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Advancement on Uncertainty Modeling in Humanitarian Logistics for Earthquake Response

A dissertation presented by

Rubel Das

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in the subject of

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The dissertation titled "**Advancement on Uncertainty Modeling in Humanitarian Logistics for Earthquake Response**" submitted by Rubel Das, student no # 10D51482, has been accepted as satisfactory in partial fulfillment of requirement for the Doctor of Philosophy in the subject of transportation logistics.

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Declaration

It is hereby declared that this dissertation or any part of it has not been submitted elsewhere for the award of any degree.

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Rubel Das

March 2014

Dedication

To My Parent

Dr. Shinya Hanaoka Rubel Das

Advancement on Uncertainty Modeling in Humanitarian Logistics for Earthquake Response

Abstract

Disaster management has four phases: Mitigation, Preparation, Response, and Recovery. Policy makers emphasize on soft measures (i.e., training, evacuation drilling) for preparation and ignores the policies to diminish the suffering of victims after disaster. Victims need relief (i.e., food, water, shelter, medicine) to recover the losses after a disaster. Thus, Humanitarian Logistics (HL) becomes an underpinning task of disaster management for relief planning. The importance of HL is comprehended after the failure in relief distribution after recent disasters Indian Ocean tsunami 2004, Hurricane Katrina 2005 and Haiti earthquake 2010. The response activities after disasters show the limitation of current logistical strategies. It is reported that human suffering and economical losses (due to productivity reduction) escalates due to poor HL. Moreover, recent studies find out that number and impact from disasters are increasing gradually. Earthquake is not predictable and entails complexity. Nonetheless, there are several bottlenecks in HL such as multiple layers of decision-making, shortsighted policy bias, strict control on relief of government, imperfect information aftermath of disaster, and lack of preparedness.

An emerging surveillance on HL is coherent planning of resources in the preparation and utilization of those resources in the response. Herewith, response is a critical phase where decision–maker requires prescribing decisions on inventory, coordination and resources allocation. Due to unique features of HL,

it becomes a new branch of study and academician finds attention in suggesting systematic measures in HL. However, there are lacks of mathematical/ quantitative models in HL.

This study provides three sequential mathematical models for relief operation to illustrate response strategies after earthquake. The three models are (i) Network model in pre-disaster stage, (ii) Relief ordering in response stage and (iii) Relief allocation in response stage. The network model integrates the pre- and post-disaster situations and comprises two mathematical formulations. The first formulation is a deterministic p-median model. This model provides the locations of inventory prepositioning for reaching victims quickly in the Asia-Oceania regions after earthquake. In this model, mean distance per capita is utilized for evaluating the performance of logistics network. It turns out that current UN-HRD (in Malaysia) is not optimally located in the ground of proposed criteria. The second formulation of network model is designed to introduce uncertainty in HL. A stochastic linear model under several constraints is proposed. The tackled uncertainties are demand, supply and facility failure. A case study is performed with earthquake scenarios in Bangladesh. The sensitivity analysis shows that a stochastic model is superior to a deterministic model in term of total expected cost. The transportation cost for distributing relief is lowest in stochastic model in comparison with deterministic and partial stochastic model. Besides, the inventory cost in stochastic model is the highest. However, the shortage cost in stochastic model is the lowest among all models.

The second model analyzes the inventory ordering policy with given logistics network. The model combines two stochastic variables that are (1) lead–time and (2) demand. The underling principal of this model is that lead–time and demand are uniformly distributed. Decision maker has the information of minimum and maximum value of both parameters. The model creates a joint distribution of lead–time–demand (LTD) and provides the prescription for inventory ordering policy via reorder quantity and reorder level. The case study of this model shows an unique reorder quantity exists for certain cost parameters.

The third model explains relief allocation in the domain of stakeholder's behavior in HL. The seemingly different objectives of stakeholders are integrated in the framework of an agent-based model. The ontology of stakeholders is explored to analyze the relationship among stakeholders. Besides, Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) is utilized to create hierarchy of urgency of relief requirement among affected areas. Finally, a new measure for HL performance evaluation is proposed, named 'acknowledgement'. The case study of this model shows that relief allocation based on urgency generates higher acknowledgement value. Additionally, the model generates equal results if sufficient resources are available.

Finally, this study proposes suggestions to the decision makers. Humanitarian depots in Asia-Oceania region for delivering relief to victim aftermath of disasters need to be expanded to tackle the 60% of total disaster among the world. Therefore, Aid organizations need to procure relief item and to store in humanitarian depot before a disaster. Aid organizations also require planning for aftermath of disaster to avoid congestion at point of entry (i.e. airport) and to allocate relief effectively. The study shows that human suffering cost is tradeoff with pre-disaster cost and cooperation among stakeholders can bring greater benefit for the social benefits.

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List of abbreviation

ABM	**:**	Agent-based model
AI	**:**	Artificial intelligence
CDC	**:**	Central distribution center
CDF	**:**	Cumulative distribution function
CL	**:**	Commercial logistics
CRED	**:**	Center for Research on the Epidemiology of Disaster
CLIM	**:**	Commercial logistics inventory management
DM	**:**	Disaster management
EMDAT	**:**	Emergency disasters database
FEMA	**:**	Federal Emergency Management Agency
GIS	**:**	Geographic information system
GPRN	**:**	Global prepositioned resource network
HL	**:**	Humanitarian logistics
HLIM	**:**	Humanitarian logistics inventory management
IFRC	**:**	International Federation of Red Cross and Red Crescent Societies
IPSC	**:**	Inventory positioning for single country
IPMC	**:**	Inventory positioning for multiple countries
PDF	**:**	Probability distribution function
POE	**:**	Point of entry
LDC	**:**	Local distribution center
LTD	**:**	Lead-time-demand
PAHO	**:**	Pan American Health Organization
RDC	**:**	Regional distribution center (or Relief distribution center)
TOPSIS	**:**	Technique for Order of Preference by Similarity to Ideal Solution
UN	**:**	United Nations
UNHRD	**:**	United Nations Humanitarian Response Depots
WFP	**:**	World Food Program

Chapter One

1. INTRODUCTION

The need on the study originates due to poor performance in relief distribution after recent disasters. This study focuses on the uncertainty in humanitarian logistics (HL) in earthquake response. Throughout the study, uncertainty is analyzed in order to develop mathematical formulation. The modeling of uncertainty in HL is aimed to provide high quality relief in the form of food, water, shelter and medicine; this issue is addressed for both pre- and post-disaster activities. Note that this study suggests strategies for known uncertainty. It is expected that the outcomes of the study are helpful for both the aid organizations and the policy maker for designing response strategy in systematically and rationally.

These factors motivate to identify the research need of formulating mathematical model for disaster response. This study uses linear programming model from Operational Research literature and Agent-based model (ABM) from Artificial Intelligence to formulate mathematical model for supporting response strategy after large-scale earthquake. Finally, each model is verified numerically to show effectiveness and stability.

The first section of this chapter presents the background of this study. The subsequent sections are dedicated to motivation and focus, to objectives, and to research methodology. The last section of this chapter discusses the description of the dissertation structure.

1.1. BACKGROUND

The background of earthquake response in the domain of humanitarian logistics is explained in three sub-sections.

1.1.1. Disaster Trend and Growing Needs of Humanitarian Aid

The Center for Research on the Epidemiology of Disasters (CRED) preserves the database of different types of disasters. The CRED calls an event as the disaster, if the event causes at least one of the followings

- 10 or more people killed
- 100 or more people affected
- Declaration of state of emergency

➢ Call for international assistance

The definition of ‘disaster’ is used to prepare the disaster database by CRED. Figure 1-1 and Figure 1-2 describe that the annual rate and the impact of disasters increase significantly in last decades. Four hundred forty natural disasters are reported in 2010; it tolls three hundred thousand human lives and leaves 280 million affected people. The economic damage from natural disaster is estimated more than $130 billion in year 2010 and over $350 billion in 2011. An assessment of United Nations (UN) in 2006 also concludes that: *"... though such figures tend to vary from year to year, overall trends suggest that disasters are becoming more frequent, severe and destructive*".

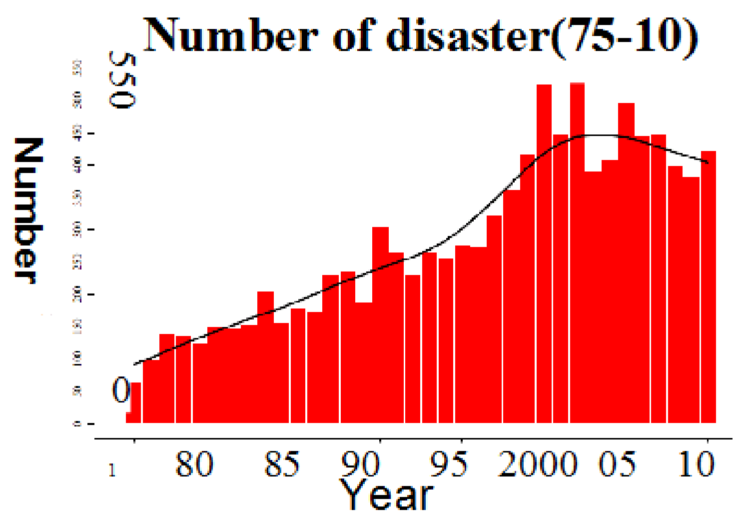

Figure 1-1: Number of natural disaster during 1975-2011 (source: CRED, 2013)

Occurrence time and coverage area influence disaster response largely. The categorization of disaster helps to understand the extent of effect due to disaster. Figure 1-3 shows the categorization of all disasters. The horizontal axis represents time dimension and the vertical axis is coverage dimension. In the Figure 1-3, several terms are used that needs to be defined. ‘slow on-set’ disasters strike slowly; aid organizations obtain longer time to reach to potential victims in order to lessen the impact of the disaster. In contrast, ‘sudden on-set’ disasters allow little to no time to response to the victims. As an example, ‘slow on-set’ disasters allow the potential victims to evacuate the affected area, while ‘sudden on-set’ disasters allow limited scope of evacuation. Similarly, ‘localized’ and ‘dispersed’ represent the relative affected area. There is no threshold value of area to distinguish between ‘localized’ and ‘dispersed’ and the classification is conditional on personal conviction. For example, tornado starts suddenly and leaves its footprint in localized area. On the other hand, drought starts slowly and affects dispersed geographical area.

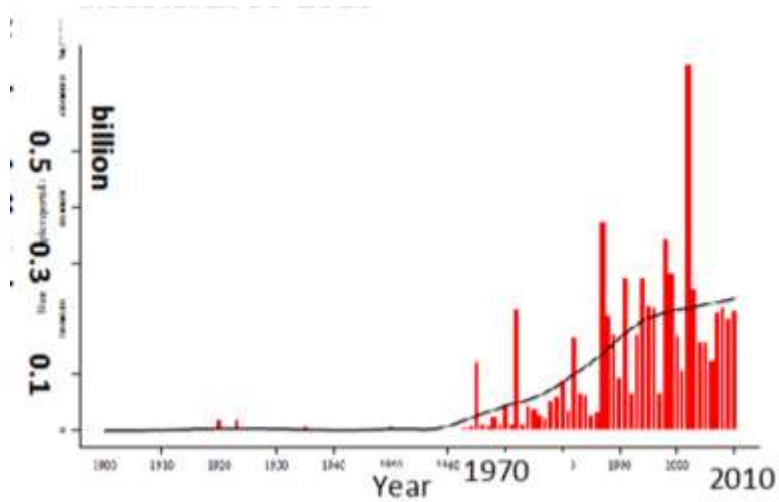

Figure 1-2: Number of affected people by natural disaster during 1900-2010 (source: CRED, 2013)

Each disaster claims particular response actions. Evacuation for particular disaster should be rapid (for example, in case of nuclear disaster); in contrast, evacuation can be done gradually for flood. In addition, the difficulties in response actions are different from one quadrant in Figure 1-3 to another quadrant. Intuitively, the level of difficulty in response is less onerous in the case of localized –slow-onset disasters (*i.e.*, third quadrant). The disasters inserted in the first quadrant in Figure 1-3 are the cause of higher level of difficulty in response actions. Earthquake as well as resulting tsunami is an example of this group and is the focus in this study.

Furthermore, impact of earthquake and level of difficulty in response are higher in developing countries (Thomas and Kopczak, 2007) due to low level of disaster preparedness (*i.e.*, low capacity, poor construction methods). The lack of capacity for disaster response of a developing country generates the necessity of assistance as well as reconstruction and development support after large-scale earthquake. As an example, a magnitude 7.0 M_w earthquake in Haiti in 2010 tolls 159,000 human lives (University of Michigan, 2010) while a magnitude 9.0 M_w earthquake in developed country Japan in 2011 tolls 15,883 (NPAJ, 2013). The number of casualty signifies the effect of preparedness for disasters. However, aid organizations are solely motivated by humanity in responding disaster and do not consider country’s economy in making decisions.

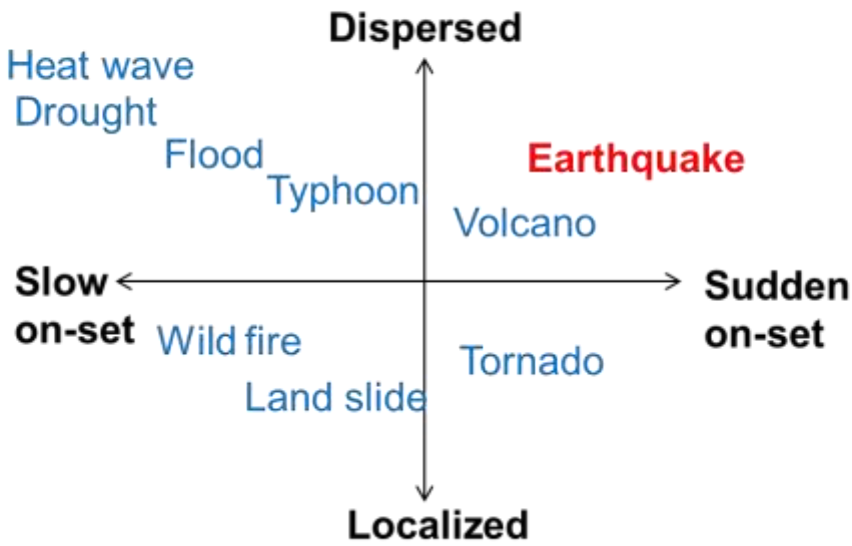

Figure 1-3: Classification of disasters (modified from Apte, 2009)

Aid organizations collect fund from philanthropic donors and commit to use the fund for specific purpose. Global philanthropic aid become more than doubles over the 1990s, from $2.1 billion at the beginning of the decade to $5.9 billion in 2000 (Buchanan-Smith and Randel, 2002). Albeit the philanthropic market is expanding recently, it is not yet sufficient to meet global demand. To maintain and even improve the level of assistance to the victims, the disaster response effort requires becoming considerably more efficient and effective in terms of cost, time and quality.

1.1.2. Comparisons between Commercial and Humanitarian Logistics

The word 'logistics' comes literally from the medieval Latin 'logisticus' of *calculation*, from Greek 'logistikos', *skilled in calculating*, from 'logizesthai', *to calculate*, from 'logos', *reckoning, reason.* It means many things to many people. To business, it is defined as a planning framework for the management of material, service, information, and capital flows. To humanitarians, it comes with different aspect. Recently, Thomas and Mizushima (2005) defined humanitarian logistics as "*the process of planning, implementing, and controlling the efficient, cost-effective flow of and storage of goods and materials as well as resulted information, from point of origin to point of consumption for the purpose of meeting the beneficiary's requirements* ".

Aid organizations are about thirty years behind their commercial sector counterparts. Just as the commercial sector, humanitarian organizations are recognizing the fact that humanitarian logistics:

- is crucial to the performance (effectiveness and speed) of current and future operations and programs (Van Wassenhove, 2006)
- serves as a bridge between disaster preparedness and response, between procurement and distribution, and between headquarters and the field (Thomas and Mizushima, 2005)
- provides a rich source of data; since logistics department handles the tracking of goods, which can be used to analyze effectiveness (Thomas and Mizushima, 2005)

Table 1-1 : Properties of commercial and humanitarian logistics

Item	**Commercial logistics**	**Humanitarian logistics**
Demand forecasting	Historical database	Based on quick assessment
Network structure	Predetermined	Dynamic
Aim	Generating profit	Minimizing suffering
Product value	has monetary value	Does not measure in monetary value
Planning period	Long time	Generally, short time
Fleet size	Unlimited	Limited
Inventory type	Strategic inventory	Social inventory (Whybark, 2007)
Preferred acquisition	Low -cost source	Nearest source
Benefit of inventory	Higher service level	Saving human lives
Out of stock	Waiting for scheduled arrival	Finding the responsive supplier

After the awareness of importance of humanitarian logistics, aid organizations become interested to improve it. However, humanitarian logistics struggles with very special characteristics that make difficulty in improvement. The dominating characteristics of humanitarian logistics are as follows (Balcik and Beamon, 2008):

- Unpredictability of relief demand (*i.e.,* occurrence of disaster), in terms of timing, location, type, and scale
- High stakes associated with adequate and timely delivery
- Lack of resources (supply, people, technology, transportation, and money)
- Differences in goals of stakeholders
- Non-monetary profit after the distribution of additional unit of relief

The above-mentioned properties make the differences between commercial logistics and humanitarian logistics and impose the need of new models for humanitarian logistics. The objective of humanitarian logistics is to provide relief to areas affected by large-scale disasters, to minimize the human suffering and death. On the other side, business logistics aims for generating monetary profit. Table 1-1 shows the difference between commercial logistics and humanitarian logistics. Commercial and humanitarian logistics have dissimilarities in many aspects.

1.1.3. The Overview of Earthquake Response

Tufekci and Wallace (1998) suggest that disaster response efforts consist of two stages: pre-disaster and post-disaster response. Pre-disaster tasks include predicting and analyzing potential dangers and developing necessary action plans for mitigation. Post-disaster response starts while the disaster is still in progress. At this stage, the challenge is locating, allocating, coordinating, and managing available resources. FEMA (2009) describes disaster management in terms of four phases: Mitigation, Preparedness, Response, and Recovery (Green, 2002; Waugh, 2000; Godschalk, 1991; Waugh and Hy, 1990). The four-phase approach covers all of the actions described in Tufekci and Wallace's (1998) classification while providing a more focused view of disaster management actions. The performance of post-disaster response is highly dependent on pre-disaster actions.

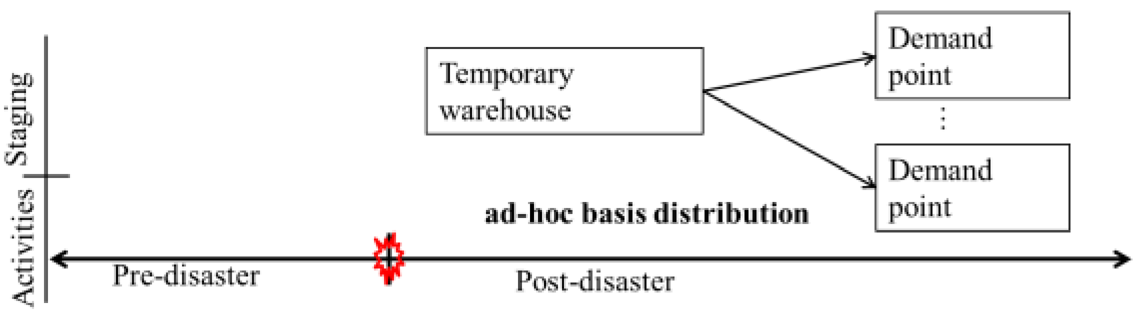

Figure 1-4: Current humanitarian logistics (in general)

Figure 1-4 shows that pre-disaster activities for relief distribution are ignored in general. Stoddard (2004) founds that aid organizations follow the reactive strategy (*i.e.*, takes actions after a disaster) instead of the proactive strategy (*i.e.*, takes actions before a disaster). Therefore, victims do not get relief in earliest time. There is substantial gap between disaster and delivering relief to the victims. Furthermore, fund allocation is not balanced in all phases of disaster management. There are limited allocation of fund in three stages of disaster management namely mitigation, preparedness, and recovery. Pre-disaster activities are considered as the vital stage to improve the performance of response actions. The imbalance in fund allocation and the delay to reach victims ultimately emphasizes the necessity of extensive research to improve the earthquake response.

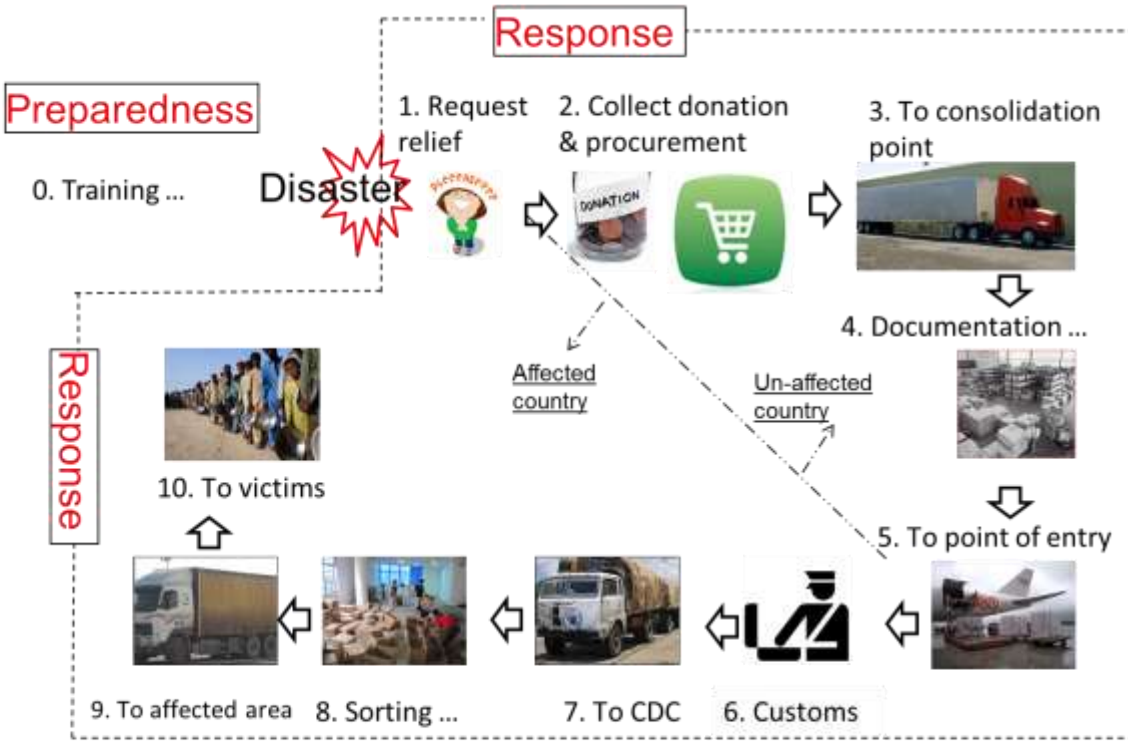

Figure 1-5: Relief flow

*CDC = Central distribution center

Figure 1-5 shows the activities and stages of relief flow. The warehouses where relief is stored for future disasters in other countries are known as ‘Humanitarian depot’. Storing relief in ‘Humanitarian depot’ is not globally popular and is absent in the figure. Central distribution center (CDC) is generally located near point of distribution. In contrast, ‘local distribution center’ (LDC) establish at the affected areas after a disaster and relief is stored here for disaster still in progress. LDC is established temporarily. The humanitarian depot, CDC, LDC, the demand points, and the transportation create a humanitarian logistics network and it improves the ability for disaster response. The ability of aid organizations’ logistics directly influences the aim of aid organizations that is described as delivering right amount of goods in right time at right cost to right people.

In preparedness, according to PAHO (2001) and Thomas (2001), preposition, or the storage of relief at or near the probable affected areas is the possible response strategy for reducing time-gap between disaster occurrence and delivering relief. The design of humanitarian logistics network, particularly geographic location of depot and quantity of relief, is a vital action in preparedness stage. However, these issues are difficult to determine due to several stochastic parameters.

While preparedness increases the probability of prompt-action and availability of relief, aid organizations require designing response plan integrating with humanitarian logistics network to reach victims as soon as possible after large-scale disaster. Aid organizations face uncertainty in different stage of relief as shown in Figure 1-6. Uncertainties are classified in three broad groups: demand uncertainty, supply uncertainty and network uncertainty. Demand uncertainty prevails in pre and post disaster environment. It is always difficult to identify the location of victims and requirements. On the other hand, supply and network uncertainty commence in post disaster. Supply uncertainty includes reduction of capability of supplier or fuzziness in total amount of donation. Lastly, network uncertainty includes transportation related and aid organizations related events.

It requires logistical knowledge to overcome the complexities of response strategies. However, aid organizations do not apply the logistics knowledge in response actions. They bring relief (item) to the disaster sites without being concerned of outcome. The response strategy triggers high wastage of relief, shortage of storage capacity and uneven distribution among demand points. The aftermath is that some victims get abundant relief while others get nothing.

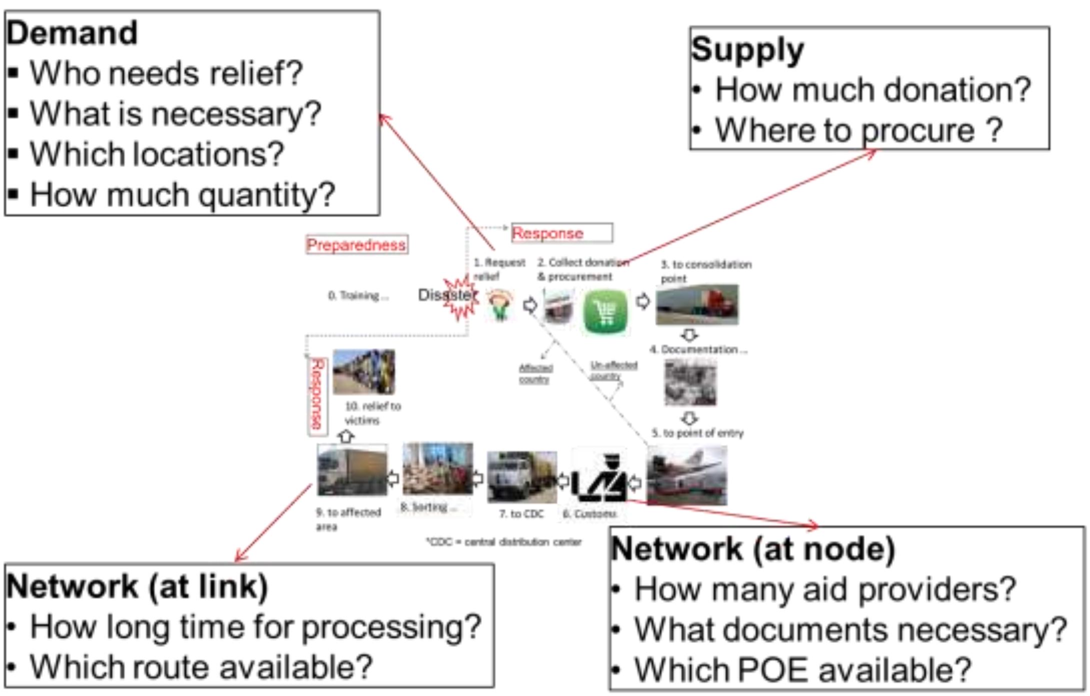

Figure 1-6: Uncertain information in relief flow

Response plan consists of several management issues, for instance transport management, inventory management, demand management and supply management. Transport is the second largest cost to relief operations after personnel. The most wide used vehicle type in relief distribution is 4X4 vehicle and the total fleet size of 4X4 vehicles in large international humanitarian organizations is estimated between 70,000 and 80,000 units (Martinez *et al.*, 2010). Several studies propose mathematical model for *transport management* and suggest for utilizing modern technology for improving the usage to transport resources. However, aid organizations still manage transport resources in ad-hoc basis and hire transport on spot (Balcik and Beamon, 2008). Then, *demand management* that needs a consideration of cultural differences in disaster regions (Wichmann, 1999). Demand is unpredictable regarding timing, scale, and locations (Long and Wood, 1995). In case of *supply management*, aid agencies receive many unsolicited and sometimes even unwanted donations (Chomolier *et al*., 2003). These can include drugs and foods that are ended their expiry dates (Murray, 2005).

Among them, *inventory management* gains less attention despite its importance. Aid organizations setup local distribution center in affected areas for distributing relief and need to have a plan for relief supplies. A local distribution center cannot place order (or request for relief) of unlimited quantity in a single ordering from the Humanitarian response depot due to transport bottleneck and supply limitation. In current response strategies, supplies arrive in disaster areas in unmanageable forms and clog airport and warehouses (Cassidy, 2003; Murray, 2005). The characteristics of logistical activities depict the importance of inventory management and aid organizations require ordering policies models to gear up the response actions.

Another important aspect of response planning is resource allocation that arises in specific situations; particularly in a case of limited resources. After receiving relief at local distribution center from Humanitarian response depot (or from donation), aid organization requires making plan for effective utilization of relief. If degree of relief urgency is the criteria for relief distribution, the highest index victims should get first. Indeed, aid organizations face difficulties in making hierarchy among victims due to uncertainty of information that leads to inefficient relief distribution.

1.2.MOTIVATION AND FOCUS

Natural and man-made disasters are always coupled with a series of negative consequences – internal displacement of person, water and food shortage, inaccessibility, and break down of services and infrastructure damage/destruction (Hampton, 2000). Figure 1-1 shows that total number of disaster in last decade (2000 – 2010) is around 500 per year. These include the Iran (Bam) earthquake 2003, the Kashmir earthquake 2005, the Indian Ocean tsunami 2004, the Hurricane Katrina 2005, the China (Sichuan) earthquake 2008, the Haiti earthquake 2010 and the great east Japan (Tohoku) earthquake 2011. CRED (2013) reports that affected people per year by disasters are about 200 million. According to recent studies, the rate and impact of disaster are expected to increase by a further multiple of five times over the next fifty years (Thomas and Kopczak, 2007).

Figure 1-7 shows the causes for the importance of humanitarian logistics. The five causes are high stake of time, donors' pressure, social responsibility, lack of resources at peak time, and competing among different agencies. 'High stake of time' represents that there are urgency of relief and the effectiveness of relief will be diminished if relief is delivered to victims late. Next 'donors' pressure' suggests that the philanthropic donor expect the proper utilization of funds and can deny supporting aid organization in future if aid organization does not use the fund properly. Then, 'competition among different agencies' brings the idea of market mechanism where aid agency (organization) tries to attract donors and show the performance on effective utilization of funds. Then, 'social responsibility' embraces the ethics of relief distribution and the obligation of aid organizations to deliver quality relief to victims. Last, 'lack of resources at peak time' supports the claim in Figure 1-8 that the existing response strategy makes the shortage of relief item in peak period. The five-causes model highlights the importance of humanitarian logistics.

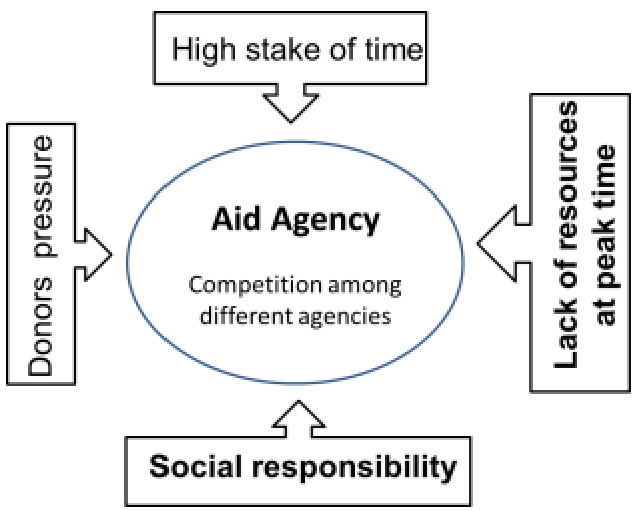

Figure 1-7: Five- causes model for importance for humanitarian logistics

Recently, the number of publication on humanitarian logistics has increased drastically. The number of publications and special issues on this topic has risen recently considerably, which indicates good pedagogics development. Academician gets attention in humanitarian logistics due to poor logistical outcomes in recent disasters. Despite substantial number of publications on humanitarian aid and disaster relief appear; there are only limited mathematical models on humanitarian logistics. However, most articles on the topic of humanitarian logistics propose conceptual framework. These take the form of field reports and evaluations and cover one or more disaster response that highlight the general challenges and issues in HL, often accompanied by recommendations for further improvement (Beamon, 2004). Russell (2005), collaboration with the Fritz Institute, uses the Indian Ocean tsunami 2004 to carry out a survey among logisticians from the participating international organizations, with the aim of documenting common challenges and problems as a means of improving preparation for the next disaster relief efforts. They find out that aid organizations attain decisions on ad-hoc basis. Kovacs and Spens (2007) streamline the focus by reviewing humanitarian logistics research until 2005 and shows that logistics are still undervalued in disaster response. There are a few mathematical models for emergency response strategy to support decision-making. Despite mathematical models are essential, those models appear lately. Some of the models propose transportation routing and scheduling (Haghani and Oh, 1996; Ozdamar *et al*, 2004), helicopter planning (Barbarosoglu *et al.*, 2002; Barbarsoglu and Arda, 2004), medical aid location planning (Mete and Zbinsky, 2010), and Network planning (Akkihal, 2006; Balcik and Beamon, 2008; Ukkusuri and Yushimito, 2008). Beamon and Kotleba (2006) attempt man-made disaster for formulating inventory model. Caunhye et al. (2012) show that HL encounters more uncertainty than business logistics does.

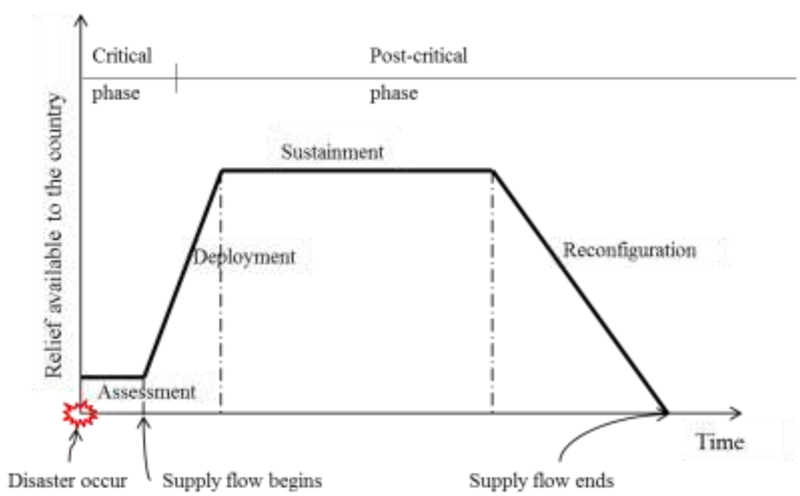

Figure 1-8: Available relief in affected country (edited from Thomas, 2001)

Some of above mentioned studies have incorporated stochastic parameters of demand side. The uncertainties from supplier side and transportation side get less attention. It is obvious that a model must include uncertainties from demand side, supplier side, and transportation side. Thus there are still scopes to improve the models after incorporating stochastic parameters.

Tufekci and Wallace (1998) suggest that an effective emergency response plan should integrate both pre- and post-disaster stages within its objective; otherwise, strategy may lead to suboptimal solution to the overall problem. With this in the mind, **this study integrates pre- and post-disaster actions to solve uncertainty specifically on inventory issues**. Inventory issues are chosen since aid organizations face shortage of resources in critical phase (*i.e.*, 48 hours to 72 hours immediate after disaster); it needs proper planning even in post-critical phase (*i.e.*, after 72 hours of disaster occurrence). Figure 1-8 depicts the resources available at affected sites after disaster. During the assessment phase, aid organizations collects fund from donors and estimate relief demand. Longer duration for assessment and deployment in critical phase may harm the human lives and increases fatalities. This study proposes models to reduce delay and distribution cost in critical phase and propose inventory-prepositioning model.

