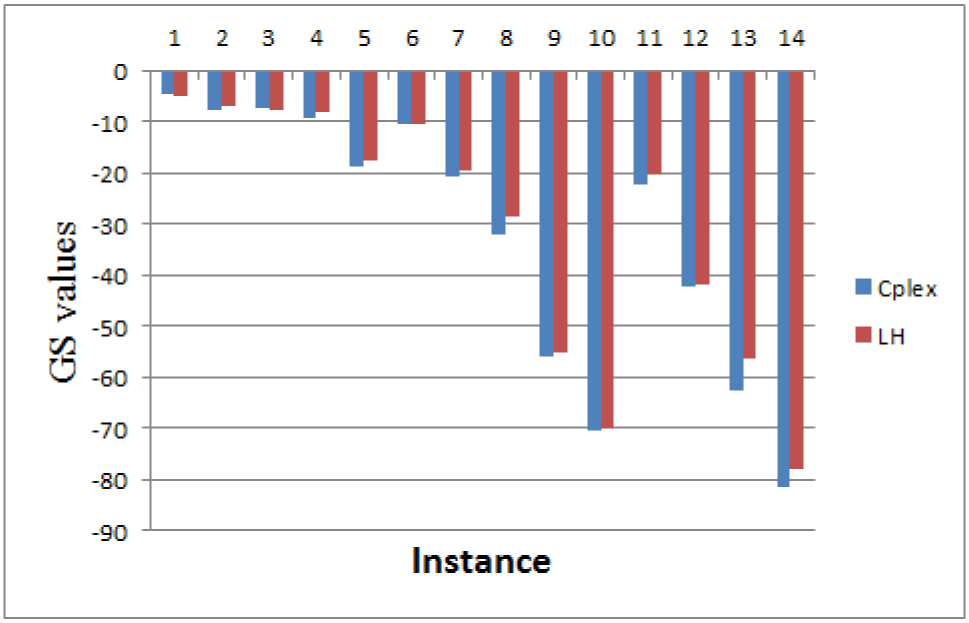


Figure 28. Comparisons of GS attribute values obtained from LH method and Cplex

5.2.3.3 Efficiency of the heuristic of second lexicographic level

Now, the results of second lexicographic levels will be compared. Figure 29 shows the deviations of OFVs of HADS2 obtained by LH from that of Cplex. As can be seen, except for instance#7, the Cplex results are better than LH results. In fact, although the two methods are not directly comparable, it is worthwhile to mention that the maximum standardized weighted deviation from best values of attributes is lower for Cplex than that of LH.

5.2.3.4 Effect of lexicographic level#3:

The objective of the HADS2 model is to minimize the maximum standardized deviation from best values of different attributes. When solving this model, the criteria of total

