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MODELLING ESTABLISHMENT OF TEMPORARY LOGISTICS HUB FOR HUMANITARIAN RELIEF OPERATIONS

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In loving memory of my father Ramesh Maharjan (1961-2011).

ABSTRACT

Disaster response operations are inherently complicated. Despite the complexities, uncertainties, and lack of sufficient information about the extent of the damages, disaster response facilities must be set up quickly after the occurrence of the disaster. Disaster response facility like temporary logistics hub plays a momentous role in increasing the efficiency and effectiveness of humanitarian relief operations. Establishment of temporary logistics hubs (TLH) requires multitude of decisions be made within a very short span of time while also taking account of multiple objectives, multiple actors, need for evaluation of both qualitative and quantitative attributes, and consideration of uncertain and time-varying nature of parameters. Moreover, the decision on whether to open, how many to open, where to locate, when to open, how to allocate open facilities to demand points, and determining the order of establishment of TLHs is based purely on the amount and the quality of information available during the decision-making time. This necessitates involvement of range of decision-makers with diverse background to be involved in the decision making process so as to enable synthesizing more and better information.

This study deals with the establishment of TLHs. The study developed mathematical models, decision-making approach involving multiple decision-makers, and has amalgamated mathematical models with decision-making approach to enable comprehensive TLH establishment decision-making. Firstly, a multi-period multi-objective model with multi-sourcing is developed to determine the location of the TLHs. A fuzzy factor rating system (FFRS) under the group decision-making (GDM) condition is then proposed to determine the weights of the objectives when multiple objective and multiple decision-makers exist. Second, a possibilistic multi-objective location-allocation model for relief supply and distribution considering uncertain and time-varying nature of demand, costs, and available quantities of relief, time-varying coverage is developed while also accommodating qualitative attributes necessary to determine when and where to establish (TLH) along with their numbers in each working period. Finally, a decision support system that considers multiple decision-makers and subjective attributes, while also addressing the impreciseness inherent in post-disaster decision-making is developed for ordering the establishment of TLHs. To do so, an optimization model was combined with a fuzzy multi-attribute group decision-making approach.

Numerical illustrations were performed for the three models using data from the April 2015 Nepal earthquake. The methodology developed herein offers managerial insights for post-disaster decision-making within a short span of time when resources are limited and their effective utilization is vital. The optimization results provide useful managerial insights for decision-makers by considering the trade-off between two non-commensurable objectives; determining the optimal number along with where, when, and in what order to establish TLHs. The interview with decision-makers shows the heterogeneity of decision opinions, thus substantiating the importance of group decision-making. The results also highlight the importance of considering the opinions of multiple actors/decision-makers to enable coordination and avoid complication between the growing numbers of humanitarian responders during disaster response.

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CHAPTER 1 Introduction

1.1 Background

In the recent years, the world has witnessed several devastating disasters and a significant growth in human life losses, economic losses, and material damages caused by natural disasters such as earthquakes, flood, tsunami, and storm. Disaster management entails all the activities taken before, during, and after the disaster with the aim of getting back to normalcy while minimizing its impacts. Although knowing what to do, how to do it, and having the resources to actually do it helps to increase the chance of survival and limits damages, given the disaster's unpredictability of the occurrence and its corresponding impacts, preparedness and mitigation activities often tend to be very costly to implement. Therefore, effective disaster response becomes critical to ensure success of disaster management activities.

Effective disaster salvage requires implementing different disaster response facilities immediately after a disaster has occurred. The location of facilities, particularly distribution centers, warehouses, medical centers, and shelters, plays a significant role in ensuring the success of emergency humanitarian relief operations. From a logistics point of view, an effective response to a crisis demands setting up logistics hubs and/or distribution centers in appropriate locations. In the pre-disaster stage, facility location planning includes finding locations for warehouses, distribution centers, and evacuation centers based on assumed scenarios, while in the post-disaster stage, such planning includes locating emergency shelters, medical centers, relief distribution centers, and logistics hubs for a particular disaster-affected area.

Of the numerous types of facilities prevalent in humanitarian operations, this study focuses on those intended for relief distribution. These facilities can be categorized as permanent or temporary based on the length of their operational horizon. Permanent facilities operate before the disaster and have long or even infinite operational horizon, whereas temporary response facilities only operate once the location of the disaster is known and have a short operational horizon. While determining the location for a permanent facility is a strategic decision, doing so for temporary facility is a tactical/operational decision with which decision-makers are faced after a disaster.

In the ideal situation, vulnerable countries should prepare designated spaces for these facilities along with safety stockpiles in advance of any disaster occurring, however, the situation in reality is often different. Although no specific correlation between investment in disaster preparedness and a country's GDP has been established, developed countries are typically better prepared to tackle the consequences of disasters compared with developing nations. If we examine the earthquakes that have recently impacted developed countries such as New Zealand and Japan, namely the earthquake in Christchurch in 2011 and the Great East Japan earthquake in 2011, respectively, although they caused widespread damage, the resulting fatality rate was relatively modest (Lubkowski, 2014). By contrast, even relatively moderate earthquakes in developing nations still lead to large losses of life. The earthquakes in Haiti in 2010 and Nepal in 2015 are prime examples (Lubkowski, 2014).

The lack of advance preparedness in emerging countries suggests the need for an appropriate, effective, and efficient response. Moreover, the unpredictability of disasters prevents authorities from determining an exact location for emergency facilities beforehand and given that permanent facilities alone may be insufficient, emergency temporary facilities become especially important in developing countries where disaster preparedness falls short. One important feature of these facilities is their short operational horizon (i.e., they are removed soon after the response stage is over) (WFP, 2016). Temporary facilities have been deployed in recent emergency humanitarian response operations such as the April 2015 Nepal earthquake (Figure 1.1) and April 2016 Ecuador earthquake (Figure 1.2). In figure 1.1, rectangular shape shows the location of staging areas and circles shows the location of regional logistics hubs. It can be observed that Kathmandu and Bharatpur operates as staging area with much bigger capacity than the logistics hubs. The different size of the circles represents difference in the capacity of the logistics hubs: a bigger circle represents a higher capacity and vice versa. Regional logistics hubs in Dhulikhel, Deurali, Chautara, Chariokot, Bidur, and Dhadingbesi have capacities in descending order.

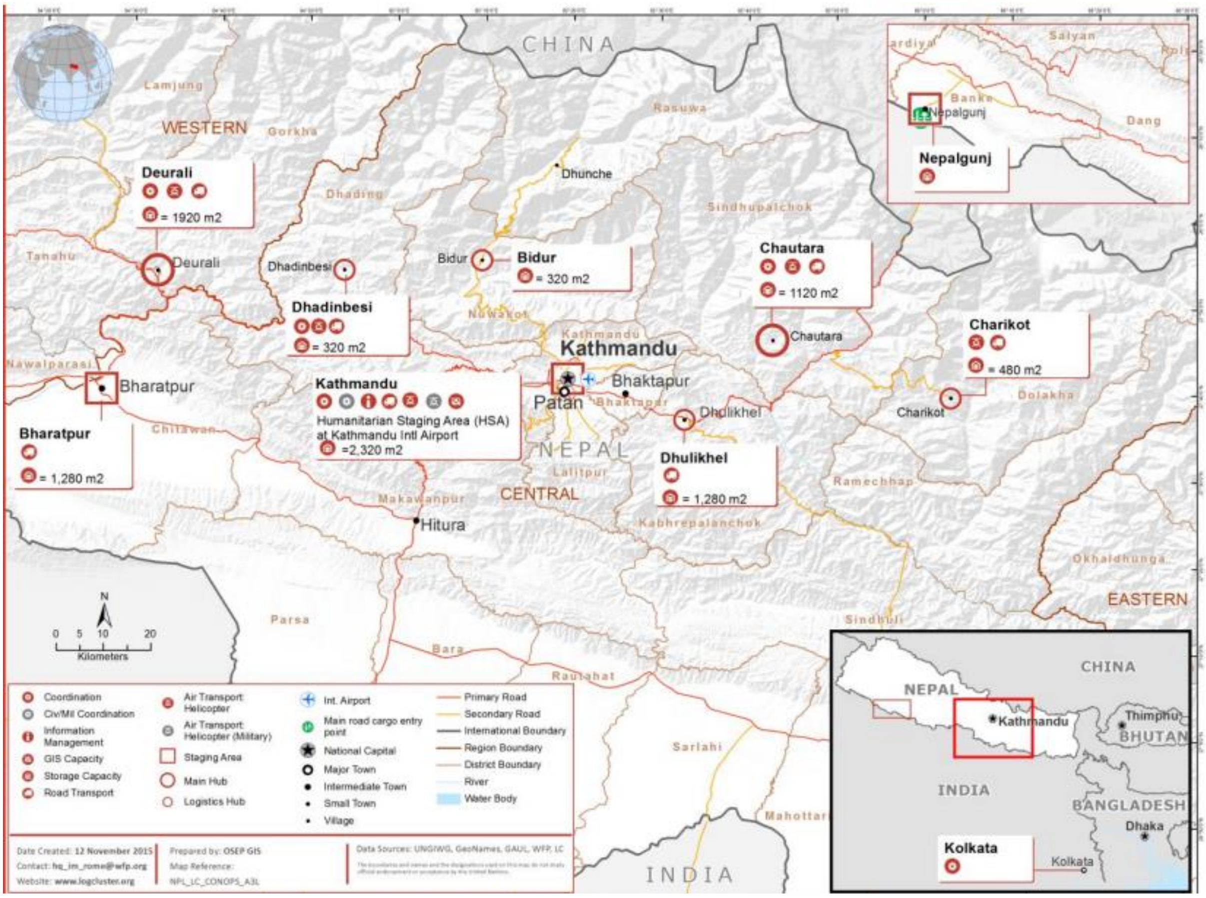


Figure 1.1: Regional logistics hubs established during Nepal earthquake 2015

Source: Logistics Cluster, Nepal 2015

The appropriateness of a logistics hub's location can determine the success or failure of a humanitarian relief operation. However, the unpredictability of disasters makes it difficult to ascertain the precise location of logistics hubs beforehand. Moreover, high inventory holding costs, as well as limited funds and operating resources often restrict the number of permanent facilities. Therefore, the temporary nature of such facilities is an indispensable part of humanitarian relief operations (Maharjan and Hanaoka, 2018). A typical location problem includes ascertaining the number, spatial location, and the allocation of demand to open facilities. On the other hand, locating TLHs during disaster response also requires determining the timing and the order of establishment of the facilities when resources are limited. The disaster response operation in most emerging countries is resource constrained and requires the effective allocation of resources to ensure their effective utilization. During the initial response stage of the 2015 Nepal earthquake, the number of mobile storage units available in-country was limited, which resulted in several hindrances faced during establishment of regional logistics hubs—including delay in establishment and mobile storage units having insufficient capacity.