The proper utilization of inventory is also burning issue in post-critical phase due to the facts of duplication of relief efforts in particular affected areas and the lack of relief in other affected areas. This issue becomes inevitable in a situation of scarcity of resources. Recent disaster relief operations were not efficient in using the available resources. Some affected areas get more relief and some affected areas get nothing. Relief must be distributed based on proper evaluation; otherwise, it may create social dissatisfaction and unrest. Indian Ocean tsunami (2004) and Haiti earthquake (2010) relief operations are the evidence of these claims. Unfortunately, aid organizations face difficulties in making hierarchy among victims which may lead to inefficient relief distribution which motivate to formulate model for inventory utilization through demand management

1.3. RESEARCH QUESTION AND OBJECTIVES

The fast growing trends of number of disaster in a year, the unique differences of humanitarian logistics from commercial logistics, and the stochastic environment in using of funds necessitate the formulation of robust, flexible and simple response strategies to minimize the negative impacts of large-scale disaster. Recently, aid organizations also begin to assess improving response strategies and utilizing the experiences for tackling future disasters. Specific circumstances (*e.g.*, uncertainty in transport network and in demand) and internal information (*e.g.*, resource availability, capacity constraints) are major components for planning the response strategies. In this context, we address the following scientific problem in this research:

How uncertainties in relief flow can be resolved to improve performance in HL after earthquake?

Relief is the most essential item during response actions. Herewith, aid organization spends significant portion of money for logistics of relief distribution and there is still, unfortunately, large time gap between the disaster occurrence and the reaching victims. In this study, time and cost are the performance criteria. Accordingly, aid organizations need mathematical tools so that outcomes of actions are further observed/ assessed for improving response strategies. From the scientific problem stated above, the study defined the main objective as the conceptualization/ formulation of management of relief against uncertainty to reach victims effective and efficient way. In order to tackle the scientific problem stated above, we divided the research questions in three parts. They are:

1. What logistical factors influence the performance in HL?
2. How network design can improve the performance in HL?
3. What post-disaster planning can improve the performance in HL?

Based on our research agenda, this study aim to achieve following objectives:

1. To identify causes for poor performance of HL after earthquake

2-1. To formulate a deterministic network model for multi-nations disaster response.

2-2. To formulate a stochastic network model for single-nation disaster response.

3-1. To clarify effects of uncertainty in relief ordering.

3-2. To create relief operation model for aid organization and to simulate the performance of aid organization.

Objective (1) identified decision-making difficulties in uncertain environment. While objective (2-1) does not tackle the uncertainty explicitly, objective (2-2) explores demand and supply uncertainty for establishing a network for relief distribution. In this objective, network uncertainty is also introduced implicitly. Objective (3-1) and (3-2) are post-disaster planning. Objective (3-1) investigates uncertainty of demand and network (in the form of lead-time) for planning relief ordering. Lastly, objective (3-2) suggests policy for dynamic environment. Here, uncertainty is involved implicitly in demand calculation and presence of other aid organizations.

1.4. METHODOLOGY

The study has roots in practical problems facing the community. It formulates mathematical models that contribute to overcome the bottlenecks for practical problem. It employs Operational Research (OR) and Artificial Inteligence (AI), while necessary empirical foundation is created through literature review and on-line reports. Figure 1-9 illustrates the proposed study method, which is described below.

This study interviewed World food program (WFP) and Disaster Risk Reduction section in UN-ESCAP in September 2011. Interviewees were section chief, manager, and service employee. The discussion agenda was mainly difficulties in relief operation and future planning. Besides, a series of real disaster observations are conducted since 2010. They allow us to collect and analyze data towards the understanding of aid organizations response strategy. Thus, a complete relief deployment process is identified and it supports the background of mathematical model formulation. Nonetheless, it is found that the data gleaned through the case study have limited applicability for the assessing the models. In this context, some paramters are assumed for model testing. Therefore, the results provides only understanding for the response strategies.

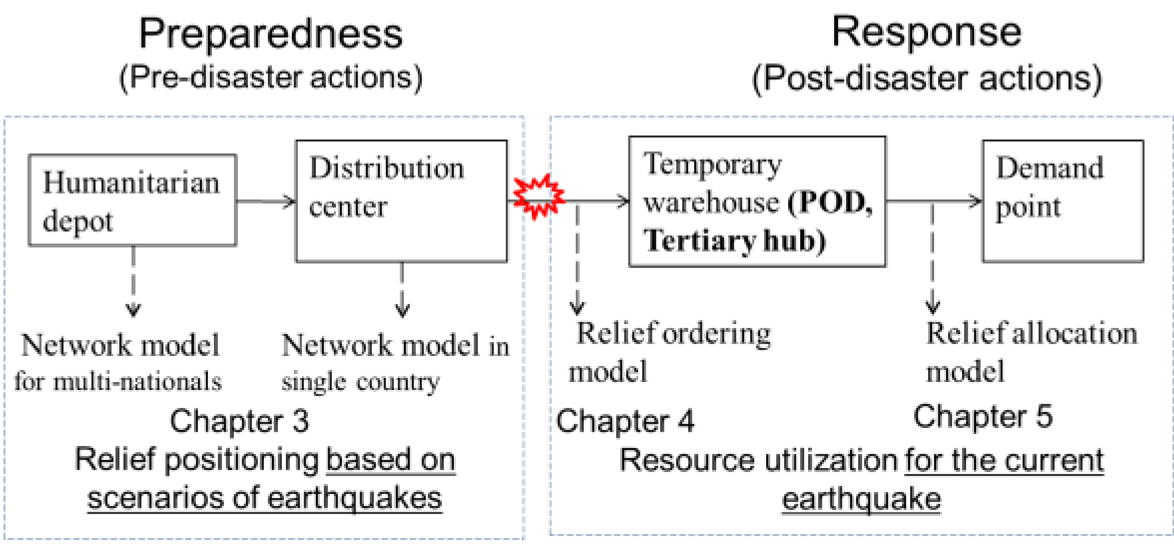

Figure 1-9: Research method

This study analyzes the effect of logistics network in relief distribution. Afterwards, relief ordering and allocation model capture the operational characteritics of the relief distributiom. This study proposes inventory prepositioning model or network model, inventory model and releif allocation model. The study proposes two pre-disaster models and two post-disaster models. While the relief ordering model explores the stochasticity of post-disaster environment, the relief allocaiton model is an operational model that analyze the dynamic environment of relief distribution after disaster.

Pre-disaster tasks is seting network for inventory positioning. A deterministic linear programming model for network design is proposed in order to support quick response in multi-nationals after large-scale earthquake. The historical database for Asia-Oceania regions is collected from EM-DAT. Another network model incorporates stochasticity to support the uncertain environment in a affected country. The model incorporates supply and demand uncertainty.

The relief ordering (inventory model) and relief allocation, are explained subsequently. The inventory model adopt the stochastics logistical parameters and proposes strategies for ordering relief. Since data are not available/relieable after large scale earthquake, this model assume uniform distribution of parameters which allows decision maker finding solution through solving simple model. Relief allocation model incorporates the outcome of network model and inventory model. The model allocates the relief with given network and resources. Then, this model evaluates the performance of logistics systems. The software and other properties of each model are tabulated in Table 1-2.

Table 1-2: Properties of model

Model	**Model type (software)**	**Data**	**Application**
Network model for multi nationals	Deterministic (COIN-OR LP code (clp))	EM-DAT	• Before disaster for a region (e.g. Asia) • Historical disaster.
Network model for single country	Stochastic (Gurobi)	On line reports	• Before a disaster in a country • For scenario of disasters
Relief ordering model	First order differential equation (R)	Interview, report	• After a disaster in a country • Uncertainty in current disaster
Relief allocation model	Agent-based Model(NetLogo and R)	Tohoku earthquake report	• After a disaster in a country • Dynamic environment in current disaster

Researching a complex topic like response strategy after large-scale earthquake poses a series of challenges. There are few academic papers available that aim of formulating mathematical models. This study proposes several models to analyze the process. Author admit that there are scope of debates on proposed models. However, those models can be good starting point for formulating advance models for humanitarian logistics. The contributions of this study are listed below

- The network model for multi-nations uses a new measure per capita-distance which is used to evaluate the vulnerability of each people. This measure can also be used for network models for other services such medical aid network, fire stations design.
- The network model for single country includes supply uncertainty and demand uncertainty for strategic decisions. This model also incorporates facility failure probability. Despite failure probability is difficult to estimate, the incorporation of failure probability deserves attentions. Because many facilities are unable to deliver their services after disaster. Thus, this study may bring attention on this issue.
- The inventory model makes this study significant. This model is transformed in closed form and solved it via open source software. It shows the computation methodology of two stocahstic variables.
- The relief allocation model is a new tool in humanitarian logistics. This study proposed a new approach in agent based model framework for relief demand management.
- The agent based model is also used for evaluating the performance of logistics systems. Here, a parameter is introduced for aggregrated value.

This research also has several limitations. Since the contibutions of the study are model development, the study could not follow single disaster to analyze the models. Some parameters were not possible to measures based on real data. However, we tried to assume the parameters to represent real situaitons.

1.5.DISSERTATION STRUCTURE

This dissertation is divided into six chapters, as shown in Figure 1-10, in order to describe all the activities undertaken during the study. After this introductory chapter, literature review is presented in second chapter. Then, models are presented in three subsequent chapters.

The second chapter explores the state-of-art of response strategies and the theoretical base of mathematical models. This chapter also meet the first objective this study. Additionally, it also shows the contribution of this study for improving the theoretical knowledge.

The third chapter describes the link between pre- and post-disaster task. It illustrates the importance of preparedness for improving efficiency of post-disaster response. Two different network models are described aiming of improving efficiency of post-disaster response. The first model aims for reduction of time gap between the time of disaster occurrence and that of arrival of relief. This study focuses on large-scale earthquake, however, this model incorporate meteorological disaster as well as earthquake. Other model incorporates stochasticity of logistics parameter to show trade-off between pre- and post-disaster cost. This chapter fulfills four objectives of this study (objective 2-1 and 2-2)

Building upon network and inventory quantity from chapter 3, the fourth chapter presents an inventory model, which embraces post-disaster circumstances. The novel approach combines stochastic lead-time and demand parameters, which are uniformly distributed. By adopting the algorithm proposed by Glen *et al.* (2004), the model computes the joint distribution of these two parameters. This chapter accomplishes objective 3-1 of this study.

The fifth chapter presents the relief allocation in post-disaster circumstances. It initially explores the stakeholders of humanitarian logistics and draws the conflict in objectives among stakeholders. Then, this study proposes an agent-based model, where the network built in chapter 3 and the resources accumulated in chapter 4 are plugged in. This model allocates resources among demand points and provides the value of performance of logistics. This chapter accomplishes objective 3-2 of this chapter.

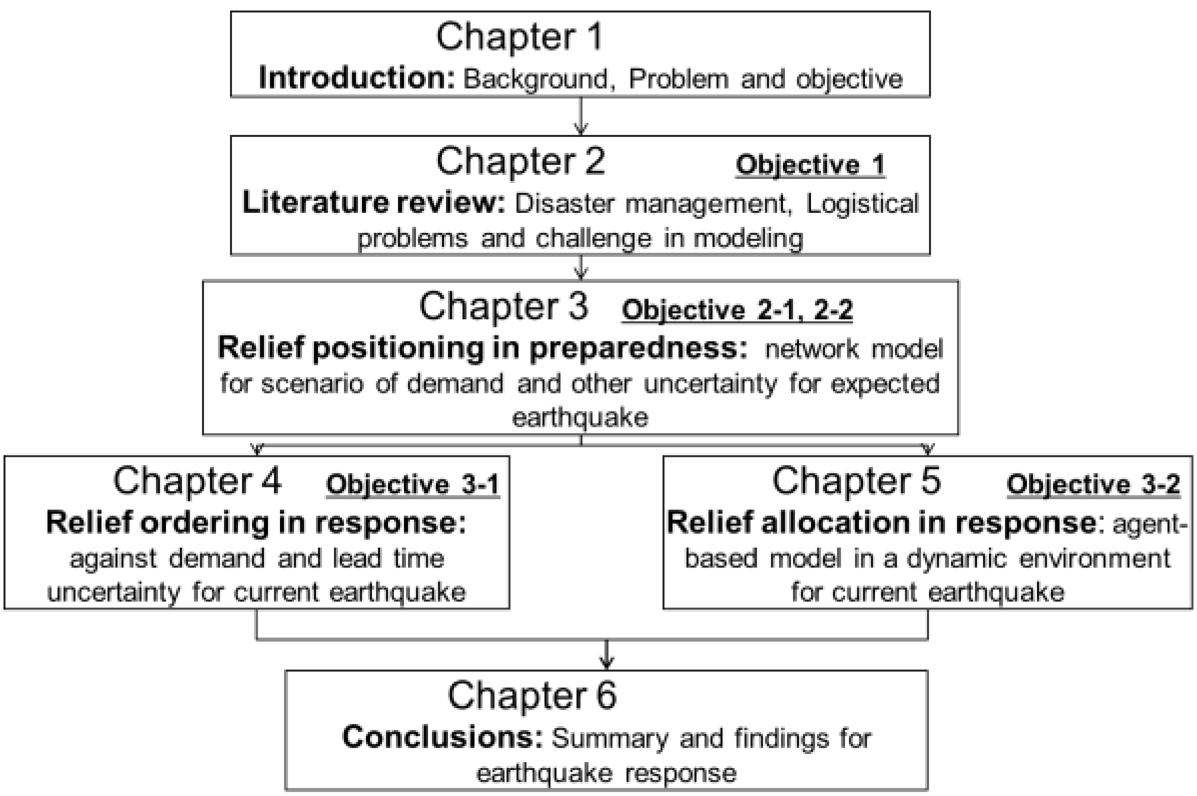

Figure 1-10: Dissertation structure

Finally, the last chapter summarizes the study and all the steps taken to reach its outcomes: i) network design for quick response, ii) inventory management after disaster and iii) relief allocation after disaster. The study outcomes are summarized and both successes and limitations are reported. This chapter closes by highlighting the future study needs.

Chapter One

1. INTRODUCTION

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Chapter Two

2. LITERATURE REVIEW

Common logistical decisions in HL include - Where should the warehouse be located? Which product should be procured from which supplier? Which product should be stored? How much of which product should be kept? What transport mode/route should be used? What should the time gap between two consecutive relief deliveries be? Which facilities should be built? What should the relief allocation approach be?

A certainty in disaster is that uncertainties appear in the decision-making processes in the context of HL. Altay and Green (2006) suggest that Operation Research/ Management Science (OR/MS) studies are recognized in disaster management for facilitating rational decisions. They provide a holistic review of the use of OR/MS methods in disaster management until 2004 and recognize the need for research in this area.

The chapter ultimately builds the basic knowledge necessary to achieve the main objective of this study. In Section 2.1, the concept of disaster management is explored. Then, uncertainty in disaster management is explained in section 2.3. In section 2.4, the state-of-art of planning in preparedness and planning is presented. Section 2.5 and 2.6 explain the relief ordering model and relief allocation model.

2.1.DISASTER MANAGEMENT

Disaster Management (DM) has become a broad discipline dealing with risk management, response and recovery. It aims at either avoiding a disaster or reducing its impact on communities and economies. Several studies have been undertaken in the context of engineering, geology, psychology, policy making, resilience and many other disciplines to propose framework for DM. Outcome from different fields have helped to frame DM under specific management structures aiming at coordinated response. Logistics is recognized as critical activities in incident command system.

2.1.1. Disaster Management Concepts

A series of concepts is presented in this sub-section in order to explore different facets from Disaster Management. This subsection starts by defining disaster events and the four Disaster Management components, i.e. Mitigation, Preparedness, Response, Recovery.

2.1.1a. Disaster events

All hazards are not disaster; some hazards are named as 'disaster' considering their impacts. In order to define disaster events, the definition of hazard is presented. Hazards are potential physical instances, phenomenon or human activity that can harm a community and damage to its infrastructure. The Cambridge Dictionary also associates hazards with danger (an instance likely to cause damage) and risks (probabilities of events to produce harm or create damage) (Cambridge, 2008)

Disasters or extreme events are the result of the combination of hazards and vulnerabilities, which overwhelm community's ability to cope with the situation; therefore, incurs in loss of life and/or damage to infrastructures. The situation can be motivated by the geophysical or biological environment (natural disaster) or by human action or error (man-made disaster). CRED (2009) summarize this conceptual topic by referring to extreme events as uncertain outcomes from either natural or man-made hazards, which creates potential damage and broad consequences to communities.

Finally, an disaster event represents a present or imminent disaster or extreme event, which prompts co-ordinated actions among people and organizations in order to protect life and/or property or reduce death and/or damage. disaster events necessarily involve response and coordination towards risk reduction (for imminent disaster) or impact reduction (for present disasters).

2.1.1b. Mitigation

Mitigation involves pre-event actions taken in order to comprehend and reduce risks associated with hazards. The understanding of potential hazards reduces community's vulnerability and increases its ability to cope with disasters situations. FEMA (2009) formally defines "Mitigation is the effort to reduce loss of life and property by lessening the impact of disasters. Mitigation is taking action now—before the next disaster—to reduce human and financial consequences later (analyzing risk, reducing risk, insuring against risk)."

Numerous frameworks and projects propose different paradigms for mitigation as it is acknowledged that future disasters cannot be exactly predicted. For instance, FEMA (2009) made available to the general public a standardized methodology and software (HAZUS-MH) containing models to estimate loses due to a number of events (e.g. earthquake, flooding, hurricane). In summary, mitigation can be defined as a group of actions taken before an extreme event in order to comprehend the relationships between communities (people and systems) and the surrounding physical environment. Such an approach has been already proven successful for disaster's prevention and reduction.

2.1.1c. Preparedness

The second DM component focuses on readiness or planning. The Cambridge Dictionary (Cambridge, 2008) defines the adjective ready as being prepared and suitable for immediate activity. According to basic premises from disaster preparedness, organization and people should exercise and plan in advance so they can be ready for immediate response.

A common framework used for preparedness refers to previous planning, mutual assistance agreements, resource inventories, equipment and formal training. A practical three objective program is proposed by the IFRCRCS (2002) comprising the following:

- To increase efficiency, effectiveness and impact of disaster response by developing regular training, system's testing and establishing clear policies.
- To strength community preparedness by supporting local population through National Programs; and
- To develop activities addressing everyday risks faced by communities

2.1.1d. Response

The comprehension of risks (mitigation) along with response planning (preparedness) supports people and organizations to quickly and effectively respond to extreme events. It usually aims at reducing potential impacts associated with the occurrences of an extreme event according to specific situations, conflicting priorities and resources limitations.

Response is defined as co-ordinated actions taken immediately before, during or shortly after a disaster occurs. They refer to short term activities aiming at managing the situation through public communication, search and rescue activities, medical assistance, evacuation, and well-being/hosting. These activities are performed under strict levels of co-ordinations so conflicting priorities and resources limitations can be properly taken into consideration before resources can be deployed.

2.1.1e. Recovery

Recovery targets the reparation and restoration of communities and systems up to acceptable levels of operationability after a disaster occurrences. Sullivan (2003) explores more this concept by describing recovery as activities undertaken immediately after the initial response, which bring self-sustainability to affected communities so external support frameworks and resources are no longer needed.

2.1.1f. Logistical activities in four stages

Table 2-1 summarizes the activities in four stages of disaster management

Table 2-1: Activities in four stages of disaster management

Mitigation	Preparedness
• Zoning and land use controls to prevent occupation of high hazard areas • Barrier construction to deflect disaster forces • Active preventive measures to control developing situations • Building codes to improve disaster resistance of structures • Tax incentives or disincentives • Controls on rebuilding after events • Risk analysis to measure the potential for extreme hazards • Insurance to reduce the financial impact of disasters	• Recruiting personnel for the emergency services and for community volunteer groups • **Emergency planning** • Development of mutual aid agreements and memorandums of understanding • Training for both response personnel and concerned citizens • Threat based public education • Budgeting for and acquiring vehicles and equipment • **Maintaining emergency supplies** • Construction of an emergency operations center • Development of communications systems • Conducting disaster exercises to train personnel and test capabilities
Response	**Recovery**
• **Activating the emergency operations plan** • **Activating the emergency operations center** • Evacuation of threatened populations • Opening of shelters and provision of mass care • Emergency rescue and medical care • Fire fighting • Urban search and rescue • Emergency infrastructure protection and recovery of lifeline services • Fatality management	• Disaster debris cleanup • Financial assistance to individuals and governments • Rebuilding of roads and bridges and key facilities • Sustained mass care for displaced human and animal populations • Reburial of displaced human remains • Full restoration of lifeline services • Mental health and pastoral care

Source: Altay and Green, 2006

2.1.2. Disaster Management in the Context of Humanitarian Logistics

Increasing natural disasters have led to heightened interest in identifying and reducing the vulnerability of infrastructure networks (Auerswald et al., 2005). In a disaster situation, local and central government agencies as well as civil organizations mobilize their resources immediately to rescue victims and to supply medical care, machinery, and relief commodities to the affected areas. In addition to the time-critical operations carried out by the agencies, some residents will be on the roads trying to evacuate the affected areas while others will try to reach the area to provide humanitarian aid and to help their relatives. As a result, the proper functionality of the transportation network is essential for the success of the rescue and relief operations. It is commonly observed that a disaster may render some of the links of the transportation network non-functional, leading to the blockage of some routes and/or disconnectedness of some areas in need of aid. Above mentioned issues inspire to include humanitarian logistics in disaster management.

Humanitarian logistics focuses on particular task in disaster management and aims in providing relief. Humanitarian organizations are supposed to make decision under certain humanitarian principal including Humanity, Impartiality, Neutrality, Independence, and Empowerment. Short description of these principals has given below

- **Humanity:** Human suffering should be addressed wherever it is found. The dignity and rights of all victims must be respected and protected
- **Impartiality:** Humanitarian assistance should be provided without discriminating as to ethnic origin, gender, nationality, political opinions, race or religion. Relief of the suffering of individuals must be guided solely by their needs and priority must be given to the most urgent cases of distress.
- **Neutrality:** Humanitarian assistance should be provided without engaging in hostilities or taking sides in controversies or a political, religious or ideological nature
- **Independence:** The independence of action by humanitarian agencies should not be infringed upon or unduly influenced by political, military or other interest.
- **Empowerment:** Humanitarian assistance should strive to revitalize local institutions, enabling them to provide for the needs of the affected community. Humanitarian assistance should provide a solid first step on the continuum of emergency relief, rehabilitation, reconstruction and development.

It utilizes the knowledge of transport modeling, disaster management and commercial logistics. The inclusion of humanitarian logistics in disaster management has drawn a new research prospect, which is under investigation in this thesis. There are necessities of mathematical model for humanitarian logistics and this study proposes mathematical models for relief distribution for uncertain environment.

2.2. FAILURE IN DISASTER RESPONSE

The failure in disaster relief response is observed after each major disaster in the world. Several studies identify the reasons of failure from different ground, particularly highlight the complexity in decision making. Sobel and Lesson (2006) utilize public choice theory to identify six problematic incentive structures confronted by government actors when managing the disaster caused by Hurricane Katrina in United States of America (USA). The private sector's response to Hurricane Katrina was swift and effective when compared to the government's response. Companies like Wal-Mart, Home Depot, and State Farm insurance made preparations for the impending disaster weeks before Katrina hit, and were willing and able to bring resources to bear on the disaster area days before government agencies could manage to do so. In contrast, government recognition and response to Katrina was confused, chaotic and much slower. The widespread example of successful private action in equivalent circumstances after Katrina clearly demonstrate that there government failures were not endemic to the situation – they were potentially avoidable under the right incentive structure. The reasons of failure in disaster response are mentioned below.

1. **Many layers of decision makers:** Government agencies like FEMA suffer from a problem of too much government oversight. When disaster relief is centralized and managed by government, it necessary become bureaucratized. In this situation, action requires the permission of many different and often unrelated individuals. At each layer of the bureaucratic process is a key political decision maker who can stall the process, since his sign-off is required before any proposed action can be considered at the next level of political decision making. Thus, agencies like FEMA may face bureaucracy in different levels. For instance, FEMA prepares for response to victims after the president of the country declares a disaster.

2. **Fear of criticism:** Government agencies like FEMA follow the rule of "*wait and see*" that prone to commit type-II error. In statistics, two types of errors are identified : type-I error and type-II error . Type-I errors involve mistakes that result from under cautiousness. If USA Food and Drug Administration (FDA) approves a new drug, which turns out to make millions seriously ill, FDA has committed a type-I error. The visibility and public backlash is larger for type-I error. In contrast, type-II error involve mistakes that result from over

cautiousness. If the FDA fails to approve a drug that could save thousands of lives, FDA has committed a type-II error. However, the harm is not easily associated with the FDA. Both type-I and type-II errors can result in injuries or harm to the public. But, type-II error is less visible and thus much less likely to result in admonishment. If government agencies waits to response to disaster victims, it might be blamed for acting slowly. But this blame is far less than what it might receive if it response to victims immediately, before an effective plan were totally worked out. Thus, over cautiousness in disaster response causes delay in disaster response.

3. **Shortsighted policy bias:** Political decision makers are biased toward current over future benefit. It causes the failure to invest current resources for future benefit. It is called 'shortsighted policy bias'. This biasness contribute the massive destruction of transportation and communication infrastructure.

4. **Delayed acceptance of foreign aid:** There are always hesitation and delay in making decision on acceptance of foreign aid. Many international donors expressed frustration over the delay in shipment approval to the U.S. (Chua et al., 2007). The government of Myanmar blocked the entry of international relief to the country after Cyclone Nargis 2008. The Myanmar government agreed to accept international relief 21 days after the landfall of cyclone (Belanger and Horsey, 2008).

5. **Government approval:** The most disturbing stories of government failure in New Orleans after Hurricane Katrina were those of government forcibly preventing both for-profit and non-profit disaster relief suppliers from helping those in need, and confiscating the resources of those who did enter with supplies (Sobel and Leeson, 2006). In this incident IFRC "*begged to be allowed to go in [New Orleans] to do the distribution*" of essential relief supplies, but were prevented by government officials from doing so (Sobel and Leeson, 2006). The intervention of government hampers the flow of relief distribution.

6. **Information conflict:** Paramount of any disaster relief response is timely and accurate information. An organization need to know what was needed, who needed it, and when and where it was needed in what amounts. There are two reasons why a government agency cannot get accurate information. These are (1) the victims needing assistance had no incentive to truthfully reveal their preferences. However, State and local officials have an incentive to request a larger than efficient amount of resources when they are not bearing the cost. Thus State and local officials requests more relief than the efficient amount and

(2) Government provide relief for free of cost, there are no prices to guide resource allocation decisions or profit and loss signals on the basis of which to evaluate government's actions. The government agencies generally fail to understand the economic behavior of relief and to identify the characteristics of demand. The question arise after it that how to make best use of dispersed information to coordinate demands with available supply.

7. **Collapse of responders:** The damage of responders after disaster causes failure of disaster response. For example, the National Response Plan of USA designates the National Guard s the military's first responders to the crisis. The National Gurad at Louisiana were preoccupied with protecting their headquarters and rescuing soldiers who could not swim (Chua et al., 2007). They lost 20 vehicles which could have carried soldiers around the city (Lipton et al.,2005). Similarly, the UN headquater in Haiti was damaged after earthquake 2010.

8. **Lack of preparedness:** A key cause of response failure is little knowledge of the nature and impact of disasters. Therefore, local people and aid organizations ignore the importance of preparedness. The importance of early warning system, education program, emergency protocols and drills were absent in most of disaster affected areas.

9. **Failure in vulnerable identification:** The aid organizations face difficulties in identifying the most vulnerable in the aftermath of disaster. Besides, women, the elderly, children and the physically incapacitated needs especial attention in disaster response.

10. **Lack of need assessment coordination:** In establishing the urgent provisions required following a disaster, thorough, "need assessment" is by its very nature normally fraught with logistical and coordination difficulties. The majority of the needs assessment were made separately by the international aid agencies for their own particular requirement. Aid organizations prefers working independently in relief distribution. These causes ineffective and inefficient relief distribution. The UN Office for Coordination of Humanitarian Affairs (OCHA) leads the coordination between aid organizations after Indian Ocean tsunami 2004. There were nearly 72 coordination meeting per week in Banda Aceh (Indonesia) alone (Perry, 2007). However, the success of coordination among aid organizations was questionable.

11. **Lack of logistical expertise:** Perry (2007) found that disaster relief response have to overcome several logistical challenges. A major problem during Indian Ocean tsunami 2004 was the sheer quantity and associated chaos of donated relief supplies, magnified by the shortage of logistics expertise and lack of warehouse capacity, moving equipment and suitable transport.

An available cadre of logisticians has been seen to be a crucial part of disaster response, as part of needs assessment and for procuring, transporting and distributing the relief supplies. Logisticians are essential contributors to the planning and decision-making process and the aid agencies should give importance to increased logistical capacity building. It makes sense that more logisticians be trained locally in vulnerable regions. Local sourcing is also helpful because the supplies bought will be according to the needs of the local people and it boosts the local economy. Logistics coordination is also imperative to prevent agencies having competing supply chains causing duplication and wastage of resources.

2.3. DECISION MAKING IN UNCERTAINTY

Solving purely technical (quantitative) problems is comparatively simple, compared to tackling problems encountered in humanitarian logistics that are associated with social, economic, cultural, and ethical concerns, requiring subjective interpretations, vis-a-vis rational and objective answers. In addition, most planning problems are poorly structured, defying straightforward analysis. For example, a technical problem of inventory management could be closely linked to economic problem, with social, ethical, and political implications. Naturally, there is no clear cut boundary, and the ‘‘technical’’ problem we thought we originally faced is now transformed into a cluster of problems, often called a ‘‘problematique’’, because it has properties that none of its parts have.

Another theme that has haunted logisticians in almost every sector of planning is the problem of uncertainty. Uncertainty arises from several sources. First, there is the uncertainty that stems from a lack of knowledge about the disaster that is, sometime, called ‘black swan’ and the consequent inability to predict the outcome of possible actions. Second, there is the uncertainty arising from an inability to predict the effect of disaster and particularly identifying the damaged transport link aftermath a hazard. Third, there is the uncertainty arising from inability to predict the victims and the degree of relief urgency.

The problem of uncertainty is concerned with three basic questions: (a) how do decision makers conceptualize uncertainty? (b) how do decision makers cope with uncertainty? and, (c) what are the relationships between different concepts of uncertainty and different methods of coping? (Lipshitz and Strauss, 1997).

Conceptualizing uncertainty in planning is highly subjective in the sense that different individuals may experience different doubts regarding identical situations about the future. The conception of uncertainty is also case-specific depending on its effects on the proposed action, resulting in confusion. It is useful to examine a set of common planning situations stemming from different means-ends configurations, as shown in Table 2-2, based on Thompson's research (1967).

It will be readily seen that if there is certainty about both means and ends connected with a specific project, then decision making boils down to a computational exercise, falling in cell A. If on the other hand, our goals are certain but our technologies (or strategies) to attain our ends are limited, then decision-making entails a good deal of professional judgment, represented by cell B. Cell C represents the situation when the use of proven strategies, coupled with uncertain goals, calls for compromise among contending actors for coming up with an acceptable solution. And lastly, when there is uncertainty about both our goals as well as our means, then probably what is called for is inspirational leadership or random groping, depending on how complicated the problem is, and this situation is represented by cell D. Planners have described this cell as ‘‘the land of the lost or crazy’’, because this is where the ‘‘wicked problems’’ reside that is very similar to the situations faced in HL.

Table 2-2: Means-end configuration

Means	**Ends (goals and objectives)**	
	Certain	**Uncertain**
Certain	(A) Computation	(C) Compromise
Uncertain	(B) Judgment	(D) Chaos

(source: collected from Khisty and Arslan, 2005)

2.3.1. Uncertainty in Relief Distribution

The study team did field survey for gathering knowledge of HL and interviewed five logistics experts from WFP and UN-ESCAP. The interviewee discussed about the difficulty in relief operation and cooperation with other agencies. This section summarizes the uncertainty observed during the field survey. The uncertainty for HL is classified into two broad groups: disaster uncertainty and environmental uncertainty. Environmental uncertainty is further subdivided into three groups: demand uncertainty, provider uncertainty, and network uncertainty. The properties of each group are presented below:

Disaster uncertainty: Global warming is the major cause for increasing the frequency and severity of weather-related hazards (Arnold et al., 2005). Some hazards can be predicted and this includes avalanches, droughts, famines, hurricanes, and tornadoes, among others. In contrast, some disasters cannot be predicted and this includes earthquakes. World Bank identifies natural disaster hotspots, areas at relatively high risks of losses from one or more natural hazards (Arnold et al., 2005) and assigns hotspot index for each zone. Arnold et al. (2005) identify that some places in the world are vulnerable to multiple disasters –for example, India and New Zealand, are subject to both earthquakes and meteorological disasters. The hotspot index for each location will change with the inclusion of various disasters in the analytical model.

One common assumption of disaster occurrence is that a disaster will strike only a single place (Balcik and Beamon, 2008; Mete and Zabinsky, 2010; Huang et al, 2010) and other places will remain unaffected. However, this assumption is not always true, disasters may strike different places simultaneously, or several hazards may successively affect the same place in a short amount of time. For instance, the relief requests of the Pakistan flood (2010) and the Haiti earthquake (2010) overlapped and the relief operation during the Pakistan therefore faced a significant amount of shortages. Another example is that, Cholera broke out in Haiti during the relief operation for the Haiti earthquake (2010).

Demand uncertainty: Demand estimation is a crucial task aftermath of a disaster. The complexity in demand assessment arises about what, and how much is needed and who needs what. The situations become complicated with the presence of artificial demand (*i.e.*, requests for aid from people who are not disaster-affected). It becomes traumatic in poor country. If hazards affect the poor society, donors face difficulties in distinguishing disaster-generated-needs (*i.e.*, affected by disaster) from regular-needs (i.e., non-affected by disaster).

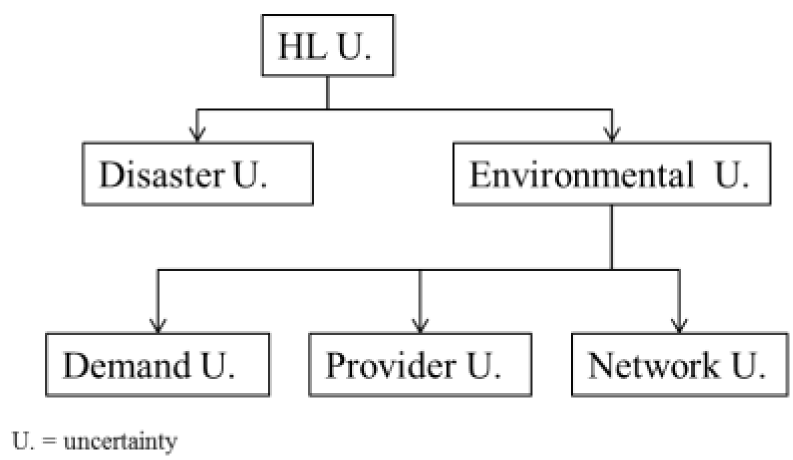

Figure 2-1: Uncertainty classification

According to field survey in Bangladesh, donor organizations use their local-knowledge to predict the relief demand, and NGOs that do not have branch offices in hazard areas face difficulties in identifying demand locations and quantities. Some NGOs admits that victims in accessible areas get more relief than those in remote areas.

It is understandable that local-knowledge is crucial for preliminary assessment of demand. However, local-knowledge is a fuzzy term and provides subjective value. Sometime, it generates information-chaos and decision makers are unable to obtain the actual value of demand. The importance of local-knowledge for demand assessment is recently realized.

The issue of local-knowledge motivates this study to propose a relief operational model. The model assumes that local-knowledge is obtainable and reliable.

Provider uncertainty: Provider uncertainty represents situations in which donors are unable to reach victims because of their own failure (*i.e.,* facility failure, shortage of work force, shortage of relief item). It is generally accepted that facilities are everlasting and will not fail. However, it is not always true. For example, the Pakistan flood (2010) damaged the food in warehouses and health facilities. The World Food Program also lost its aid commodities during the relief operations. The Haiti earthquake (2010) damaged the warehouse of the Haitian Red Cross societies'. In addition to facility failure, operational difficulties may also serve as provider uncertainties -for instance, trucks are often stopped and looted or deviated from their intended destinations during disaster relief (Cassidy, 2003). WFP's warehouses were looted during relief operations.

An adequate workforce is a necessary component of a functional system. However, skilled staff is always in short supply during disaster response (Van Wassenhove, 2006). The aid distribution experience for Hurricane Katrina shows that there were limited numbers of aid workers available in field (Holguin-Veras et al., 2007). In contrast, our survey in Bangladesh shows different results from that of Van Wassenhove (2006). According to our survey, there were sufficient numbers of volunteers available to take part in relief distribution and assistance. A large number of volunteers came from different districts of Bangladesh. According to NGOs, the reason behind this success was probably the presence of many NGOs in Bangladesh.

Despite there are several evidence of provider failure, this issue does not gain attention in disaster management. This study takes account of it and incorporate provider failure parameter in relief location model.