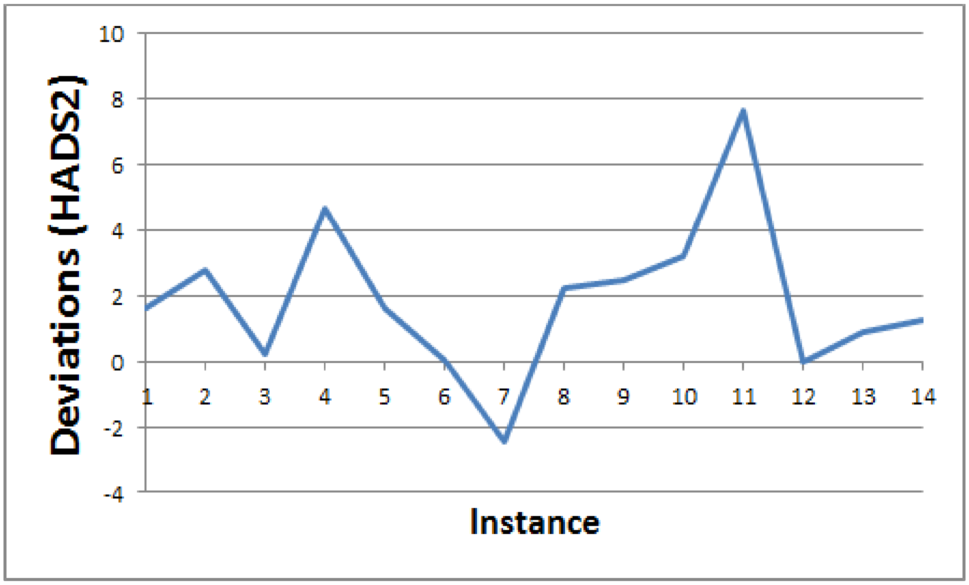


Figure 29. Deviations of OFVs of HADS2 OFVs obtained from LH method from Cplex results

standardized weighted deviation can also be calculated. In other words, each HADS2 solution has a value for total deviation. When solving HADS3, using the results of HADS2, the objective is to minimize the total deviation. By comparing the values of total deviation obtained from HADS2 and HADS3, we can assess the amount of improvement that HADS3 causes on the total deviation. Figure 30 shows the total deviation values obtained in HADS2 and HADS3. As can be seen, the effect of HADS3 is significant (total deviation values of HADS3 are significantly lower). This justifies the use of third lexicographic level in the system.

5.2.3.5 Efficiency of the heuristic of third lexicographic level

Now we investigate the difference between Cplex and LH for lexicographic level#3. Figure 31 shows the deviations of OFVs of HADS3 obtained by LH from that of Cplex.

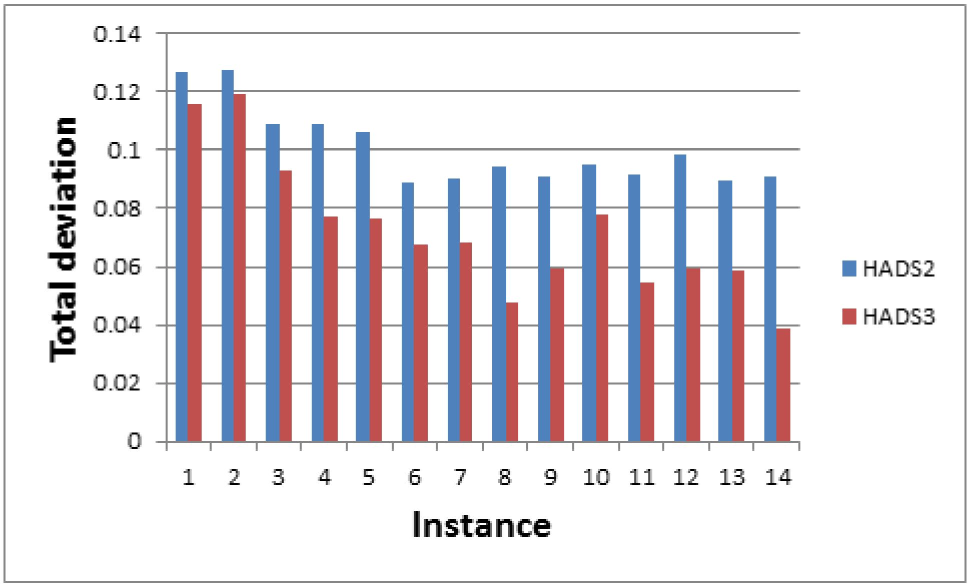


Figure 30. Comparisons of total standardized weighted deviations of attributes in HADS2 compared to that in HADS3