Figure 1.2: Regional logistics hubs during Ecuador earthquake 2016

Source: Logistics Cluster, Ecuador 2016

Selecting where, when, and in what order to locate temporary facilities for emergency operations is an important task. On the contrary, response operations are inherently complicated. This is often complicated by time-varying and uncertain nature of the disaster impact, the growing number of humanitarian actors, prevalence of multiple and often conflicting objectives, need to evaluate non-quantitative attributes, and inherent complexity and uncertainty of the situation. These factors can significantly affect the overall performance of the relief chain network.

Time-varying nature may arise due to a number of reasons. These reasons include aftershock damages, people returning to greater self-sufficiency, beneficiaries moving between different areas in hopes of finding greater relief, or unexpected challenges such as outbreak of disease epidemics, issues with availability of relief, and the market dynamics induced by the disaster. Due to the chaotic situation in the critical period, the information is always incomplete, inaccurate and changing over time.

Uncertainty may arise due to randomness or/and fuzziness (Pishvaee and Torabi, 2010, Pishvaee et al. 2012, and Tofighi et al. 2016). Randomness stems from the random nature of data for which, discrete or continuous probability distributions are estimated based on available but sufficient objective/historical data. Fuzziness arises due to the impreciseness in predicting the parameter value either due to lack of knowledge regarding their exact values i.e., facing with epistemic uncertainty about these data (Kabak and Ulengin, 2011, Pishvaee and Torabi, 2010) or due to information asymmetry. In the context of disaster response operations, uncertainty arising due to random nature of disaster can be avoided since the location of disaster and demand can be obtained soon after the occurrence of disaster. However, the uncertainty arising due to fuzziness may persist long after its occurrence. This type of uncertainty includes those data such as demand of relief items, costs, and relief availability. Factors like inefficiency in needs assessment, information asymmetry, lack of information, and lack of coordination between the responding entities are the major sources of this kind of uncertainty. Moreover, depending on the location of disaster occurrence, the districts in need may be situated in remote areas, and the disaster site might be in a state of chaos making a complete overview impossible to achieve (Thomas and Kopczak, 2005).

The inclusion of multiple actors is important to build a sense of ownership of the established facilities, a lack of which was identified to be one of the bottlenecks in the successful operation of regional logistics hubs during the April 2015 Nepal earthquake (WFP, 2016). While the humanitarian code of conduct prioritizes minimizing victims' suffering, the budgetary limitations and organizational and environmental constraints creates a trade-off situation. In reality, relief organizations commonly plan and execute logistics activities within the confines of a limited budget (Cook and Lodree, 2012) highlighting the importance of minimizing operational costs where a balance is always sought between the humanitarian and cost based objectives.

In location decision-making, traditional network models take into account quantitative factors and aim to minimize the total cost or to maximize profitability or coverage. Non-quantitative criteria—such as, manpower qualifications, geographical characteristics, and road networks—are also important in deciding location. While optimization approaches can be used for evaluating quantitative factors, this evaluation of qualitative factors is often accompanied by ambiguity and vagueness (Önüt et al. 2010). This is particularly true in the aftermath of a disaster, when the environment is chaotic, and there is limited information and time. In the aftermath of a disaster the decision-making process typically involves multiple decision-makers with varying interests and opinions. Indeed, the growing complexity and uncertainty of decision situations make it less and less possible for a decision-maker to consider all relevant aspects of a problem, thereby necessitating the participation of multiple experts in the decision-making process (Ben-Arieh and Z. Chen, 2006). As such, achieving a proper balance among them is a significant challenge.

Essentially, disaster managers have to make myriad of reactive operational decisions to solve complex dilemmas with little to no information under immensely stressful conditions as they respond to emergencies. Moreover, current guidance suggests that within the humanitarian coordination architecture, decisions should be made by a group rather than by individuals (IASC, 2009, 2015). As the number of actors involved in disaster response operations has continued to grow, a complex network that often struggles to efficiently coordinate efforts has emerged (Balcik et al., 2010; Bharosa et al., 2010; Bealt et al., 2016). This highlights the need for a simple and inclusive methodology. Under these circumstances, an appropriate decision-making strategy would require that the resolutions and opinions of a group of decision-makers be taken into account when evaluating the subjective and objective attributes in the TLH selection process.

Indeed, Ortuno et al. (2013) concluded the need to use a decision support system incorporating optimization tools to enhance applicability in real life. However, existing studies that focus on temporary facilities (Afshar and Haghani, 2012; Lin et al., 2012; Khayal et al., 2015; Stauffer et al., 2016; Cavdur et al., 2016) formulate their problems as single objective optimization problems without concerning for uncertainty arising due to impreciseness. Moreover, the amalgamation of optimization models and decision-making approaches with group decision theories to determine the location of temporary facilities for emergency operations is also lacking in the literature.

1.2 Research motivation

With the advent of a disaster, one can only attempt to minimize its impact and corresponding damages and suffering caused. Irrespective of the level of preparedness, the inherently unpredictable nature of disasters prevent determining the precise location of the response facilities beforehand. Moreover, the level of disaster preparedness is non uniform in the different parts of the world. The developing and underdeveloped countries lag far behind their developed counterparts. In situations like this, temporary response facilities plays a very important role in enhancing the disaster response operations.

Recent humanitarian disaster response operations have seen growing utilization of temporary nature of response facilities for example during the disaster response in Nepal earthquake 2015 (Figure 1.1) and Ecuador earthquake 2016 (Figure 1.2). This dissertation gains its motivation from the April 2015 Nepal earthquake. Having closely observed disaster response operations performed by government, national and international humanitarian organizations, community organizations religious groups during Nepal earthquake 2015, one thing was for sure that the temporary nature of response facilities are very important to facilitate relief distribution to affected people/communities. Traditionally, key decisions to make regarding temporary response facilities are (1) how many facilities to establish; (2) where to establish; (3) how to allocated demand to open facilities. However, due to the dynamics of the situation additional aspects regarding (4) how to accommodate multiple decision-makers who may have same or varying preferences; (5) how to account for uncertainty arising due to impreciseness; (6) how to effectively utilize limited resources etc.

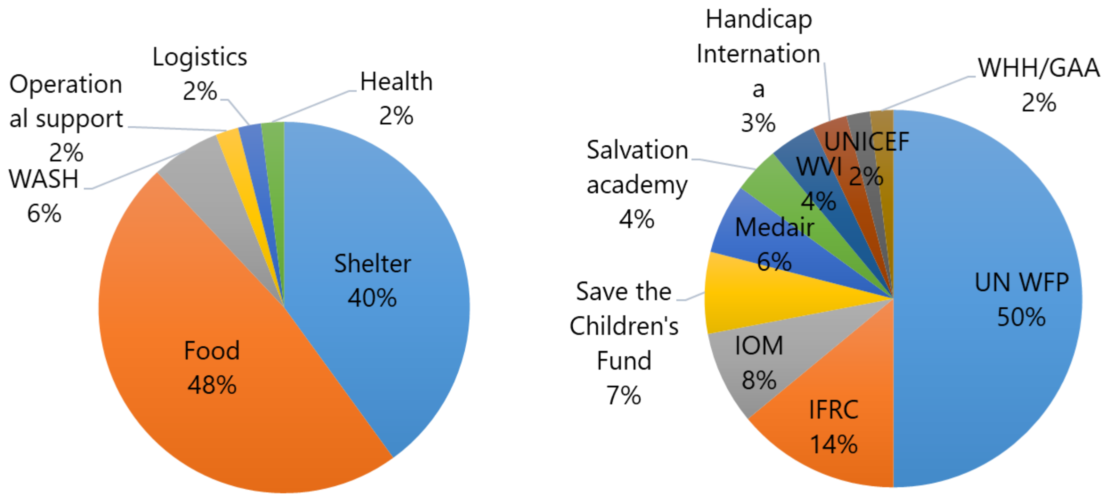


Figure 1.3: Use of storage services in Dhulikhel hub
(a) Storage per sector in % of total m^3 stored (b) Top 10 users in terms of m^3 stored
Source: Logistics Cluster, 2015

Nepal's disaster response operations involved establishment of nine hubs in different parts of the country and 117 organizations have used the storage service, a total of 37,227 m^3 was stored in the hubs until the end of September. Number of organizations using the hubs range between four in Dhunche to 86 in Kathmandu. Figure 1.3 shows the usage of storage service in

Dhulikhel hub where multiple relief items and multiple organization's involvement can be observed from (a) and (b). However, one of the main shortcoming of the entire operational strategy was the time it took to identify the location and set up hubs. The earliest identification of the hub location took as long as two weeks (Logistics cluster, 2016). Further, the operation of established hubs faced ownership issues because organizations were willing to use but not willing to take responsibility of its operation.