Network uncertainty: Transport network uncertainties represent the most common issue in relief distribution and are crucial for humanitarian logistics. Network information is not readily available in the aftermath of a disaster and it therefore takes several days to obtain route-maps. Uncertainties arises from several sources. For instance, (1) Unexpected events can also occur while vehicles are en route. Vehicles require maintenance after driving for hours on rough and damaged roads. (2) The service network (including work-shops or filling stations) creates additional difficulties for vehicle operation. (3) Road accessibility changes frequently and unpredictably due to the features of the terrain. (4) A number of commercial transport providers voluntarily support relief work aftermath of large-scale disasters. These organizations (commercial transport providers) are not secured by any contracts with aid organizations. They can withdraw their support during any stage of the relief operation. (5) According to the field survey in Bangladesh, NGOs do not possess vehicles and hire vehicles instead. They, if situation allows, share transportation with other NGOs or donors.

This study does not include network uncertainty in mathematical model explicitly. Rather, the models assumes that the capacity of transport network is decreased due to disaster and the logistics cost will be increased after disaster.

2.3.2. Modeling of Uncertainty in Humanitarian Logistics

Many studies aimed at formulating the uncertainty for logistics last couple of decades and some approach are also proposed for HL to cope with different uncertainties. Table 2-3 summarizes the general classification of modeling approaches of uncertainty. Three different modeling approaches, namely analytical model, intelligent artificial based model and simulation model are used to solve uncertainty. Each model is equally popular to researcher for representation of uncertainty. This study utilizes stochastic programming for network model, probabilistic distribution model for relief ordering model and multi-agent based model for relief allocation model.

Table 2-3: Classification of the general types of uncertainty models in HL

Analytical model	
Hierarchy processes	
Mathematical programming (LP, MILP, NLP, DP, and MOP)[a]	
Stochastic programming	
Value function	
Enterprise modeling	
Intelligent artificial based model	**Simulation model**
Expert system	Monte Carlo technique

Fuzzy set theory	Probabilistic distribution
Fuzzy logic	Heuristic method
Neural network	Network modeling
Genetic algorithm	Queuing theory
Multi-agent system	Dynamic system

[a]LP = linear programming, MILP = mixed-integer linear programming, NLP = nonlinear programming, DP = dynamic programming, MOP = multi-objectives programming

Now, this section explores representations of random variables that are presented in logistics decisions in different implementation stages. The detailed descriptions are as follows:

Disaster uncertainty: Balcik and Beamon (2008) propose a model for identifying inventory locations for global responses. They use a mixed-integer model based on demand scenarios and show trade-off between pre- and post-disaster budgets. They utilize historical earthquake epicenter to predict the probability of disaster in a particular location. Fiedrich et al. (2000) propose a dynamic programming model for allocating resources during search-and-rescue period after an earthquake aiming to minimize the number of fatalities. They compute the probability of demand from past earthquakes reports. This study includes the probability of an additional disaster during search-and-rescue period, named second disaster. The impact of secondary disaster is computed by multiplying the probability of failing to stabilize an area by the number of people.

This study combines the historical database of earthquake and meteorological disaster for Asia-pacific zone. Additionally, the network model for preparedness in a single country utilizes earthquake data of Bangladesh.

Demand uncertainty: Drezner et al. (2006) propose a model for casualty collection points and use the deterministic approach for a mini-max regret multi–objective model. The proposed model aims to minimize the maximum percent deviation of individual objective function values. Beamon and Kotleba (2006) develop an operational model of inventory ordering strategies in which demand is characterized as uniformly distributed. Lodree and Taskin (2008) address the inventory planning problem encountered by donor organizations using variants of the news-vendor model. Proactive actions to maintain inventory levels are compared with financial investment in an insurance policy. Demand is described as having a uniform distribution in the model. Salmeron and Apte (2010) use a stochastic optimization model for resource planning prior to a disaster. The model includes different degree of severities in different regions after a hurricane. The degree of severities differentiates the demand in one zone to another zone. Sheu (2010) proposes a model of data-fusion for treating multi-source information.

It is found that demand is represented by three different approaches. First approach is deterministic, second is scenario probability and third is uniform distribution. Scenario probability is designed based on historical data of relief operation and is used for logistical decisions in preparedness (i.e. 2^{nd} stage of disaster management.). On the other hand, uniform distribution, implicitly, is persuaded the application of local knowledge after math of disaster and is used for logistical decision in Response (i.e. 3^{rd} stage of disaster management).

Provider uncertainty: Tamura et al. (2000) describe the value function for investment under the risk of low-probability and high-consequence disasters. They use different disaster scenarios to improve infrastructure stability, minimize the probability of death, and minimize the cost of restoring damaged infrastructure. Ukkusuri and Yushimito (2008) propose a facility model that incorporates the reliability of each link and identify the facility as the most reliable path. Doerner et al. (2009) propose a model for existing public facilities in coastal areas, taking the risks of inundation by tsunamis into account. They use multi-objective optimization model: the first objective is the weighted mean of maximum coverage, the second is the minimization of tsunami risks, and the third is the minimization of costs. Huang et al. (2010) propose a model for large-scale emergencies and assume that most facilities in a city may stop functioning. They use a dynamic programming approach for the location of a path network and show the differences between the p-center and the p- large scale disaster center problem (LSECP) models. They observe that facility failure increases the objective values by 20% - 30% on average and that relative differences decrease according to the number of facilities, therefore, they suggest the location of more facilities. Lin et al. (2010) use HAZUS-MH software to create earthquake scenarios and analyze the effect of depot location, number of vehicles, and number of clusters on relief distribution.

Network uncertainty: Academic studies suggest using helicopter to reach victims due to network uncertainty. Ozdamar (2011) optimizes helicopter operations in the last mile of relief distribution with the objective of minimizing the total mission time under the aviation constraint. Barbarosoglu and Arda (2004) propose a two-stage stochastic programming model to plan first-aid commodities for disaster-affected areas based on random demand. Furthermore, uncertainty arising from the vulnerability of the transportation network is presented in scenarios approaches

2.3.3. Drawback in Uncertainty Modeling

In addressing uncertainty, different modeling approaches have been adopted and models are implemented in different stages of disasters. Most models incorporate uncertainties in demand and some incorporate supply uncertainties and network reliability. However, there are still ways to incorporate uncertainty to generate a practical model. I have also found that practitioners face difficulties in making logistical decisions in several environments that have not been considered in logistics models. I have tabulated the differences between research and practice in table 4. The differences are presented based on our classifications of uncertainties. Some representative issues are mentioned in each group. It is hoped that researchers can continue to push the boundaries of modeling uncertainty in HL through the incorporation of the problems that occur during relief operations.

Table 2-4: Comparison of uncertainty presentation in real case and modeling

	Real case	**Modeling**
Disaster uncertainty		
1. Disaster location	Can be multiple locations	One place
2. Number of disasters at particular time	Can be multiple disasters	Single disaster
3. Disaster probability	Unknown	Deterministic
Demand Uncertainty		
1. Victim location	Depends on topography of area	Deterministic
2. Product need	Need is dynamic	Deterministic in general
3. Demand urgency	Relief shortage force to consideration of victim severity	It is not highlighted in general
4. End link	Victims also value social conditions	Victim come to DC to receive aid (or stay in shelters)
5. Required product type	Unsolicited products present	Known
Provider Uncertainty		
1. Road safety	Trucks are sometime looted	Roads are always safe
2. Volunteers	Skilled staff are in short supply	No shortage of volunteers
3. Facility failure	Facilities can be affected by disasters	Facilities are not affected by disasters
Network uncertainty		
1. Vehicle parameters	Vehicles are hired on the spot	Deterministic
2. Customs processing	Complicated process	Not considered
3. Vehicle fleet	Dynamic	Deterministic in general
4. Road capacity	Dynamic	Deterministic
5. Lead time	Does not gain attention	Combined with demand
6. Temporary facility	Government- suggested place or depending on logistics cost or other reason	Depending on logistics costs

2.4. PLANNING IN PREPAREDENESS AND RESPONSE

Stoddard (2004) shows that aid organizations follow the reactive strategy (*i.e.,* takes actions after a disaster) instead of the proactive strategy (*i.e.,* takes actions before a disaster). Therefore, there is substantial gap between the time of disaster and that of delivering relief to the victims. Prepositioning of inventory is generally suggested solution for reducing time gap. International community suggests also for proper planning of response for efficiency of logistical operation. This sub-section explores the state-of-art for strategies for reducing time gap.

2.4.1. Facility Location Model in Preparedness

Facility location models are several types on the criteria of their objectives, constraints, solutions, and other attributes. Different classifications of facility location models for distribution systems have been proposed in the literature (Klose and Drexl, 2004). The short description of different types of model are described below.

Topological characteristics: Topological characteristics of the facility and demand sites lead to different location models including continuous location models (Plastria, 2004), discrete network models (Daskin, 1995), hub connection models (Campbell, 1996). In each of these models, facilities can only be placed at the sites where it is allowed by topographic conditions.

Features of facility: Features of facilities also divide location models into different kinds. For instances, facility restrictions can lead to models with or without service capacity. Capacity constraints also cause variations in location models (*i.e.,* un-capacited or capacited). Location models can be further divided by the type of supply chain considered (*i.e,*. single-stage model vs. multi-stage model). Single-stage models focus on service distribution system with only one stage, whereas multi-stage models consider the flow of service through several hierarchical levels.

Input parameter: Another popular way to classify the location models is based on the features of the input parameters to the problem. In deterministic models, the parameters are forecast with specific values and thus the problems are simplified for easy and quick solutions. However, for most real-world problems are unknown and stochastic/probabilistic in nature. Stochastic location models capture the complexity inherent in real-world problems through probability distributions of random variables or considering a set of possible future scenarios for the uncertain parameters.

Objectives: The objective is an important criterion to classify the location models. Covering models aim to minimize the facility quantity while providing coverage to all demand nodes or maximize the coverage provided the facility quantity is pre-specified. The objective of covering models is to provide 'coverage' to demand points. A demand point is considered as covered only if facility is available to service the demand point within a distance limit. *P*-center models have an objective to minimize the maximal distance (or travel time) between the demand nodes and facilities. They are often used to optimize the locations of facilities in the public sector such as hospitals, post offices and fire stations. In the location literature, the *P*-center model is referred to as the min-max model since it minimizes the maximal distance between any demand points and its nearest facility. *P*-median models attempt to minimize the sum of distance (or average distance) between demand nodes and their nearest facilities. Companies in the private sector often use *P*- median models to make facility distribution plans so as to improve their competitive edge. This study modifies the *P*-median model. Therefore, the state-of-art of *P*-median model is provided below.

***P*- median model**: While the average distance decreases, the accessibility and effectiveness of the facilities increases. This relationship applies to both private and public facilities such as supermarkets, post offices, as well as emergency service centers, for which **proximity is desirable.** The *P*-median model, introduced by Hakimi (1964), takes this measure into account and is defined as: determine the location of *P* facilities so as to minimize the average distance between demands and facilities. Carbone (1974) formulates a deterministic *P* median model with the objective of minimizing the distance traveled by a number of users to fixed public facilities such as medical or day care centers. Recognizing the number of users at each demand node is uncertain, the author extended the deterministic *P*-median model to a chance-constrained model. The model seeks to maximize a threshold and meanwhile ensure the probability that the total distance is below the threshold is smaller than a specified level α. Berlin et al. (1976) investigated two *P*-median problems to locate hospitals and ambulances. The first problem pays major attention to patient needs and seeks to minimize the average distance from the hospitals to the demand points and the average ambulance response time from ambulance bases to demand points. In the second problem, a new objective is added in order to improve the performance of the system by minimizing the average distance from ambulance based to hospitals.

This study proposes a modified *P*-median model that uses weighted distances from the facility to the demand point. The parameters are considered deterministic and the supply chain consists of single stage. Topologically, the model is discrete network model and puts potential facility location on the nodes.

The *P*-median model extends to stochastic model afterward. The supply uncertainty and demand uncertainty are introduced in the model. Accordingly, the objective function and the constraints are modified to represent the humanitarian logistics properties.

2.4.2. Relief Distribution in Response

The distribution system used in humanitarian logistics may depend on each situation's characteristics. Response planning consists of several management issues, for instance transport management, inventory management, demand management and supply management. Transport is the second largest cost to relief operations after personnel. The most wide used vehicle type in relief distribution is 4X4 vehicle and the total fleet size of 4X4 vehicles in large international humanitarian organizations is estimated between 70,000 and 80,000 units (Martinez *et al.*, 2010). Several studies propose mathematical model for *transport management* and suggest for utilizing modern technology for improving the usage to transport resources. However, aid organizations still manage transport resources in ad-hoc basis and hire transport on spot (Balcik and Beamon, 2008). Then, *demand management* that needs a consideration of cultural differences in disaster regions (Wichmann, 1999). Demand is unpredictable regarding timing, scale, and locations (Long and Wood, 1995). In case of *supply management*, aid agencies receive many unsolicited and sometimes even unwanted donations (Chomolier *et al*., 2003). These can include drugs and foods that are past their expiry dates (Murray, 2005). Few studies have paid serious attention to quantitative inventory modeling for relief operation

2.4.2a. Relief ordering to LDC

Typically, relief transfers through different stages of the logistics network via a series of long-haul and short-haul shipments. According to Figure 2-2, the stages in relief flow within a disaster-affected country are point of entry, central warehouse, local distribution center (LDC) and demand points. Since there are several stages and activities in relief flow, it requires longer time for transferring relif from origin to destination, In other words, the lead-time (i.e., the gap between the time of placing order and the time of receiving the product) for relief flow is considerably long. The larger lead-time (and cost issues) motivates for modeling inventory model.

Figure 2-2: Stage of relief flow (modified from UNDP, 1993)

Inventory management needs to address both existing inventory within the organization and 'in-country sources of supplies which can be accessed at short notice' (Long and Wood, 1995).Though commercial logistics considers the lead-time as an important factor of service level, lead-time does not gain attention in humanitarian logistics. Commercial inventory management is a core logistics function which is dominated by 'pull' systems. In contrast, Whybark (2007) asserts that disaster relief follows 'push' strategy in initial situation and turns into 'pull' system later to catch up with disaster situations.

UNDP (1993) suggests that manager needs to consider lead-time in making decision of relief ordering in either 'push' system or 'pull' system.

Beamon and Kotleba (2006) address the problem of man-made emergencies (such as war). The inventory model is noble in humanitarian logistics and assumes that lead-time is deterministic. The stochastic demand is uniformly distributed. Ozbay and Ozguven (2007) analyzed the inventory problems associated with supporting hurricane survivors living in shelter. They assume that lead-time-demand (LTD) is a multivariate normal distribution.

Typically, inventory model assumes single stochastic parameter (*i.e.*, either lead-time or demand) (Beamon and Kotleba, 2006) and proposes the solution in 'closed form'. However, no paper (in the knowledge of author) proposes closed form for two stochastic parameters. This study proposes an inventory model that assumes stochastic lead-time and demand; it proposes the solution in 'closed form'.

2.4.2b. Relief allocation to demand points

The significance of studies on relief allocation to areas suffering from disasters had been addressed previously (Knott, 1987; Long and Wood, 1995), followed by the emergence of diverse linear programming models proposed for emergency logistics planning model (Fiedrich et al., 2000; Barbarosoglu, et al., 2002; Ozdarmar et al. 2004). Therein, a number of researchers tended to formulate the resulting relief transportation issues as multi-commodity multi-modal flow problems with time windows (Haghani and Oh, 1996). By incorporating knowledge-based rules into a linear programming model, the issue of vehicle scheduling for supplying bulk relief of food to a disaster area has been addressed in Knott (1987). Brown and Vassiliou (1993) developed a sophisticated real-time decision support system using optimization approaches, simulation techniques as well as the decision maker's judgement for both relief resource allocation and assignment following a disaster. Considering the multi-commodity supply problems under emergency condition, three linear programming formulation are proposed in Rathi et al. (1992), where the routes and the supply amount carried on each route are assumed to be known in each of the given origin–destination (O–D) pairs. Their purpose, in reality, is to assign a limited number of vehicles loading multiple types of goods in given pairs of origins and destinations such that the induced multi-commodity flow problem is solved within minimal penalties caused by delivery inefficiency, e.g., early and late delivery as well as shipping on non-preferred vehicles.

In Fiedrich et al. (2000), a dynamic combinatorial optimization model is proposed to find the optimal resource rescue schedule with the goal of minimizing the total number of fatalities during the search and rescue (SAR) period, which refers to the first few days after the disaster. Although the model proposed by Fiedrich et al. (2000) aims merly to deal with rescue resource allocation problems, their approach is unique in the estimation of fatality probabilities in various rescue scenarios during the SAR period. The work of Fiedrich et al (2000) motivates to work further in the same research direction.

However, no systems allow the next and more important step, namely decision on allocating relief of the available resources to the demand points for long term. Additionally, the above-mentioned models lack the properties of agents' behaviors. Humanitarian logistics consists of several actors/agents that need to be addressed in decision-making. This study applies the agent-based model for relief allocation.

Based on the above discussion, Figure 2-3 shows the position of the study in literature in humanitarian logistics.

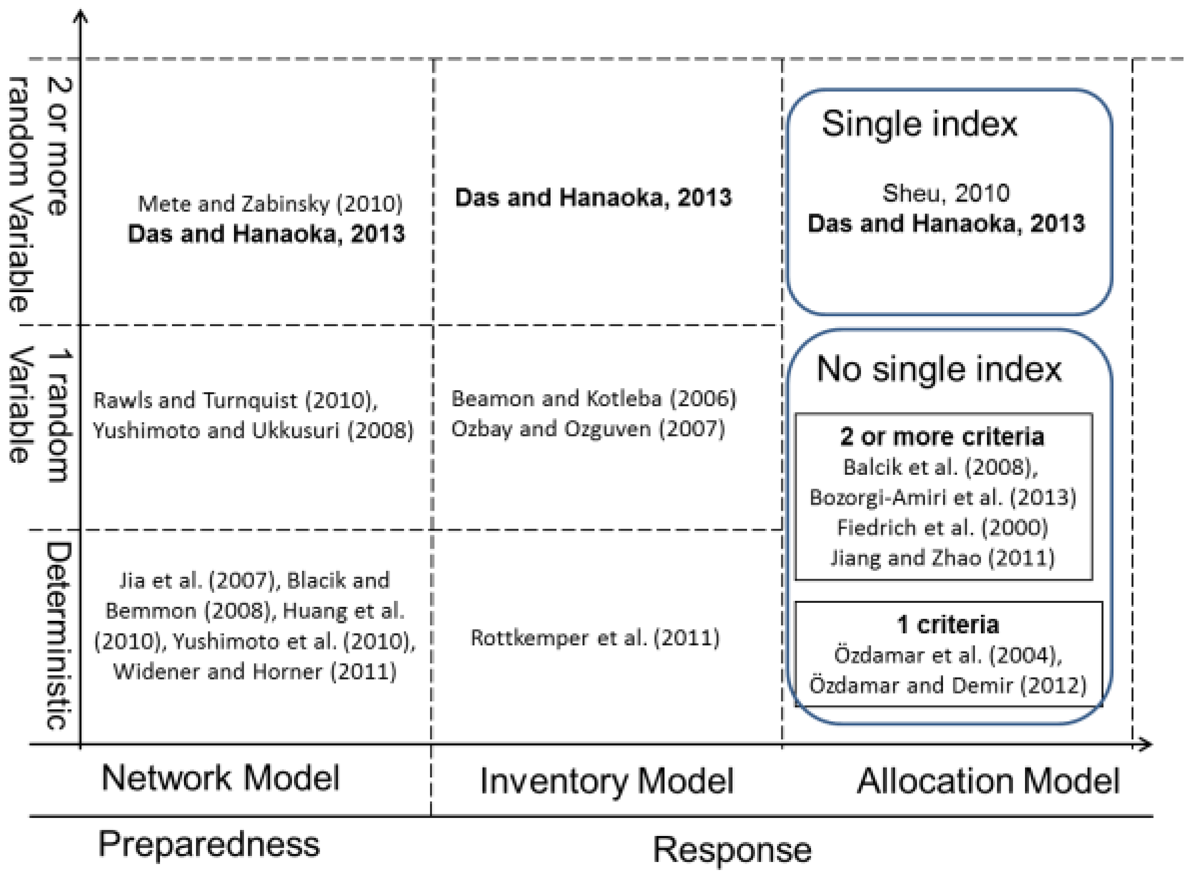

Figure 2-3: Study position in literature

2.5. STOCHASTIC INVENTORY MODEL FOR RELIEF ORDERING

The control and maintenance of inventories of physical goods is a common problem to all sector of a given economy. Two fundamental questions that must be answered in controlling the inventory of any physical goods are when to replenish the inventory and how much to order for replenishment. The <Q, r>

inventory model attempt to answer the two question under a variety of circumstances and are widely used in business and industry. This model aims to reduce inventories without hurting the level of service. Safety stock is a function of the cycle service level, the demand uncertainty, the replenishment lead-time, and lead-time uncertainty. For a fixed-cycle service level, a decision maker thus has three factors that affect the safety stock – demand uncertainty, replenishment lead-time and lead-time uncertainty

The reduction of lead-times and their variability is a key element of process improvement and vast literature are available for corporate logistics. Here, some key finding from corporate logistics are reported, since no literature is published on this topic for humanitarian logistics.

A larger lead-time results in a larger leadtime-demand, so it is necessary to require a higher base-stock level to compensate the higher possibility of stock-out. However, a larger leadtime does not necessarily result in a higher average cost. In contrast, high variability of lead-times increases average cost. If the lead-times in two system have the same mean but the lead-time in system 1 is more variable, that leads the optimal average cost in system 1 is higher. In contrast, optimal base-stock level is dependent on penalty cost (*p*) and holding cost (*h*) (Song, 1994). Another important fact that a more variable lead-time lead to a more variable leadtime-demand

Table 2-5: The effect of lead-time uncertainty

	Lead-time (L)	
	Stochastically larger	More variable
Optimal base-stock level	Larger	Higher if $\frac{p}{p+h} > 0$
		Lower, otherwise
Minimum average cost	Higher for exponential L	Larger
	Higher or smaller in general	

Typically, a normal approximation has been used to estimate the relationship between safety stock and demand uncertainty, replenishment lead-time and lead-time uncertainty. According to Eppen and Martin (1988), this approximation is often justified by using an argument based on the central limit theorem. The normality assumption is unwarranted in general and this procedure can produce a probability of stocking out that is egregiously in error. Tyworth and O'Neill (1977) also address this issue in a detailed empirical study and reveal that “the normal approximation method can lead to large errors in contingency stock”.

This study propose a model to overcome the complexity in solving stochastic lead-time and demand.

2.6. AGENT-BASED MODEL FOR RELIEF ALLOCATION

Agent-based model is a relatively new approach to modeling complex systems composed of interacting, autonomous agents. Application of agent-based modeling span a broad range of areas and disciplines. Applications range from modeling agent behavior in the stock market and supply chain, to predict the spread of epidemics and the threat of bio-warfare, from modeling the adaptive immune system to understanding consumer purchasing behavior, from understanding the fall of ancient civilizations to modeling the engagement of forces on the battlefield or at sea and many others.

2.6.1. Structure of Agent-based Model

A typical agent-based model has three elements:

- A set of *agents*, their attributes and behaviors. Agents are endowed with behaviors that allow them to make independent decisions. There is no universal agreement in the literature on the precise definition of an agent beyond the essential property of autonomy. Casti (1997) argues that agents should contain both base-level rules for behavior and higher-level rules that are in effect ‘rules to change the rule’
- A set of agent relationships and methods of *interaction*. The two primary issues of modeling agent interactions are specifying who is, or could be, connected to who, and the mechanisms of the dynamics of the interactions. One of the tents of complex systems and agent-based modeling is that only *local information* is available to an agent. Three is no central authority that either pushes out globally available information to all agents or controls their behavior in an effort to optimize system performance.
- The agents’ *environment*. Agents interact with their environment in addition to other agents. The environment may simply be used to provide information on the spatial location of an agent relative to other agents or it may provide a rich set of geographic information, as in a GIS. An agent’s location, included as a dynamic attributes, is sometimes needed to track agents as they move across a landscape, contend for space, acquire resource, and encounters other situations (Macal and North, 2010).

The structure of agent based model is shown in Figure 2-4.

2.6.2. Agent-based Model Implementation

Agent-based modeling can be done using general, all-purpose software or programming languages, or it can be done using specially designed software and toolkits that address the special requirements of agent modeling. Spreadsheets, such as Microsoft Excel, in many ways offer the simplest approach to modelling. It is easier to develop models with spreadsheets than with many of the other tools, but the resulting models generally allow limited agent diversity, restrict agent behavior.

General computational mathematics systems, such as MATLAB, can also be used quite successfully; however, these systems provide no specific capabilities for modelling agents. General programming languages, such as Python, Java, and C^{++} and C also can be used, but development from scratch can be prohibitively expensive given that this would require the development of many of the available services already provided by specialized agent modeling tool.

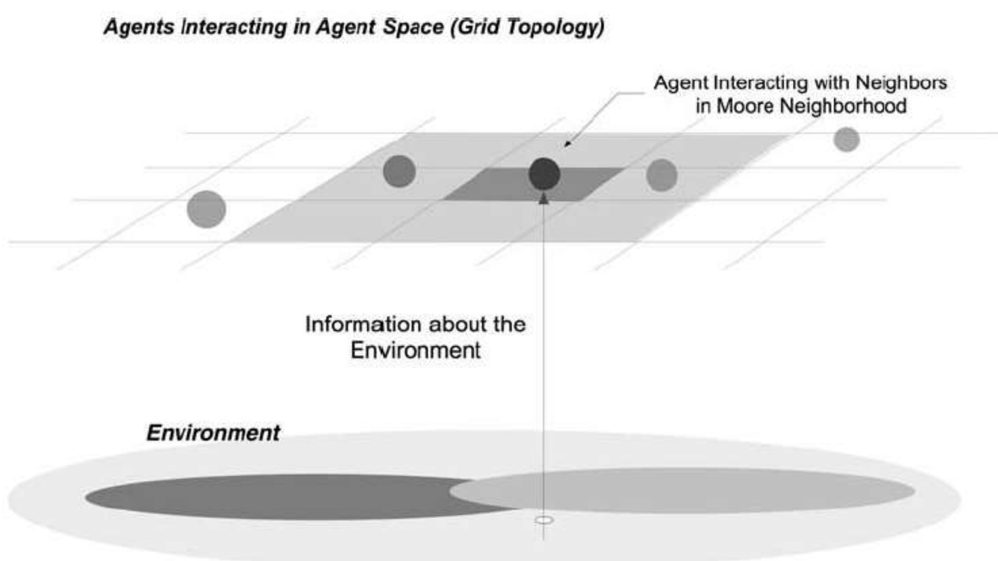

Figure 2-4: The structure of typical agent-based model (Epstein and Axtell, 1996)

Figure 2-5 represents the comparison of available software for agent-based model implementation. There are three common approaches for model implementation, depending on how much support the implementation environment provides for the modeler: (1) the library-oriented approach, (2) the integrated development environment (IDE) approach and (3) the hybrid approach.

In the library-oriented approach, the agent modelling tool consists of a library of routines organized into an application programming interface (API). Examples include the Java archives used by Repast for Java, MASON, the binary libraries used by Swarm; and the Microsoft.NET assemblies used by Repast for the Microsoft.NET framework.

The IDE approach to project specification uses a code or model editing program to organize model construction. Example includes NetLogo.

The hybrid approach to project specification allows modelers to use the environment as either a stand-alone library or a factored multiple-file IDE. Examples include Repast Simphony and AnyLogic.

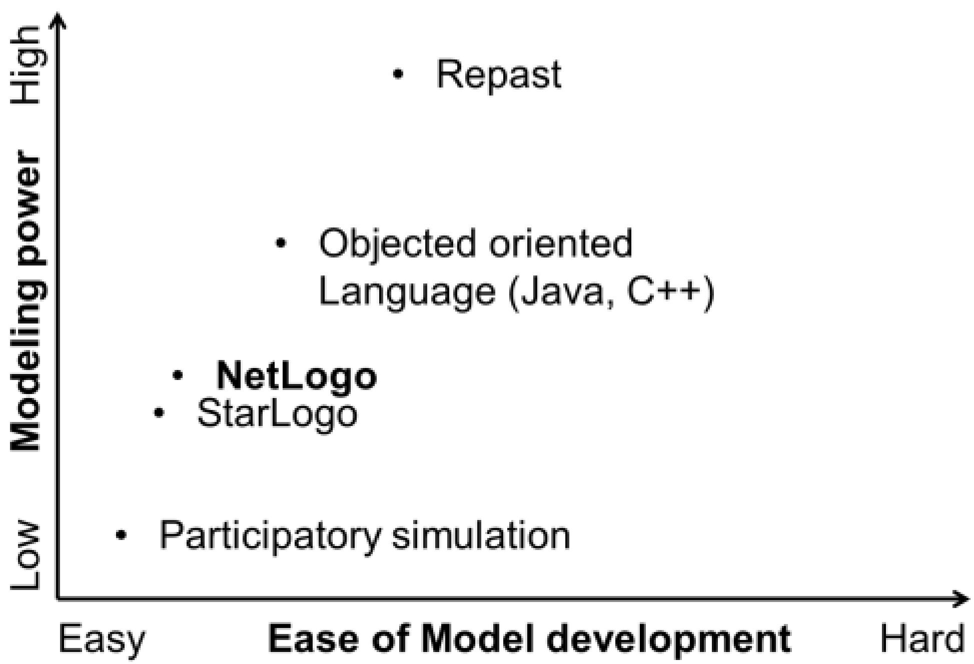

Figure 2-5: Software comparison

2.7. SUMMARY

HL entails complex planning that is associated with social, economic, temporal, technological, cultural, and ethical concerns. It requires subjective interpretations vis-a-vis rational and objective answers. HL is not a sole discipline but a combination of multiple disciplines. In this study, I have identified that logistics models are required to include social and other factors. This chapter describes the uncertainties that are present in HL.

Demand uncertainty is a common parameter in HL modeling. Logistics modeling can be extended to include several other parameters to improve relief distribution systems. Quantitative models ignore the various forms of disaster uncertainties, such as multiple disasters in the same area, multiple disasters in different zones, etc. In addition, demand segregation through urgency is required to distribute limited resources. Moreover, the standing of relief providers is not a salient issue and is always ignored in quantitative modeling. Another equally important issue is the incorporation of realistic network conditions in developing models.

It is noteworthy that uncertainty has not been modeled in detail because of the difficulty of making such a model practical. Incorporating multiple layers of uncertainty can quickly lead to intractable complex models. There are also challenges in providing the capacity to use these models in a field situation with limited time and computing power.

Chapter One

1. INTRODUCTION

Chapter Two

2. LITERATURE REVIEW

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Chapter Three

3. RELIEF POSITIONING IN PREPAREDNESS

Preparedness in anticipation of disasters involves prepositioning of assets. The common questions arise in preparedness: where should assets be located? and How much they should be stored? Both questions are linked to facility location problem. Two situations can be generated in solving the problems: (1) Whether there are some existing facilities or not (2) All parameters are known definitely or not (*i.e.*, stochastic or deterministic).

This chapter analyzes above-mentioned situations and proposes two mathematical models. First model is proposed to explore the effect of existing facilities in preparedness. This model assumes deterministic parameters.

The second model introduces stochastic parameters and analyzes the benefits of including stochastic parameter. This model provides robustness in the facility. Designing robustness of facility that will not only be well suited based on the current requirement, but should continue to be the best sites for all scenarios. The model incorporates supply uncertainty, demand uncertainty and provider uncertainty.

3.1. IMPORTANCE OF INVENTORY POSITIONING

The inventory prepositioning is helpful to response victims after all disasters, particularly sudden-onset disasters. The Figure 1-8 shows that fewer amounts of resources were available in affected areas in the aftermath of sudden on-set disaster. The more quickly commodities reach the victims, the better the chance of mitigating disaster related harm. Reducing delivery time in this crucial period is the objective of prepositioning in humanitarian logistics. It significantly affects the probability of survival of the victims (Sheu, 2007; Balick and Beamon 2008). Generally, 72 hours after earthquake is known as critical period because survival probability of earthquake victims reduces significantly after the critical period.

Figure 3-1 explains the effect of asset positioned before disaster. Natural disaster affects humanitarian, economic and ecology ical sector of a country. Humanitarian effects include loss of life, affected people and psychological post-disaster effects; Ecological effect comprises the loss of arable land, forests and damage to ecosystems. Economic effects are usually grouped into three groups: direct (i.e., physical damage of infrastructure), indirect (i.e, production loss due to physical damage of infrastructure) and macroeconomic (i.e., loss of gross domestic product (GDP)).

The recovery from disaster impacts requires assistance from others. The assistance can save the lives of victims and turns the victims' to work-force again. According to Figure 3-1, the optimally inventory prepositioning reduces distance between the relief and the victims' locations. Thus, it reduces lead-time of first wave of relief. However, several factors (for instance visa processing) increase lead-time. After arrival of relief, victims get means for resuming regular activities. The country resumes economic productivity after recovering from disaster impact. Finally, the importance of pre-positioning lies in the reduction of the lead-time and of the relief shortage.

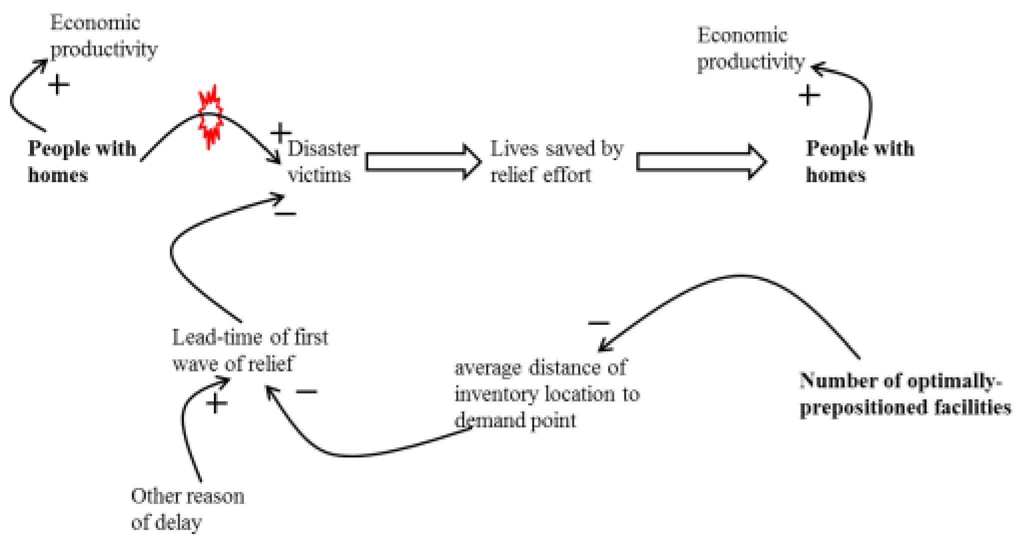


Figure 3-1: Anticipated impact of strategic inventory prepositioning (source Author)

3.2. CURRENT STATE OF GLOBAL PREPOSITIONED

The World Food Programme (WFP) is the largest humanitarian aid-agency in the world. The WFP manages the United Nations Humanitarian Response Depot (UNHRD) in five places around the world (Figure 3-2): **Subang, Malaysia; Dubai, UAE; Accra, Ghana; Brindisi, Italy; and Panama City, Panama**. UNHRD is capable of sending relief anywhere in the world within 24-48h to meet the needs of people affected by natural disaster and complex emergencies (WFP, 2013). The UNHRD hubs allows managing inventory for other aid organization. With the help of UNHRD, World Vision International (WVI) creates a logistics unit for emergency response named global prepositioned resource network (GPRN). GPRN maintain non-food item (NFI) for up to 225,000 beneficiaries in eight strategically located global warehouses (including five from UNHRD) around the world (in Figure 3-3): **Denver, USA;** Panama City, Panama; **Frankfurt, Germany**; Brindisi, Italy; Dubai, UAE; **Brisbane, Australia**;

Kuala lumpur, Malaysia; and Accra, Ghana. These warehouses are operated and managed by numerous partners, including WVI's support offices, the UNHRD, various consortia and corporate partners. One depot has granted coverage areas and it covers in general several countries. In contrast, several aid organizations keeps inventory for single country. For instance, Australian Government and three humanitarian relief agencies started the Joint Emergency Stores Warehouse in Brisbane on October 29, 2008. The joint arrangement of the facility will lower administration costs, ensuring more aid is delivered to those who need it. The warehouse will contain about 100 tonnes of supplies, valued at approximately $1 million (Ausaid, 2012).