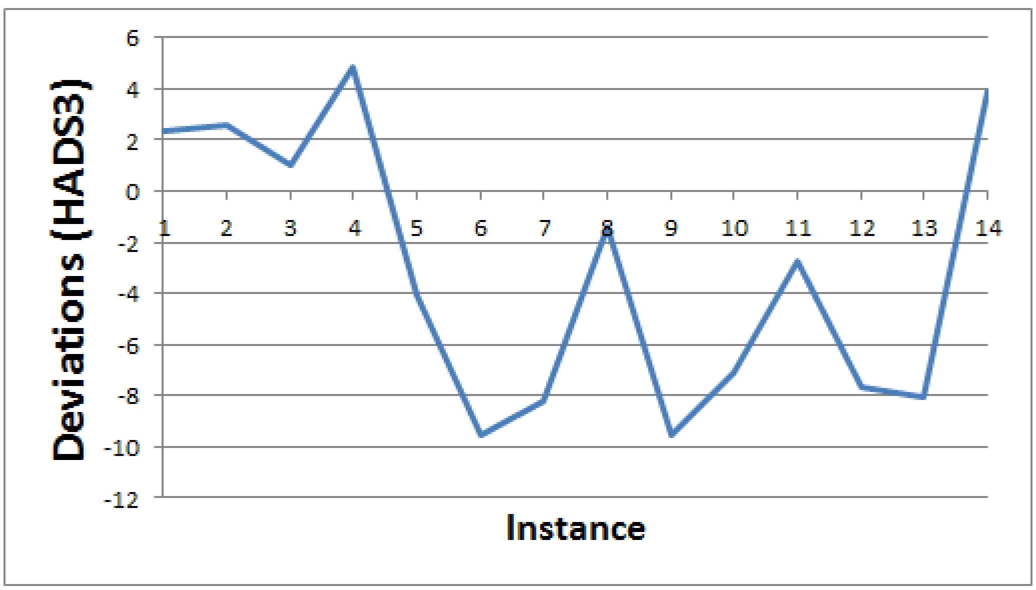


Figure 31. Deviations of OFVs of HADS3 values obtained from LH method from Cplex results

Unlike HADS2, the deviations of LH from Cplex for HADS3 are mostly negative, meaning that total weighted deviation is lower for LH compared to that of Cplex. This result was expected because in HADS2, using LH, almost all the results were worse than those of Cplex, meaning that maximum standardized deviation from best values of attributes (i.e., $D_{\infty}{}^{*}$) were higher for LH method. This causes the solution of HADS3 to be more flexible: in HADS3, considering the result of HADS2 (i.e. maximum deviation), the total standardized deviation is calculated. The higher the maximum deviation ($D_{\infty}{}^{*}$), the larger the feasible region of HADS3. In other words, if one tries to minimize the total weighted deviation while keeping the maximum deviation to a low value, he or she will have more limited choices. But, if this maximum deviation is a high value, it is possible to keep the actual maximum deviation lower than $D_{\infty}{}^{*}$, while having more choices (i.e., larger feasible region) for the total deviation (i.e., $D^{*}{}_{1}$). Hence, as a valuable conclusion, there is a trade-off between the results of HADS2 and HADS3: by increasing the result of HADS2 (as an input for HADS3), the result of HADS3 can be improved. In order to be more specific about this conclusion, we run this trade-off for data of instance #5. Figure 32 shows the selected values for HADS2 (i.e., maximum deviation percentages) as well as their related HADS3 values (i.e., total deviation percentages). The original (optimal) HADS2 result is 2.6798 percent and its related HADS3 value is 7.6545. Now, as an input for HADS3, if we assume that HADS2 value is say, 3 percent, then the HADS3 result will be 6.5685, which has an improvement of 14%. Based on the opinions of the decision makers, the sensitivity analysis can be performed and ideal combination of HADS2 and HADS3 values can be chosen.