This dissertation aims to address the shortcomings faced during Nepal earthquake and build on the existing literature in humanitarian logistics by developing comprehensive models and methodologies for making establishment decisions.

1.3 Temporary logistics hub (TLH)

Temporary logistic hub is a place designated for short term storing, sorting, consolidating, deconsolidating, and distributing emergency relief materials to the final distribution centers. It acts as an intermediator between the central warehouse or point of entry and the points of distribution (POD). Figure 1.4 shows the positioning of the TLH in the humanitarian relief chain. It is established in the response phase of the disaster (especially appropriate in the developing countries where the level of disaster preparedness is low). Often mobile storage units (MSUs) or movable warehouses (also referred to as WiikHalls or RubbHalls) are used as TLHs where hard structures are unavailable or inadequate. Features of temporary logistic hub:

- Its operational horizon is short, which essentially depends on the scale of disaster, severity of its impact, population size, and economic situation of affected areas, accessibility issues, and market functionality.
- TLHs are time-varying in nature which can be opened, closed, and relocated within the operational horizon.
- TLH uses storage units that can be assembled, dissembled, and transported within a short period of time without much hassle.

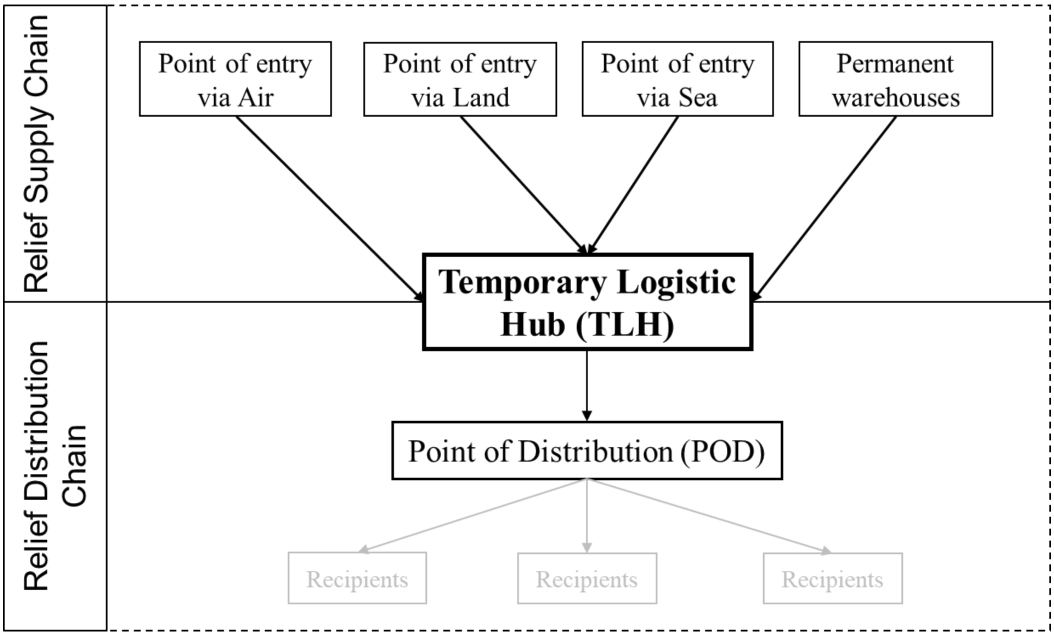


Figure 1.4: Structure of humanitarian relief chain

MSUs can be easily assembled, disassembled, and transported. These mobile storage units are fire retardant, waterproof, rot proof, and UV stabilized and are usually costly. MSUs are most often used in sizes 10×20 meters to 10×32 meters. Most systems can be erected in 4 meter lengths, allowing for customization between these sizes. They are steel or aluminum frame (aluminum being much lighter and therefore cheaper for shipment) with heavy polyester cover. MSUs should be erected on flat hard earth, on raised elevation to protect against flooding. When planning locations, care should be taken that trucks have sufficient access. Pallets should be used to raise stored goods off the ground. It is possible to install MSUs with local labor – WFP will often provide technical oversight if requested. WFP contractors, and other private companies are also options for support in erecting the MSUs. Key features of MSUs can be summarized as:

- Fast set up with three to four personnel without use of lifting equipment or working on heights. Figure 1.7 shows schematic of MSU setup.
- Made of durable aluminum box profiles and hot-dipped galvanized hardware, with covers of durable fire retardant and UV resistant translucent PVC fabric and fully HF welded for long life.
- Designed to withstand high winds up to 31 m/s (<110 km/h) and can be used in both hot and cold climates.

Figure 1.5: Mobile storage units

MSU transport crates are too large for commercial airlines, so transportation will be via sea or large cargo planes. For planning the size of warehouse needed, WFP estimates a

- 10x24m MSU can store 350-500 metric tons of food goods;
- 10x32m will hold 500-750 metric tons.

In this study, we use a 10m x 32m MSU. Different humanitarian organizations have different sizing, features and preferences for the type of MSUs they use, figure 1.5 and figure 1.6 shows examples of MSUs used by different organizations. Figure 1.6 shows the details of MSU used by WFP with dimension and materials. The modularity of MSUs enables ease in capacity expansion and reduction since the length of the MSUs can be endlessly extended with addition of extra modules. The application of this modularity can be observed from figure 1.1, where logistics hubs of different sizes and capacities were established in different locations. In addition to having proper vehicle accessibility to the TLHs, it is also important to ensure that forklifts (shown in figure 1.8) are available to handle relief goods within the established MSUs.

Dimensions	
Standard size	6.5 m x 8 m
Total living area	52 m^2
Main floor	52 m^2
Centre height	3.90 m
Width	6.50 m
Ridge height	8.00 m
Side wall height	2.50 m
Total size	2.90 m x 3.00 m
Modular frame	Aluminium box profiles 2.70 m – 3.50 m: Hot dipped galvanized steel apex base plates and other steel components
Materials	
Outer tent	Roof, wall, gable covers: 700 gsm PVC coated polyester, white, UV protected
Ventilators	The gable ends are fitted with high placed large ventilators with removable mosquito netting and adjustable rain flap.
Doors	Both gable ends are fitted with lace up doors, 290X300 cm.
Modularity	The length of the shelter can be endlessly extended with modules of 6.5 x 3 m or 6.5 x4 m

Figure 1.6: Details of MSU used by WFP

Figure 1.7: Setup of mobile storage units

Figure 1.8: Forklift used for handling relief materials in mobile storage units

1.4 Aims and objectives

The aim of this dissertation is to introduce the concept of temporary logistics hubs for effective disaster response and answer the questions of where, when, in what order should TLHs be established and how to allocate demand to open facilities in the disaster response period. In doing so, the study aims to develop models that take account of the trade-off relationship between different objectives, qualitative attributes, multiple decision-makers, challenges faced by the decision-makers during the chaotic and often ambiguous disaster response period.

To achieve this aim, the following specific objectives are drawn:

1. To develop a multi-actor multi-objective optimization approach for determining the location of TLHs during disaster response and identify if the multi-actor existing in disaster management/response will have different preference for different objectives.
2. To develop a multi-objective optimization model that determines the location and allocation of TLHs under epistemic uncertainty in parameters.
3. To determine the order of establishment of TLHs taking account of quantitative and qualitative attributes to ease TLH setting up process post disaster.

1.5 Scope and limitations of the study

The study focuses on model development for distribution network design on strategic/tactical level decision-making from humanitarian organization's perspective. The aim of this dissertation is to enable TLH establishment decision-making. Whilst it is important to account for operational decision-making like last mile distribution, there has been plenty of studies already focusing on that. The choice of objectives for model building represent the interest and intention from the relief provider's side (humanitarian organizations) and the humanitarian objective. Limitations regarding assumptions are explained in each chapters before the model development.

- This study does not take account of time necessary to reach affected people when deciding on the TLH establishment decision.
- This study considers a single package of relief which weighs 10 kilogram and consists up of food, basic medical supplies, and a blanket that is enough to sustain an individual for a week. Therefore, prioritization of goods are not considered within the scope of this study.
- The decision-makers are assumed to be homogeneous and therefore have equal importance, which might not hold true in real-world disaster operations. Developing a method to determine the relative importance of decision makers and incorporating into the model is thus a possible extension.

- The nature of uncertainty presented in this study accounts only for impreciseness in the data.
- This study does not take account of equity issues.

1.6 Outlines and approach of the study

The thesis comprises of six chapters, Figure 1.9 shows the organization, flow, and the relationship between chapters of the dissertation. Chapter one introduces the background, the concept of TLH, the scope and limitation, and the organization of the dissertation and finally highlights the contribution of this study.

Chapter two reviews the extant of literature on facility location problem (FLP) in humanitarian logistics with special focus on (1) single objective FLP, (2) multi-objective FLP, (3) temporary FLP, (4) uncertainty based FLP, and (5) multi-criteria FLP aimed for both pre and post-disaster operations with special focus on post-disaster operations. We also review decision-making approaches and the nature and sources of uncertainty prevalent in humanitarian operations.

Chapter three answers the question of where to locate TLHs. To do so, we develop a multi-actor multi-objective optimization approach for locating TLHs during disaster response. The model accounts for the time dependent nature of parameters. The preference of multiple actors/decision-makers is identified. A fuzzy factor rating system (FFRS) under group decision-making (GDM) condition is proposed to determine the weight of the objectives in a multi-objective optimization problem while taking account of multiple decision-makers.