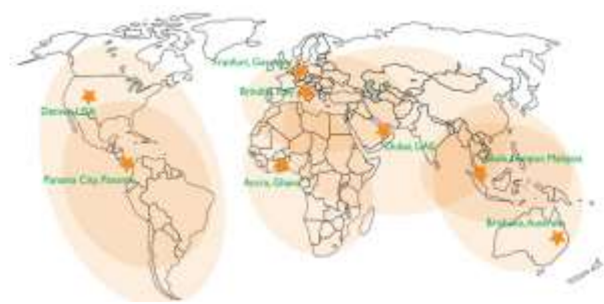


Figure 3-2: Map of UNHRD hub

Figure 3-3: GPRN of World Vision

3.3.RELIEF CHAIN

Humanitarian logistics is the process of planning, implementing and controlling the efficient, cost-effective flow and storage of goods and materials, as well as related information, from the point of origin to the point of consumption for alleviating the suffering of vulnerable people (Thomas, 2001). Figure 3-4 illustrates the activities of relief distribution from the 'point of origin' to the 'point of consumption'. The key properties of the Figure 3-4 are explained below.

Inventory prepositioning implies that 'the point of origin' is vendor's location and 'the point of consumption' is victim location. Additionally, the segment of relief chain from vendor's location to 'humanitarian response depot' accomplishes before disaster. Likewise, the segment from 'humanitarian response depot' to victim location accomplish after disaster. Here after 'humanitarian response depot'' are named as '*facility*'. The transportation from vendor location to facility is not time sensitive action, rather cost sensitive since it takes place before disaster.

The time sensitive activities commence after disaster. It is customary that disaster-affected country ask international organizations to assist. The aid organizations evaluate the appeal and estimate the demand. After appeal is granted, the pre-stocked commodities load on truck and shift to nearby airports.

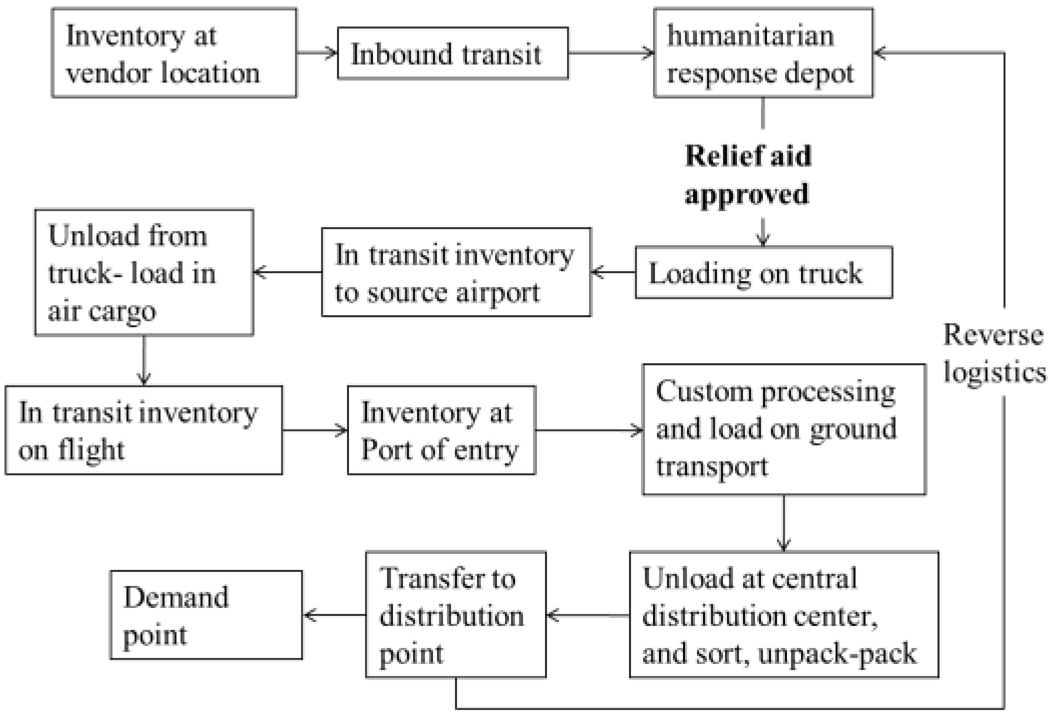


Figure 3-4: Relief chain

Herewith, sufficient documents (*i.e.*, invoice, consignee documents, and visa) are required and the preparation of documents is a source of delay to response. The waiting time at port of entry will be prolonged in the case of incomplete documents. After customs processing, the commodities are carried to central distribution center. The delivery chain ends with distribution of aid to the victims. As relief demand is unpredictable, there is possibility of supply and demand mismatch. Unused aid or non-consumable aids are returned. The reverse flow of aid is named as reverse logistics.

Some activities in Figure 3-4 reduce through assumptions for mathematical formulation. To make the model tractable, the activities in delivery chain are simplified.

- One assumption about facility location is that it is located adjacent to an airport. Facility adjacent to airport reduces the travel-time by decreasing the 'in-transit' to airport. This assumption is supported by the World Food Program (WFP) policies. WFP follows this strategy to establish UNHRD in five locations. Ghana UNHRD is established near Kotoka International airport, Malaysia UNHRD is near Subang Military airport; Italy in military airport, Panama in Tocumen International airport and UAE in Dubai international airport.

- The Custom processing time is consistent across the range of disaster and geographic location of facility. The transportation time inside a disaster-affected country (*i.e.*, after entering the port of entry) is also not dependent on the geographic location 'prepositioned stock pile'. The activities of custom processing and last mile distribution are relaxed in this model.

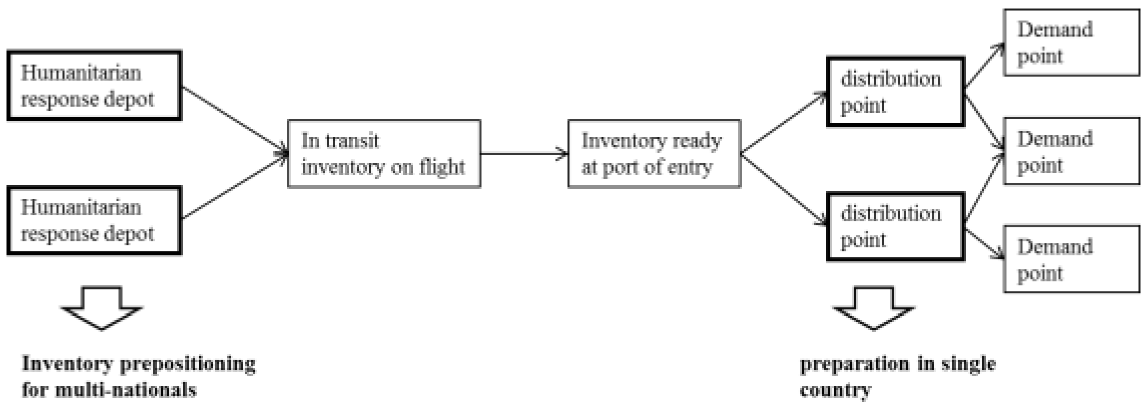


Figure 3-5: Modified relief chain

After application of the simplification of activities, Figure 3-4 turns to Figure 3-5 that depicts staging of inventory in relief chain. It also shows the importance of preparedness strategy for multi-nationals and in a single country. Both prepositioning are importance for quick response to the victims. The models for both strategies are explained below with some more assumptions.

3.4.INVENTORY POSITIONING FOR MULTI-NATIONALS (IPMC)

3.4.1. Mathematical Formulation

The transportation time inside a disaster-affected country (*i.e.*, after entering the port of entry) is unconnected on the geographic location 'prepositioned stock pile'. Therefore, the relief chain is simplified and is presented in Figure 3-6. The simplified relief chain consists of facility location (*i*), in transit inventory on air cargo and destination country (*j*).

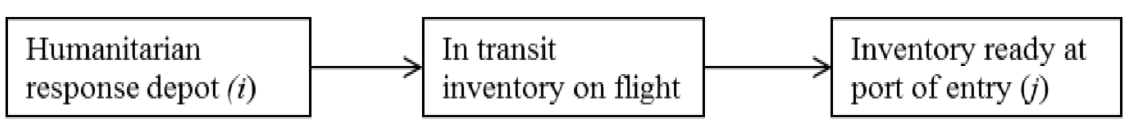


Figure 3-6: Simplified relief chain

Assumptions for the model is asserted below

- Relief is transported by air-cargo to port of entry and all air-cargo is flown in same speed (500 km/hr).
- There is no capacity limitation of a facility.
- Total affected people in stricken area is the proportional to demand for aid.

Based on these assumptions, this study proposes a *p*-median facility location model (Hakimi, 1964). This model seeks to place *p* facilities strategically among the candidate locations. It consists of finding optimal location for *p* facilities to meet specified demands at the lowest possible logistics cost. The *p*-median problem uses the average distance between service and demand points to determine the servicing costs of a given location. The *p*-median problem is also known as the binary program.

$$\min \sum_{i \in I} \sum_{j \in J} f_j d_{ij} x_{ij} \tag{3-1}$$

Subject to,

$$\sum_{i \in I} x_{ij} = 1 \quad \forall j \in J \tag{3-2}$$

$$\sum_{i \in I} y_i = p \tag{3-3}$$

$$x_{ij} \le y_i \quad \forall i \in I, j \in J \tag{3-4}$$

$$x_{ij}, y_i \in \{0,1\} \tag{3-5}$$

In this formulation, f_j represents demand at location *j*. y_i is a binary variable for showing open site and x_{ij} binary variable to allocate location *j* to open facility *i*.

Eq. (3-2) satisfies the victims demand from one facility only (*i.e,* single allocation model). The model aims to satisfy full demand that can be delivered from any open facility. While Eq. (3-3) provides freedom to decision makers who make decision of total number of facility that can be opened (or sited). Eq. (3-4) ensures that an unopened facility cannot assign to any demand points. Finally, Eq. (3-5) is the binary constraints of the model.

A metric is proposed for evaluating the efficiency of logistics decisions. The metric is mean-distance-per-capita that is calculated by using Eq. (3-6)

$$\min \frac{\sum_{i\in I}\sum_{j\in J} f_j d_{ij} x_{ij}}{\sum_j f_j} \tag{3-6}$$

In this model, distance (interchangeably time) and demand are the two controlling parameters. The computation method of both parameters is presented below.

3.4.1a. Response time

The Earth is sphere in shape, which prohibits using straight distance of two points. The distance (d_{ij}) is calculated by using Haversine method that generates the great circle distance between any pair of latitude (φ) and longitude (λ) coordinates on a sphere.

$$d = 2Ra\tan 2(\sqrt{a}, \sqrt{1-a}) \tag{3-7}$$

$$a = \sin^2\frac{\Delta\varphi}{2} + \cos\varphi_1.\cos\varphi_2.\sin^2\frac{\Delta\lambda}{2} \tag{3-8}$$

Where $\Delta\varphi$ and $\Delta\lambda$ represent the difference between latitude and longitude difference between two points and R is earth equilateral radius (6377 km). It assumes that port-of-entry of a country is the country capital and coordinates for each capital is collected through Google. Here, transportation time is a linear function of distance to the demand point and is calculated by Eq. (3-9).

$$time = \frac{distance}{speed} \tag{3-9}$$

3.4.1b. Demand

Relief demand is a function of several parameters. Researchers attempts to estimate relief demand by using proxy variable. Arnold et al (2005) recognize high-risk geographic areas based on historical worldwide disaster frequency and mortality data, population data, and economic indicator. Balcik and Beamon (2008) use mortality as an proxy for demand. FEMA's Hazus software is an assessment tool that can estimate losses from potential hurricane, earthquake and flood.

This study assumes that demand is a function of '*total affected'* people due to a hazard. The '*total affected*' is summation of '*injured*', '*homeless*', and '*affected*'. Definitions of *injured, homeless* and *affected* are provided below (EM-DAT, 2013):

- *Injured*: People suffering from physical injuries, trauma or an illness requiring medical treatment as a direct result of a disaster

- *Homeless*: People needing immediate assistance for shelter
- *Affected*: People requiring immediate assistance during a period of emergency; it can also include displaced or evacuated people.

Maximum value of *total affected* generated historically from different disasters represents demand of the concerned region. This value corresponds to demand.

$$total\ affected = injured + homeless + affected \tag{3-10}$$

$$f_j = \max(historicallly\ total\ affected\ by\ one\ hazard\ in\ region\ j) \tag{3-11}$$

The total affected people for each hazard from 1980 to 2011 in a country are collected and the maximum value for single disaster in each country from this list is identified.

Demand data is aggregated for a country to make the calculation tractable. Demand for the country is aggregated in capital city of the country. It is customary that aid organizations use port of entry at capital to facilitate the customs processing. It is important to note that segregation of large countries (i.e., China and India) in different regions may provide better results. Note that disaggregated demand data is utilized in the model of inventory positioning for single country.

3.4.1c. Calculation steps

The analysis consists of two steps: free form and status–quo. The descriptions of this two steps are provided below:

- Free form assumes that there are no existing facilities available. In placing facilities in this analysis, optimality is sought such that the sum of the length of all delivery chain paths is minimized.
- Status-quo takes the account of presence of UNHRD location. Status-quo adds a constraint Eq. (3-12) in the model. The status-quo intends to maximize the utilization of existing facilities.

$$y_i = 1 \quad \forall i = existing\ \ facilities \tag{3-12}$$

It is highly probable that the network configurations differ for two different analysis methods. The criterion for measuring efficiency of new network is mean distance per capita that is calculated using Eq. (3-6). The value of mean distance per capita is limited to equal or less than 500 km per capita that is approximately one-hour transportation time. This metric is the desired service level.

3.4.2. Case study

The proposed model is implemented for Asia–Oceania zone. EM-DAT database is a great source for gathering disaster related information. EM-DAT database stores data about country, disaster group, disaster type, date, killed, injured, homeless, affected, total affected, estimated damage.

3.4.2a. Motivation for selecting case study area

Disaster trend shows that the number and the impact of disasters in worldwide are not evenly distributed. Figure 3-7 and Figure 3-8 compare disaster situation in different continents. Asia-Oceania region is facing 60% of total disaster (IFRC, 2010). Total affected in this region is higher than any other continents. 90% of total affected during 2002-2010 lives in this region.

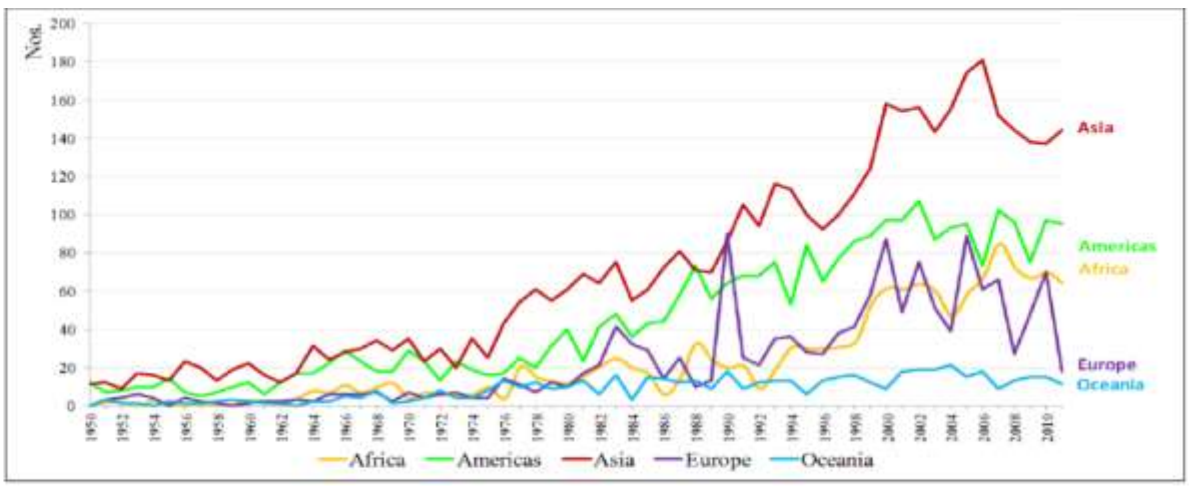


Figure 3-7: Occurrence of reported natural disasters by continent: 1950–2011 (CRED Crunch, 2013)

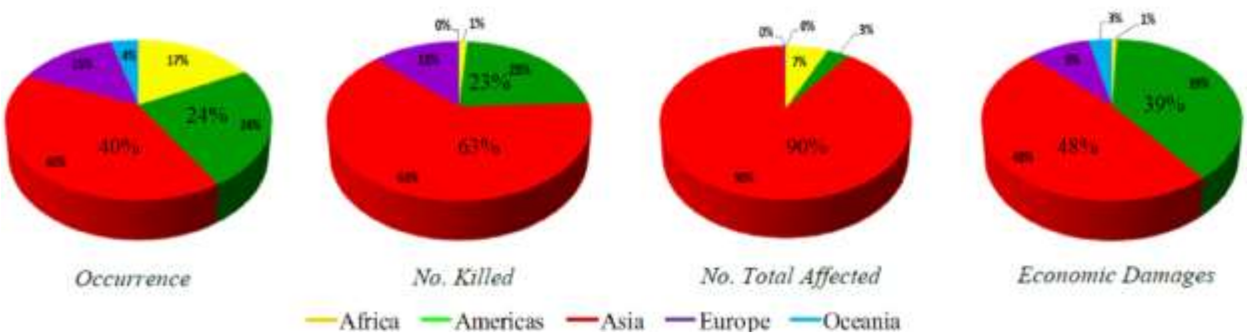


Figure 3-8: Compartive impacts of disaster by continent: 2002–2011 (CRED Crunc, 2013)

Disasters that contribute to the greatest impact in Asia–Oceania regions are storms and earthquake. Asia bears more than 800 thousand affected people per storm, caused by short-lived/small to meso scale

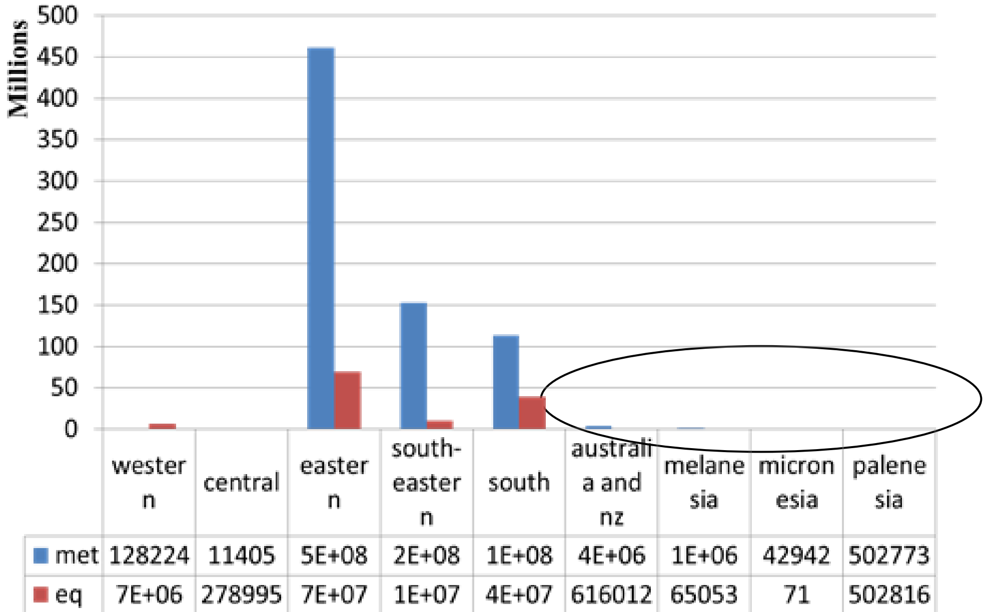


Figure 3-9: Total affected in study area (1980-2011)

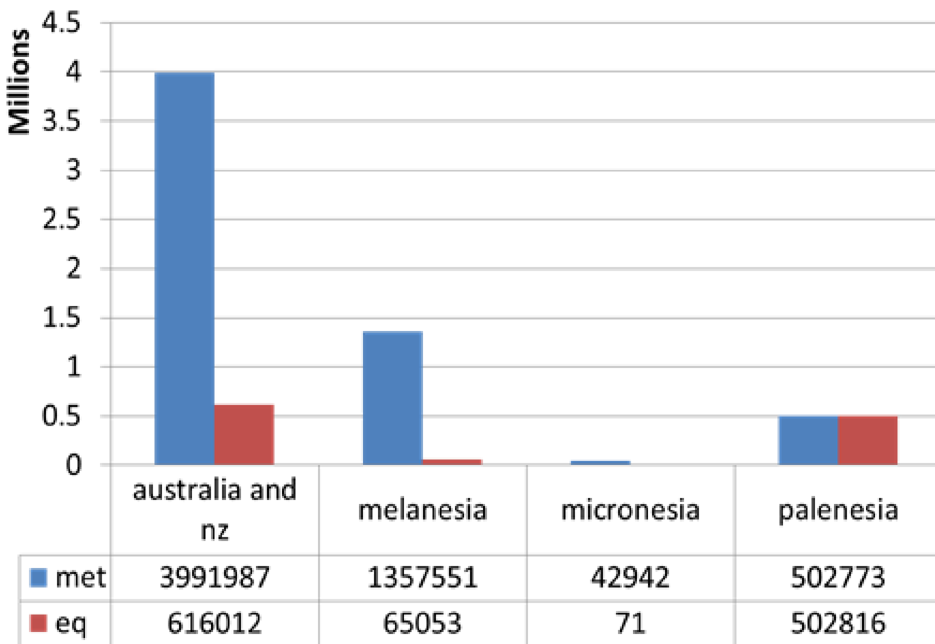


Figure 3-10: Total affected in Oceania (1980-2011)

atmospheric process. The mean affected per storm in Africa, America and Europe is 78 thousand, 44 thousand and 23.75 thousand respectively.

The mean affected people in Asia per earthquake disaster are more than 100 thousand that is larger than other parts of world. Figure 3-9 and Figure 3-10 show the demand characteristics of each region. The highest impact from each disaster in this zone has led to intense pressure on the aid organizations to improve operational effectiveness of disaster relief efforts in this zone. An interview with WFP manager reveals that WFP plans to expand the response capacity in Asia-Oceania zone.

3.4.2b. Data

The study area is grouped in 29 regions conditional on geographic location. Twenty-five regions among the total regions represent twenty-five countries in Asia and the remaining four regions belong to Oceania.

Since Oceania consists of hundreds of islands, Oceania is clustered in four groups: Australia and New Zealand, Polynesia, Melanesia, and Micronesia. Note that, this study does not include UN defined Western-Asia considering proximity from two UNHRD depots: one is in Dubai and another one is in Italy. The study area regions are shown in Table 3-1. The third column represents the population of the region in the year 2012 that is collected from World Bank database. The fourth column represents the maximum number of 'total affected' people by an earthquake during the period 1980 – 2011. The fifth column represents the maximum number of 'total affected' people by a storm during the period 1980 – 2011.

Table 3-1: Zonal data for population and disaster impact (1980-2011)

id	country	population (thousand)	max *total affected* in a year for earthquake	max *total affected* in a year for storm
c1	Australia	22,327	5,025	2,860,414
c2	Bangladesh	164,425	15,200	15,439,149
c3	Bhutan	708	20,016	65,000
c4	Brunei	407	0	0
c5	Cambodia	14,138	0	178,091
c6	China	1,338,300	47,437,647	107,403,094
c7	East Timor	1,171	0	8,730
c8	India	1,170,938	6,321,812	13,870,008
c9	Indonesia	232,517	3,215,982	10,000
c10	Japan	127,380	543,187	331,039
c11	Lao PDR	6,436	0	1,000,000

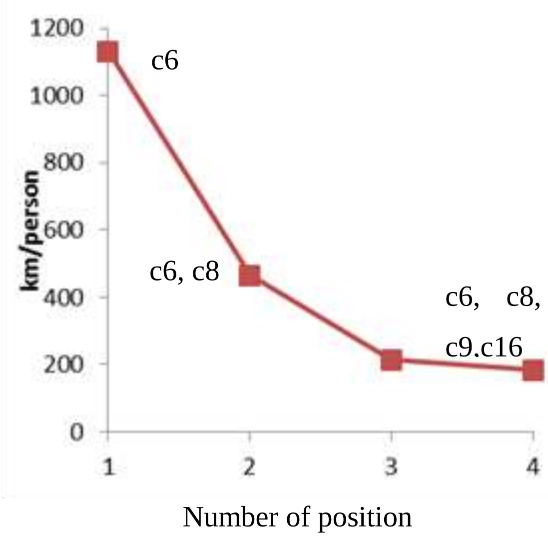
c12	Malaysia	27,914	5,063	41,000
c13	Maldives	314	27,214	23,849
c14	Melanesia	8,800	14,100	117,500
c15	Mongolia	2,701	0	1,071,000
c16	Myanmar	50,496	21,277	2,420,000
c17	Micronesia	546	71	8834
c17	Nepal	29,853	7,367	165
c18	New	4,371	301,845	2,000
c19	Korea,	23,991	0	88,625
c20	Pakistan	173,383	5,128,309	1,650,000
c21	Papua new	6,888	20,200	162,140
c22	Philippines	93,617	1,632,072	12,221,663
c23	Polynesia	668	5,585	195,000
c24	Singapore	5,140	0	0
c25	Korea, Rep.	48,875	0	627,180
c26	Sri Lanka	20,452	1,019,306	375,000
c27	Taiwan	23,071	108,918	2,307,523
c28	Thailand	68,139	67,007	1,894,238
c29	Vietnam	88,362	0	15,651,884

3.4.2c. Results

Free form: Free form analysis is performed for earthquake and storms in the beginning. The number of facilities is determined to meet desired service level that is equal or less than 500 km per capita. The required number of facilities to meet the desired service level for earthquake is two (Figure 3-11). The potential locations are c6 and c8. Two facilities ensure the mean distance per capita is 464 km that meet the desired service level.

In case of single facility (*i.e.*, p = 1), the model suggests to establish a facility at c6. The facility at c6 make the mean distance per capita is 1131 km. The maximum distance of demand point from facility location is 9024 km.

The similar analysis for storms is carried out. The minimum required facility to meet desired service level is four (Figure 3-13). The potential locations for storms are c6, c28, c8, c1. The mean distance per capita is 397 km/person that meet the desired service level. The maximum distance of demand point from nearest facility is 3288 km.



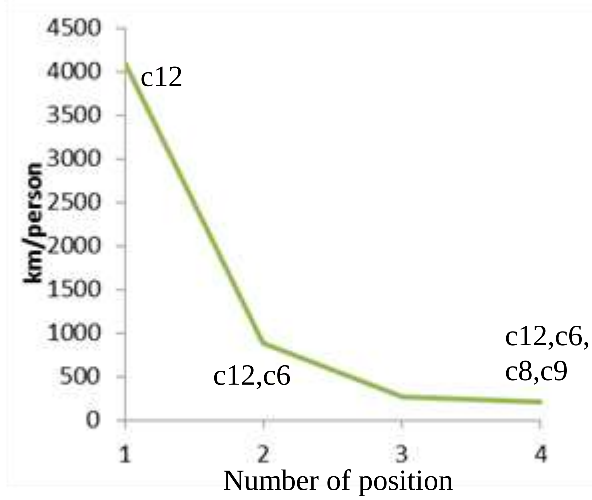
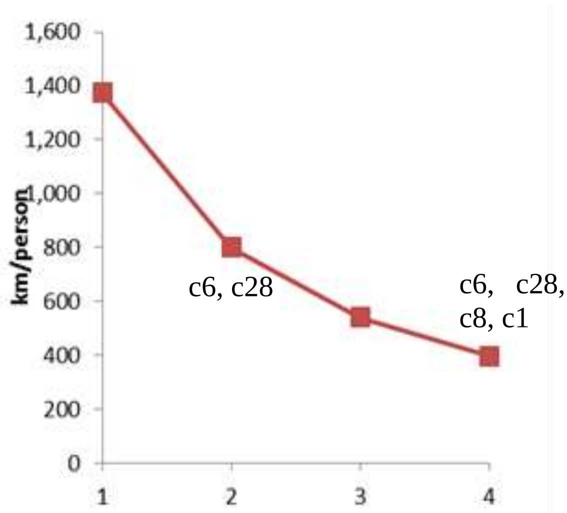


Figure 3-11: For earthquake (free form)

Figure 3-12: For earthquake (status quo)

Status quo: Status quo model conditions that the UNHRD in Malaysia (c12) is functioning (*i.e.*, $y_{c12} = 1$). Since aid organization can use UNHRD to stock the commodities, the extension of network is designed with respect to c12.



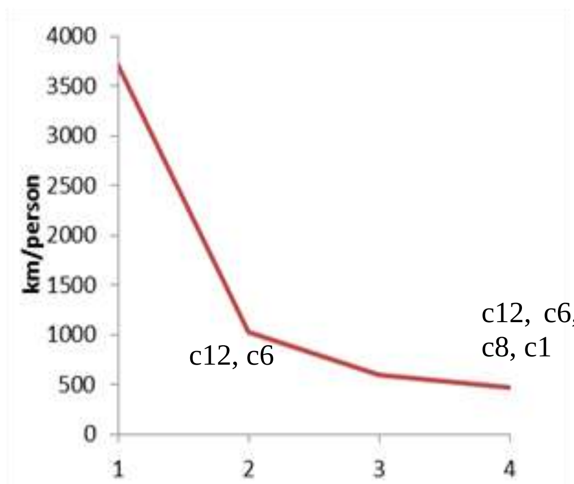


Figure 3-13: For storm (free form)

Figure 3-14: For storm (status quo)

With the single facility at c12, the mean distance per capita for earthquake reveals 4110 km/per person (Figure 3-12). After addition of one new facility at c6, the mean distance per capita for earthquake decreases to 885 km/person. In contrast, after addition to one facility at c6, the mean distance per capita for storm was 1020 km/person (Figure 3-14). Both measures are more that desired service level which is 500 km/ per capita. To achieve this target, another facility at c8 is required.

3.4.2d. Sensitivity

The improvement (*i.e.*, reduction in distance) of service level achieved after adding single facility to the system is calculated as the 'mean distance per capita' of current iteration minus the 'mean distance per capita' from the previous iteration. A steeper slope indicates a more significant impact in the reduction of per capita distance. It is observed that each additional facility makes a lesser impact. It shows the trend of diminishing return on positions. The slope of curve in Figure 3-15 and Figure 3-16 indicate the marginal impact of each additional position to the system. The status quo situation has substantial impact after adding second facility in the network.

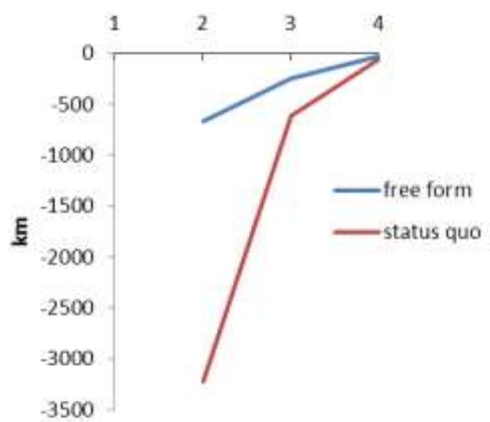


Figure 3-15: Diminish return on position for earthquake

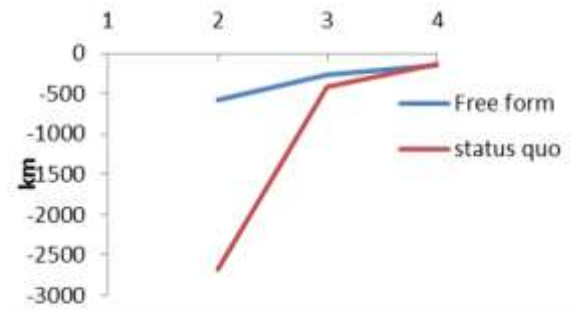


Figure 3-16: Diminish return on position for storms

Table 3-2: Diminish return on position for earthquake

Number of facility	1	2	3	4
status quo		-3224	-612	-62
free form		-667	-251	-31

Table 3-3: Diminish return on position for storms

Number of facility	1	2	3	4
status quo		-2685	-419	-128
free form		-573	-259	-145

Figure 3-17shows the three optimal locations for earthquake response in the case of free form. These three points are India, China and Indonesia. The prepositioned facilities correlate with the demand points.

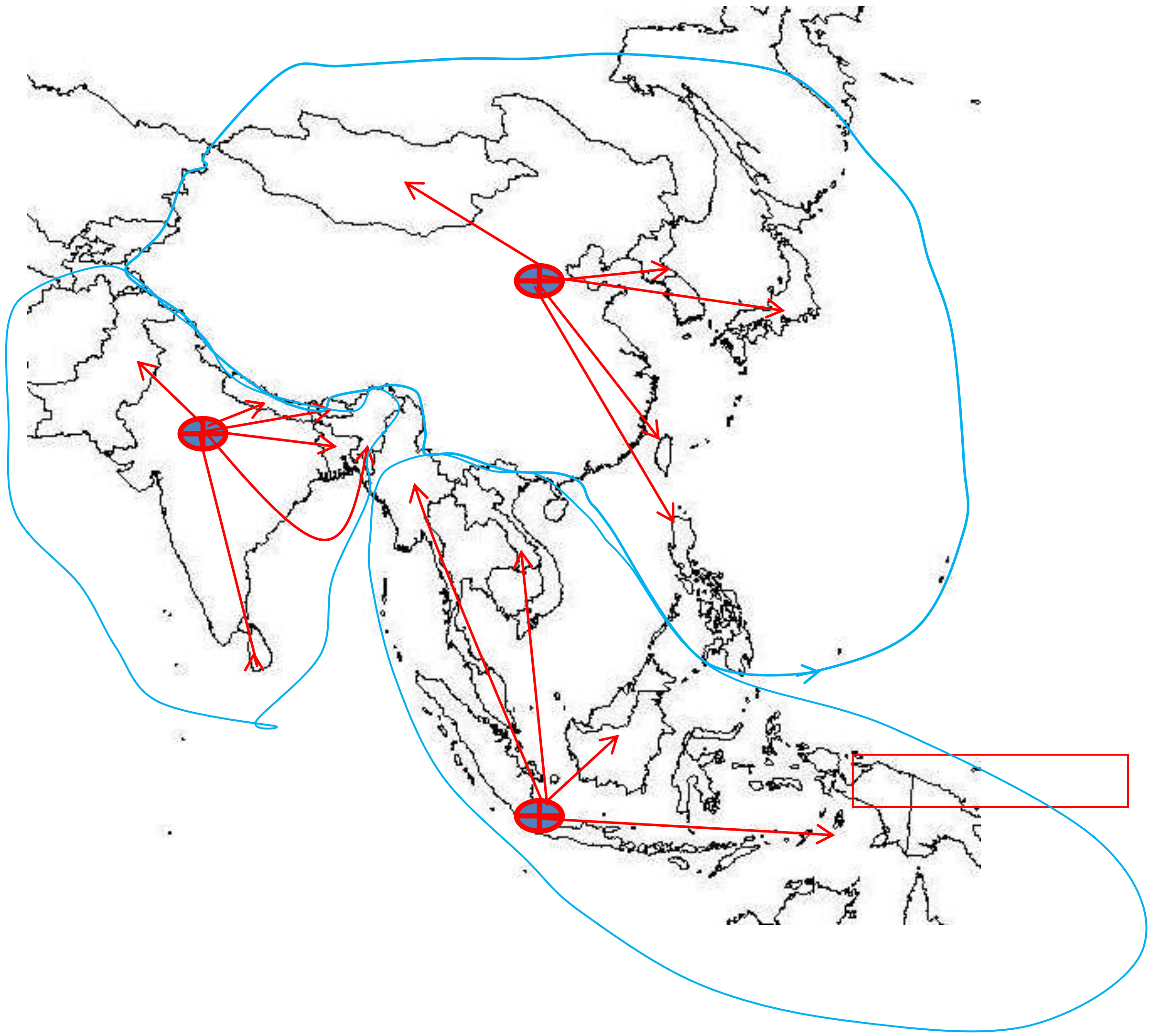


Figure 3-17: Three optimally located position (earthquake) on free form

3.4.2e. Effect of deterministic model

Disaster data reveals that the vulnerability of Asian countries for sudden on-set disasters is the highest in the world. Among the Asian countries, China is the utmost affected country by both earthquake and storms. India and Pakistan are the second and third most affected country for earthquake hazard respectively. In contrast, data of storms shows different trend where second and third most affected countries are Bangladesh and Vietnam respectively.