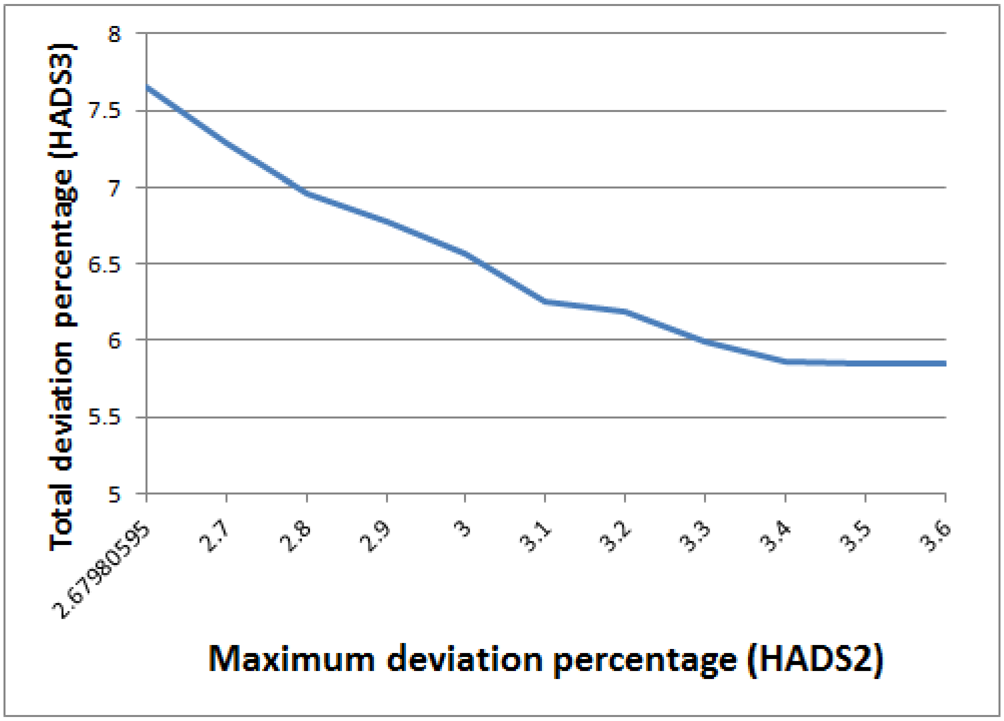


Figure 32. Results of trade-off between OFVs of HADS2 and HADS3

5.2.3.6 Percentage of opened LRCs

Finally, we plot the percentage of opened LRCs for each instance, in Figure 33. As can be seen, there is no trend in the plot, meaning that percentage of opened LRCs is independent from dimensions of instances, for our experiment.

As a conclusion of this chapter, it should be mentioned that both of the LH heuristics that is used to solve the pre-positioning and real-time facility location problems performs efficiently and the deviations from optimal values are below 5%. Moreover, because the pre-positioning and the real-time models of this dissertation are novel variants of basic models, their solutions are not comparable with other models. Thus, in order to prove the efficiency of the LH method, we compared the results of LH with the results of the Cplex. As a future study, both the models can be solved using other heuristics and the results can be compared with those from LH.