Chapter four answers the question of where and when to locate the TLHs and how to allocate the demand to the open TLHs. In doing so, we develop a credibility based multi-objective optimization model that determines the location and allocation of TLHs under epistemic uncertainty and time-varying nature of parameters. Pertaining to the time-varying and uncertain nature of parameter values, the corresponding impact on the location of TLH is analyzed in this chapter.

Chapter five answers the question of where and in what order TLHs should be established. An optimization model with the objective of minimizing total unsatisfied demand is amalgamated with a fuzzy multi-attribute group decision-making (FMAGDM) approach that takes account of multiple decision-makers' decision-opinion when evaluating the set of alternatives versus selected attributes is proposed to determine the order of establishment of TLHs under resource constrained situation. The impact of heterogeneity of decision-makers is also explored. Though we have used a single objective optimization approach for generating the optimal TLH number and their spatial location alternatives in this chapter, the multi-objective optimization models both the deterministic one and the possibilistic models in chapter 3 and chapter 4 can also be used to generate alternatives. Depending on the actual need of the situation, appropriate mathematical model can be used in the first phase.

Chapter six summarizes the findings and concludes what has been achieved through this dissertation. Potential implications for real life location decision-making is also illustrated.

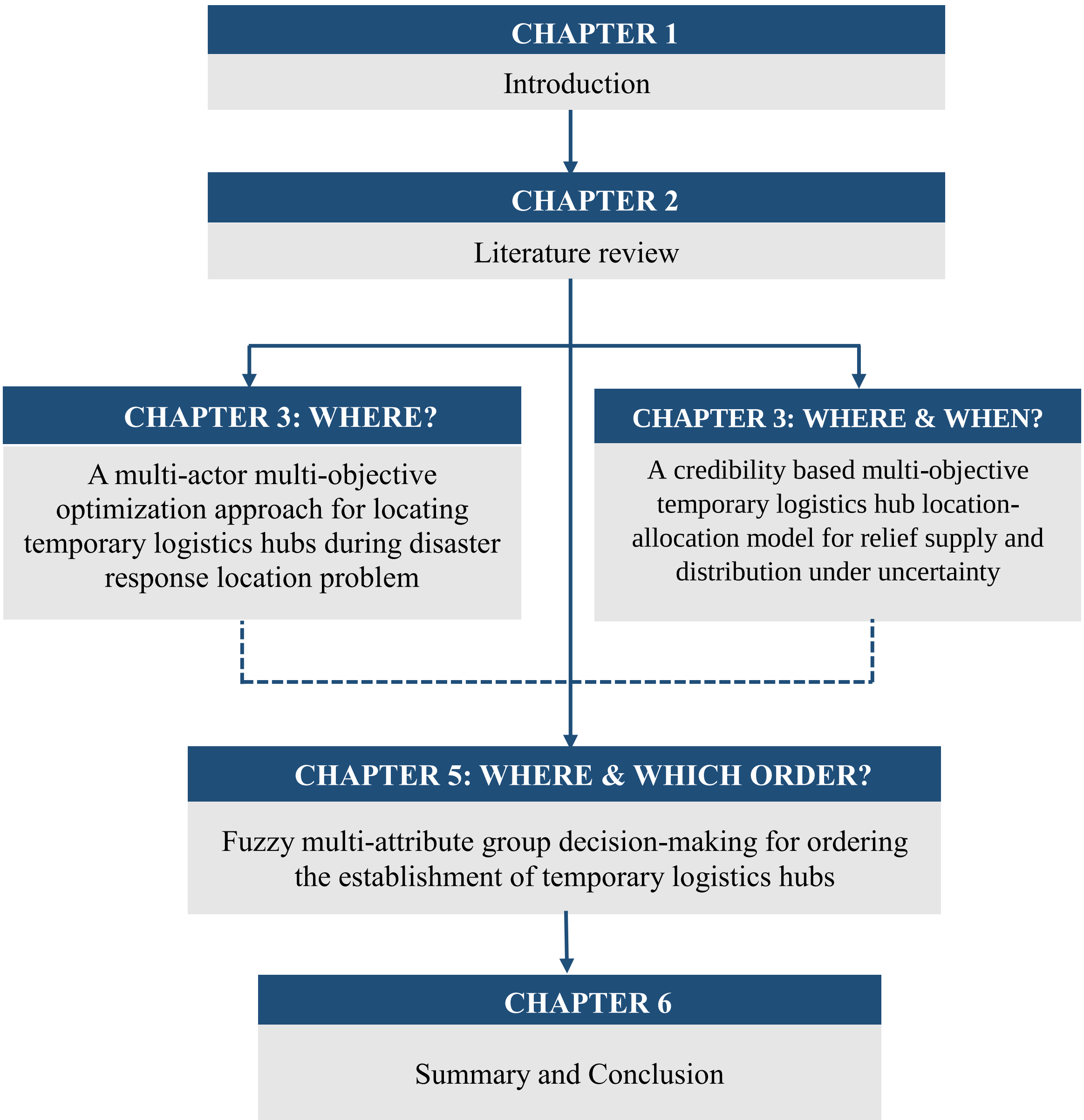


Figure 1.9: Organization of the dissertation

1.7 Contributions of the study

The contribution of this study is manifold. First, the contribution lays on the exploration of different dimensions of TLH location problem. This study answers the question of where, when, what order TLHs should be established along with the allocation of the demand to the open TLHs. Ordering the establishment of TLHs is a new concept that we have introduced in this study. This allows for effective utilization of TLHs under resource constrained situation. Prior studies have only focused on where to locate them.

Second, this study develops deterministic and possibilistic mathematical models that can take account of humanitarian and cost based objectives, time-varying and uncertain nature of parameter values, and TLH's short operational horizon.

Third, the concept of multi-sourcing is introduced. The mathematical model developed in this study investigates the impact of single sourcing versus multi-sourcing strategy and therefore highlighting its significance.

Fourth, the study uses a FFRS under GDM to calculate the weight of objectives in a multi-objective optimization problem. The difficulty in calculating the weight of objectives is one of the major challenges preventing the use of the weighted sum method; thus, the application of the FFRS under GDM is a novel feature of this study among those focusing on humanitarian operations.

Fifth, this study develops approach based on fuzzy set theory and fuzzy linguistic variables which enables dealing with the vagueness and imprecision inherent in evaluating subjective and objective attributes in post-disaster decision-making scenarios which involves multiple decision-makers.

Finally, this study shows that amalgamating an optimization model with multi attribute decision-making approach enables the evaluation of both subjective and objective attributes, and has enhanced applicability to real life scenarios.

CHAPTER 2 Literature review

2.1 Chapter overview

As the entirety of this study revolves around locating ‘temporary’ facilities in the post disaster phase, this chapter provides an overview of the published literature relating to the research topic which has been outlined from the broad view of the disaster management and humanitarian logistics before moving on to the specific topic. Even though the temporary nature of facilities brings in further dynamics to the location problem, fundamentally we are dealing with FLP, therefore the literature review has explored research concepts and methods that are used for locating facilities in humanitarian logistics. In doing so different types and aspects of facility location modeling are also explored.

The second section starts with the general and a brief introduction to disaster and disaster management where we explore the significance of disaster response period in humanitarian operations. The third section briefs on the role of logistics in ensuring successful humanitarian assistance and also brings into perspective the role of facilities within the humanitarian context. In the fourth section we review the extant of literature on facility location in humanitarian context. In the following three sections we review decision making approaches, the nature, and source of uncertainty in humanitarian operations. In section eight we explain the positioning of this dissertation in the current literature. The final section summarizes all the sections.

2.2 Disaster and disaster management

A disaster is a sudden, calamitous event that seriously disrupts the functioning of a community or society and causes human, material, and economic or environmental losses that exceed the community’s or society’s ability to cope using its own resources. The advent of the disaster prompts for coordinated actions among people and organizations to protect life, property, reduce human loss and damage. The field of disaster management deals with these kinds of issues. The Red Cross and Red Crescent Society defines disaster management as the organization and management of resources and responsibilities for dealing with all humanitarian aspects of emergencies, in particular preparedness, response and recovery in order to lessen the impact of disasters. A disaster management life cycle consists of four phases: mitigation, preparedness, response, and recovery. Mitigation involves all the preventive activities performed beforehand to comprehend and reduce the risks associated with disaster. Examples of mitigation activities includes building codes and zoning, vulnerability analyses, and public education. Preparedness focuses on activities as emergency planning, construction of emergency operation centers, and prepositioning of emergency supplies in anticipation of disasters. Response phase involves coordinated actions like activation of emergency plan, search, rescue and evacuation of people, medical care, relief distribution, fatality management and all other activities taken during and shortly after the disaster. The recovery phase includes all the activities performed to repatriate and restore the systems, people, and communities to acceptable level of operation which will eventually bring self-sustainability to affected communities. The following figure shows the schematic of the disaster management cycle.