Since humanitarian organization responses to all type of disasters, while designing the logistics network, the decision maker requires to consider both the storm and the earthquake. Because, one country is highly vulnerable for earthquake, another is for storm.

The model is evaluated by using two criteria mean distance per capita and maximum distance. In the case of single facility (*i.e.*, $p = 1$), the facility at c6 can minimize the mean distance per capita while the facility at c1 can minimize the maximum distance from facility to demand point. Herewith, it is required to mention that according to the analysis it shows that Malaysia UNHRD is not in optimal location. However, facility location decision also depends on other criteria such as land availability, political stability, transportation network etc. as well as mean distance per capita criteria. Since other criteria are difficult to measure (if not impossible), this study employs mean distance per capita to show prepositioned sensitivity for immediate response.

3.5. INVENTORY POSITIONING FOR SINGLE COUNTRY (IPSC)

This section explains a model for inventory positioning for single country (IPSC).

3.5.1. Similarities and Dissimilarities between IPSC and IPMC

The IPMC and IPSC models have several similarities and dissimilarities. The similarities of the models are as follows:

- Both models are used for planning purpose in pre-disaster stage.
- Both models aim to reduce the gap between the disaster occurrence and the arrival of relief.
- Both models determine the inventory location and quantity.
- Both models show tradeoff between pre – and post –disaster cost.

The differences between IPMC and IPSC are as follows

- The IPSC incorporates uncertainty of different parameters.
- There are no bottlenecks of port-of-entry delay in IPSC model.
- IPMC determines the location of humanitarian depot (i.e., 1st stage in Figure 3-18). In contrast, IPSC determines the Relief distribution center (i.e., 2nd stage in Figure 3-18).

3.5.2. Network Setting and Assumptions for IPSC

The IPSC is useful for both country government and aid organizations. The decision maker is assumed risk-neutral. Risk-seeker ignores the importance of distribution center. On the other hand, risk-averse decision maker prepare to redundant resources. The redundancy is not justifiable due to limited budget for preparedness activities. In this regard, risk-neutral behavior may provide reasonable solution for preparedness activities. The decision makers seek optimal location of relief distribution centers (RDCs), where resources already exist and /or can be pre-positioned. The proposed disaster humanitarian logistics network becomes of three stages and two echelons as shown in Figure 3-18 which is the modification of Figure 3-5.

The first stage is the set of humanitarian response depot or donation (here forth named as supplier's location), the second stage contains RDCs and the last stage consists of demand points. Concerning the selection of the RDC locations from a set of candidate RDCs, certain issues have to be addressed, namely (1) the storage capacity of the RDCs (2) the distance to the affected people that keeps the transportation costs at minimum and (3) post-disaster supply with respect to supplier capacity.

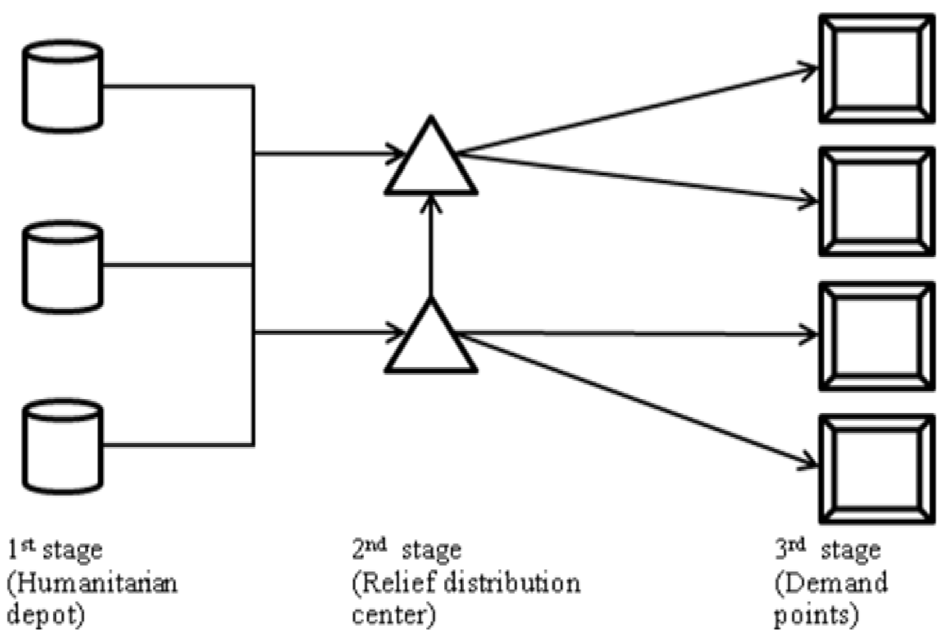


Figure 3-18: Simplified relief chain for single country

Before introducing the mathematical formulation, the assumptions for the model are described below:

- The capability of suppliers may be partially disrupted by a disaster due to transport bottleneck.
- All affected area (node) are candidate for the pre-positioned of RDCs.
- Transportation cost is not scenario dependent.
- Each demand point may be served by multiple RDCs.
- Two disaster events will not occur simultaneously.
- The relief demand is dependent on population density and earthquake intensity.

With the above assumptions in place, total cost minimization for the network model is adopted. Although cost minimization is not sole objective of humanitarian logistics, total cost is a good measure to compare different outcomes.

3.5.3. Mathematical Formulation

In this section, two-stage, stochastic mixed-integer model is introduced. This is a location model with the features of linearity and robustness. This model is explained in two steps. First framework of the model, system properties and introduction variables are presented. In the second step, mathematical model starting with basic stochastic model is illuminated.

3.5.3a. Model framework

In the aftermath of a disaster, there will be demand for relief at specific locations $k \in K$. However, the demand for commodity *c* at location *k* is not known definitely at the planning stage and is assumed scenarios dependent. Uncertainty is represented through the use of a set *S* of discrete scenarios indexed by $s \in S$, each with a probability of occurrence, p_s. The definition of a scenario *s* includes the forecasted demand d_{kcs} by commodity *c* and location *k*.

Relief can be pre-positioned at a location *j* if RDC is made available there. For costing purpose, we define facilities to be in one of discrete set, *L*, of size categories, indexed by $l \in L$. The overall capacity (e.g. square meter of available space) of a RDC in category *l* is N_l and choosing to open a RDC of size category *l* in location *j* incurs a fixed cost, F_{jl}. Let z_{jl} be a binary decision variable equal to 1 if there is a RDC of capacity category *l* located at node *j* , and 0 otherwise. This is one of first stage decision in the two-stage model.

If a RDC is made available at location *j* various commodities can be stocked there, subject to the capacity limits of the RDC. Let b_c be the unit volume for commodity *c* and q_{ijc} be the amount of commodity c pre-positioned at location j supplied from supplier i. The q_{ijc} is another first stage decision in the model. A decision to stock a particular commodity results in a unit procurement cost, PC_c. commodity of type c is not used in scenario s, denoted, o_{jcs}, incurs additional cost, θ_{kc} (accounting for general inventory holding cost or overflow cost). On the other hand, if demand for particular commodity cannot be met, denote ϕ_{kc}, as the shortage cost of commodity c.

After a disaster, the inventory of the various commodities is distributed across demand points. To reflect the connection between the RDC location and the demand points of the problem, we assume that the demand locations and potential RDC locations are at nodes in the transportation network. In general, the set of locations of interest may be a subset of all the nodes in the network, and transportation links *(i, j)* are assumed to be elements of an arc set *A*, with $i \in I$, $j \in J$. Let $TC_c^{'}$ be the transporting cost of commodity c from supplier to RDC and $TCR_c^{'}$ is the transportation cost from RDC to affected area. Let x_{ijcs} be the amount of commodity c procured from supplier i and transferred to RDC j in the scenario s.

Following is the explanation of variables, parameters and sets. Units are stated within square brackets (.) at the end of each of the definitions. Table 3-4 is the collection of all sets definition. Table 3-5 is the definition of all parameters. d_{kcs}, p_s and ρ_{ics} are scenario dependent parameters.

Table 3-4: Indices and index sets

Set	Definition
C	set of commodities indexed by $c \in C$
I	set of suppliers indexed by $i \in I$
J	set of candidate RDCs indexed by $j \in J$
K	set of affected areas indexed by $k \in K$
L	set of size of RDC indexed by $l \in L$
S	set of scenarios indexed by $s \in S$

Now model parameters

Table 3-5: Deterministic and stochastic parameters

Type	Symbol	Definition
Pre-disaster parameter	F_{jl}	fixed cost of opening a RDC of size l at location j ($)
	N_l	capacity of RDC size l
	b_c	volume of a unit commodity c (m^3)
	SC_{ic}	delivery capacity of supplier i of commodity c
	PC_c	procuring cost of a unit commodity c before disaster ($ per unit)

	TC_c	transportation cost for a unit commodity *c* before disaster ($ per unit of *c*)
Post-disaster parameter	$PC_c^{'}$	procuring cost of a unit commodity *c* after disaster ($ per unit of *c*)
	$TC_c^{'}$	transportation cost for a unit commodity *c* after disaster from supplier to RDC($ per unit of *c*)
	$TCR_c^{'}$	transportation cost for a unit commodity *c* after disaster from RDC to affected area ($ per unit of *c*)
	θ_{kc}	unit overflow cost for commodity *c* at affected area *k* ($ per unit of *c* at *k*)
	ϕ_{kc}	unit shortage cost for commodity *c* at affected area *k* ($ per unit of *c* at *k*)
	λ	parameter for post-disaster deviation-cost
	γ	parameter for balance control ($)
	M	a very large positive number
Stochastic parameter	d_{kcs}	amount of demand for commodity *c* at affected area *k* in scenario *s* (unit)
	p_s	probability of scenario s
	ρ_{ics}	ratio of capacity of commodity *c* at the supplier *i* in scenario *s*

Table 3-6 is the list of decision variables. Here, z_{jl} and q_{ijc} are first stage decisions of the model and the remaining variables in Table 3-6 are second stage variables.

Table 3-6: Decision variables

Variables	Definition
z_{jl}	1 if RDC with capacity category *l* is located at candidate RDC *j*; 0 otherwise
q_{ijc}	amount of commodity *c* procured from supplier *i* and stored at the RDC *j* ()
s_{kcs}	amount of shortage commodity *c* observed in scenario *s* at affected area *k*
o_{kcs}	amount of extra commodity c delivered in scenario *s* at affected area *k*
x_{ijcs}	amount of commodity *c* transferred from supplier *i* to RDC *j* in scenario *s*
y_{ikcs}	amount of commodity *c* transferred from RDC *j* to affected area *k* in scenario *s*. If *j*=*k*, it represents both RDC and affected area in same location
ω_s	cost variability for scenario *s*
φ_{jcs}	amount of deviation of commodity *c* at RDC *j* in scenario *s*

Table 3-7 represents two analogous variables that are introduced for simplification of the model

Table 3-7. Combination of analogous variables

Symbol	Definition
Bt	pre-disaster cost (*i.e.*, Eq. (3-17)
A_s	summation of post-disaster procurement cost and transportation cost (*i.e.,* Eq. (3-19))

3.5.3b. Formulation

At first, the basic structure of the model is explained for simplifying the presentation of the model. Then the full model is introduced.

$$\min \; Bt + E_{\xi}[Q(t,,\xi)] \tag{3-13}$$

Subject to,

$$At \geq b \tag{3-14}$$

$$h(\omega) - T(\omega)t = Wy \tag{3-15}$$

$$t \geq 0 \tag{3-16}$$

The objective function Eq. (3-13) expresses the cumulative cost. First term in Eq. (3-13) represents pre-disaster cost (*Bx*) and second term represents post-disaster cost $E_{\xi}[Q(x,\xi)]$. The pre-disaster cost consists of setup cost, procurement cost, and transport cost. Thus pre-disaster cost is

$$Bt = \sum_{j \in J, l \in L} z_{jl} FC_{jl} + \sum_{i \in I, j \in J, c \in C} (PC_c + TC_c) q_{ijc} \tag{3-17}$$

Then, the post-disaster cost is scenario-dependent cost that includes procurement cost, transportation cost and deviation-cost. If the deviation-cost is equivalent to zero, the expected post-disaster cost is greater or equal to the summation of procurement cost and transportation cost. So

$$E_{\xi}[Q(x,\xi)] = \sum_{s \in S} p_s A_s \tag{3-18}$$

where,

$$A_s = (\sum_{i \in I, j \in J, c \in C} (PC_c^{'} + TC_c^{'}) x_{ijcs} + \sum_{j \in J, k \in K, c \in C} TRC_c^{'} y_{jkcs}) \tag{3-19}$$

If the deviation-cost is equivalent to non-zero, the deviation-cost generates from two sources. One source of deviation cost is the differences of post-disaster cost from the average post-disaster cost for all scenarios. The treatment of this sort of deviation-cost is adopted from Li (1996) and is added ω_s in Eq. (3-18). Another source of deviation-cost is the balance constraint of commodity. Mulvey and Ruszczynski (1995) suggested adding φ_{jcs} to treat the deviation-cost. In this way, the model gains robustness characteristics. After the addition of deviation-cost in the Eq. (3-18), it becomes

$$E_{\xi}[Q(x,\xi)] = \sum_{s \in S} p_s A_s + \lambda \sum_{s \in S} p_s[(A_s - \sum_{s \in S} p_s A_s) + 2\omega_s] + \sum_{s \in S, j \in J, c \in C} \gamma p_s \varphi_{jcs} \tag{3-20}$$

As shown above, the objective function of the stochastic model becomes as follows with addition of penalty cost

$$\min \; Bt + \sum_{s \in S} p_s A_s + \lambda \sum_{s \in S} p_s[(A_s - \sum_{s \in S} p_s A_s) + 2\omega_s] + \sum_{s \in S, j \in J, c \in C} \gamma p_s \varphi_{jcs} + \sum_{k \in K, c \in C} (\theta_{kc} o_{kcs} + \phi_{kc} s_{kcs}) \tag{3-21}$$

Subject to,

Balance control:

$$\sum_{i\in I} x_{ijcs} + \sum_{i\in I} q_{ijc} - \sum_{k\in K} y_{jkcs} = \varphi_{jcs} \quad \forall j \in J, c \in C, s \in S \tag{3-22}$$

RDC location:

$$\sum_{l\in L} z_{jl} \le 1 \quad \forall j \in J \tag{3-23}$$

$$y_{jjcs} \le Md_{jcs} \sum_{l\in L} z_{jl} \quad \forall j \in J, c \in C, s \in S \tag{3-24}$$

$$\sum_{k\in K} y_{jkcs} \le M \sum_{l\in L} z_{jl} \quad \forall j \in J, c \in C, s \in S \tag{3-25}$$

$$\sum_{k\in K} x_{ijcs} \le M \sum_{l\in L} z_{jl} \quad \forall j \in J, c \in C, s \in S \tag{3-26}$$

RDC capacity constraint:

$$\sum_{i\in I, c\in C} b_c q_{ijc} \le \sum_{l\in L} N_l z_{jl} \quad \forall j \in J \tag{3-27}$$

Post-disaster demand management:

$$y_{jkcs} \le M(\sum_{l\in L} z_{kl} + d_{kcs}) \quad \forall j \in J, k \in K, c \in C, s \in S \tag{3-28}$$

Post-disaster supplier's capacity:

$$\sum_{j\in J} x_{ijcs} \le \rho_{ics} SC_{ic} \quad \forall i \in I, c \in C, s \in S \tag{3-29}$$

Mean absolute value:

$$A_s - \sum_{s\in S} p_s A_s + \omega_s \ge 0 \quad \forall s \in S \tag{3-30}$$

Non-negativity constraint:

$$z_{jl} \in \{0,\ 1\} \quad \forall j \in J, l \in L \tag{3-31}$$

$$q_{ijc},\ \ x_{ijcs}, y_{jkcs}, \omega_s, \varphi_{jcs} \ge 0 \quad \forall i \in I, j \in J, k \in K, c \in C, l \in L \tag{3-32}$$

Penalty function:

$$y_{kkcs} + \sum_{k \neq j \in J} y_{jkcs} - d_{kcs} + s_{kcs} - o_{kcs} = 0 \quad \forall k \in K, c \in C, s \in S \tag{3-33}$$

The above mentioned two-stage model makes the trade-off between the pre-disaster costs and the post-disaster costs. The objective function of the model is Eq. (3-21) and the constraints include Eq. (3-22)–(3-33). The objective function consists of pre-disaster cost, post-disaster cost and deviation cost. The deviation cost can be formulated in different ways. The proposed model utilizes two different types of deviation cost for the sake of tractability.

Eq. (3-22) is a balance control constraint of the in-coming flow and the out-going flow of relief. One RDC cannot delivery relief more than the summation of inventory and post-disaster procurement. The constraints Eq. (3-23) – (3-26) represent feasibility of RDC locations and deliver-ability from RDC. The constraint Eq. (3-24) explains that one RDC will not deliver more than the demand in same location. The Eq. (3-27) bound maximum storage limitation. It cannot be more than the RDC capacity. Eq. (3-29) bounds the post-disaster procurement and right hand sight of this constraint is scenario dependent. In other words, supplier's capacity is scenario-dependent. Supplier capacity can be reduced for several reasons including transport network disruption and damaged of product at supplier. The Demand management Eq.(3-28) restricts the flow more than the demand at affected area. The Eq. (3-30) shows post-disaster cost variability. This constraint aims to reduce the post-disaster cost variation in different scenarios. The Eq. (3-31)–(3-32) are non-negativity and variable type restriction. The penalty function Eq. (3-33) adds penalty for either shortage or extra-inventory.

Both Eq. (3-33) and objective Eq. (3-21) contain shortage unit (s_{kcs}), and over-supply unit (o_{kcs}) and Eq. (3-33) is equality constraint. These properties force us to add artificial variables and using 'two phase' or 'big M' (Scharge, 1991) method to solve the model. However, those methods will add many extra variables. To solve the model, we have changed the objective function and penalty function in line with Yu and Li (2000).

The objective function turns to

$$\begin{aligned} \min \; & Bt + \sum_{s \in S} p_s A_s + \sum_{s \in S, j \in J, c \in C} \gamma p_s \varphi_{jcs} + \lambda \sum_{s \in S} p_s [(A_s - \sum_{s \in S} p_s A_s) + 2\omega_s] + \\ & \sum_{c \in C, s \in S} p_s (\sum_{k \in K} (\theta_{kc} (y_{kkcs} + \sum_{k \neq j \in J} y_{jkcs} - d_{kcs} + \delta_{kcs}) + \phi_{kc} \delta_{kcs})) \end{aligned} \tag{3-34}$$

The Eq. (3-33) turns to

$$-y_{kkcs}-\sum_{k\neq j\in J}y_{jkcs}+d_{kcs}-\delta_{kcs}\leq 0 \quad \forall k\in K, c\in C, s\in S \tag{3-35}$$

$$\delta_{kcs}\geq 0 \quad \forall k\in K, c\in C, s\in S \tag{3-36}$$

The Eq. (3-33) transforms to Eq. (3-35) introducing single variable δ_{kcs}. After transformation of the Eq. (3-33), the variables s_{kcs} and o_{kcs} turns to single variable δ_{kcs} and thus the number of variables are reduced in the whole system. The Eq. (3-36) is added to ensure the positive value. In the final model, the objective function is Eq. (3-34) and the constraints are Eq. (3-22)–(3-32) and Eq. (3-35)–(3-36).

The stochasticity is introduced in the model via scenario generation. One interesting benefit of it is that the stochastic model can be converted in an equivalent deterministic model. After converting to equivalent deterministic model, the model can be solved by algorithms that are proposed for linear optimization model. This model is implemented on open-source solver Gurobi. However, it is important to develop model specific solver for result reliability.

3.5.4. Case Study

3.5.4a. Study area

This model selects Bangladesh for case study that is surrounded by several active tectonic faults. These are Himalyan arc, Shillong and Dauki fault system in the north, Burmese arc and accretionary wedges in the east and Naga–Disang–Haflong thrust zone in the north-east. The earthquake records suggest that since 1900 more than 100 moderate to large earthquake occurred in Bangladesh, out of which 65 events occurred after 1960. The increase in earthquake activity in Bangladesh is an indication of fresh tectonic activity of propagation of fractures from adjacent seismic zones (Khan et al., 2001). In a study by Villacis et al. (1999) on 20 cities of the world, Dhaka appeared to have one of the highest values of earthquake disaster risk index (EDRI) mainly due to its inherent vulnerability of building infrastructure which lacks earthquake resistant features, high population density and poor emergency response and recovery capability. Alam et al. (2011) analyzed the earthquake scenarios in Bangladesh and we consider four scenarios, s1… s4 with occurrence probabilities of 0.4, 0.3, 0.2 and 0.1 respectively. Alam *et al.* (2011) reported five scenarios for representing earthquake scenarios. We remove one scenario from the list that has the lowest earthquake magnitude; because, there is no relief demand after the lowest magnitude earthquake. In this way, we keep the number of variables tractable without losing the generality.

According to Figure 3-19, we consider three suppliers, named supp1, … , supp3 (Dhaka, Chittagong, and Rajshahi). They are the major cities of the country and are the hubs for supplying product all over the country. Seven demand points (*i.e.,* nodes), named dem1, … , dem7 (Dhaka [Dhk], Chittagong [Ctg],

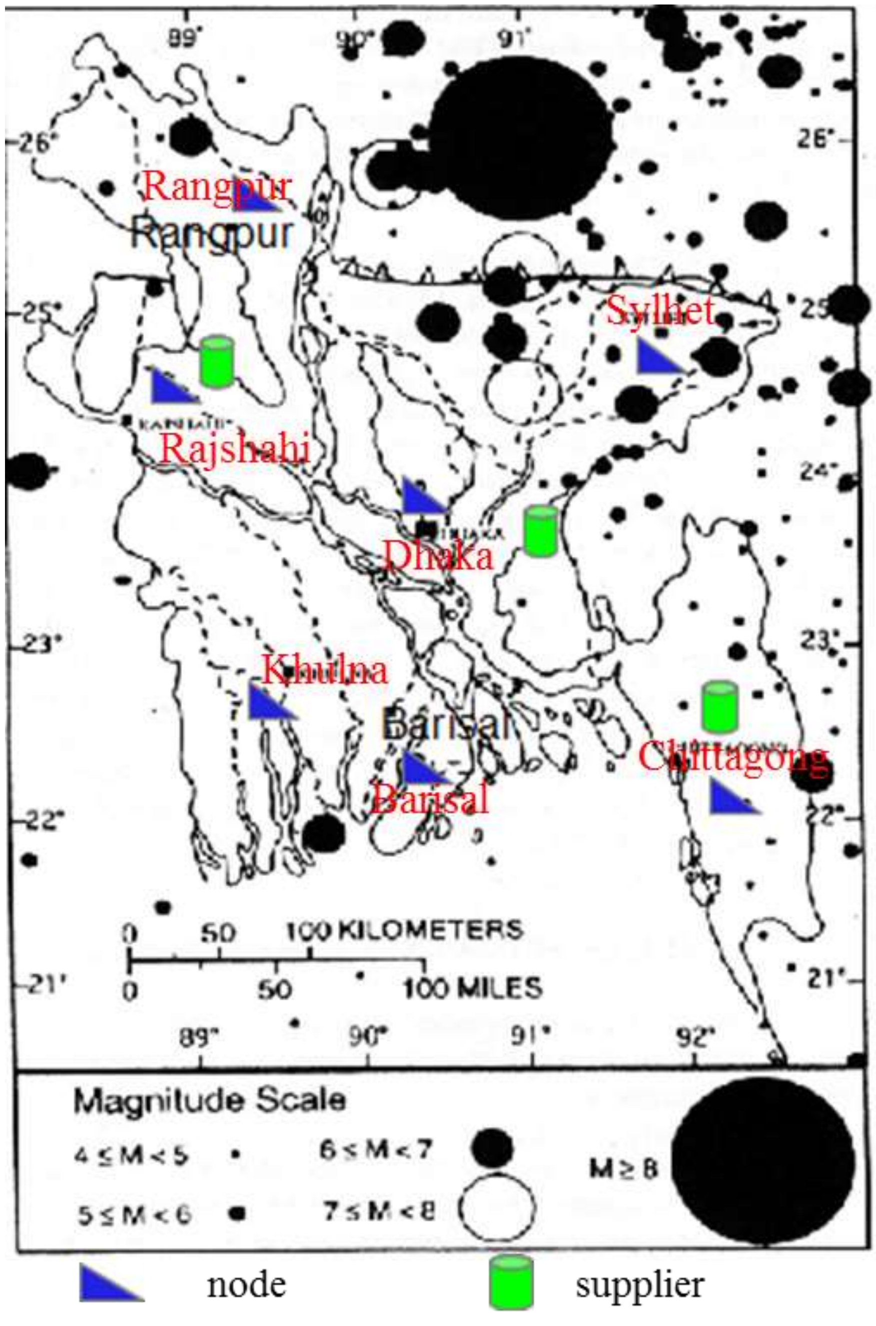


Figure 3-19: Location of earthquake epicenter in Bangladesh period 1750 to 2000 (source: United States geological survey; adapted from Khan et al, 2001),node and supplier added.

Rajshahi[Raj], Rangpur[Ran], Barisal[Bar], Khulna[Kul], and Sylhet[Syl]) are the most crowded cities in the country and are spread geographically over the entire map in Figure 3-19. Since city is highly vulnerable for distress from earthquake, demand points are selected within cities only. The demand in sub-urban areas are combined with demand in city.

3.5.4b. Data

Two commodities, namely prod1 (water) and prod2 (shelter), may be pre-positioned in storage facilities. One unit of prod1 consists of 1000 liter of water and one unit of prod2 is equivalent of 1000 unit of shelter. We assume the RDC sizes are available with specific cost as shown in Table 3-8. RDC setup cost depends on the storage capacity.

Table 3-8: RDC fixed cost and capacity

Size	Fixed cost (F_l) (10^3\$)	Capacity (N_l) (10^3 m^3)
small	500	10
medium	800	16
large	1200	24

Procurement price and transportation cost per unit distance are calculated based on local currency. On-line reports are used for data gathering. Procurement price in post-disaster situation is more than that of pre-disaster situation. Transportation cost in post-disaster is also higher than the pre-disaster transportation cost. The higher cost in post-disaster situations can also be considered as proxy of delay cost and human suffering. Costs of different items are shown in Table 3-9.

Table 3-9: Unit procurement price, transportation cost, and volume

Commodity	Procurement price (10^3\$/unit)	Transportation cost (10^3\$/unit-km)	Unit volume (m^3/unit)
prod1	0.5	0.6	4.5
prod2	20	1.8	120

The demand for each scenario is assumed by using the population density and earthquake intensity, collected from Alam et al. (2011). Note that there is no well accepted methodology for relief demand estimation and researchers (Akkihal, 2006, Balcik and Beamon, 2008) suggest using historical relief demand for earthquake disaster. The demand data are shown in Table 3-10.

Table 3-10: Demand data

	Dhk (prod1, prod2)	Ctg (prod1, prod2)	Raj (prod1, prod2)	Ran (prod1, prod2)	Bar (prod1, prod2)	Kul (prod1, prod2)	Syl (prod1, prod2)
s1	(319,106)	(222,74)	(238,79)	(225,75)	(0,0)	(0,0)	(579,193)
s2	(476,143)	(1339,446)	(0,0)	(0,0)	(75,25)	(30, 10)	(20,7)
s3	(76,10)	(187,62)	(0,0)	(0,0)	(100,33)	(100,33)	(0,0)
s4	(177,59)	(166,55)	(990,330)	(1654,551)	(21,7)	(20,7)	(94,31)

In the response phase, the available supplier's capacity is scenario dependent and is shown in Table 3-11. It is assumed that supplier's capacity changed for both commodities.

Table 3-11: Fraction of available supplier's capacity

	Dhk	Ctg	Raj
s1	0.94	0.95	0.9
s2	0.95	0.95	1.0
s3	1.00	0.99	1.0
s4	0.99	1.00	0.9

The post-disaster procurement prices are assumed to be 1.5 times of the pre-disaster procurement price and the increment of procurement price also represents delay of delivery of the commodity. The post-disaster unit transportation cost from supplier to RDC is assumed to be 1.8 times of that of the pre-disaster phase and from RDC to affected area is 2.0 times. These data are assumed to be fixed among scenarios. The cost of transportation between nodes is dependent of distance between two nodes. The distances between different nodes are collected by using car-route option from the Google Map. It is natural that unit overflow cost (θ) is lower than the unit shortage cost ($\emptyset$). The unit overflow cost is assumed to be kept equal to pre-disaster procurement price of the corresponding commodity. The unit shortage cost is assumed to be the ten times the pre-disaster procurement price of the corresponding commodity (Raws and Turnquist, 2010.) The value of λ is equivalent to two. It is a weight parameter for difference between the mean-value of A_s and the A_s for each scenario among different scenarios.

3.5.5. Results

In this section, the behavior and the results of proposed model is presented. The problem is solved using the mixed-integer linear programming solver 'Gurobi' from neos-server (Czyzyk et al, 1998). Gurobi uses branch and cut algorithm for solving mixed-integer problem. The results are described in this section. Table 3-12 shows that three of five opened RDC are specialized for storing prod1 and prod2. The remaining two RDC do not maintain inventories and assist relief distribution in different scenarios. The total cost of designing the distribution network is 8.3 million dollar.

Table 3-12 also explains the quantity of each commodity that will be stored in pre-disaster period. The supplier city (Table 3-11) in which a RDC is located can take advantage of its relief commodities from supplier to RDC in lower cost. One exception is in Sylhet where supplier is not present but established the RDC and maintain inventory. Table 3-13 represents the relief distribution in scenario 4.

Table 3-12: Location and inventory

RDC	Size	prod1	prod2
Dhk	small	323	10
Ctg	small	184.5	62
Raj	small	-	-
Syl	small	20	7
Kul	small	-	-

The sensitivity with the number of RDC is presented in Figure 3-20. It can be seen that the objective value decreases when the possible number of RDCs increases until a certain number. After passing the threshold number, the objective value increases again. Thus it concludes that the best value of RDCs is five. In order to arrive at an appropriate solution such that the decision maker will be able to see trade-off between the pre-disaster cost and the post-disaster cost.

Table 3-13: Relief commodities transferred from RDCs to demand points (for Scenario 4)

	Dhk (pd1,pd2)	Ctg (pd1,pd2)	Raj (pd1,pd2)	Ran (pd1,pd2)	Kul (pd1,pd2)	Bar (pd1,pd2)	Syl (pd1,pd2)
Dhk	(177,59)	-	-	(146,0)	-	-	-
Ctg	-	(166,55)	(0,7)	-	(21,0)	-	-
Raj	-	-	(550,100)	(254,200)	-	-	-
Syl	-	-	-	-	-	-	(94,31)
Kul	-	-	-	-	(0,7)	(21,7)	-

In Figure 3-21 and Figure 3-22, sensitivity analysis is performed for solution and model robustness against the multiplier of gamma. Figure 3-21 shows expected cost increases exponentially by increasing the value of gamma. On the other hand Figure 3-22 demonstrates the penalty cost $p_c\phi_{kc}\gamma$ will eventually drop to zero with an increase in the value of gamma. Both figures indicate that decision maker can choose

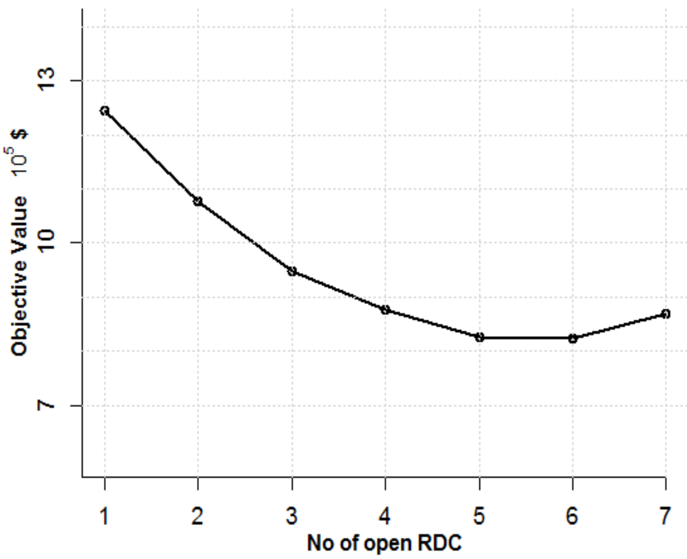


Figure 3-20: Sensitivity of total cost with the No of open RDC

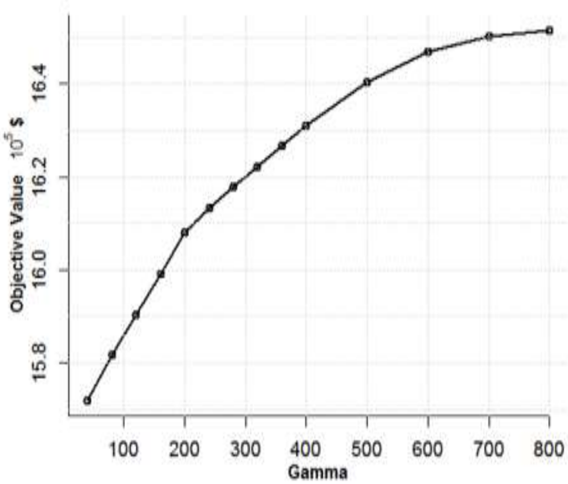


Figure 3-21: Sensitivity of solution robustness with respect to gamma

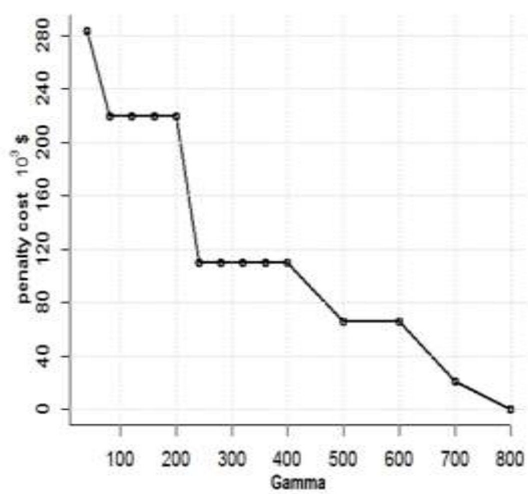


Figure 3-22: Sensitivity of model robustness with respect to gamma

gamma value based on the preference. It is suggested to decision maker to select higher gamma value to avoid risk of shortage of relief. Then, we have performed the sensitivity of lambda (λ) value. The model is run for lambda values of ‘1’, ‘2’, ‘3’, ‘5’, and ‘10’. The objective value of model does not differ noticeably because we have only four scenarios.

To highlight the role of uncertainty in modeling, three models results (1) deterministic demand and deterministic supply (DDS), (2) deterministic demand and stochastic supply (DDSS), and (3) stochastic demand and stochastic supply (SDSS) are compared. In DDS model, we assume that demand and supply parameters are known certainty. While DDSS model is designed with assumption that demand parameter are known certainly (demand parameters (d_{kcs}) are not scenario dependent), SDSS model represents complete stochasticity of demand (d_{kcs}) and supply (ρ_{kcs}) parameters. This comparison is made to show the benefit of considering stochastic parameters. To quantify the cost saving by considering the various sources of uncertainty, each typical model is solved for the case problem and results are shown in Figure 3-23. The cost of relief distribution is much higher than the SDSS. The DDS model have little cost benefit is scenario three. The remaining three scenarios cause much higher cost in DDS compare with all uncertain models. The similar phenomenon is also observed in DDSS model which gains lower cost compare with DDS model. It can be said that stochastic model gain cost benefits. This result also supports the benefit of risk-neutral behavior of decision maker. Risk-averse decision would be highly costly for scenario 3. By doing this analysis, we can also calculate the value of stochastic solution (*VSS*). The *VSS* provides relative advantage of stochastic model. In situations in which one cannot gather more information about the future, however, it may be more pertinent for decision makers to know how well the deterministic model solutions perform relative to solutions from more complicated stochastic programs (Birge, 1982).

$$VSS = C_{deterministics} - C_{stochastic} \tag{3-37}$$

where, first term in right hand side of Eq. (3-37) represents average solution of DDS model and second term is that of SDSS model. In the example, the VSS is 0.34 million dollar.

In the last, Figure 3-24 shows the components of the average cost in three different models explained above. The SDSS model incurs higher inventories cost compare with other two models. The SDSS model gain benefit in post-disaster situations and transportation cost is much lower in SDSS model. The penalty cost is also much lower in SDSS model that shows the robustness of this model.