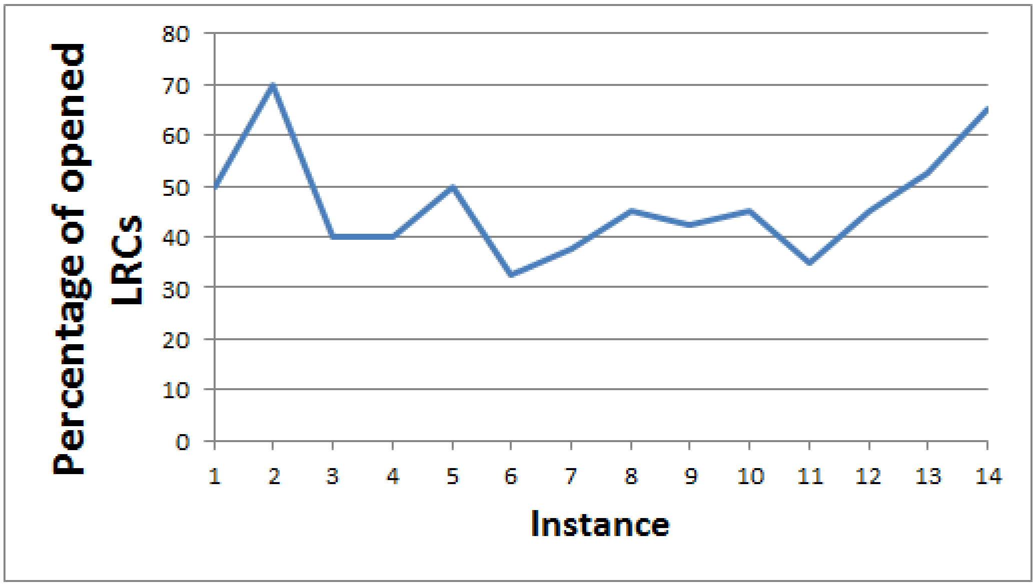


Figure 33. Ratio of opened LRCs for all the instances

CHAPTER 6
CONCLUSIONS

In this dissertation, we developed a two-stage network for humanitarian logistics which is also called as relief chains. The first stage should be used before the occurrence of the disaster while the second stage covers the aftermath of the disaster. Each model has two stages. In the pre-positioning model, the first stage is the location problem for RRCs and the pre-positioning amount at each RRC while the second stage is the location problem for LRCs as well as the flow of material between RRCs, LRCs, and AAs. In the real-time model, the first stage is the location problem for LRCs while the second stage is the material flow problem between RRCs, LRCs, and AAs.

6.1 Conclusions

The main contributions of this dissertation are as follows:

- The comprehensive pre-positioning model and its heuristic (LH) provides a solution for the relief chains where relief materials should be pre-positioned and distributed in the aftermath of a disaster. In none of the current two-echelon models, the service quality, direct shipments, and capacitated supply sources are considered. Also, here, the maximum delivery duration is considered not only in first echelon, but in the entire delivery process. Therefore, this model and its solutions are closer to reality.

- The real-time facility location model, which is a continuation of the pre-positioning model, completes the two-stage network design. The first aspect of this model is that it is location-allocation, not solely location. This way, the location of the LRCs will be determined according to real-time data. Also, the model is multi-product and considers different relief materials such as food, blankets, water and medical supplies as distinguishable elements. Moreover, availability of the direct shipments allow the model to use many elements of the Lagrangian heuristic, which is based on exact methods such as Cplex and therefore, the solutions are close to optimum.

- In current literature, the trade-off between lexicographic levels #2 and #3 in the real-time model is not considered. In this dissertation, we concluded that such a trade-off exists, meaning that there is a relationship between the maximum variation among all attribute values and total variation of attributes. Minimizing the maximum variation causes the sum of variations to be less flexible (higher value). Hence, after obtaining the initial values of maximum and total deviations, a sensitivity analysis can be performed in order to obtain the best combinations of the two values.

6.2 Future studies

- The most important opportunity for future studies is the third echelon of the network, which would be the vehicle routing problem. In the dissertation, the facility location problem is solved in two stages and as a result, a distribution scheme for different relief materials is developed. The next step will be the allocation of different transportation vehicles the different routes to perform the distribution task.

- Another opportunity is the development of a location-routing model for first or second echelon of the current network. The two-stage network of this dissertation is developed in a way that it does not incorporate the vehicle routing problem in any of the echelons. But, it is possible to apply the location-routing problem to each of the echelons. For the first echelon, the hypothetical location-routing problem will result in the determination of locations RRCs, LRCs, preliminary distribution scheme, and vehicle routing plan. This way, in the second echelon, only the locations of RRCs and LRCs (as well as the amount of pre-positioned materials) will be used as inputs. Then, it is again possible to conduct a location-routing problem for the second echelon. The resulting system will be s two-stage location-routing network and there will be no need to a separate vehicle routing stage.