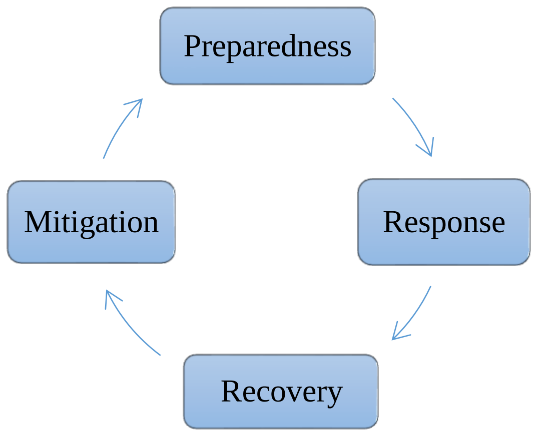


Figure 2.1: Disaster management cycle

Irrespective of the type of disaster, most of the sudden onset disasters are unpredictable in terms of the time of occurrence, their location, number of people dead, injured or affected. In such cases, depending on the scale of the disaster, preparedness alone may not always be sufficient which makes response phase one of the most important and critical components of disaster management. Response is defined as the actions taken to save lives and prevent further damage in a disaster or emergency situation. The aim of disaster response is to provide immediate assistance to maintain life, improve health, and support the morale of the affected population. Such assistance may range from providing specific but limited aid, such as assisting affected people with transport, temporary shelter, and food, to establishing semi-permanent settlement in camps and other locations. The main focus in the response phase is on meeting the basic needs of the people until more permanent and sustainable solutions can be found. Owing to its importance, this study aims to enhance response to disaster or emergency situation.

2.3 Humanitarian logistics

Humanitarian logistics is defined as the process of planning, implementing and controlling the efficient, cost-effective flow of and storage of goods and materials as well as related information, from point of origin to point of consumption for the purpose of alleviating the suffering of vulnerable people (Thomas and Mizushima, 2005). Humanitarian logistics deals with logistical issues throughout the disaster management system, including various activities such as procuring, storing, transporting food, water, medicine, and other supplies as well as human resources, necessary machinery and equipment, and the injured people before, during, and after disasters have struck (Nikbakhshand Farahani, 2011). Unpredictability of demand (in terms of timing, type, and size), suddenly-occurring demand in very large amounts, short lead times for a wide variety of supplies, high stakes associated with adequate and timely delivery, and lack of resources (supply, people, technology, transportation capacity, and money) are among the few of the factors that distinctly highlights the complexity and unique challenge of humanitarian logistics compared to commercial logistics (Balcik and Beamon, 2008).

Logistics is one of the most critical components of successful humanitarian assistance which can mean the difference between a successful or failed operation (Van Wassenhove, 2006). Therefore, the effectiveness and efficiency of humanitarian logistics operation plays an important role in delivering right assistance to the right people at the right time. Though humanitarian response is usually improved with focus on preparative activities that aims at reducing the procurement and transportation phase in disaster response (Duran et. al. 2007, Tomasini and Van Wassenhove 2009) one may argue the economic feasibility of holding huge quantities of inventories of food and non-food items in anticipation of unpredictable disasters. Therefore, an emphasis on humanitarian logistics is often placed in response to disaster (Barbarosoğlu and Arda 2004; Sheu, 2007).

Logistics operations during the disaster response involves assessment and planning, procurement, transport, customs, cold chain, warehousing and inventory management, fleet management, distribution, monitoring and evaluation, and quality control (Logcluster, 2018). However, the basic task of humanitarian logistics comprises acquiring and delivering requested supplies and services at the places and times they are needed, whilst ensuring best value for money (IFRC, 2018). The process of acquiring and delivering emergency relief supplies and services normally involves movement of emergency relief supplies between suppliers/port of origin, central warehouse, local warehouse and to the final demand areas. This process generally necessitates procurement, transport (which involves a combination of international, national, and local transport), and warehousing and inventory management done right. Given the uncertain nature of disasters it is almost impossible to determine the location of the local warehouses beforehand which makes the transportation and/or relief distribution process a complicated task. A warehouse is simply defined as a planned space for the storage and handling of goods and material. In general, warehouses are focal points for product and information flow between sources of supply and beneficiaries. However, in humanitarian supply chains, warehouses vary greatly in terms of their role and their characteristics (Logcluster, 2018). Moreover, appropriate location of warehouses plays a detrimental role in the success and failure of a humanitarian operation.

2.4 Facility location in humanitarian operations

Location decisions arise in a variety of commercial and humanitarian operations. In either cases, the success or failure of both commercial and humanitarian operations depends in part on the locations chosen for the facilities from where the operations are carried out. As one of the core problems in humanitarian logistics operations, facility location is receiving burgeoning attention from both academics and practitioners. Facility location problems deal with selecting the placement of facilities (often from a list of integer possibilities) to best meet the demanded constraints. More specifically, facility location problems serve to decide where, how many, how large, and how should demand for the facilities' services be allocated to the facilities to optimally locate them. The answer to these questions depend intimately on the context in which the location problem is being solved and on the objectives underlying the location problem (Daskin, 2013).

Generally speaking, facility location problems can be modeled using different approaches. While some studies determine locations based on qualitative and quantitative approaches together, some use them separately. Moreover, facility location problems can also be modeled as covering problems, P-median models, and P-center models. Irrespective of the modeling approach either an exact or a heuristic based solution methodology can be applied. In greater detail, facility location problems can be classified based on the length of their operational horizon, dynamicity, number of objectives, modelling approaches, and so on. However, within the humanitarian context a new classification of facilities can be done based on their role in the overall humanitarian operation. Below we explain these classifications in detail:

2.4.1 Based on length of operational horizon

Based on the length of the operational horizon as well as timing of operation, facility location models intended for humanitarian operations can be categorized as permanent or temporary. Permanent facilities are established and operate before the disaster in the pre-disaster phase and are known to have long or even infinite operational horizon, whereas temporary response facilities only operate once the location of the disaster is known in the post-disaster phase and have a short operational horizon ranging from few weeks to few months. While determining the location for a permanent facility is a strategic decision, doing so for temporary facility is a tactical/operational decision with which decision-makers are faced after a disaster. Examples of permanent facilities are warehouses and pre-designated evacuation centers where inventories of relief materials are held, whereas temporary facilities exist in the form of logistics hubs, emergency shelters, medical centers, and evacuation centers.

2.4.2 Based on state of facilities

Another popular classification of facility location models can be done based on number of periods as static location models and dynamic location models. In static location models, the inputs do not depend on time; therefore, it considers only a single period input that is a representative of set of inputs. The dynamic location models take account of multiple operational periods where we are concerned not only with the question of where to locate facilities but also with the question of when to open new facilities or to close existing facilities. In the static location models facilities sited are normally fixed whereas in the multi-period or dynamic models, the location of the facilities is time-varying hence can change within the operational horizon. In other words, in the dynamic models, facilities may be opened, closed or moved throughout the planning horizon (Ballou, 1968; Wesolowsky and Truscott, 1975). However, in some models of dynamic facility location problems, once a facility is opened it is assumed to be available for all future periods (Daskin, 2013). Dynamic FLPs can further be categorized as dynamic deterministic and dynamic uncertain models based on the nature of the parameters under consideration.

2.4.3 Based on number of objective

Based on the number of objectives, facility location models can further be classified as single objective or multi-objective location models. Facility location problems in humanitarian operations are inherently multi-objective in nature. While the humanitarian code of conduct emphasizes on minimizing human suffering, the donation based humanitarian operation is often cost constrained creating a tradeoff situation. Commonly used objectives for facility location problems in humanitarian context relates to minimizing cost, time or maximizing demand satisfaction or minimizing unsatisfied demand.

2.4.4 Based on the nature of parameters

Given the unpredictable nature of disasters, humanitarian operations are often tainted with high degrees of uncertainties, subsequently the parameters used for modeling location problems can either be deterministic or uncertain. Different studies have used different approaches; some studies model the uncertain nature using approaches like stochastic programming, robust optimization, or possibilistic programming whereas other studies assume the parameters to be deterministic.

2.4.5 Based on the role/purpose of facilities

Classifying facilities based on their purpose can be unique to humanitarian operations only. Within this context, facilities can be classified as warehouse, evacuation center, emergency shelter, and emergency medical center. Warehouse (also logistics hub) serves as a planned space for the storage and handling of goods and material (Fritz Institute) and acts as a focal point for the flow of information and relief goods between suppliers and beneficiaries. Both evacuation center and emergency shelter are planned space for providing temporary shelter to the affected people. Emergency medical center is a place designated for taking care of injured people.

2.5 Single objective FLP

As one of the most popular approach to FLP, the highest number of studies (eighteen) have used this approach to model location problem in humanitarian logistics. Table 2.1 lists the studies that have used single objective optimization approach to FLP. From Table 2.1 we can observe that almost all the studies modeled FLP considering facilities to be static and a single period of operation. Consideration of uncertainty seemed to be popular in this category and stochastic optimization using either exact algorithm or heuristic algorithm is applied. In terms of objective, minimization of expected cost or costs in general was found to be the objective of choice in most cases with few studies maximizing coverage, or minimizing distance. While single objective optimization seems to be a preferred approach for FLP targeting pre-disaster phase, Doyen et al. (2012), Ahmadi et al. (2015), Pradhananga et al. (2016), Zokaee et al. (2017), and Yahyei and Bozorgi-Amiri (2018) have accounted for both pre-and post-disaster phase.