The stochastic nature of supply and demand parameters are formulated in this study and implemented in a narrow set of experiments. The results show that this consideration can gain cost benefits over deterministic models. Although stochastic models require a large number of data sets and to solve the complex model, it is worth to apply stochastic model in strategic logistics planning for relief distribution. Additionally, model is sensitive to number of scenarios. However, scenario generation is out of scope of this study.

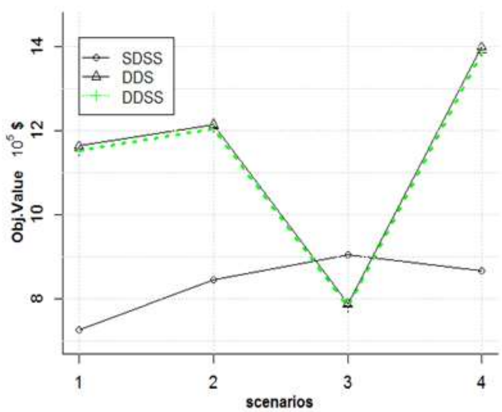


Figure 3-23: Comparison of different models in different scenarios

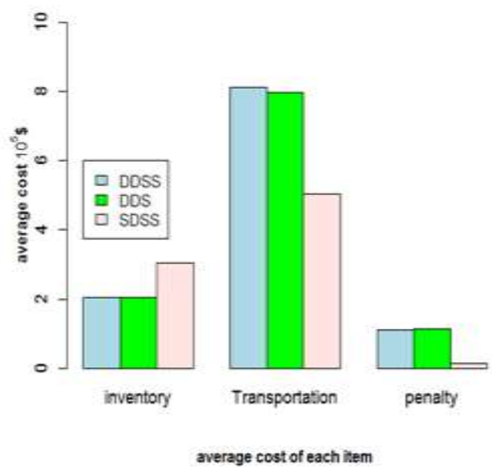


Figure 3-24: Comparison of cost items in different models

3.6. SUMMARY

This chapter shows the importance of inventory positioning and the current state of global prepositioned. It shows that inventory positioning brings beneficial in disaster response, particularly 72 hours after disaster. The current state of global prepositioning of UNHRD is capable delivering relief anywhere in the world within 24-48 hours to meet the needs of victims.

After exploration of inventory positioning network, this chapter explain the international relief delivery chain that consists of several stages. This chapter also simplifies the delivery chain with some reasonable assumptions and proposes a deterministic model, named IPMC. This model introduces a unique metric, named 'mean distance per capita'. The model also utilizes maximum distance from demand point to humanitarian depot for worst case scenarios. Disaster data from EM-DAT is utilized to show the effectiveness of the model. This model shows that the humanitarian depot in Malaysia is not in optimum location for Asia-Oceania zone. The model also suggested humanitarian depot locations for expansion of the network.

After analyzing the international relief chain, this chapter explores the potential locations of inventory positioning within a country. The IPSC model is introduced for finding suitable locations of inventory positioning (i.e., RDC). The IPSC model incorporates the demand and supply uncertainty. This model and the solutions have robustness feature. In contrast, IPMC model is a deterministic model. Deterministic model is suitable for contexts, where all parameters are known certainty. Deterministic model is easy to solve and highly sensitive to parameter changes. On the other hand, stochastic model is superior over deterministic model in terms of rational decision. Stochastic model is difficult to solve and requires sufficient amount of data. In the IPSC model, stochastic parameters were presented under scenario approach. The first stage decisions were location of RDC and inventory level in each RDC, and the second stage decisions were distribution of relief in different locations and procurement of relief. The IPSC model aims to minimize the penalty cost, distribution cost with the operational constraints. This model showed the trade-off between the pre-disaster cost and the post-disaster cost. The model also selects two RDCs (Raj and Kul) that do not maintain inventory. It is worth to mention that this model is easy to solve via open-source solver and decision maker does not need to spend money for buying commercial software to solve the model.

The case study was performed to provide insights of the model. Sensitivity analysis was also performed to show the validity of the model. The IPSC model showed that decision maker could save 0.34 million dollar by adopting stochastic model over deterministic model. Some parameter values, for instance penalty factor, robustness factor, and oversupply cost, are subject to decision maker's view to risk. Risk adverse decision maker can select higher value of parameter. Finally, the IPSC model is a generic model and possible to extend for business logistics. However, network model with supply uncertainty is highly appropriate for humanitarian logistics.

Chapter One

1. INTRODUCTION

Chapter Two

2. LITERATURE REVIEW

Chapter Three

3. RELIEF POSITIONING IN PREPAREDNESS

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Chapter Four

4. RELIEF ORDERING IN RESPONSE

Victims require food, medicine, tents, sanitation equipment, and other necessities, often for prolong period (Whybark, 2007). An advantageous relief management plan is essential to meet the demand of victims for prolong time. Inventory management is an important tool for relief management. This aspect has been neither well researched nor clearly understood so far (Whybark, 2007).

Inventory management is not an isolated tool and is dependent on preparedness, particularly on network of inventory prepositioning. The previous chapter proposes a model for designing network against random relief demand and identifies the causes of delay in delivery of relief to victims. This chapter analyzes the effect of uncertainty on demand and delivery-time in relief ordering and proposes a model for inventory management after disaster.

4.1. CHARACTERISTICS OF INVENTORY MANAGEMENT

The military sector, at first, introduced the importance of inventory management that is a matter of life and death during enemy attack. It is unlikely to know exact timing and size of enemy attack. The enemy can destroy strong military team unless the military maintain proper planning of troop deployment and of locating the troop. After the innovation by the military sector, the knowledge of inventory management is applied in various sectors. For example, hospitals utilize the knowledge for minimizing the stock-out of blood. The manufacturing sector and service industries borrow the idea of inventory management couple of decades ago. Inventory management for manufacturing sector aims for reducing the probability of stock-out of product and for improving the service level under the constraint of total cost. Despite the importance of inventory management, it is evident that most organizations do not fully understand the complexities of inventory management (Silver *et al.*, 1998), since, inventory management involves with the product, supply chain and some external specifications. Some specifications for inventory management are given below:

- Product has fixed expiry date or not.
- Demand is lost or not if cannot met on time.
- Warehouse has limited capacity or not.

- Demand can arise in any location of the network of the warehouses. Warehouse is an element of a network or not.
- Product supplies are stable or not.

Inventory management has been highlighted on its application in the context of commercial logistics (Kovacs and Spens, 2009). There are several differences between commercial logistics inventory management (CLIM) and humanitarian logistics inventory management (HLIM) in terms of planning and designing.

- The difference between these two sectors arises from decision-making domain. Commercial logistics always aims for monetary profit that is the driven force of business. In contrast, HL encompasses humanitarian domain that is shown in Figure 4-1. The domain consists of humanity, neutrality and impartiality. In other words, aid organizations attempt to help victims without being influenced by the outcome of a conflict with their intervention, and will not favor one group of beneficiaries over another.
- Humanitarian logisticians cannot get the updated information since it is probable that transport network and information network are disrupted due to disaster.

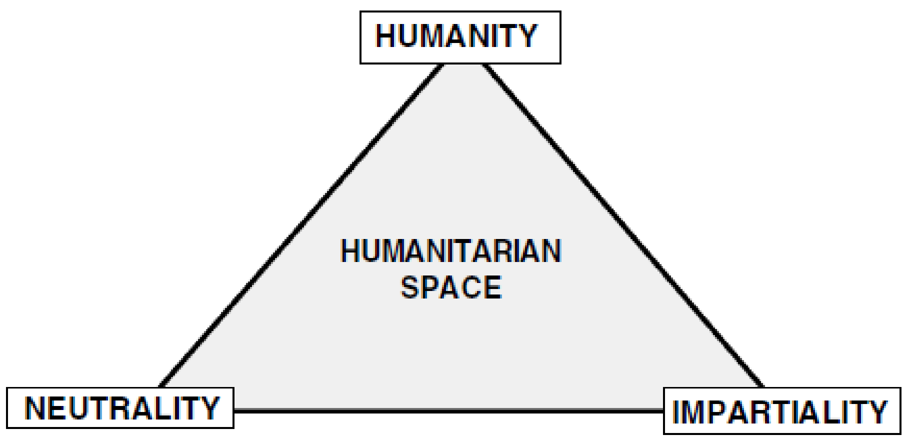

Figure 4-1: Humanitarian domain (space) (source: Van Wassenhove, 2006)

- There is little application of historical database for the estimation of relief demand. The impact of disasters is dependent on socio-economic culture of the affected regions.
- In general, HL activates after disruption of communication networks. As a result, a logistics manager cannot anticipate the actual arrival of relief.

Inventory management is considered an inseparable tool for improving customer service. It integrates supply chain properties and other externalities under the constraint of total cost. HLIM gains interest recently due to unique features after large-scale disaster.

4.2. CHALLENGES IN HLIM

Lead-time and demand are the two major parameters that are highly influenced by the supply chain specifications. Lead-time is defined as the interval between the placement of an order and the arrival of ordered goods. It consists of several actions (such as transportation, order preparation, order delivery and so on) and has the properties of randomness. The randomness and the length of the lead-time magnify the importance of inventory management. It observes that lead-time is long during earthquake relief operations, according to the internal report of International Federation of Red Cross and Red Crescent Societies' (IFRC). Table 4-1 the Indian Ocean tsunami relief response lead-time was 30 days; in comparison, the lead-times for the Pakistan and the Yogyakarta earthquake relief operations were significantly reduced. As humanitarian relief lead-time is governed by several factors (e.g. transportation, order preparation, and order delivery), its duration cannot be predicted with certainty.

Relief demand is also stochastic in day-to-day relief operation. There are several sources/reason for stochasticity of demand. First, some fraction of victims recovers soon and others are not. The recovery trend makes difficulty in demand estimation. On the other hand, some victims migrate to other places or to other relief distribution points.

The share of logistics cost during relief operation depicts the urgency of inventory management. It appears that the logistics cost (e.g. items, transport, and storage cost) in past earthquake relief operations constituted a significant share of the total cost. However, service level (defined as % of people gets the relief) is not in satisfactory level yet. For instance, only 28.02% of Indian Ocean tsunami victims get a partial or full assistance from IFRC and 30.77% is during Pakistan earthquake relief operation.

Table 4-1: Comparisons of the IFRC's performance in Indian Ocean tsunami, Pakistan and Yogyakarta earthquake

	Indian Ocean Tsunami 100,000 families	Pakistan earthquake 95,000 families	Yogyakarta earthquake 65,000 families
Families receiving at least partial package by 2 months	28,021	29,229	53,112

Average number of families served per day	445	555	613
% goods delivered from the region	13%	68%	100%
Days to activate end to end supply chain	18	10	3
Order lead time (requisition to delivery) in days	30	23	16
% of appeal items mobilized and delivered at 2 months	55%	38%	74%
Average distance of relief items (km) to families	11,805	2,962	1,617
Operations total costs at 2 months	not available	55,944,027	10,505,962
% logistics cost at 8 months (items + transport + storage value)	–	86%	87%
Cost to deliver relief package per family at 2 months	–	824	142
Cost to deliver relief package per family at 8 months	–	450	142

source: Justin Cuckow, The effect of the IFRC Regional Logistics concept on the efficiency of relief item delivery for the population affected by the Yogyakarta earthquake, Internal IFRC case study, August 24th 2006 (collected from Gatignon et al. 2010)

4.3. LEAD-TIME AND DEMAND CHARACTERISTICS

Three popular demand distribution types cited in relevant literature are uniform distribution, normal distribution, and Poisson distribution (Bagchi et al., 1986). Poisson distribution cannot demonstrate relief demand characteristics since it calculates the gap between two discrete events. In contrast, normal distribution (the most popular distribution function) requires a large amount of data to define its shape and parameters (kurtosis, mean, standard deviation, and asymmetry). As HL has limited historical data, normal distribution is not an appropriate analysis method for HLIM.

The stochastic characteristics of disaster scenarios pose another modelling challenge. For example, large-scale earthquakes destroy houses and displace a large number of people, either for immediate shelter or for better opportunities. These displaced people, who are called Internally Displaced Persons (IDP) (UN, 1995), may not visit the same POD every time when collecting relief. Hence, the variable nature of IDP activities to PODs represents the stochastic properties of relief demand at each POD.

Additionally, data collection methods for demand forecasting also emphasize the stochastic properties of relief demand. Modern data collection technology is not readily available after large-scale earthquakes. While social networking media (e.g. Facebook, Google, and Twitter) are potentially viable alternative post-disaster data collection methods, traditional sources (e.g. electronic and print media, Rescuer) are still the major data suppliers in such scenarios (Sheu, 2007). The numerical values of collected data from different sources are not identical, but rather interval-based.

With this in mind, a uniformly distributed relief demand parameter is the most reasonable model to apply to the lead-time after an earthquake disaster. It is clear that lead-time after a large-scale earthquake cannot be predicted quickly. Lead-time is combination of ordering time, collection time and transportation time. It is not possible to predict actual duration of each activity. For example, transportation time is highly unpredictable due to disruption of transport network after earthquake. Country government makes effort to improve transportation network aiming to ease relief flow. However, congestion in transportation network makes delay in receiving relief. Due to high complexity in this issue, uniform distribution is a reasonable assumption for lead-time. In addition, uniform distribution parameters can be easily estimated by efficiently assessing local knowledge, since the parameters are subjective estimates of the minimum and maximum value.

Furthermore, this study assumes both lead-time and demand are independent. This assumption, while unsuitable for CLIM, can be pertinent to HLIM. In CLIM, an order for a large quantity of product (i.e. a high-demand product) that requires longer manufacturing can result in mutually dependent lead-time and demand. However, this is not the case with HL. Aid organizations delivering disaster relief after large-scale earthquakes, such as the 2010 Haiti earthquake and the 2004 Indian Ocean tsunami, did not experience relief shortages; sufficient relief commodities were available at point-of-entry or near the affected area. Though transportation management was a major challenge in these relief operations, this can be solved via proper transport planning. The major barrier to relief delivery in these disaster scenarios was transportation management, not relief availability (Holguín-Veras et al., 2012).

The uniform distribution parameter can be easily estimated by quickly assessing the local knowledge since the parameter is a subjective evaluation of the minimum and maximum relief demand. This property increases the applicability the proposed model after large-scale disaster.

4.4. MODEL

4.4.1. System Characteristics

Figure 4-2 shows the two-stage system for distributing relief to disaster survivors; It is a simplification of the system of Figure 1-9. There are two stocking points: the first stocking point, located at the earthquake-affected area, is known as the point-of-distribution (POD); the second stocking point, located at an unaffected area, is called the central warehouse in this study.

In this two-stage supply chain model, the POD follows a continuous inventory review strategy to place orders with the central warehouse. It is assumed that the central warehouse is capable of delivering the requested amount of relief. The on-hand inventory at POD at the time of order placement with the central warehouse is r_1, which is expected to meet LTD. The placing of an order at the inventory level r_1 is called a ‘systematic order’ in this case. If the inventory level at POD reaches the threshold limit before the arrival of the systematic order, the logistics manager places an additional order — called an ‘exigent order’ — in an effort to prevent shortages. Thus, the threshold limit of the inventory at POD is r_2. Then, without losing generality, the limit of the two inventory levels is $0 \leq r_2 < r_1$.

When lead-times are stochastic, orders may not be received in the same sequence as they were placed. This phenomenon, known as an ‘order crossover’, complicates analysis. To address this problem, it is usually assumed that orders do not cross in time (Hadley and Whitin, 1963; Kaplan, 1970; Tijms and Groenevelt, 1984) or that not more than one order is outstanding at any point in time (Moinzadeh and Nahmias, 1988). This study assumes that an exigent order will arrive earlier than a systematic order; since an exigent order is delivered by an expediting service (e.g. by air or special convoy) rather than systematic services, it incurs a higher cost than that of a systematic order. The exigent supply source is assumed to be within the affected country or in a nearby country.

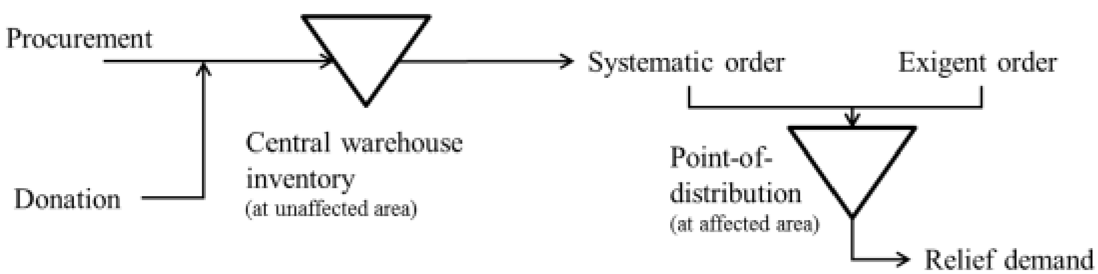

Figure 4-2: The schematic representation of an earthquake relief inventory model

In this study, we explore a strategy to prevent shortage without having to resort to an exigent order. For the purposes of analysis, we assume an infinite time horizon for the relief operation. While all relief operations in practice have a termination point, our model assumes the relief operation will continue as long as there is relief demand, and internally adjusts the decision variables as demand changes. It should be noted here that the assumption of infinite time horizon affects only the modelling formulation, since no order will be issued if there is no demand. The system properties and parameters are described below in detail.

4.4.2. Mathematical representation of LTD

Let t be a random variable of systematic-order lead –time, with range of minimum t_m and maximum t_M . The expected value *E[t]* and variance *var(t)* of t, are given by

$$E[t] = \frac{1}{2}(t_m + t_M) \tag{4-1}$$

$$\text{var}(t) = \frac{1}{12}(t_M - t_m) \tag{4-2}$$

Assuming that t is independent of the demand rate d and that d is also a random variable with the range of minimum d_m and maximum d_M, the expected value (*E[d]*) and variance (*var(d)*) of d are computed by using an equation similar to (4-1) and (4-2). Since t and d are independent, the properties of the product of lead-time and demand can be shown readily. Let D be LTD that is the product of lead-time and demand, then the mean of D is given by

$$E[D] = E[t]E[d] = \frac{(d_M + d_m)(t_M + t_m)}{4} \tag{4-3}$$

The variance of D is

$$\text{var}(D) = \text{var}(t)E[d]^2 + \text{var}(d)E[t]^2 + \text{var}(t)\,\text{var}(d) \tag{4-4}$$

$$= \frac{1}{144}(3(d_M + d_m)^2(t_M - t_m)^2 + 3(d_M - d_m)^2(t_M + t_m)^2 + (t_M - t_m)^2(d_M - d_m)^2) \tag{4-5}$$

Now, we derive the joint probability distribution of D. According to Dougherty (1990), the joint probability of two independent random variables t and d, then

$$f(D) = pr(t = x_1)\,pr(d = x_2) \tag{4-6}$$

Since the lead-time is uniformly distributed; the probability of occurrence of each point within the range will have an identical value. Hence, the probability of $t = x_1$ is

$$g_t(x_1) = pr(t = x_1) = \frac{1}{t_M - t_m} \tag{4-7}$$

Similarly, the probability of $d = x_2$ is

$$f(d) = pr(d = x_2) = \frac{1}{d_M - d_m} \tag{4-8}$$

Now, substituting Eq. (4-7) and Eq. (4-8) into Eq. (4-6), we get the probability distribution function (pdf) for D as follows:

$$f(D) = \frac{1}{(d_M - d_m)(t_M - t_m)} \tag{4-9}$$

Since lead-time and demand are ranged in the intervals (t_m ,t_M) and (d_m, d_M), respectively, the product of lead-time and demand is always positive. The study has adopted the algorithm proposed by Glen et al. (2004) to compute the distribution of the product of two uniformly distributed random variables. The joint

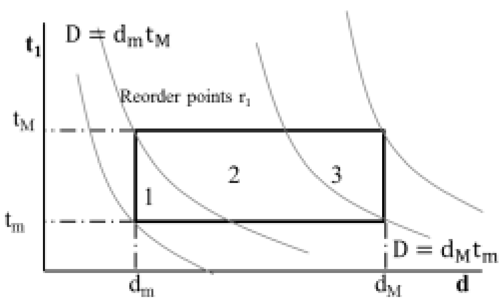

Figure 4-3: The regions of D for case 1

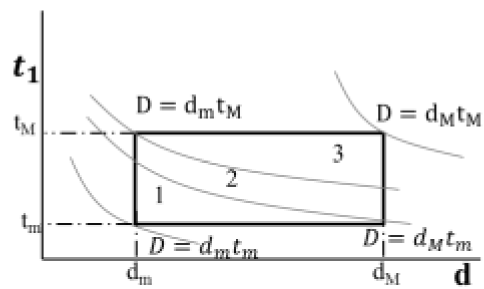

Figure 4-4: The regions of D for case 2

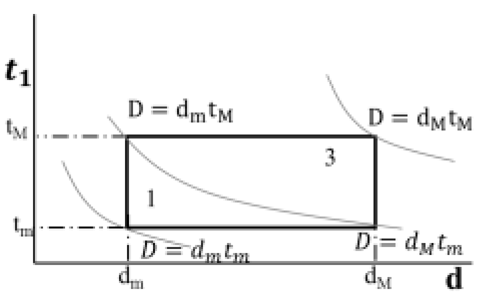

Figure 4-5: The regions of D for case 3

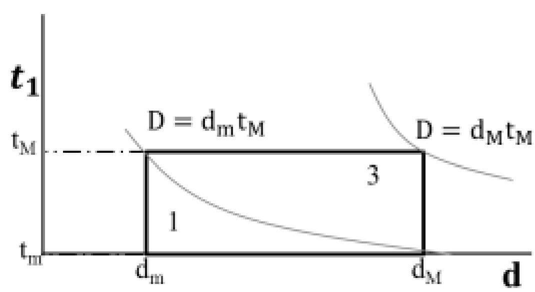

Figure 4-6: The regions of D for case 1A

probability distribution function (PDF) of d and t can be defined on a rectangular product space. The rectangular space is divided in regions depending on the values of d and t. Each region in the rectangular space is bounded by two hyperbolas. The boundary of each region corresponds to a different interval of D

for the family of hyperbola given by $td=D$. Given D, the interval of integration consists of those values of d for which the curve $td=D$ intersects the rectangle $\{(t,d)\colon t_m < t < t_M ,\ d_m < d < d_M\}$.

Table 4-2: The integral limit for different combinations of demand and lead-time range

	case 1: $d_m t_M < d_M t_m$; $d_m \neq 0$, $t_m \neq 0$	case 2: $d_m t_M > d_M t_m$; $d_m \neq 0$, $t_m \neq 0$	case 3: $d_m t_M = d_M t_m$; $d_m \neq 0$, $t_m \neq 0$	Case 1A: $d_m \neq 0, t_m = 0$
Region 1:	$d_m t_m < D < d_m t_M$	$d_m t_m < D < d_M t_m$	$d_m t_m < D < d_m t_M$	$0 < D < d_m t_M$
Region 2:	$d_m t_M < D < d_M t_m$	$d_M t_m < D < d_m t_M$	not exist	not exist
Region 3:	$d_M t_m < D < d_M t_M$	$d_m t_M < D < d_M t_M$	$d_m t_M < D < d_M t_M$	$d_m t_M < D < d_M t_M$

Since t and d are independent of each other, three different cases can occur under the condition of $d_m \neq 0$, $t_m \neq 0$, case 1 is $d_m t_M < d_M t_m$; case 2 is $d_m t_M > d_M t_m$; and case 3 is $d_m t_M = d_M t_m$. Table 4-2 provides a list of region's boundary of each case to compute the cumulative probability of D. Case 1A is a special form of case1 where $d_m \neq 0, t_m = 0$. The cumulative distribution function (CDF) of D has three distinct sections, and hence three regions, in cases 1 and 2. However, the CDF of D consists of two sections for cases 3 and 1A. Figures 2 to 5 represent the graphical illustration of the different integral limits of the regions of the four cases, respectively. In the following part of this paper, we have explained case 1; the other cases can be computed analogously.

4.4.3. Mathematical Formulation of HLIM

4.4.3a. Estimation of shortage per cycle

In this section, we derive the expression for expected shortage per cycle. Here, t with PDF g(t) and d with PDF $f(d)$ are continuous random, the PDF of $td = D$ is for Fig 2 is (Glen et al, 2004)

$$h(D) = \begin{cases} \int_{d_m}^{D/t_m} \frac{1}{d} g\left(\frac{D}{d}\right) f(d)\,dd & for\ \ region\ 1 \\ \int_{D/t_M}^{D/t_m} \frac{1}{d} g\left(\frac{D}{d}\right) f(d)\,dd & for\ \ region\ 2 \\ \int_{D/t_M}^{d_M} \frac{1}{d} g\left(\frac{D}{d}\right) f(d)\,dd & for\ \ region\ 3 \end{cases} \tag{4-10}$$

The PDF of D represents the desired probability of not running out of stock in any one ordering cycle. Note that systematic-order is placed when the inventory at POD touches r_1, in other word it is expected that D is equal or less than r_1, $D \le r_1$. The PDF of t and d are replaced by Eq. (4-9). By adopting the similar approach of Wanke (2008), Eq. (4-10) is expanded to estimate the cumulative probability of observed D to be equal or less than r_1 which is defined as service level (SL).

$$\text{Region 1: } SL(r_1) = \int_{d_m}^{r_1/t_m} \int_{t_m}^{r_1/d} f(D)\,dd\,dt \tag{4-11}$$

$$= f(D)\left(r_1 \ln \frac{r_1}{t_m d_m} - r_1 + t_m d_m\right) \tag{4-12}$$

$$\text{region 2: } SL(r_1) = \int_{d_m}^{r_1/t_M} \int_{t_m}^{t_M} f(D)\,dd\,dt + \int_{r_1/t_M}^{r_1/t_m} \int_{t_m}^{r_1/d} f(D)\,dd\,dt \tag{4-13}$$

$$= f(D)\left((t_M - t_m)\left(\frac{r_1}{t_M} - d_m\right) + r_1 \ln \frac{t_M}{t_m} - \frac{r_1}{t_M}(t_M - t_m)\right) \tag{4-14}$$

$$\text{Region 3: } SL(r_1) = \int_{d_m}^{r_1/t_M} \int_{t_m}^{t_M} f(D)\,dd\,dt + \int_{r_1/t_M}^{d_M} \int_{t_m}^{r_1/d} f(D)\,dd\,dt \tag{4-15}$$

$$= f(D)\left((t_M - t_m)\left(\frac{r_1}{t_M} - d_m\right) + r_1 \ln \frac{d_M t_M}{r_1} - \frac{t_m}{t_M}(d_M t_M - r_1)\right) \tag{4-16}$$

Accordingly, the expected shortage per cycle (B) is given by (Silver and Peterson, 1998)

$$B(r) = \int_r^{\infty} (dt - r) f(D)\,dd\,dt = \int_r^{\infty} dt f(D)\,dd\,dt - r(1 - SL(r)) \tag{4-17}$$

The double integration over each region defined in rectangular product space in Figure 4-3

$$\text{Region 1: } B(r_1) = \int_{r_1/t_m}^{d_M} \int_{t_m}^{t_M} dt f(D)\,dd\,dt + \int_{d_m}^{r_1/t_m} \int_{r_1/d}^{t_M} dt f(D)\,dd\,dt - r_1(1 - SL(r_1)) \tag{4-18}$$

$$\text{Region 2: } B(r_1) = \int_{r_1/t_m}^{d_M} \int_{t_m}^{t_M} dt f(D)\,dd\,dt + \int_{r_1/t_M}^{r_1/t_m} \int_{r_1/d}^{t_M} dt f(D)\,dd\,dt - r_1(1 - SL(r_1)) \tag{4-19}$$

Region 3: $B(r_1) = \int_{r_1/t_M}^{d_M} \int_{r_1/d}^{t_M} dt f(D) dd dt - r_1(1 - SL(r_1))$ (4-20)

$$= \frac{1}{2} f(D)(\frac{t_M^2}{2}(d_M^2 - \frac{r_1^2}{t_M^2}) - r_1^2 \ln \frac{d_M t_M}{r_1}) - r_1(1 - SL(r_1)) \qquad (4\text{-}21)$$

The integrations are in closed form, and the integration result only for region 3 is shown. The integration of the other two regions can be performed analogously.

4.4.3b. Estimation of the average number per cycle and cycle length

The expected inventory level in a cycle induces holding cost. Lau and Lau (2002) compared different methods for estimating the average inventory level in a (Q, r) system. While they assumed either a deterministic lead-time or a deterministic demand in all cases, we propose an approximation method to estimate the expected inventory levels for simultaneously stochastic lead-time and demand. The formulation of expected inventory level for each region, which largely depends on r_1, is shown below. The expected inventory per cycle denotes the area under the inventory line in Figure 4-7. As illustrated in Figure 4-7 an order cycle consists of two distinct periods: L, the replenishment systematic order lead-time, and t_0, the time between the arrival of one systematic order and the next. As demand of relief is stochastic, the reduction rate of inventory may not be constant. However, for the simplicity of the model, it is assumed that the reduction rate of inventory is strictly decreasing in constant rate. In addition, cycle length is not fixed in the system. It is dependent on observed demand. As demand and lead-time are stochastic, the cycle length is also become stochastic. Cycle length shows complex distribution.

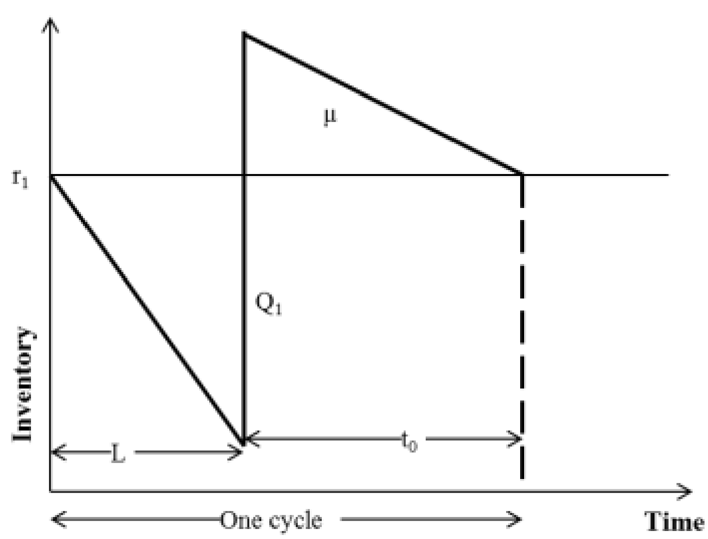

Figure 4-7: Expected inventory level in cycles with no EOs

D appears to be equal to (or less than) r_1 with probability ($SL(r_1)$). Here μ represents the average demand. First two-terms of Eq. (4-22) computes the average inventory level during period L and remaining two terms are during period t_0 in Figure 4-7.

$$oh(r_1) = \int_{d_m}^{r_1/t_M} \int_{t_m}^{t_M} (r_1 - dt) f(D) dddt + \int_{r_1/t_M}^{d_M} \int_{t_m}^{r_1/d} (r_1 - dt) t f(D) dddt + \int_{d_m}^{d_M} \int_{t_m}^{t_M} \frac{(Q_1 - dt)^2}{2\mu} f(D) dddt$$

$$+ \int_{d_m}^{d_M} \int_{t_m}^{t_M} \frac{(Q_1 - dt)^2}{\mu} f(D) dddt \tag{4-22}$$

$$= f(D)(\frac{r_1^3 t_M}{2} - \frac{d_m r_1}{2}(t_M^2 - t_m^2) + \frac{d_m^2}{6}(t_M^3 - t_m^3) - \frac{r_1^3}{6 d_M} - \frac{d_M r_1 t_m^2}{2} + \frac{d_M^2 t_m^3}{6}) + \frac{Q_1^2}{2\mu} - \frac{Q_1 E[D]}{\mu} +$$

$$\frac{f(D)}{18\mu}((t_M^3 - t_m^3)(d_M^3 - d_m^3) + \frac{Q_1 r_1}{\mu} - \frac{r_1 E[D]}{\mu} \tag{4-23}$$

The average cycle length is also derived from Figure 4-7. Let T denote the average length of a cycle.

$$T = \int_{d_m}^{r_1/t_M} \int_{t_m}^{t_M} \frac{r_1}{d} f(D) dddt + \int_{r_1/t_M}^{d_M} \int_{t_m}^{r_1/d} \frac{r_1}{d} f(D) dddt + \int_{d_m}^{d_M} \int_{t_m}^{t_M} \frac{Q_1 - dt}{\mu} f(D) dddt \tag{4-24}$$

$$= f(D)(r_1(t_M - t_m) \ln \frac{r_1}{t_M d_m} - \frac{r_1^2}{d_M} + r_1 t_M - r_1 t_m \ln \frac{t_M d_M}{r_1}) + \frac{Q_1}{\mu} - E(t)) \tag{4-25}$$

Here, we have shown that the cycle length for r_1 lies in region 3. The cycle lengths for r_1 in regions 1 and 2 can be computed analogously.

4.4.3c. Expected total cost

The expected cost in cycle $TC(Q_1,r_1)$ comprises the systematic-order's fixed cost (f_1), as well as variable cost (c_1), the inventory holding cost (h), and the shortage cost (s). Then $TC(Q_1,r_1)$ is given by

$$TC(Q_1, r_1) = f_1 + c_1 Q_1 + hE[oh] + sE[B] \tag{4-26}$$

To obtain the expected cost per unit time (ECUT), the total cost is divided by the expected cycle length.

$$ECUT(Q_1, r_1) = \frac{TC(Q_1, r_1)}{E[T]} = \frac{(f_1 + c_1 Q_1 + hE[oh] + sE[B]}{E[T]} \tag{4-27}$$

The partial derivative of the ECUT with respect to Q_1 is

$$\frac{\delta\ (ECUT)}{\delta Q_1} = 0 \tag{4-28}$$

Solving Eq. (4-29), (see the appendix for details), the optimal Q_1 is given by

$$Q_1 = \frac{1}{h}(-(\mu(A_1 + hA_2 - c_1) + h(E[D] - r_1)) \pm \sqrt{((\mu(A_1 + hA_2 - c_1 - 2h(\mu A_1 A_2 - A_3)) + h(E[D] - r_1))^2})$$

(4-29)

where,

$$\mu = E[d] = \frac{1}{2}(d_M + d_m) \tag{4-30}$$

$$A_1 = c_1 + \frac{h}{\mu}(r_1 - E[D]) \tag{4-31}$$

$$A_2 = f(D)(r_1(t_M - t_m)\ln\frac{r_1}{t_M d_m} - \frac{r_1^2}{d_M} + r_1 t_M - r_1 t_m \ln\frac{d_M t_M}{r_1}) - E[t] \tag{4-32}$$

$$A_3 = \mu f_1 + h\mu(f(D)(\frac{r_1^2 t_M}{2} - \frac{d_m r_1}{2}(t_M^2 - t_m^2) + \frac{d_m^2}{6}(t_M^3 - t_m^3) - \frac{r_1^3}{6d_M} - \frac{d_M r_1 t_m^2}{2} + \frac{d_M^2 t_m^3}{6}) + \frac{f(D)}{18}(t_M^3 - t_m^3)(d_M^3 - d_m^3) - r_1 E[D]) + \mu s E[B] \tag{4-33}$$

The Eq. (4-29) generate two values. The value of Q_1 is always positive; negative value of Q_1 must be ignored, if appears. In the case of two positive value of Q_1, the value that is larger than r_1 will be selected.

4.4.4. Multi-commodity Inventory Algorithm

We present the algorithm for the multi-commodity inventory model. Multi-commodity inventory model may gain benefit of cost sharing of joint replenishments (Goyal and Satir, 1989). If there is no ordering cost reduction after joint replenishment, each commodity inventory policy is planned using a single commodity inventory model. On the other hand, if ordering cost is dependent on the number of orders placed in one period, multi-commodity model is beneficial over single commodity model.

Simmons (1972) proposed an algorithm for solving the problem. Let f_1 to be not fixed and varies from one scheduling period to the next, depending on the number of orders placed in each scheduling period. We further assumed that f_1 can be evaluated or approximated with satisfactory degree for any given set of reorder quantities; that is, in functional notations, we assumed that

$$f_1 = Z + z(Q_1, Q_2\ , \ \dots\ , \ Q_n) \tag{4-34}$$

where Z is constant for ordering cost, and $z\ (Q_1, \ \dots, \ Q_n)$ represents either an ordinary analytical function or a convergent computational algorithm.