- In terms of solving methods, for both of the models, other heuristic methods can be considered. For instance, in the pre-positioning model for very large instances, the number of constraints and decision variables are very large. It is possible that meta heuristics such as simulated annealing that use randomization work better for such instances. And generally, other methods such as Branch and Price or Bender Decomposition that are popular for similar problems can also be tested.

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APPENDIX A

LINGO CODE OF PRE-POSITIONING MODEL

```
sets:
rrc/1..5/:f,u;
lrc/1..20/;
demandp/1..100/;
item/1..1/:v,e;
scenario/1..4/:alpha,pr,gam;
store(rrc,item):h,h1,s;
indirect(rrc,lrc,demandp,item,scenario):a,x;
direct(rrc,demandp,item,scenario):b,y;
demand(demandp,item,scenario):dem,p,c;
extra(rrc,item,scenario):r,z;
fixed2(lrc,scenario):g,q,m;
bin1(rrc,lrc,demandp,scenario):ti,b1;
bin2(rrc,demandp,scenario):tim,b2;
shortage(item,scenario);
endsets

data:
pr = @OLE( 'Prep.xls' ,pr);
f = @OLE( 'Prep.xls' ,f);
s = @OLE( 'Prep.xls' ,s);
e = @OLE( 'Prep.xls' ,e);
v = @OLE( 'Prep.xls' ,v);
h = @OLE( 'Prep.xls' ,h);
a = @OLE( 'Prep.xls' ,a);
b = @OLE( 'Prep.xls' ,b);
dem = @OLE( 'Prep.xls' ,dem);
r = @OLE( 'Prep.xls' ,ro);
g = @OLE( 'Prep.xls' ,g);
ti = @OLE( 'Prep.xls' ,ti);
tim = @OLE( 'Prep.xls' ,tim);
c = @OLE( 'Prep.xls' ,co);
q = @OLE( 'Prep.xls' ,q);
enddata
```

```
min= @sum(rrc(i):f(i)*u(i)) +
@sum(fixed2(j,n):pr(n)*g(j,n)*m(j,n))+@sum(demand(k,l,n):pr(n)*c(k,l,n)*p(k,l,n))
 +
@sum(indirect(i,j,k,l,n):pr(n)*a(i,j,k,l,n)*x(i,j,k,l,n))+@sum(direct(i,k,l,n):pr(n)*b(i,k,l,n)*y(
i,k,l,n))
+ @sum(store(i,l):h(i,l)*h1(i,l));


@for(bin1(i,j,k,n):@sum(indirect(i,j,k,l,n):x(i,j,k,l,n)) <= 10000000*b1(i,j,k,n));

@for(bin2(i,k,n):@sum(direct(i,k,l,n):y(i,k,l,n)) <= 10000000*b2(i,k,n));

@for(demand(k,l,n):dem(k,l,n)-@sum(indirect(i,j,k,l,n):x(i,j,k,l,n))-
@sum(direct(i,k,l,n):y(i,k,l,n)) = p(k,l,n));

@for(extra(i,l,n):r(i,l,n)*h1(i,l)-@sum(indirect(i,j,k,l,n):x(i,j,k,l,n))-
@sum(direct(i,k,l,n):y(i,k,l,n)) >= 0);

@for(store(i,l):(h1(i,l)) <= s(i,l)*u(i));

@for(fixed2(j,n): @sum(indirect(i,j,k,l,n):x(i,j,k,l,n)*v(l)) <= q(j,n)*m(j,n));

@for(demand(k,l,n):p(k,l,n)  <=  dem(k,l,n)*(1-gam(n)));

@sum(scenario(n):pr(n)*gam(n))  >=  alpha;

@for(bin1(i,j,k,n):ti(i,j,k,n)*b1(i,j,k,n) <= 150);

@for(bin2(i,k,n):tim(i,k,n)*b2(i,k,n)<= 150);



@for(rrc:@bin(u));
@for(bin1:@bin(b1));
@for(bin2:@bin(b2));
@for(scenario:@bin(gam));
@for(fixed2:@bin(m));


END
```