Table 2.1: List of single objective optimization based studies on FLP

S.N	Author	Year	Classification based on				Solution algorithm	Approach	Phase of disaster	Objectives
			No. of period	State of facilities	Objective	Nature of parameter				
1	Chang et al.	2007	SP	Static	SO	US	H	Q_n	Pre	Minimize costs
2	Balcik & Beamon	2008	SP	Static	SO	US	E	Q_n	Pre	Maximize total expected demand coverage
3	Ukkusuri & Yushimito	2008	SP	Static	SO	D	E	Q_n	Pre	Minimize costs
4	Rawls & Turnquist	2010	SP	Static	SO	US	H	Q_n	Pre	Minimize expected costs
5	Duran et al.	2011	SP	Static	SO	D	E	Q_n	Pre	Minimize the expected average response time
6	Doyen et al.	2012	SP	Static	SO	US	H	Q_n	Pre+Post	Minimize total cost
7	Rawls & Turnquist	2012	MP	Static	SO	US	E	Q_n	Pre	Minimize the expected costs
8	Yushimito et al.	2012	SP	Static	SO	D	H	Q_n	Pre	Maximize the coverage of affected regions while minimizing human suffering
9	Galindo & Batta	2013	SP	Static	SO	D	E	Q_n	Pre	Minimize total expected cost
10	Rennemo et al.	2014	SP	Static	SO	US	E	Q_n	Pre+Post	Maximizes utility
11	Ahmadi et al.	2015	SP	Static	SO	US	E+H	Q_n	Post	Minimize costs
12	Salman and Yucel	2015	SP	Static	SO	US	H	Q_n	Post	Maximize expected demand coverage
13	Pradhananga et al.	2016	SP	Static	SO	US	E	Q_n	Pre+Post	Minimize pre and post disaster costs
14	Tofighi et al.	2016	SP	Static	MO	US	E+H	Q_n	Pre	Minimize total cost
15	Zokaee et al.	2016	SP	Static	SO	UR	E	Q_n	Pre+Post	Minimize total cost
16	Baskaya et al.	2017	SP	Static	SO	D	E	Q_n	Pre	Minimizes average distance travelled
17	Maharjan & Hanaoka	2017	SP	Static	SO	D	E	Q_n	Pre	Maximize coverage
18	Elci & Noyan	2018	SP	Static	SO	UC	E	Q_n	Pre	Minimize total cost
19	Yahyaei & Bozorgi-Amiri	2018	SP	Static	SO	UR	E	Q_n	Pre+Post	Minimize total cost

SP: Single period; MP: Multi-period; SO: Single objective; D: Deterministic; US: Uncertain stochastic; UR: Uncertain robust; E: Exact algorithm; H: Heuristic algorithm; Q_n: Quantitative approach MO: Multiple objective;

Table 2.2: List of multi-objective optimization based studies on FLP

S.N	Author	Year	Classification based on				Solution algorithm	Approach	Phase of disaster	Objectives
			No. of period	State of facilities	Objective	Nature of parameter				
1	Tseng et al.	2007	MP	Static	MO	D	E	Q_n	Post	Minimize total cost Minimize total travel time Maximize minimum satisfaction
2	Doerner et al.	2009	SP	Static	MO	D	E+H	Q_n	Pre	Minisum facility location criterion and maximal covering location criterion Minimization of tsunami risk Minimization of costs
3	Salmeron & Apte	2010	SP	Static	MO	US	E	Q_n	Pre	Minimize expected number of casualties Minimize expected unmet transfer population
4	Bozorgi-amiri et al.	2013	SP	Static	MO	U	E	Q_n	Pre	Minimize sum of expected value and variance of total cost Minimize sum of maximum shortage
5	Abounacer et al.	2014	SP	Static	MO	D	E+H	Q_n	Pre	Minimize the total transportation duration Minimize the total number of agents Minimize the non-covered demand
6	Barzinpour & Esmaeili	2014	SP	Static	MO	D	E	Q_n	Pre	Maximize cumulative coverage Minimize total cost
7	Rezaeo-Malek & Tavakkoli-Moghaddam	2014	SP	Static	MO	UR	E	Q_n	Pre	Minimize average response time Minimize total operational cost
8	Wang et al.	2014	SP	Static	MO	D	H	Q_n	Pre	Minimization of the maximum vehicle route travelling time Minimization of relief distribution cost Maximization of the minimum route reliability
9	Bozorgi-amiri and Khorsi	2016	MP	Static	MO	US	E	Q_n	Pre+Post	Minimizes maximum unsatisfied demand Minimize total travel time Minimize pre- and post-disaster cost
10	Yilmaz and Kabak	2016	SP	Static	MO	D	E	Q_n	Post	Minimizing distance Minimizing number of facilities

Table 2.2 (contd.): List of multi-objective optimization based studies on FLP

S.N	Author	Year	Classification based on				Solution algorithm	Approach	Phase of disaster	Objectives
			No. of period	State of facilities	Objective	Nature of parameter				
11	Haghi et al.	2017	SP	Static	MO	U	E+H	Q_n	Pre+Post	Maximize response level Minimizing total cost
12	Jha et al.	2017	SP	Static	MO	US	H	Q_n	Pre+Post	Minimize total cost Maximize customer satisfaction
13	Sahebjamnia et al.	2017	SP	Static	MO	D	Simulation	Q_n	Pre	Total cost Reduce response time
14	Babaei & Shahanaghi	2017	SP	Static	MO	U	E+H	Q_n	Pre	Minimize loss or logistic cost Maximize chance of demand satisfaction Maximize budget
15	Vahdani et al.	2018	MP	Static	MO	UR	H	Q_n	Pre+Post	Minimizing total cost Minimizing total time Maximize route reliability
16	Tavana et al.	2018	MP	Static	MO	D	H	Q_n	Pre+Post	Minimize preparedness cost Minimize total relief operational cost Minimize total operational relief time

Table 2.3: List of studies focusing on temporary FLP

S.N	Author	Year	Classification based on				Solution algorithm	Approach	Phase of disaster	Objectives
			No. of period	State of facility	Objective	Nature of parameter				
1	Afshar & Haghani	2012	MP	Static	SO	D	E	Q_n	Pre	Minimize total weighted unsatisfied demand
2	Lin et al.	2012	MP	Static	SO	D	H	Q_n	Post	Minimize logistics and penalty costs
3	Khayal et al.	2015	MP	Dynamic	SO	D	E	Q_n	Post	Minimize logistics and penalty costs
4	Cavdur et al.	2016	SP	Static	SO	US	E	Q_n	Post	Minimize total distance travelled, unmet demand, and total number of facilities in terms of cost.
5	Stauffer et al.	2016	MP	Static	SO	D	E	Q_n	Pre+Post	Minimizes total vehicular costs over the planning period.

2.6 Multi-objective facility location problem

Despite the popularity of single objective optimization models, many studies have used the multi-objective approach to model different types of problems within humanitarian logistics. Moreover, multiple objectives are a distinguishing feature of humanitarian logistics operations unlike in the commercial sector where the minimization of logistics costs is the primary motivation. Table 2.2 tabulates the studies which have considered more than one objective when determining the location of logistical facilities. From Table 2.2 we can observe that the objectives of: (1) minimizing cost; (2) minimizing travel/response time; (3) maximizing satisfaction; (4) minimizing unsatisfied demand; (4) maximizing coverage are the different types of objectives considered by different studies. Cost can be observed as the most popular objective amidst the studies using multi-objective approach to FLP. The objectives of concern can broadly be categorized into the cost and the humanitarian objectives.

Among a total of sixteen studies adopting multi-objective optimization approach to FLP, most of the studies (eleven) focus on the pre-disaster stage where the facilities under consideration are static whereas, Tzeng et al. (2007), Bozorgi-Amiri and Khorsi, (2016), Haghi et al. (2017), Jha et al. (2017), Vahdani et al. (2018), and Tavana et al. (2018) focuses both on the pre- and post-disaster stage. While facilities are assumed to be static in almost all the studies, the studies focusing on pre- and post-disaster stage considers uncertainty in parameter values. In terms of solution algorithm studies have adopted both exact and heuristic algorithm. However, the review of these studies reveal that none of the studies using multi-objective approach has addressed the temporary FLP.

Within the genre of multi-objective optimization problem there exists several solution methods. The solution methods can broadly be classified into:

2.6.1 A priori method

A priori method requires that sufficient preference information is expressed before the solution process. Well known examples of a priori methods include scalarization, lexicographic method, and goal programming. This method is especially useful when decision-makers are available and their preference can be elicited. One disadvantage of this method is that it cannot produce all the Pareto optimal solutions.

2.6.2 A posteriori method

A posteriori methods aim at producing all the Pareto optimal solutions or a representative subset of the Pareto optimal solutions. Most a posteriori methods fall into either one of the following two classes: mathematical programming based a posteriori methods, where an algorithm is repeated and each run of the algorithm produces one Pareto optimal solution, and evolutionary algorithms where one run of the algorithm produces a set of Pareto optimal solutions. The main advantage of evolutionary algorithms, when applied to solve multi-objective optimization problems, is the fact that they typically generate sets of solutions, allowing computation of an approximation of the entire Pareto front. The main disadvantage of evolutionary algorithms is their lower speed and the Pareto optimality of the solutions cannot be guaranteed. It is only known that none of the generated solutions dominates the others.

2.7 Temporary facility location problem during disaster response

In this section we review the studies that have used the term 'temporary facility/hub' in their studies to provide a state of the art in temporary FLP. The term temporary came into light just recently and has been gaining growing attention. Table 2.3 shows summarized review of the studies using the term 'temporary' for facility location. In the study conducted by Afshar and Haghani (2012), temporary facilities receive, arrange, and ship the relief commodities through a distribution network during the initial response stage for deployment to lower levels. The authors' model integrated logistics disaster operations by minimizing total weighted unsatisfied demand. Their model considers vehicle routing, pickup/delivery schedules, and the optimal location of temporary facilities. Lin et al. (2012) define temporary depots as an intermediator between the central depot and demand points. They propose a two-phase heuristic approach to locate temporary depots and allocate covered demand by minimizing logistics and penalty costs. Khayal (2015) develops a network flow model for the dynamic selection of temporary distribution facilities and allocation of resources for emergency response planning by minimizing logistics and penalty costs. In their study, they allow for the transfer of excess resources between temporary facilities operating in different time periods to reduce deprivation.