In order to find the optimal (r_i, Q_i) policies in our joint setup cost environment, Eq. (4-34) must hold. The value of f_1 that was used in Eq. (4-29) to calculate the optimal order quantities is recalculated after plugging the value of (r_i, Q_i) into Eq. (4-34). For an n-product problem, there are n- equations of Eq. (4-29) plus Eq. (4-34). There are $5n+1$ with simultaneous computation of Eq. (4-30) –(4-33), This system will usually be impossible to solve directly. Therefore the algorithm for solving the model is

Step 1: Set $f_1 = Z$.

Step 2: Treating f_1 as a constant per-order setup cost, solve the Eq. (4-29)

Step 3: Use the functional relation Eq. (4-34) to calculate a new value of f_1. If it is sufficiently close to the previous value, stop; otherwise return to step 2.

Observe that for any finite positive reorder, quantities per period will be finite, and the per-order setup cost will lie somewhere between Z and $z + Z$. In particular, the value f_1 increases after step (3) has been executed for the first time.

4.5. CASE STUDY

This section presents a case study to illustrate the HLIM model. In order to verify this approach, the case study is small enough to be solved in its extensive form using open-source software (R Core Team, 2012), but detailed enough to be of interest as an illustration. Table 4-3 summarizes the key parameters of the commodity (e.g. water) that is assumed for this case study. There is no methodology to measure the cost of human suffering due to relief shortage. The general assumption is that the shortage cost is higher than the expenditure per unit (Balcik and Beamon, 2008; Rawls and Turnquist, 2010). In this study, we assume that the shortage cost per unit is 50 times higher than the variable cost per unit. We select a low holding cost since it represents POD’s operational cost. (Note that, although these values are useful for exploratory purposes, they may not match the values that may be estimated by the ultimate users of the model.) After plugging the base data into the proposed model, the following results are obtained.

Figure 4-8 shows the CDF of lead-time-demand that is derived from the combination of Eq. (4-12) (i.e. region 1), Eq. (4-14) (i.e. region 2) and Eq. (4-16) (i.e. region 3). The cumulative probability of LTD being in region 1 is less than 0.2. There is an 80% probability of shortage if the reorder level is 260 units. The upper boundary of region 2 is 500 units, and the cumulative probability of LTD being in region 2 is less than 0.5. The expected value of LTD is 600 units, and the cumulative probability that it lies in region

Table 4-3: Base data and model parameters

f($)	c($/ unit)	s($/unit)	h($/day-unit)	t_m(day)	t_M(day)	d_m(unit/day)	d_M(unit/day)
10000	0.3	15	0.000003	10	30	10	50

3 starts at 0.5 and increases rapidly as it ultimately approaches 1.00.

Figure 4-9 reveals the relationship between expected shortage unit and reorder level. The expected shortage unit decreases linearly in regions 1 and 2 for the increment of reorder level. However, the expected shortage unit decreases exponentially in region 3.

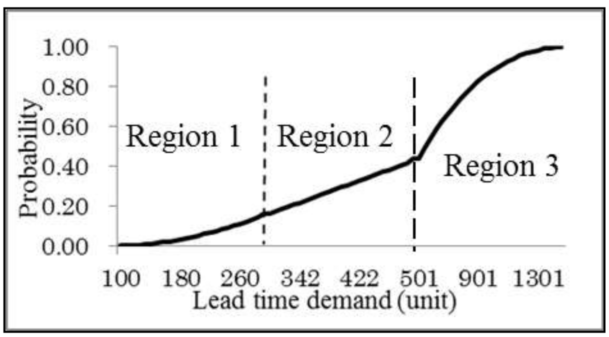

Figure 4-8: Cumulative distribution function of LTD

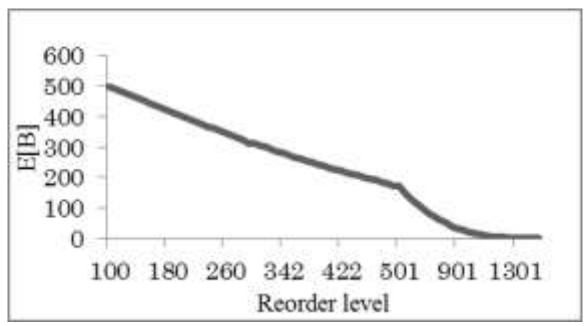

Figure 4-9: Expected shortage with Reorder level

We then investigated the relative effect of cost parameters on order quantity through a series of sensitivity tests. With this aim, we modified each parameter and compared the resulting order quantity with that corresponding to a base case with specific parameter values. At the given level of holding cost and shortage cost, Figure 4-10 displays the change in order quantity with respect to different variable costs. The change in order quantity is equal to Eq. (4-35)

$$\text{The change of order quantity} = \frac{(Q_a - Q_0)100\%}{Q_0} \tag{4-35}$$

Where, Q_a = New order quantity after parameter change

Q_0 = Base order quantity calculated with base data

Increasing the variable cost by 10% results in a decrease in order quantity; similarly, decreasing the variable cost by 10% or 20% results in an increase in order quantity. However, the order quantity is not sensitive to the variable cost at the reorder level of 661 units (near the expected *D*), and all the curves converge to zero. The convergence value is also influenced by the fixed cost of placing an order. Judging by these model dynamics, change of variable cost is possible in three cases: (1) if the relief goods are procured at a higher rate; (2) if donation goods are available in sufficient amounts; and (3) if transport companies offer discount rates for relief goods.

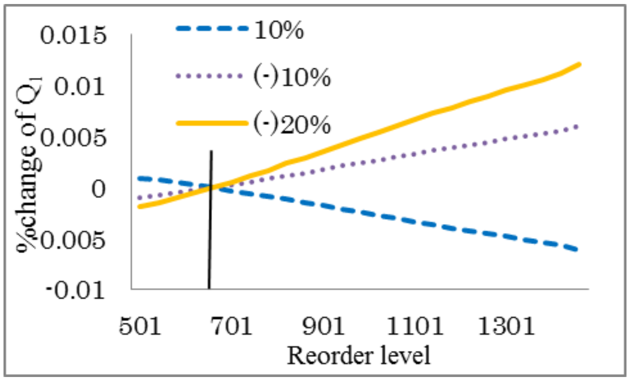

Figure 4-10: Effect of variable cost

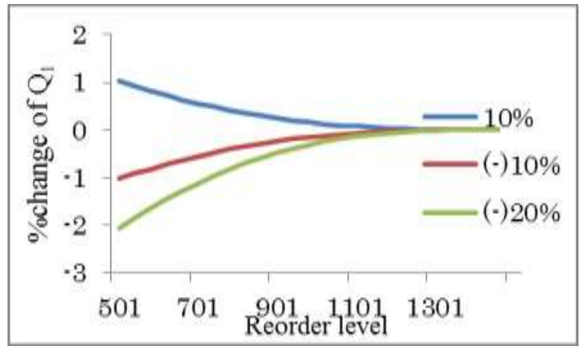

Figure 4-11: Effect of shortage cost

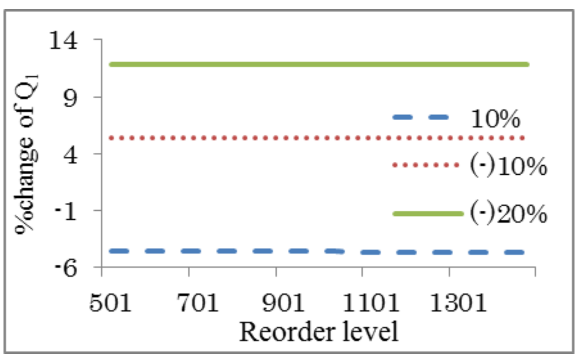

Figure 4-12: Effect of holding cost

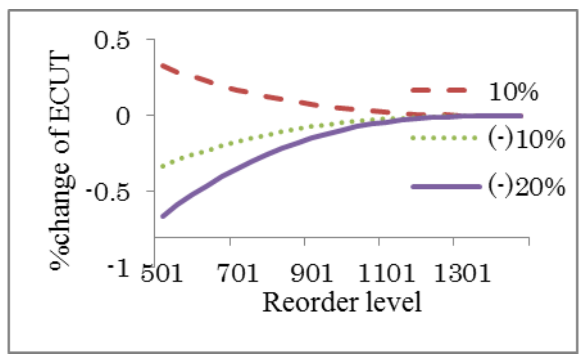

Figure 4-13: Effect of shortage cost

In contrast, the order quantity changes exponentially with a change in shortage cost, as displayed in Figure 4-11. The order quantity at a reorder level of 501 units increases by 1.02% when the shortage cost increases by 10%, and decreases by 1.03% when the shortage cost decrease by 10%. At a reorder level of 1,341 units, all the curves converge to zero. Figure 4-12 depicts the changes in order quantity caused by the changes in holding cost. The order quantity changes proportionately with the reorder level. It decreases by 4.6% when the holding cost increases by 10%, and increases by 5.4% when the holding cost decreases by 10%. Finally, Figure 4-13 describes the change in ECUT sensitivity with changing shortage cost. All the curves converge to zero at a reorder level of 1,241 units.

4.6. SUMMARY

Relief operation is a highly challenging, diverse, and extensive effort. Logistics manager faces several problems after a disaster. Inventory management is one of them, which are highly ignored by academic and professional. The basic properties of both CLIM and HLIM are similar (i.e., product dependency, supply chain dependency and other external factors). However, HLIM possess several distinct properties that motivate to formulate new mathematical model for HLIM.

The performance data after past disasters shows that lead-time after large-scale earthquake is long. The lead-time after Indian Ocean tsunami was 30 days. Furthermore, lead-time after disaster is random due to the disruption of the communication network. HL after disaster is explored to show independency between lead-time and demand (in contrast, lead-time and demand are dependent in CLIM). This chapter proposes a model stochastic lead-time combining with stochastic demand.

Using a uniform distribution model for the two stochastic variables (i.e. lead-time and demand) allows us to compute the probability of relief shortage and its treatment. The model presented here is a stochastic optimization model based on a first-order differential equation that attempts to determine the order quantity and reorder level necessary to prevent relief disruption for a given probability, which would be most applicable to decision-makers who do not possess the actual LTD curve. An algorithm for multi-product inventory system is also proposed. The cumulative probability curve of LTD is formulated and it shows that the mean demand lies in third region in the lead-time and demand rectangular space. Similarly, the expected shortage for certain reorder level is also calculated. In the case of the reorder level equivalent to 501 units, the expected shortage is less than 200 units. The sensitivity of expected cost and reorder quantity against cost parameters are also presented. The case study presented here addressed the stochastic nature of LTD relief demand in a practical context and revealed the model's sensitivity to changes in the cost parameter.

Chapter One

1. INTRODUCTION

Chapter Two

2. LITERATURE REVIEW

Chapter Three

3. RELIEF POSITIONING IN PREPAREDNESS

Chapte Four

4. RELIEF ORDERING IN RESPONSE

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Chapter Five

5. RELIEF ALLOCATION IN RESPONSE

Humanitarian assistance providers face several bottlenecks in distributing relief to the right person, at the right time, and at the right cost. To assist for achieving aid organization's aim, the third chapter in this dissertation presented two models for relief prepositioning and the fourth chapter presented a model for relief ordering in response. In this chapter, relief allocation in response is explored. The importance of this model generates from the mismatch between demand and supply after disaster.

As a hypothetical example, consider a large-scale earthquake that has caused varying degrees of damage in different areas. This disaster generates enormous relief demand in a given condition of limited resources. The coordinator faces difficulties in allocating available relief because of resource constraints. Additionally, the coordinator requires coordinating among stakeholders. Thus, general questions arise after disaster is what is the method to allocate resources among victims? Is it possible to make hierarchy among victims? These issues are addressed in this chapter.

5.1. CURRENT PROVISION OF AGENTS IN HL

Humanitarian operations are characterized by multiple actors, feedback loops, time pressures, resource constraints and uncertainty (Besiou et al., 2011). Typically, no single stakeholder of HL has sufficient resources to respond effectively to a major disaster (Bui, 2000). Therefore, stakeholders must depend on each other even though they may have different interests, mandates, capacities, and logistics expertise (Balcik et al., 2010). To investigate the various interests of stakeholders, the mandates of various aid organizations are presented. For example, Oxfam focuses on water distribution and sanitation, the United Nations High Commissioner for Refugees (UNHCR) and the International Federation of Red Cross and Red Crescent (IFRC) focus on shelter, and the World Food Program (WFP) focuses on food. Although these organizations have entirely different targets, their common aim is to reach more victims. Logistics providers also play an important role in relief distribution by providing services outside of their regular service area, and generally aim to reduce transport-related costs. Logistics providers may also have their own preference; for example, during the relief efforts following Hurricane Rita, many of the vehicles and drivers expected to distribute relief supplies abandoned New Orleans after hearing reports of violence (Hoguin-Veras et al., 2007). Thus, aid organization and transport service providers have seemingly different preferences.

Figure 5-1: Different focuses of different aid organizations (clockwise from top-left: Oxfam, UNHCR, IFRC, and WFP)

Figure 5-2: Transportation of relief items

To enable coordination among different agencies, the United Nations Joint Logistics Centre (UNJLC) was formed in 2002 as an umbrella organization to handle operational logistics in the disaster relief environment and encourage the best use of limited logistics resources (Kaatrud et al., 2003). The United Nations (UN) and aid organizations have established various committees and offices, such as the Office of the Coordinator for Humanitarian Affairs (OCHA) and the Inter-Agency Standing committee

(IASC), to improve coordination within the relief community (Reindorp, 2002; Kehler, 2004; Balcik et al., 2010).

5.2. STAKEHOLDERS

Kovacs and Spens (2008) list donors, aid organizations, NGOs, governments, military, logistics service providers, and suppliers as the stakeholders involved in HL network. Oloruntoba and Gray (2006) add aid recipients (beneficiaries) to the list. van Wassenhove (2006) adds the media as a stakeholder of disaster relief. This study investigates the ontology of stakeholders in the last-mile relief distribution, as shown in Figure 5-3. The stakeholders include the aid organization, carrier, demand agent, and society (e.g., national authority, evaluation team, media, etc.). Figure 5-3 shows the objectives and activities of each stakeholder, and provides details as follows.

Donors are not obliged to fund and if they do, they often donate funds to aid organizations to increase their own social esteem (Cermak *et al.,* 1994)**.** However, aid organizations want to generate more funds by gaining trust of donors. Total funds of an aid organization are modeled as positive function of social benefits generated by the organization and efficiency of the organization (Preston, 1989)

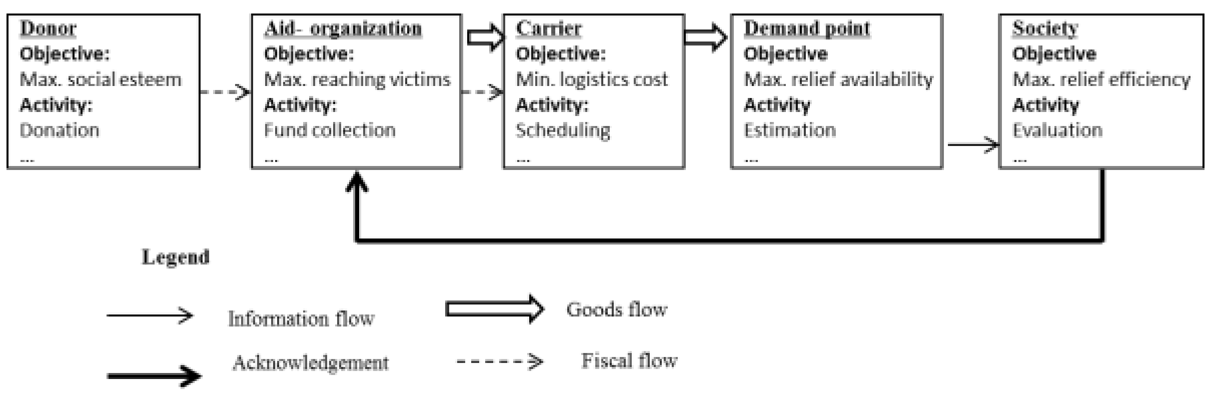

Figure 5-3: Stakeholders' ontology of humanitarian logistics

Aid organization agent (AOA): The AOA is a key player in HL, and is responsible for collecting funds from donors and for managing relief. This AOA aims to reach more victims. In the proposed model, the AOA is assigned the role of a tertiary hub.

Carrier agent (CAA): The CAA follows the behavior of business logistics, and wants to maximize monetary profit. The CAA performs several activities, such as transporting, loading, and unloading. The goals of the CAA are to minimize transport costs and waiting time. However, the CAA faces the constraint of fleet capacity and operator working hours.

Demand agent (DA): The DA, who performs demand estimation, orders relief items, receives relief items, and distributes relief items to victims, is assigned the role of a demand point, and represents the last key stakeholder in the supply chain. The DA receives relief from the tertiary hub and distributes it to victims. The DA attempts to bring in more relief to their demand point, and therefore exhibits very local-specific (*i.e.*, selfish) behavior. The DA and AOA may be two different sections of the same organization. However, we classify them in two groups to distinguish their functionalities.

Society agent (SA): The SA does not have decision-making power in the relief chain. However, the SA evaluates the aid organizations' efforts, and may be a representative of an evaluation team.

Coordinator agent (COA): The COA is responsible for coordinating the overall relief flow. The COA did not exist in all relief operations of past disasters. However, The United Nations (UN) and aid organizations have established various committees and offices, such as the Office of the Coordinator for Humanitarian Affairs (OCHA) and the Inter-Agency Standing committee (IASC), to improve coordination within the relief community (Reindorp, 2002; Kehler, 2004; Balcik et al., 2010). In addition, national disaster management agency (for instance, Federal Emergency Management Agency (FEMA) in United States of America) may work as COA.

5.3. TASK CHAINS

Figure 5-4 (top) provides an illustration of relief flow (modified from Balcik et al., 2008). First, the relief item transfers from various locations to a primary warehouse. Next, relief item is shipped to tertiary hubs via a secondary hub. Finally, tertiary hubs deliver relief item to demand-points (victims). The relief distribution from the tertiary hub to the demand point, known as last-mile distribution (LMD), is the most challenging section, and requires special attention (Balcik et al., 2008). Therefore, LMD requires critical analysis when allocating logistics resources in each tertiary hub to maximize social benefits. This topic is the focus of this paper, and agent based model (ABM) is implemented for relief distribution in LMD. The proposed ABM is a normative model (i.e. this model aims to maximize social welfare). In the model COA is smart enough to for making rational decision.

Figure 5-4 (bottom) shows the task chains that are linked to relief allocation. This figure shows that relief item is received in the tertiary hubs from secondary hubs. Simultaneously, demand points request relief from the tertiary hub. The tertiary hub evaluates the relief request under the resource constraints and deploys relief to the demand point accordingly. Finally, the whole operation is evaluated with the aim of maximizing social benefit.

Social benefit from a project is often intangible, hard to quantify, and difficult to attribute to a specific organization. Fortunately, the social benefit of distributing relief can be linked to the relief delivery that is shown in Eq. (5-1)

$$SB(x) = supplied\_relief \times benefit\_of\_unit\_relief \tag{5-1}$$

where,

$SB(x)$ = social benefit from x available resources

Although social benefit is the aim of relief distribution, resource constraints often force decision-makers to distribute relief depending relief urgency. This study defines the effort of aid organizations as follows:

$$acknowledgement = \frac{SB(x)}{cost} \tag{5-2}$$

Society computes the value of acknowledgement and imposes it on aid organizations. Therefore, aid organizations that create a higher acknowledgement by providing relief tend to garner more donations, whereas those that squander their resources receive lower future donations (Cermak et al., 1991). For example, Lily Duke, an independent film producer, arrived in New Orleans with a single fleet of donated

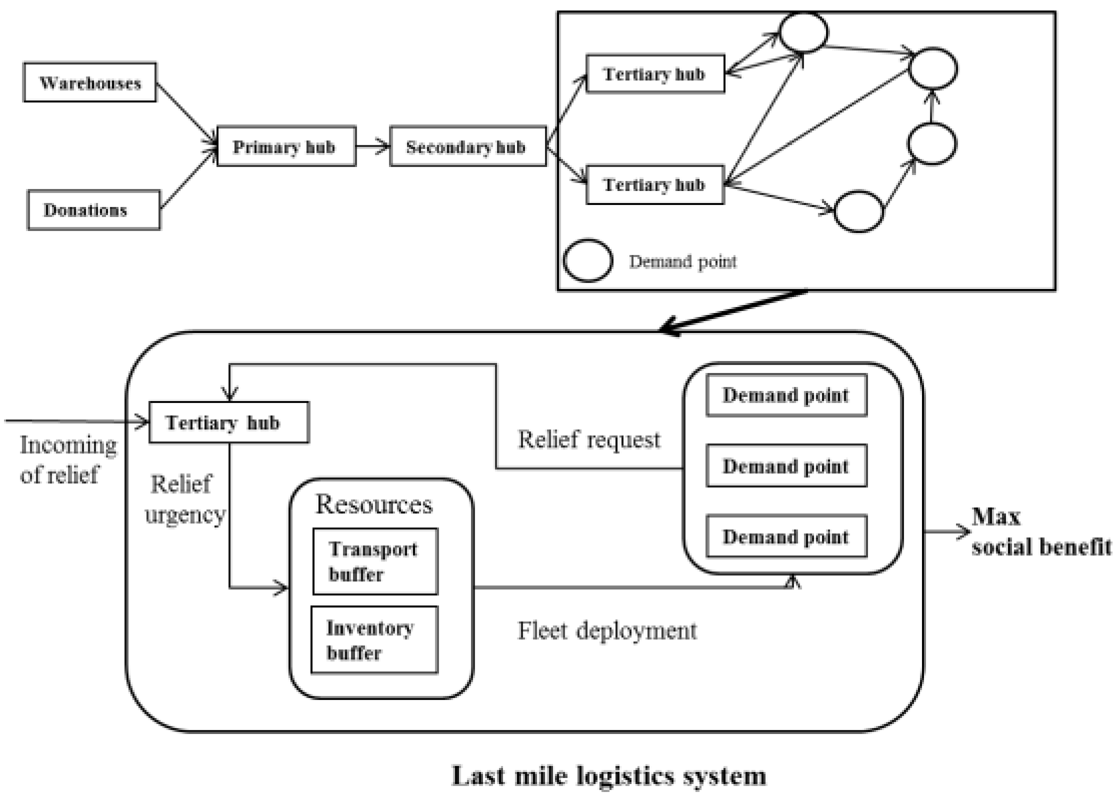

Figure 5-4: Supply chain of HL and task chains in the last-mile

food. The residents of this highly damaged area by Hurricane Katrina were satisfied and media highlighted the news of effectiveness of relief distribution. Duke's effort was considered effective strategy for relieving victims suffering. Within three months of the disaster's onset, Duke was operating three distribution centers that served 20,000 people a day (Sobel and Lesson, 2007). The value of effectiveness of relief distribution strategy is computed by acknowledgement in this study. The acknowledgement value for Duke's efforts is higher due to larger numerator value in Eq. (5-2).

5.4. OPERATION OF THE ABM

Consider a large-scale earthquake that has contributed to different degrees of damages. All victims need assistance in the aftermath of this disaster, and the circumstance requires that limited resources be utilized with proper judgment. This section proposes a fleet allocation model for this type of situation. After explaining the task chains and the study focus, we explain the behaviors of stakeholders in last-mile distribution. This section concludes with an illustration of the ABM architecture and operation.

The target relief item is consumed daily (*i.e.,* it is a meal box). The demand for the product is generated every day and is lost unless it is met within a specified time period. The unsatisfied demand incurs a penalty cost. The relief allocation includes a series of decisions including DA selection, delivery time, and fleet composition.

Figure 5-5 shows the relationships among agents. The ABM is used to assign a specific type of

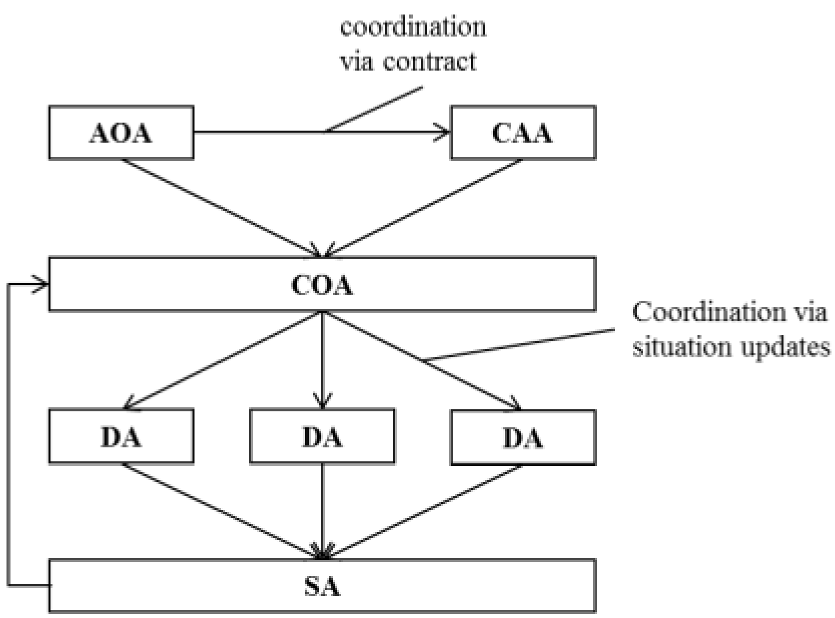

Figure 5-5: Architecture of agent based model

agent to each function in relief distribution. The carrier agent (*CAA)* manages the transportation required for the entire planning period. They follow the rule of minimizing logistics cost. The demand points are distributed among demand agents (*DA:* $DA_n=1,\ldots, n$). A DA is responsible for only one demand point, and cannot exchange information with other DAs. DA expects relief as much they need.

The coordinator agent (COA) is responsible for the coordination of local planning of the DA, AOA, and CAA. The AOA makes a contract with CAA, and provides a fleet composition plan to the COA. AOA wants to reach more victims. The relationship between the AOA and COA resembles that of a client and server. The AOA, in the role of a client, submits a resource plan to the COA, and the COA returns the solution to the AOA. Finally, the SA evaluates the performance of the logistics system based on urgency-based mechanisms.

Next, we explain the simulation flow of the model. Figure 5-6 shows the steps in the simulation, which runs until it meets the termination criteria.

5.4.1. Phases 1 to 2:

In Phase (1), the AOA submits a plan of fleet composition and relief quantity

In Phase (2) the relief distribution to demand point is carried out in six steps. In step (2.1), the CAA submits cost information to the COA. Eq. (5-4) and (5-5) are the constraints for COA.

$$\min \sum_{r} \sum_{k} c_{rk} y_{rkt} \tag{5-3}$$

$$\text{Subject to, } \sum_{r} y_{rkt} = V_{kt} \quad \forall k,t \tag{5-4}$$

$$y_{rkt} = \{0,1\} \quad \forall r,k,t \tag{5-5}$$

where,

c_{rk} = cost for route r with vehicle type k

y_{rkt} = binary variable for selecting route r, vehicle k on time t

V_{kt} = the available vehicle of type k in period t.

In step (2.2), the DA estimates demand using a method proposed by Sheu (2007)

$$D_i(t) = \max\{a_1 \delta_i(t)\bar{L} + z_{1-\alpha} STD_i(t)\sqrt{\bar{L}}, \quad 0\} \tag{5-6}$$

In this equation, a_1 represents the average hourly demand of target product. $\bar{L}$ represents the upper bound preset to regulate the temporal headway between two successive relief distributions to any given affected area without exceeding the corresponding maximum value. $Z_{1-\alpha}$ represents the statistical value when the tolerable possibility of time varying relief demand shortage is set to be α. $\delta_i(t)$ represents the estimated number of victims in the affected area i in a given time interval t. $STD_i(t)$ represents time-

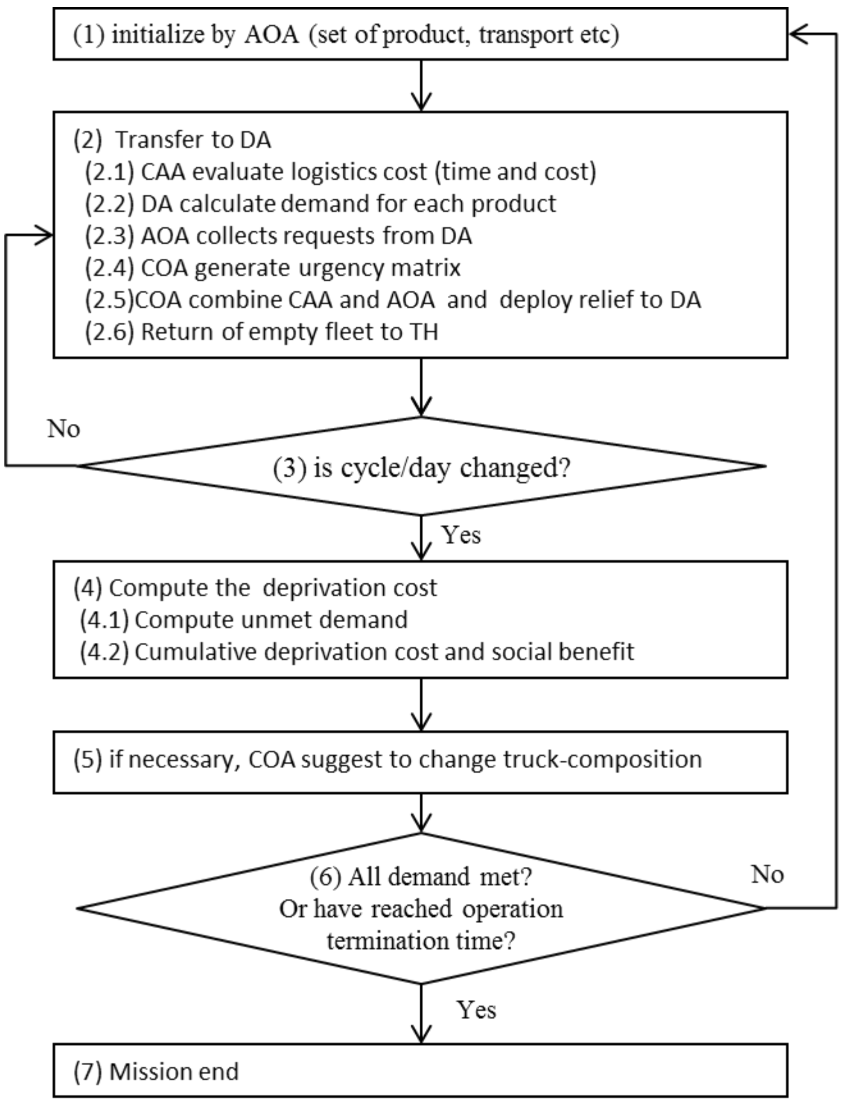

Figure 5-6: Simulation flow of agent-based model

varying standard deviation of relief demand associated with the delivered relief and affected area i. This allows the model to incorporate uncertainty.

In step (2.3), the DA places request for relief and the AOA collects information from all DAs to create a hierarchy of demand points to reach more victims. The AOA attempts to minimize the penalty cost differences among different demand points, as shown in Eq. (5-7). The satisfaction rate is the ratio between the delivered amount and the demand. This value is calculated as Eq. (5-8):

$$\min \quad \sum_i (1 - s_i) f \qquad \forall i \in I \tag{5-7}$$

$$\text{subject to, } s_i = \frac{\sum_t x_{it}}{\sum_t d_{it}} \tag{5-8}$$

$$x_{it} \le d_{it} \quad \forall i, t \tag{5-9}$$

$$\sum_i x_{it} \le F_t \quad \forall t \tag{5-10}$$

$$\sum_i x_{it} \le Cap_k V_{kt} \tag{5-11}$$

where,

x_{it} = the amount of relief delivered to node i in period t, and

d_{it} = the demand of relief during period t for demand point i.

s_i = the satisfaction rate of delivering relief.

f = penalty cost for relief item shortage

F_t = the available relief item in period t

Cap_k = Capacity of vehicle type k

In step 2.4, the COA generates an urgency matrix for the system based on the technique for order of preference by similarity to ideal solution (TOPSIS) method (Deng et al, 2000, Sheu, 2010). The TOPSIS method is as follows.

A set of demand agents is compared to a set of the criteria $C=\{C_j, j=1,\ldots, m\}$; Five criteria are selected to form the hierarchy of demand points. These criteria are as follows (Sheu, 2010):

C1. The time-varying demand for relief product.

C2. The population density associated with a given area.

C3. The ratio of frail population (e.g., children and older adults).

C4. The time difference between the present time and the last delivery.

C5. The damage condition of area. This value lies within 1 to 10.

Note that each criteria *j* is in different scales. For instance, C3 (i.e, *j*= *3*) is ratio type data and C5 (i.e., *j* = *5*) is an ordinal data (i.e., Likert scale). Let, $P_{ij}^{'}$ is the value of criteria *j* for DA *i*.

Therefore, $P_{ij}^{'}$ are normalized as

$$p_{ij} = \frac{P_{ij}^{'}}{\sum_{i=1}^{n} P_{ij}^{'}}, \quad i = 1, \ldots, n \tag{5-12}$$

Where, p_{ij} = the normalized value of criteria *j* for DA *i*

thus, an assessment matrix for this problem can be obtained as

$$P = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1m} \\ p_{21} & p_{22} & \cdots & p_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ p_{n1} & p_{n2} & \cdots & p_{nm} \end{bmatrix} \tag{5-13}$$

Next, each criteria weight in Eq. (5-13) can be measured by the entropy value e_j (Deng et al., 2000) as

$$H_j = -k \sum_{i=1}^{n} p_{ij} \ln p_{ij} \tag{5-14}$$

Here $k = \frac{1}{\ln n}$ is a constant. This ensures that $0 \le H_j \le 1$.

The degree of divergence (g_j) of the average intrinsic information contained by each criterion is calculated as

$$g_j = 1 - H_j \tag{5-15}$$

and The criteria weight (k_j) for each criterion is thus given by

$$k_j = \frac{g_j}{\sum_{j=1}^{m} g_j} \tag{5-16}$$

After determining the rating of each criterion, the next step is to aggregate rating to produce an overall relief-urgency for each zone. This aggregation process is based on the positive ideal solution (A^+) and the negative ideal solution (A^-), which are defined, respectively, as

$$A^+ = \left(\max_i (p_{i1}), \ldots, \max_i (p_{im}) \right) = (p_1^+, \ldots, p_m^+) \tag{5-17}$$

$$A^- = \left(\min_i (p_{i1}), \ldots, \min_i (p_{im}) \right) = (p_1^-, \ldots, p_m^-) \tag{5-18}$$

The members of vector A^+ are the positive ideal values of each criterion and the members of the vector A^- are the negative ideal values of each criterion. Therefore, the lengths of vector A^+ and A^- are equal to total number of criterions. Equations (5-13), (5-17), and (5-18) show that the weighted Euclidean distance between A_i and A^+, and between A_i and A^- are calculated, respectively, as

$$d_i^+ = \sqrt{\sum_{j=1}^{m} w_j (p_j^+ - p_{ij})^2} \quad \forall i = 1, \ldots, n; j = 1, \ldots, m \tag{5-19}$$

$$d_i^- = \sqrt{\sum_{j=1}^{m} w_j (p_{ij} - p_j^-)^2} \quad \forall i = 1, \ldots, n; j = 1, \ldots, m \tag{5-20}$$

Therefore, the overall relief urgency of each zone can be computed by

$$\mu_i = \frac{d_i^-}{d_i^+ + d_i^-} \tag{5-21}$$

A larger index value indicates a more urgent zone.