APPENDIX B

CPLEX CODE OF REAL-TIME FACILITY LOCATION MODEL

There are total of three models in the real-time facility location system. In order to get the idea of how they are coded, the Cplex model of lexicographic level #2 is presented.

```
range rrc = 1..RRC ;
range lrc =1..LRC;
range AA = 1..aa;
range items=1..ITEMS;
range att=1..ATT;
int v[i in items] = ...;
float q [j in lrc]= ... ;
float g [j in lrc]= ... ;
float s [l in items][i in rrc] = ...;
float d [l in items][k in AA]= ...;
float t1 [i in rrc][j in lrc]= ...;
float t2 [j in lrc][k in AA]= ...;
float t3 [i in rrc][k in AA]= ...;

float logr1 [i in rrc][j in lrc]= ...;
float logr2 [j in lrc][k in AA]= ...;
float logr3 [i in rrc][k in AA]= ...;
float logq1 [i in rrc][j in lrc]= ...;
float logq2 [j in lrc][k in AA]= ...;
float logq3 [i in rrc][k in AA]= ...;
float a [i in rrc][l in items][j in lrc] = ...;
float b [j in lrc] [l in items] [k in AA]=...;
float c [i in rrc] [l in items] [ k in AA]=...;
dvar float+ x [rrc][items][lrc];
dvar float+ y [lrc][items][AA];
dvar float+ z [rrc][items][AA];
dvar boolean b1 [i in rrc][j in lrc];
dvar boolean b2 [j in lrc][k in AA];
```

```
dvar boolean b3 [i in rrc][k in AA];
dvar boolean m [j in lrc];
dvar float+ at1 [j in lrc];
dvar float+ at2 [k in AA];
dvar float U[s in att];

float alpha [s in att]=...;float Ub[s in att]=...;
float Uw[s in att]=...;
dvar float obj2;

dvar int opened;


dvar float obj;
minimize obj;
subject to
{

forall(i in rrc,l in items)
  ct1:
 sum (j in lrc)(x[i][l][j])+sum (k in AA)(z[i][l][k]) <= s[l][i];

 forall(j in lrc)
   ct2:
     sum(i in rrc , l in items)(x[i][l][j]*v[l]) <= q[j]*m[j];

     forall(j in lrc,l in items)
  ct3:
  sum(i in rrc)(x[i][l][j]) == sum(k in AA)(y[j][l][k]);

   forall(k in AA,l in items)
  ct4:
    sum(j in lrc)(y[j][l][k]) + sum(i in rrc)(z[i][l][k]) == d[l][k];

     forall(i in rrc,j in lrc)
  ct5:
    sum(l in items)(x[i][l][j]) <= 1000000000*b1[i][j];

      forall(j in lrc,k in AA)
  ct6:
    sum(l in items)(y[j][l][k]) <= 1000000000*b2[j][k];

      forall(i in rrc,k in AA)
  ct7:
    sum(l in items)(z[i][l][k]) <= 1000000000*b3[i][k];



  ct8:
```

```
    U[1] == sum(i in rrc,j in lrc,l in items)(x[i][l][j]*t1[i][j]) + sum(j in lrc,k in AA,l in items)(y[j][l][k]*t2[j][k])+sum(i in rrc,k in AA,l in items)(z[i][l][k]*t3[i][k])+ sum(j in lrc)(m[j]*0.0000000001);

    forall(i in rrc,j in lrc)
  ct9:
     at1[j] >=t1[i][j] - 100000000*(1-b1[i][j]);

    forall (k in AA,j in lrc)
   ct10:
     at2[k]>=at1[j]+t2[j][k] - 100000000*(1-b2[j][k]);

      forall (k in AA,i in rrc)
   ct11:
       at2[k]>=t3[i][k]- 100000000*(1-b3[i][k]);

       forall(k in AA)
    ct12:
         U[2]>=at2[k];

    ct13:
   U[5]== sum(i in rrc , j in lrc)(logq1[i][j]*b1[i][j]) +  sum(k in AA , j in lrc)(logq2[j][k]*b2[j][k]) +  sum(i in rrc , k in AA)(logq3[i][k]*b3[i][k])- sum(j in lrc)(m[j]*0.0000000001);


   ct14:
   U[4]== sum(i in rrc , j in lrc)(logr1[i][j]*b1[i][j]) +  sum(j in lrc,k in AA)(logr2[j][k]*b2[j][k]) +  sum(i in rrc , k in AA)(logr3[i][k]*b3[i][k])- sum(j in lrc) (m[j]*0.0000000001);


        U[3] == sum(i in rrc, j in lrc, l in items)(a[i][l][j]*x[i][l][j]) + sum(j in lrc, k in AA, l in items)(b[j][l][k]*y[j][l][k])+sum(i in rrc, k in AA, l in items)(c[i][l][k]*z[i][l][k])+
        sum(j in lrc)(g[j]*m[j]);


forall (s in att)
   ct15:
   obj >= alpha[s]*(Ub[s]-U[s])/(Ub[s]-Uw[s]);




   ct16:
       obj2 == sum(s in att)(alpha[s]*(Ub[s]-U[s])/(Ub[s]-Uw[s]));

    ct17:
       sum(j in lrc)(m[j]) == opened;

              forall(i in rrc,j in lrc)
    ct18:
```

```
                at1[j] >=0;

                 forall (k in AA,i in rrc)
     ct19:
        at2[k] >=0;

    ct20:
   obj>=0;



}
```