In Cavdur et al. (2016), temporary disaster response facilities serve disaster victims until central disaster response units arrive. The authors develop a two-stage stochastic program for allocating temporary disaster response facilities in short-term disaster operations by minimizing the total distance travelled, unmet demand, and the cost of facilities. Finally, in Stauffer et al. (2016), a single objective dynamic hub location model with the option for temporary hubs for managing the vehicle fleet is developed. The model minimizes total vehicular costs over the planning period to determine the location of temporary hubs for vehicles. The temporary hub only opens after a mega disaster and operates as a regional hub for vehicles if sufficient vehicles are in the disaster location. Nevertheless, it is important that a single temporary facility can provide the minimum services for short-term storing, sorting, and handling that involves consolidating and deconsolidating emergency relief materials.

From the review of the studies focusing on temporary FLP, we can conclude that single objective optimization using either exact or heuristic algorithm has been a popular research direction, however these studies do not to take account of important aspects like the short operational horizon, time-varying nature of temporary facilities, inherent uncertainty in decision making during disaster response situations, uncertainty arising due to impreciseness, and multiple decision-makers prevalent in post-disaster decision-making.

2.8 Multi-criteria FLP

Multi-criteria decision making (MCDM) indicates a discipline of operations research that considers decision problems in the context of a number of decision criteria (Triantaphyllou et al., 1998). Specifically, MCDM includes a series of techniques "aimed at supporting decision-makers faced with evaluating alternatives taking into account multiple, and often conflictive, criteria" (Thokala and Duenas, 2012). Multi-criteria FLP is another approach used for determining the location of facilities in humanitarian logistics. Within the context of MCDM, multi-attribute decision-making method (MADM) is one popular method used for decision-making process which involves evaluation of qualitative and quantitative attributes. Of the many MADM methods reported in the literature (Saaty, 1980, 2000; Hwang and Yoon, 1981, Chen and Hwang, 1992; Yoon and Hwang 1995; Olson, 1996; Triantaphyllou and Sanchez, 1997; Zanakis *et al*., 1998; Gal *et al*., 1999; Triantaphyllou, 2000; Figueira *et al*., 2005) simple additive weighing (SAW), Analytic Hierarchy Process (AHP), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), PROMETHE, ELECTRE are among the few important methods that have been frequently applied in decision-making problems. Table 2.4 lists the studies that uses multi-criteria approach to FLP for determining the location of facilities in the humanitarian context. From Table 2.4 we can elicit that AHP is the most popular multi-criteria approach used followed by PROMETHE, ELECTRE, TOPSIS, and goal programming. While most of the studies focus on the pre-disaster stage Vitoriano et al. (2011) and Turgut et al. (2011) develops model for post-disaster stage. The choice of attributes/criteria differ based on the context of each study however, cost seems to be common to almost all the studies. In terms of the number of decision-makers considered, He et al. (2017) and Timperio et al. (2017) are the only two studies that include more than one decision-maker in the decision-making process. Nonetheless, these studies neither deal with temporary facility location problem nor consider attributes pertinent to these facility's establishment highlighting the need for further studies on this topic.

Table 2.4: List of multi-criteria FLP studies

S.N.	Author	Year	Approach	MCDM-Method	Phase of disaster	Decision makers	Attributes/Criteria
1	Zhang et al.	2009	Q_l	AHP	Pre	N	Safety and reliability Transportation condition Situation of disaster affected area Natural environment
2	Vitoriano et al.	2011	Q_l	Goal programming (GAMS+CPLEX)	Post	N	Total cost Equity Priority Reliability Security
3	Turgut et al	2011	Q_l	AHP	Post	N	Cost Transportation Infrastructure Geographical location Suitability of climate
4	Degener et al.	2013	Q_l	PROMETHEE I+II	Pre	S	Cost Delivery time Spatial distance Infrastructure Climate Economic aspects Personnel-related aspects
5	Bozorgi-Amiri & Asvadi	2015	Q_l	AHP	Pre	S	Availability Risk Technical issues Cost Coverage
6	Roh et al.	2015	Q_l	AHP + Fuzzy TOPSIS	Pre	M	Location National stability Cost Cooperation Logistics
7	He et al.	2017	Q_l	ELECTRE-II	Pre	S	Traffic condition Capacity Surrounding environment Distance Cost
8	Timperio et al.	2017	Q_l	Fuzzy AHP	Pre	M	Coverage Access to affected zone Risk Access to infrastructure Access to corridor Congestion National development plan

N: Not specified; S: Single decision-maker; M: Multiple decision-makers; Q_l: Qualitative approach

2.9 Decision making during disaster response

Simply defined, decision-making is a thought process of selecting a logical choice from the available options. Decision-making for/during disaster response is a rather complicated task faced in the aftermath of a disaster. Numerous decisions ranging from strategic, tactical, and operational decision are to be made for preparing and responding to humanitarian emergencies. Strategic decisions are usually long-term decisions which includes determining the location of permanent warehouses in anticipation of disasters. Tactical decisions are made for an operational horizon ranging from medium to long-term, this includes deciding the location of temporary hubs, and evacuation centers. Operational decisions are short term decisions made for daily or weekly operations, this may include selecting the location of last mile relief distribution centers of point of distributions.

The complexity in making these range of decisions arises due to the growing number of humanitarian actors, prevalence of multiple and often conflicting objectives, need for evaluating several qualitative and quantitative attributes, and inherent complexity and uncertainty of the situation. While prevalence of multiple actors is a distinctive feature of humanitarian operations existing studies focusing on facility location problem have not taken account of it. However, Roh et al. (2015) discusses about prevalence of multiple decision-makers in their study and Timperio et al (2017) is one such study which has taken account of multiple experts for evaluating location alternatives in their study. Vitoriano et al. (2011) notes a lack of attention on development of mathematical models and solution algorithms for strategic and tactical decisions in the field of humanitarian logistics. Furthermore, our review of studies on FLP in humanitarian logistics shows that only a small number of studies has taken account of complexity of decision-making post disaster and the need for including multiple decision-makers.

Humanitarian operations often receives attention and response from diverse group of responders coming from different backgrounds. Many a times disaster response sees involvement of national government, international communities, nonprofit humanitarian organizations, logistics companies, local communities, and religious groups. This diversity necessitates studies to take account of both homogeneity and heterogeneity among the decision-makers. Therefore, nature of the decision-makers and their decision opinions can lead to the generation of four situations:

(1) When the decision-makers are homogeneous and their decision opinions are also homogeneous

(2) When the decision-makers are homogeneous but their decision opinions are heterogeneous

(3) When the decision-makers are heterogeneous but their decision opinions are homogeneous

(4) When the decision-makers are heterogeneous and their decision opinions are also heterogeneous.

2.10 Group decision making (GDM)

Group decision making is the process of making a judgement based on the opinion of different individuals. A GDM process can be defined as a decision situation where (1) there are two or more individuals' different preferences but the same access to information, each characterized by his/her own perceptions, attitude, motivations, and personalities; (2) all recognize the existence of a common problem; and (3) all attempt to reach a collective decision (Bui, 1987). The inherently multi-actor nature of decision-making during large scale disaster can hugely benefit from GDM. The concept of GDM can be used to incorporate multiple decision-makers' decision opinions. While moving from a single decision-maker to a multiple decision-maker setting plays an important role in successful decision making, it also introduces a great deal of complexity into the analysis. Fuzzy multi-attribute methods are often coupled with GDM to address the vagueness and imprecision inherent in location decisions. The GDM concept can be applied to the popular MADM techniques like SAW, AHP, and TOPSIS (Rao, 2007 pp. 38).

2.11 Uncertainty in humanitarian operations

Generally, disasters are characterized by a high degree of uncertainty. Oxford Dictionary defines uncertainty as the state of being uncertain; Uncertain is defined as not able to be relied on; not known or definite. Uncertainties can prevail both in pre-disaster planning stage and the post-disaster response phase. In the pre-disaster stage uncertainties arises due to the unpredictable nature of disasters, while in the post-disaster stage uncertainties arise due to the lack of information, poor quality of information, due to information asymmetry, or due to lack of cooperation and coordination between the involved parties. Existing studies on humanitarian operations have considered uncertainties arising in demand, product prices, supply availability, affected areas, demand location, and transportation network (Liberatore et al. 2013).

Uncertainties may arise due to randomness, fuzziness, fuzzy randomness and greyness. From the viewpoint of optimization theory, there is no difference among the uncertainties such as randomness, fuzziness, fuzzy randomness and greyness except for the arithmetical operations on them. Liu (1999) named the optimization theory in uncertain (random, fuzzy, fuzzy random, grey, etc.) environments the *uncertain programming.* Based on the extant of literature uncertainty can be modeled in three different approaches:

2.11.1 Stochastic optimization

In Stochastic Optimization, the uncertain numerical data are assumed to be random. In the simplest case, these random data obey a known in advance probability distribution, while in more advanced settings, this distribution is only partially known. Stochastic location models assumes scenarios of disaster occurrence and its impact and assumes the values of parameters to follow a probability distribution with each possible scenario. The uncertainty here refers to the uncertainty associated with the occurrence of disaster and its accompanying impacts in terms of affected people, transportation accessibility among other issues. Stochastic location models are typically applied for preparedness planning.

2.11.2 Robust optimization

Robust optimization is a field of optimization theory that deals with optimization problems in which a certain measure of robustness is sought against uncertainty that can be represented as deterministic variability in the value of the parameters of the problem itself and/or its solution. Robust optimization works with a deterministic, set-based description of the uncertainty. The robust optimization approach constructs a solution that is feasible for any realization of the uncertainty in a given set. Unlike stochastic location models, robust location models do not presume the knowledge of probability distribution of parameters to be preexisting, rather a set of possible scenarios are developed/considered. The concept of uncertainty here is similar to uncertainty in stochastic location models. Robust location models are also typically applied for preparedness planning.