In step (2.5), the COA creates a joint evaluation matrix after incorporating information of the AOA and the CAA. The aid organization and carrier both adopt the weighted sum method (Zadeh, 1963) after incorporating the urgency of relief for each demand agent.

$$Z_t = \max\{ \min_{i,r,k} \{ w_1 (1 - s_i) f \ (1 - \mu_i) + w_2 c_{rk} y_{rkt} \}, \ 0 \} \tag{5-22}$$

where $w_1 + w_2 = 1$ (5-23)

Eq. (5-22) combines the objectives of the aid organization and the carrier. w_1 and w_2 are weight factors. Generally, $w_1 > w_2$, which indicates a relatively high penalty cost. If $w_1 = w_2$, then the carrier is reluctant to consider the victim's suffering. If $w_1 < w_2$, then the carrier agent exhibits opportunistic behavior. In the

Table 5-1: Pseudo-code of the decomposition approach (Modified from Lin et al., 2011)

a. Randomly select a demand point that is not included in any group

b. Find the nearest demand point (not currently included in any group) to the last assigned demand point in the group, and repeat the process until the predefined number of demand points in a group is met or there is now ungrouped demand point left.

c. Find the average distance of the group member from tertiary hub, put the new group to lowest distance tertiary hub (J_h)

d. **IF** there is a demand point that does not belong to any group, **Go to step a**

e. **Else** equally assign a number of vehicles L_h to each group $h \in H$, where $H = \{1, \dots, h\}$ is the collection of groups $\sum_h L_h = total\_vehicle$ and $J_p \cap J_q = \phi \quad \forall p \neq q$. The original problem has now been decomposed into g sub-problems with assigned demand points and vehicles, respectively and each sub-problem is labeled as SP_h

f. For each sub-problem SP_h, all feasible tours are enumerated and constructed using the shortest time principal.

g. For each sub-problem, construct the mathematical model based on L_h , J_h and the corresponding demand demand points in the sub-problem; Solve SP_h by a solver and get the objective value z_h and the total objective value $z_{all} = \sum_h z_h$. If (iteration) $i = 0$, set the best total objective value $z^*_{all} = z_{all}$

h. Find a pair of groups (p, q) that has the minimum and maximum objective value, respectively.

i. **IF** $L_p > 2$, then remove a random number of vehicle v from L_p where $1 \leq v \leq L_p - 1$ and assign to L_q

j. Go to **step f,** update z_p , z_q, and z_{all}.

k. **IF** $z^i_{all} < z^*_{all}$ update $z^*_{all} = z^i_{all}$, **Go to step f**

l. **ELSE** set $i = i + 1$

m. **IF** $i \leq \bar{i}$ **Go to step a**

n. **ELSE** find the next maximum objective value group, **stop and exit.**

special case of $w_2 = 0$, the carrier provides voluntary transport to support aid organizations. Finally, f is the penalty cost for relief item shortage.

The COA then deploys the fleet to the DA. This deployment can happen in different ways, and this study presents a comparison of the two deployment methods. The first is the enumeration method, and the second is the decomposition-type approach. The enumeration approach is popular for benchmarking the effectiveness of the proposed approach. It appears in numerous research papers (Aykin, 1995; Yu and Egbelu, 2008). Other approaches for this task include random demand points, Drop solution, Drop and interchange solution (Akin, 1995).

In this study, the enumeration approach is a simple myopic approach and the value of w_1 is zero. In other words, this approach generates a DA hierarchy based on the distance from the nearest tertiary hub, and deploys the fleet to the nearest DA that requires relief. However, not all fleet can go to particular DA since fleet cannot deliver more relief than the requirement in DA. Besides, the satisfaction rate (s_i) changes after decision on deployment of fleet to DA (i.e, before arrival of fleet at DA). Thus, urgency index (μ_i) is changed after each decision of deployment. The following discussion presents the decomposition algorithm used in this study.

First, the decomposition approach decomposes the entire problem into several sub-problems by forming a group of demand points with a pre-defined maximum number of demand points per group. This approach allocates fleets to different sub-groups to maximize the benefit from available resources. It is reasonable to assume that the number of fleet vehicles is greater than the number of tertiary hubs. Therefore, a portion of the fleet is assigned to each sub-problem. The proposed approach is described in *Table 5-1*. Levels a – d of the algorithm decompose the original problem into several sub-problems. In other words, these steps categorize the demand points in several sub-groups. The number of sub-group is identical to the number of tertiary hub. Each sub-group of demand point is assigned to particular tertiary hub according to the rule of the algorithm. In Level e, the fleet is distributed among the sub-problem (i.e., tertiary hub). At the first iteration, fleet is allocated evenly to each sub-problem. The objective values of sub-problems and overall objective values are obtained in Level g. Levels f – n aims to improve the solution by adjusting the vehicle assignments among groups.

If the fleet carries more load than demand in target area, it visits another demand point after delivering the initial target demand point. In step (2.6), after distributing all relief, the fleet returns to the tertiary hub.

5.4.2. Phases 3 to 7:

Phase (3) is a logical condition in which the COA checks the work status. Phase (4) is performed once in each cycle, and is an evaluation of the efforts. In step (4.1), the SA calculates the difference between the requested and supplied relief.

In step (4.2), the value of the relief effort is calculated. Holguin-Veras et al. (2010) propose a methodology of calculating the deprivation cost that assumes that the deprivation cost increases with a late delivery.

$$dc_i(\Delta t) = n_i(t)\, e^{(\omega + \xi \Delta t)} \tag{5-24}$$

We propose new formulation for deprivation cost after incorporation of relief urgency index.

$$dc_i(\Delta t) = \mu_i n_i(t)\, e^{(\omega + \xi \Delta t)} \tag{5-25}$$

If there are two strategies for relief distribution, say strategy 1 and strategy 2, and they generate deprivation cost dc_{i1} and dc_{i2} respectively. Then, the social benefit is

Similarly, this study presents a hypothesis that the benefit of relief decreases if delivery is late, and this benefit reduction rate increases exponential with late delivery. This formulation incorporates the relief urgency. Thus, the social benefit is

$$SB_i(\Delta t) = dc_{i1}(\Delta t) - dc_{i2}(\Delta t) \tag{5-26}$$

where
dc_i = deprivation cost
n_i = shortage of relief
Δt = time gap between two deliveries,
ω, ξ = parameter

The following equation provides the acknowledgement value

$$acknowledgement = \frac{\sum_i SB_i(\Delta t)}{cost} \tag{5-27}$$

In Phase (5), the COA suggests that the AOA should change the fleet composition to minimize the deprivation cost. The operation terminates after meeting all demands or meeting stopping criteria.

In Phase (6), the model checks the termination criteria. If termination criteria are satisfied, the mission ends in Phase (7).

5.5. EMPIRICAL ANALYSIS

The ABM adopted in this study is implemented in open-source tool NetLogo that utilizes integrated development environment (IDE) for implementation of model environment. The NetLogo is developed by North Western University (available on http://ccl.northwestern.edu/netlogo/). In the proposed model, several optimization sub-models are included. The optimization is solved by another open-source tool R. Here, 'RNetLogo' package is used to connect two open-source tools. The ABM was tested on an Intel (R) Core (TM) i3-3220 PC operating at 3.30 GHz. The following section describes the test concept and the results.

5.5.1. Case Study

The 'Great East Japan Earthquake' destroyed an untold number of roads and buildings. The most severely affected prefectures were Fukushima, Miyagi, and Iwate, which had pre-disaster populations of 2.35 million, 1.33 million, and 2.03 million, respectively. In this case study, we collected data for five of the most-affected cities in these three prefectures. Miyagi prefecture lost 3.11% of its population (10,739 victims) to the disaster. Iwate prefecture had fewer fatalities, but lost 4.35% of its population. Fukushima

Table 5-2: Features in five cities of three prefectures

Prefecture	City	victims in shelter	%Fatalities	frail people	Density (people per km^2)
Fukushima (hub1)	Iwaki (A1)	341983	0.1	0.065	270
	Namie-machi (A2)	18866	0.97	0.065	99
	Minamisoma(A 3)	69171	1	0.065	170
	Soma (A4)	37843	1.21	0.0658	190
	Shinchi-machi (A5)	7141	1.58	0.0658	191.3
Miyagi (hub 2)	Natori(A 6)	69311	1.47	0.06	727
	Higashimatsushima (A7)	35522	3.32	0.060	420
	Ishinomaki (A 8)	160835	3.65	0.060	295
	Minami-sanriku (A9)	16294	2.3	0.060	120
	Kesennuma (A10)	63841	7.4	0.060	220
Iwate (hub3)	Rikuzentakata (A 11)	21262	10.03	0.067	100
	Kamaichi (A12)	41360	3.03	0.067	92.9
	Otsuchi (A13)	13811	11.63	0.067	83
	Yamada-machi (A14)	16959	4.98	0.067	77
	Miyako (A 15)	57406	1.34	0.067	46

had a much smaller number of fatalities (Vervaeck et al., 2011; Holguín-Veras et al., 2012). Table 5-2 shows the victims in shelters, fatalities, frail population, and density for the five most-affected cities in each prefecture. Victims-in-shelters and %fatalities are post-disaster data. In contrast, frail population and density are pre-disaster data. The NetLogo computes the transportation time from tertiary hub to demand point internally. The demand point keeps the record of each delivery time. In the TOPSIS method, time of last delivery that is a dynamic parameter, is a criterion for computation of urgency index. In this analysis, the 15 shelters are the demand points. For the network setting, three tertiary hubs were placed in three prefectural offices. Fleet compositions of 9, 12, 15, 18, 21, 24, and 27 were used. The parameter value for Eq. (5-6) a_1 is 3, and the standard deviation is assumed to be 10.

Table 5-3: Summary of parameters

Parameter	**setting**
Hourly demand	0.125
Upper bound of two delivery $(\bar{L})$	24 h
Lead time (L)	6 h
$z_{1-\alpha}$	1.95
Vehicle capacity	1600 unit
Planning periods	2 days
Working hours	10 h
Fleet operation cost	.79 $ / km
Penalty cost	ω = 1.63
	ξ = 0.00002

5.5.2. Results

This case study was analyzed using the decomposition approach and the enumeration approach. The decomposition approach employs Eq. (5-22) as an objective function in step 2.5 of the simulation flow stated in Figure 5-6. In the decomposition approach, w_1 and w_2 are assumed identical value (i.e., 0.5). On the other hand, the enumeration approach employs Eq. (5-3).

Table 5-4 represents the result of the TOPSIS method for calculating the hierarchy of each demand point in terms of relief urgency. Here, A1 to A15 represent cities in three prefectures. Among them, A8 (Ishinomaki) is the most urgent demand point and A5 (Shinchi-machi) is the least urgent demand point at Day 0. In the case of relief shortage and no transport capacity limitation, the AOA serves the demand points sequentially, starting from A8. However, the urgency index of each demand point changes with time. It is interesting to see that there is no dominating parameter. All parameters are treated in simultaneously. At Day 0, Criterion 5 in the TOPSIS method (*i.e.*, the time difference between the present time and the last delivery) is equal for all points. The hierarchy of demand points changes after each delivery

Table 5-4: Relief urgency index for demand points at Day 0

id	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14	A15
μ $(X10^{-2})$	4.5	9.5	4.0	3.7	2.8	9.1	8.1	12.5	6.1	10.0	10.1	4.4	7.9	4.4	3.1

The average deprivation cost of the complete planning period was calculated to compare the two deployment methods, and Table 5-5 presents the results. The decomposition approach dominates the enumeration approach for all fleet compositions. This model generates routes and allocates the fleet to deliver relief to all demand points. If one demand point does not receive relief for two consecutive days, the deprivation cost increases exponentially. In the decomposition approach, the fleet visits each point at least once per day, whereas in the enumeration approach, the fleet distributes relief to closer demand points and other demand points are left un-served.

Table 5-5: Fleet allocation for various hubs to minimize the deprivation cost

Total fleet number	Allocation of fleet			avg. deprivation cost	
	Hub 1	Hub 2	Hub 3	Decomposition approach	Enumeration approach
9	3	4	2	36.37	5127.73
	2	5	2	72.74	5127.73
12	3	5	4	24.22	4766.33
	3	4	5	25.36	4766.33
15	4	7	4	15.58	3694.11
	5	6	4	26.95	3694.11
18	5	7	6	27.25	3058.67
	6	6	6	26.83	3058.67
21	7	7	7	25.62	2676.64
	6	10	5	25.787	2676.64
24	6	10	8	25.80	1331.81
	8	10	6	26.15	1331.81
27	7	13	7	15.82	1384.37
	8	12	7	27.92	1384.37

We compute shortage of relief in each method. The relief shortage depends on the available capacity of the fleet. This is directly plausible because HL fleet management assumes that all vehicles operate with full truck loads under operational time constraints. Figure 5-7 and Figure 5-8 show the changes in total shortage and transportation cost as the fleet volume changes in enumeration and in decomposition approach respectively. According to both Figures, the relief shortage decreases linearly as the fleet volume increases. This implies that the fleet maximizes its utilization capacity. The fleet moves from one demand point to another demand point until it delivers all carrying relief. This system is in line with the model proposed by Ozdamer et al. (2004), in which the fleet gets a call from its last position rather then returning to depot to get a new order. In contrast, the transportation cost changes every operational day in decomposition approach and remains unchanged in enumeration approach. This implies that the fleet must run longer distances to meet the demands of the most urgent demand points in decomposition approach. This proves that the urgency index has an effect on the selection of the target demand points. This study employs a linear cost function of distance for transportation cost. Therefore, it is natural that an increase in resources would lead to a higher transportation cost and a lower deprivation cost. We successfully simulate this phenomenon in the virtual world to analyze the effects of transportation measures The enumeration approach and the decomposition approach produce the same total relief shortage.

To compare the effects of urgency-based relief distribution, we must compute the acknowledgement value. The benefit is computed based on the difference between the deprivation costs of the enumeration approach and decomposition approach. The denominator in Eq. (5-27) is computed by the transport cost differences between the enumeration and decomposition approach. The formula is shown in Eq. (5-28):

$$acknowledgement\_gap = \frac{dc_{decom} - dc_{enu}}{TC_{decom} - TC_{enu}} \tag{5-28}$$

According to Figure 5-9, the acknowledgement values decreases exponentially as fleet number increases from 9 to 12, 15, 18, 21, 24, and 27. This implies that the decomposition approach is more effective when resources are limited. The decomposition approach and the enumeration approach both generate identical benefit if there are sufficient resources, and the acknowledgement value is similar to he benefit-cost ratio computation

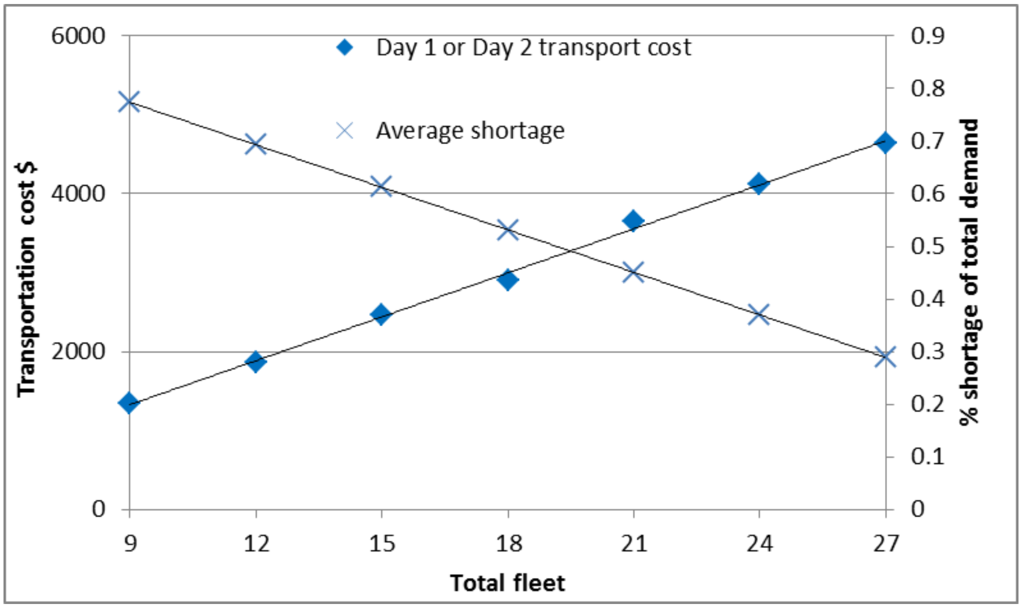

Figure 5-7: Change of transportation cost and shortage in enumeration approach

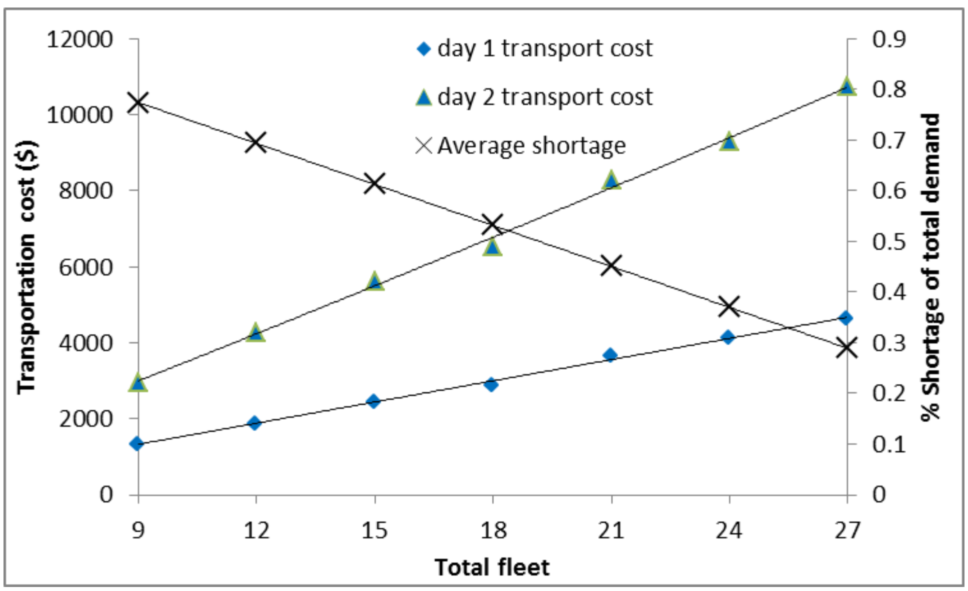

Figure 5-8: Change of transportation cost and shortage in decomposition approach

Finally, all agents follow their own preferences in attempting to maximize their own objectives. The aid organization agent aims to minimize the differences among various demand points. On the other hand, the carrier agent wants to deliver in shorter distances. The coordinator agent finally reaches a solution for both parties. Table 5-5 shows the combined effects of each agent's preferences observed through changes in deprivation cost. The demand agent strives to obtain more relief, whereas the social agent evaluates the efforts of the aid organization based on relief urgency.

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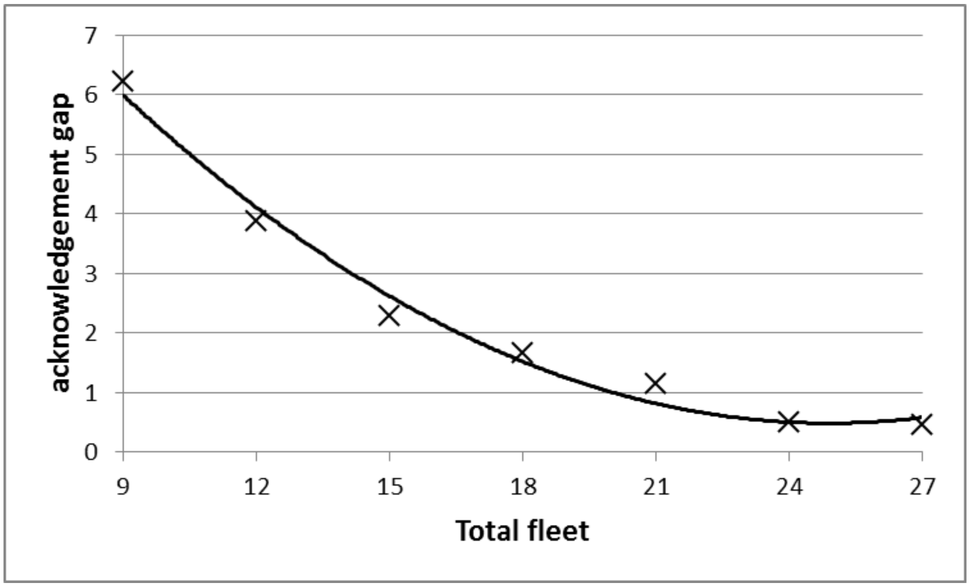

Figure 5-9: Change of Acknowledgement

5.6. MODEL COMPARISONS AND EXTENSION

The ABM presented in this chapter has several benefits over other models, particularly over linear programming (LP) model. One distinctive benefit is the capability in changing the parameter value in dynamic environment. Generally a linear programming is static in nature and provides optimal results. To facilitate the changing of parameter values, dynamic linear programming becomes popular. However, ABM provides better flexibility and functionality than dynamic linear programming.

A similar approach of ABM is game theory that is based on rational choice theory. According to Von Neumann and Morgenstern (1944), there are two problems in game theory. First, there is ample psychological evidence that rational choice theory are at odds with reality. Second, rational choice theory relies on objective probabilities for decision making when in reality decisions are made within complex and changing environments where objective probabilities are unobtainable. On the other hand, rule of thumb and bounded rationality are easily accommodated in ABM.

In the proposed ABM, coordinator is assumed to have enormous power and to be smart enough to make sound decisions. However, reality does not preserve such situations. The coordinator, as a human being, is also susceptible human errors and manipulation for the sake of particular interests. In mathematic term, smartness (i.e. ability of neutral decisions) of coordinator need to be modeled before implementing the model in practice. Another interesting extension would be incorporation of transport network uncertainty or congestion. Congestion can be occurred due to general car users who want to access the affected area or want to go out from affected area. Such phenomenon creates delay in relief distribution. In the case study, transportation capacity is introduced by limiting the number of fleet. However, in reality, destruction of road infrastructure prohibits to distribute relief. In this case, relief need to be distributed to some places that are not posited in top rank of relief urgency. The model can be extended in following avenue

- Formulation of agent based model for in imperfect information
- Cooperation strategies of different stakeholders in relief logistics
- Predicting stakeholders behavior in emergency

5.7. SUMMARY

A simulation model can be used to help emergency logistics decision-makers for better understand the dynamics of an emergency response situation. A decision-maker wants to maximum utilization of resources. The ABM is a good tool for analyzing the effects of resource allocation. This approach is much less risky than actually waiting for another disaster to happen and then test the model in a real-life situation. This model allows actors to investigate the effects of transport measures and to understand the mechanisms of demand management in a dynamic environment.

Relief distribution aims to maximize the overall social benefit. To solve this problem of integrated transport operation and demand point selection, the proposed ABM includes five types of agents: aid organization agent, carrier agent, demand agent, society agent, and coordinator agent. The ABM focuses on dynamic environment after earthquake, rather than uncertainty, rather uncertainties are incorporated in estimating demand. Relief demand calculation is adopted from Sheu (2010). In this model, demand equation contains standard deviation of demand to represent uncertainty.

The ABM was tested using data obtained from the Great East Japan Earthquake. This study shows the benefits of an alternative relief distribution method, examines the effects of resource allocation, and analyzes the improvement strategies of relief distribution from a more strategic viewpoint. The results of this analysis lead to the following conclusions:

- TOPSIS uses both qualitative and quantitative parameters to compute relief urgency. This method helps determine effective resource allocation.

- The decomposition approach generates more social benefit because it considers relief urgency in a relief allocation situation.
- The fleet allocation strategy greatly affects relief distribution. The proposed model demonstrates the fleet allocation. The enumeration approach generates benefits for victims staying near the depot.
- The decomposition approach helps achieve higher social benefits.

Chapter One

1. INTRODUCTION

Chapter Two

2. LITERATURE REVIEW

Chapter Three

3. RELIEF POSITIONING IN PREPAREDNESS

Chapter Four

4. RELIEF ORDERING IN RESPONSE

Chapter Five

5. RELIEF ALLOCATION IN RESPONSE

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Chapter Six

6. CONCLUSIONS

Disasters are always coupled with a series of negative consequences. For example, a large number of people displaced from their living places. Moreover, food and water shortage are common consequences after large-scale disaster. The uncertainties in relief distribution are analyzed throughout the dissertation. This chapter summarizes the vital findings in this study. Most importantly, the implication and application of this study are emphasized in the succeeding sections of this chapter. Finally, recommend some potential extensions of this study.

6.1. SUMMARY OF FINDINGS

This study has addressed some empirical issues in understanding the uncertainty in humanitarian logistics. The general objective of this study was to construct robust response strategies. This is done by incorporating the uncertainty in pre-disaster conditions and post-disaster conditions. In the case pre-disaster conditions are presented in Chapter 3 while post-disaster conditions are presented in Chapter 4 and 5. Besides, Chapter 2 presents the overall scenarios of disasters.

At first I explore the concept of disaster management in Chapter 2. There are four stages in disaster management: Mitigation, Preparation, Response and Recovery. HL encompass Preparation, Response and Recovery. I have analyzed and identified the causes of response delay among the three stages. After that I categorize the uncertainty in HL and analyze decision making strategies in uncertain environment.

At the beginning of the analysis in Chapter 3, I proposed a model for humanitarian depot for multinational, represented by Asia-Oceania region. In this model, I demonstrate how location affect the victims and service level. Most importantly, I used a metric, named mean distance per capita. After that supply uncertainty and demand uncertainty are introduced in the IPSC model. It shows that the expected cost in stochastic model is lower than that in deterministic model. The IPSC model incorporate deviational cost and the results shows that the model is robust.

After developing the network, I focus on post-disaster situations. I propose a model for bringing relief from humanitarian depot to LDC in Chapter 4. The major contribution of this chapter is that the model is closed form, despite the model incorporate two random parameters. Besides, I propose model for computing expected time cycle and expected inventory level in each cycle. This model is easy to apply since decision maker does not require large data base. Local experience and some observational data can be used to realize the PDF for random parameters.

After establishing network and bringing relief in LDC, I introduce an ABM in Chapter 5. I explore objectives and activities of stakeholders in HL. The ABM is optimization based simulation. Each stakeholder aims to maximize own objective under certain constraints. I also propose a modified decomposition approach for comparing the result with the enumeration approach. The shows that modified decomposition approach generate less deprivation cost compare to enumeration approach.

The key summary of the findings are outlined in the following paragraphs.

6.1.1. Objective 1: Causes of poor performance

I investigated response strategies in past disasters and identified eleven major reasons of response delay. It shows that the decision making process of concerned organizations (i.e., FEMA) is the main reason for response delay within a country. Multi layers of decision makers, fear of criticism, and shortsighted policy bias are the example of ineffective decision making process of concerned organizations. Secondly, hesitation of accepting foreign aid creates delay in response. Visa and other document processing takes longer time. Moreover, intervention of government during relief distribution created difficulties. Third, the ignorance of humanitarian logistics also makes response delay. There are lot of provisions of improving response strategies by strengthening humanitarian logistics.

6.1.2. Objective 2-1: Deterministic network model

Relief chain is complex and comprises of several stages. I explore the activities and stages of international relief chain. I show that some activities in chain can be dissolved by taking some initiatives. After that, I modify the relief chain to formulate p-median model for locating humanitarian depots for storing relief. This model proposes a metric, named mean distance per capita. After that this model is extended to analyze two situations: (1) status quo (i.e., including the UNHRD) and (2) free form. This model assumes that '*total affected people*' (defined by EMDAT) represents demand for relief. The p-median model is applied for analyzing the effect of relief prepositioning for Asia-Oceania region that faces 60% of total disasters. Since different countries in this zone encounter different disasters, I include meteorological disaster (i.e., storm) and geophysical disaster (i.e., disaster) for estimating relief demand. The mean distance per capita in free form analysis for single location is 1132 km/capita while that in status quo for single location is 4110 km/capita. This analysis shows the current location of UNHRD is not optimally located for Asia-Oceania region. However, Asia-Oceania region requires more than one humanitarian depot for gaining the service level of 500 km per capita. Finally, three locations are suggested for free form. These are China, India and Indonesia. The service level is improved with the addition of humanitarian depot. The sensitivity of network extension shows the trend of diminishing return on positions after new humanitarian depot.

6.1.3. Objective 2-2: Stochastic network model

Decision maker encounters several uncertain parameters in designing logistics network. I proposes two stage linear optimization model for supply and demand. The first stage decisions are location of RDC and quantity of relief item. Then, the second stage decisions are procurement of relief and other operational variables. The model contains several constraints: balance constraint of inflow and outflow of relief, RDC locational constraint, capacity constraints and other relevant constraints. The model tackles deviation cost variability that are generated from balance constraint and scenario differences. Deterministic model is easy to solve and highly sensitive to parameter changes. On the other hand, stochastic model is superior over deterministic model in terms of rational decision. Stochastic model is difficult to solve and requires sufficient amount of data. The IPSC model showed that decision maker could save 0.34 million dollar by adopting stochastic model over deterministic model.

6.1.4. Objective 3-1: Effect of uncertainty in relief ordering

I explore differences in inventory management between commercial logistics and humanitarian logistics. I observe that aid-organizations bring large volume of relief at once. As a result port of entry becomes congested that creates long waiting time at port of entry. It motivates to proposes inventory model for HL. Researchers encounter difficulties in finding closed form formula for the combination of stochastic parameter lead-time and demand. I propose a model for computing reorder level and reorder quantity in the condition of random lead-time and demand. The model also calculates CDF for LTD and expected shortage in particular reorder level. Finally, I found a closed form formula for random lead-time and demand. The case study shows that expected cost and reorder quantity are sensitive to cost parameters (i.e., shortage cost, ordering cost, and holding cost). However, the expected cost and reorder quantity converge to zero at the reorder level 1,241 units. The results meet my expectation that the reorder level must be higher than the mean LTD for inventory management in HL.

6.1.5. Objective 3-2: Relief operational model

After developing HL network and bringing relief at RDC, the decision maker faces difficulties in relief allocation. This issue is complicated and requires to integrate socio-economic characteristics of victims for making decision on relief allocation. I propose an ABM for relief allocation among victims. I explore the ontology of stakeholders in HL. I observe that aid organization and carrier have seemingly different objective. By introducing a coordinator, ABM combined all stakeholders to generate optimum solution. In the case study, TOPSIS method is used to generate hierarchy among victims. It shows that Ishinomaki region was the top in relief urgency (at day 0) after the Great East Japan earthquake. The model shows that transportation cost and social satisfaction will be increased in urgency based (i.e., decomposition approach) relief allocation. Finally acknowledgement for relief effort is calculated. It shows that relief effort generate similar acknowledgement if there are sufficient resources.

6.2. POLICY RECOMMENDATION

This study recommends following recommendation for relief response improvement based on the findings:

- **Strengthening humanitarian depot network**

Aid organizations need to expand the humanitarian depots in Asia-Oceania region for delivering relief to victims aftermath of disasters. Asia-Oceania region host more that 60% of world population and bears more than 60% of total disasters. The death rate and total affected people per disaster is the highest in this region. This region hosts a UNHRD at Malaysia. This study highly recommends establishing additional humanitarian depots in this region.

- **Reducing vulnerability in Oceania**

Oceania consists of hundreds of small islands. Aid organizations need to provide special consideration (i.e., relief prepositioning) for Oceania regions since those islands has few number of people but are highly vulnerable to meteorological disasters. A humanitarian depot in Australia can reduce delay in accessing Oceania.

- **Procurement before disaster**

Aid organizations must not rely on post disaster procurement of all relief items. Disaster also affect supplier capacity, therefore aid organizations cannot procure sufficient amount of relief aftermath of disaster. The tradeoff between pre- and post-disaster cost helps making decisions on procurements.

- **Data collection and gathering**

It is necessary to build practice of keeping relief operation data of each disaster and transfer the knowledge of relief operation for future disasters.

- **Avoid congestion at POE**

Aid organizations bring a large volume of relief items at once at POE. Aid organization should have inventory planning for avoiding congestion at POE and transportation.

- **Urgency based relief allocation**

Aid organizations must stop ad-hoc basis relief distribution. Aid organizations should use urgency based relief allocation. Since urgency index is the aggregation of several factors, it can reduce social injustice in relief allocation.

- **High value on social benefit**

Humanitarian logistics aims to maximizing social benefit. Even though, transportation cost increases to deliver relief to remote people, aid organization must attempt to reach those victims.

The above mentioned policies can improve the relief response strategies.

6.3. POTENTIAL APPLICATION OF THE STUDY

This study has various potential applications in terms of its proposed model. Some example are given in the following areas:

- **Network expansion:** Disaster strikes suddenly all over the world. Since Asia-Oceania regions faces 60% of all disasters, WFP has planned to extend UNHRD network to respond in Asia region. It is important to consider existing network for network expansion. In this regard, the IPMC model is applicable for WFP. Further, other aid organizations (for example CARE, World vision) also aims for build logistical network for strengthening relief operation. In this regards, IPSC model can be suitable model for them.
- **Procurement:** Fleet contract or transport procurement is essential for operating smooth flow of relief. The ABM can be good model for formulating fleet contract. The decision maker can analyze the each stakeholders objective and characteristics.
- **Fund allocation:** I use TOPSIS method for making hierarchy among victims. This model has potential to make ranking among provinces or among countries. For example, Indian Ocean tsunami (2004) damages many countries in Asia. It was difficult to allocate for donor in chaotic environment. TOPSIS method can be used to make hierarchy among countries for allocating fund.

- **Logistics evaluation:** The ABM can also be used for logistics service evaluation in commercial logistics and humanitarian logistics. I proposes '*acknowledgement*' for evaluating humanitarian logistics. A similar term can be used for evaluating commercial logistics.

For the moment, these are the potential applications that this study is most likely oriented to. There may be other applications that this study is of practical applications but as far as this study is concerned the above mentioned are the most approximate.

6.4.FUTURE SCOPE

Although the findings of the study are enriching and useful, there are also new interesting areas to explore further study, here are the following.

- **Field survey:**

One of the limitations of the study is the consideration of secondary source data that could be augmented into bigger set of field survey data in the future endeavors of the study. Hence, a field survey is recommended for the future work.

- **Improving the IPSC model considering other factors**

The IPSC model has several further potential improvement points. I have considered supplier capacity reduction due to network disruption. In the IPSC model, network uncertainty is not considered explicitly. Some link of transport network may be damaged fully by disaster. And some links may be partially damaged. However, the incorporation of network uncertainty is highly data intensive formulation. And the model becomes large scale. Therefore, a solution algorithm is also required.

- **Application of the IPSC model for large network**

I apply the IPSC model for small network and for only four scenarios. It will be interesting to apply the model for large network. Since the current open source software has capacity limitation, it is important to make an algorithm for solving large network. It is expected that new algorithm may also increase the efficiency of the model.

- **Exigent order for relief ordering model**

I introduce exigent order in the system description of relief ordering model and solve the model for avoiding exigent ordering. An interesting extension of the relief-ordering model will be the incorporation of exigent ordering. This system is a risky system where aid organization makes the tradeoff between opportunity cost and penalty cost.

- **Examining ABM for relief constraint and fleet contract**

I apply the ABM for allocating fleet in different demand points. The model assumes that RDC has sufficient relief item. An extension of this model can be after introducing relief item shortage. This problem can be modeled after introducing a constraint for AOA. However, the model has high potential for examining fleet contract policy for fleet operation after disaster.

- **Other activities of relief operation**

This study primarily deals with relief prepositioning and distribution. Other logistics activities that affect relief distribution might be good area for further study, for example, procurement of relief item, convergence of donation goods and transport mode selection.

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Appendix 1

Parameter of ω_s :

Li (1996) proposed a model for minimizing deviation cost. The overall purpose of this model is to minimize the deviations between the achievement of the goals (in this paper scenario) and their aspiration levels.

$$\text{(P1)} \min \sum_{s=1}^{S}(\omega_s^+ + \omega_s^-) \qquad \text{(a)}$$

$$\text{s.t } f_s(x) - \omega_s^+ + \omega_s^- - g_s = 0 \;\; \forall s = 1,\dots,S \qquad \text{(b)}$$

$$x \in F, x \geq 0 \qquad \text{(c)}$$

$$\omega_s^+, \omega_s^- \geq 0 \;\; \forall s = 1,\dots,S \qquad \text{(d)}$$

where

$f_s(x)$ = linear function of the s th scenario

g_s = aspiration level of the s th scenario

after introducing the artificial variable in Problem (P1) and using big M method

$$\text{(P2)} \min \sum_{s=1}^{S}(\omega_s^+ + \omega_s^-) + M\sum_{s=1}^{S} S_s \qquad \text{(e)}$$

$$\text{s.t. } f_s(x) - \omega_s^+ + \omega_s^- + S_s = g_s \;\; \forall s = 1,\dots,S \qquad \text{(f)}$$

$$x \in F, x \geq 0 \qquad \text{(g)}$$

$$\omega_s^+, \omega_s^-, S_s \geq 0 \;\; \forall s = 1,\dots,S \qquad \text{(h)}$$

observing the constraint (b) in (P1)

$$\omega_s^- = -f_s(x) + \omega_s^+ + g_s \geq 0 \;\; \forall s = 1,\dots,S \qquad \text{(i)}$$

substituting the constraint (i) in objective function and constraints, denoting as the equivalent formulation of (P2) is

$$\text{(P3)} \min \sum_{s=1}^{S} (2\omega_s - f_s(x)) \tag{j}$$

$$\text{s.t. } \omega_s - f_s(x) + g_s \geq 0 \ \ \forall s = 1, \ldots, S \tag{k}$$

$$x \in F, x \geq 0 \tag{l}$$

$$\omega_s \geq 0 \ \ \forall s = 1, \ldots, S \tag{m}$$

Thus, the parameter ω_s is “2”.