CURRICULUM VITAE

Seyed Soroush Moeini

Contact Information

Email: soroush.moeini@yahoo.com

LinkedIn: soroush.moeini@yahoo.com

Research Interests

Supply Chain Management, Humanitarian Logistics, Operations Research, Maintenance, Reliability Engineering, Quality Control & Statistics

Education

Ph.D. in Industrial Engineering, University of Louisville (UofL), KY, USA, 2011 – present.

Master of Science in Industrial Engineering, **Sharif University of Technology** (**SUT**), Tehran, Iran, 2008 – 2011.

Bachelor of Science in Industrial Engineering (Industrial Production), Karaj Azad University (KIAU), Karaj, Iran, 2003 – 2007

Working Experiences

LoDI Research Assistant, Department of Industrial Engineering, University of Louisville (2013 – present)

Reliability Study for Pump Stations in Louisville, KY, Louisville Metropolitan Sewer District & LoDI, Louisville, KY, USA (2012-2013).

Real-Time Decision Support System Research Assistant, Department of Industrial Engineering, University of Louisville (2011 – 2013)

Teaching assistant of Production Planning Course, Industrial Engineering Department of Azad University of Karaj, Iran, 2007.

Computer Skills & Softwares:

Analytical Software: Minitab, Lingo, CPlex, Arena, Excel

Programming Languages: C#, Matlab, Visual Basic

Common Software: Microsoft Word, Visio, PowerPoint, Access

Honors & Awards:

Research Assistant at Industrial Engineering Department of University of Louisville, 2011 - 2014.

Teaching Assistant offered by Industrial Engineering Department University of Louisville, 2011.

Ranked 7th out of 5000 Participants, Iranian National University Entrance Examination for Master of Science in Industrial Engineering, Iran, 2007.

Ranked 3rd out of 128 Students based on GPA, IE Department of KIAU, Karaj, Iran, 2007.

Affiliations:

Real-time Decision Support System (RTDSS)

Logistics and Distribution Institute (LoDI)

Institute of Industrial Engineers (IIE)

Publications:

S. Moeini, L. Bai, John.S. Usher, R. Flynn, *Reliability Study for Pump Stations in Louisville, KY*,