2.11.3 Fuzzy programming

Fuzzy programming offers a powerful means of handling optimization problems with fuzzy parameters. Fuzzy programming can address issues arising due to epistemic uncertainty.

Epistemic uncertainty arises due to lack of knowledge of decision-maker about the actual value of parameters. Unlike both stochastic and robust optimization approach, fuzzy programming only deals with the impreciseness in the values of the parameters where no presumption regarding the scenarios of disasters and probability distribution of parameter values is required. This is especially suitable for post-disaster operations.

Uncertainty in the required data is one of the issues when designing a humanitarian relief chain via optimization (Tofighi et al. 2016). Randomness and fuzziness are the two main sources of uncertainties (Pishvaeee and Torabi, 2010; Pishvaee et al. 2012; Tofighi et al. 2016). Randomness stems from the random nature of data for which, discrete or continuous probability distributions are estimated based on available but sufficient objective/historical data. Stochastic or robust programming approaches are often used to take account of the randomness where the values of the parameters are assumed to follow a probability distribution whenever random distributional information is available for input data. This usually requires events to repeat hence, it is applicable when historical data is available. Whereas fuzziness arises due to the impreciseness in predicting the parameter value either due to lack of knowledge regarding their exact values i.e., facing with epistemic uncertainty about these data (Kabak and Ulengin, 2011; Pishvaee and Torabi, 2010) or due to information asymmetry. In this study, we are interested in accounting for epistemic uncertainty.

Fuzzy decision theories attempt to deal with the vagueness—that is, fuzziness—inherent in the subjective or imprecise determination of preferences, constraints, and goals (Yager and Filev, 1994). In addition to its abundant application in commercial logistics, fuzzy group decision making is a popular approach used for facility location problems (cf. Kahraman et al. 2003; Chou et al. 2008; and Ertuğrul (2011)). However, their application in humanitarian logistics is nominal.

Table 2.5 shows the list of studies that has taken account of uncertainty in different phases of disaster for modeling location problem. From the table, we can observe that accounting for uncertainty in parameters is popular among the studies intended for location selection in pre-disaster phase. Ahmadi et al. (2015), Salman and Yucel (2015), and Cavdur et al. (2016) are the only three studies that focuses specifically on post-disaster facility location problem. Among the two sources of uncertainty, more often studies have addressed uncertainty arising due to randomness (Table 2.5) and therefore have used stochastic or robust approaches to account for it. Tofighi (2016) is one such study that has accounted for uncertainty arising due to impreciseness or fuzziness in the post-disaster phase. Tofighi (2016) developed a two-stage scenario-based possibilistic-stochastic programming approach to address a two-echelon humanitarian logistics network design problem in preparation for potential earthquakes. The study aims to minimize distribution time and cost of unmet demand and considers the uncertainty that may arise in the pre- and post-disaster phase. The study uses stochastic approach to generate disaster scenarios and a possibilistic approach to account for uncertainty in parameter values in pre and post-disaster phase. However, the study does not deal with the temporary facility location problem which comes into operation in the post-disaster phase. Further review of studies listed in Table 2.5 demonstrates that all the studies adopts a purely quantitative approach to modeling location problem.

Table 2.5: List of studies taking account of uncertainty for modeling location problem

S.N	Author	Year	Classification based on			Solution algorithm	Approach	Phase of disaster	Objectives
			No. of period	Objective	Nature of parameter				
1	Chang et al.	2007	SP	SO	US	H	Q_n	Pre	Minimize costs
2	Balcik & Beamon	2008	SP	SO	US	E	Q_n	Pre	Maximize total expected demand coverage
3	Rawls & Turnquist	2010	SP	SO	US	H	Q_n	Pre	Minimize expected costs
4	Salmeron & Apte	2010	SP	MO	US	E	Q_n	Pre	Minimize expected number of casualties Minimize expected unmet transfer population
5	Doyen et al.	2012	SP	SO	US	H	Q_n	Pre+Post	Minimize total cost
6	Rawls & Turnquist	2012	MP	SO	US	E	Q_n	Pre	Minimize the expected costs
7	Bozorgi-amiri et al.	2013	SP	MO	U	Exact	Q_n	Pre	Minimize sum of expected value and variance of total cost Minimize sum of maximum shortage
8	Rennemo et al.	2014	SP	SO	US	E	Q_n	Pre+Post	Maximizes utility
9	Rezaeo-Malek & Tavakkoli-Moghaddam	2014	SP	MO	UR	E	Q_n	Pre	Minimize average response time Minimize total operational cost
10	Ahmadi et al.	2015	SP	SO	US	E+H	Q_n	Post	Minimize costs
11	Salman and Yucel	2015	SP	SO	US	H	Q_n	Post	Maximize expected demand coverage
12	Pradhananga et al.	2016	SP	SO	US	E	Q_n	Pre+Post	Minimize pre and post disaster costs
13	Tofighi et al.	2016	SP	MO	US	E+H	Q_n	Pre	Minimize total cost
14	Zokaee et al.	2016	SP	SO	UR	E	Q_n	Pre+Post	Minimize total cost
15	Bozorgi-amiri and Khorsi	2016	MP	MO	US	E	Q_n	Pre+Post	Minimizes maximum unsatisfied demand Minimize total travel time Minimize pre- and post-disaster cost

Table 2.5 (contd.): List of studies taking account of uncertainty for modeling location problem

S. N	Author	Year	Classification based on			Solution algorithm	Approach	Phase of disaster	Objectives
			No. of period	Objective	Nature of parameter				
16	Cavdur et al.	2016	TS	SO	U	E	Q_n	Post	Minimize total distance travelled, unmet demand, and total number of facilities in terms of cost.
17	Haghi et al.	2017	SP	MO	U	E+H	Q_n	Pre+Post	Maximize response level Minimizing total cost
18	Jha et al.	2017	SP	MO	US	H	Q_n	Pre+Post	Minimize total cost Maximize customer satisfaction
19	Babaei & Shahanaghi	2017	SP	MO	U	E+H	Q_n	Pre	Minimize loss or logistic cost Maximize chance of demand satisfaction Maximize budget
20	Elci & Noyan	2018	SP	SO	UC	E	Q_n	Pre	Minimize total cost
21	Yahyaei & Bozorgi-Amiri	2018	SP	SO	UR	E	Q_n	Pre+Post	Minimize total cost
22	Vahdani et al.	2018	MP	MO	UR	H	Q_n	Pre+Post	Minimizing total cost Minimizing total time Maximize route reliability

2.12 Positioning in the current literature

This dissertation can be positioned in the current literature in temporary facility location problem with the following contributions:

- Firstly, this study provides a new dimension to the TLH location problem by incorporating the conflicting objectives, the diverse preferences of multiple decision-makers, its temporary nature, need for multi-sourcing, uncertainty in parameters, quantitative and qualitative attributes, and determining the order of establishment of the selected facilities.
- In Chapter – 3, we develop a multi-period multi-objective optimization model with multi-sourcing for the TLH location problem. It uses a FFRS under GDM condition to calculate the weight of objectives in a multi-objective optimization problem. The difficulty in calculating the weight of objectives is one of the largest challenges preventing the use of the weighted sum method; thus, the application of the FFRS under GDM is a novel feature of this study among those focusing on humanitarian operations. The fuzzy approach uses fuzzy linguistic variables to illicit the preferences of decision-makers for different objectives. This approach is suitable for multi-actor GDM problems given the uncertainty and complexity inherent in decision-making during disasters.
- In Chapter – 4, we develop a multi-objective location-allocation model for relief supply and distribution under uncertainty. The uncertainty under consideration is the epistemic uncertainty arising due to the impreciseness in predicting the parameter value. A fuzzy credibility based chance constrained programming is used to cope with epistemic uncertainty of imprecise data by using suitable possibility distribution. The model takes account of the time-varying and uncertain nature of parameters and time-varying nature of TLH location.
- In Chapter – 5, we introduce the concept of the order of establishment of TLHs, this study develops and implements a three-stage methodology aimed at the effective utilization of mobile storage units when their availability is scarce. We show that amalgamating an optimization model with the multi-attribute decision-making approach enables the evaluation of both subjective and objective attributes, and has enhanced applicability to real life scenarios. We illustrate the value of applying fuzzy linguistic variables to deal with the vagueness and imprecision inherent in evaluating

subjective attributes in post-disaster decision-making that involves multiple decision-makers.

- To support the developed methodology and contributions, we implement a numerical illustration using data from a real-life disaster—the Nepal earthquake of April 2015.

2.13 Chapter summary

In this chapter we reviewed the existing literature on facility location problem within the context of humanitarian logistics. Of the numerous types of facilities prevalent in humanitarian operations, we limited our review to studies focusing on facilities intended for relief distribution with special attention to temporary facilities. Our review reveals that most of the studies focus on the pre-disaster stage highlighting the importance of facilities for enhancing preparedness. In term of modelling approach, studies have modeled a single period assuming facilities to be static in nature. Contrary to the humanitarian code of conduct which states that highest priority should be given to minimizing humanitarian suffering the objective of minimizing cost has been the most preferred objective among all the studies we have reviewed.

From the methodological perspective, we reviewed literatures using both optimization approach and MCDM approach to location selection problem and found out that optimization is more popular as a methodology compared to MCDM. Amid the studies using optimization approach we further classified studies based on the number of objectives and found out that both single objective and multi-objective approaches are almost equally popular. In terms of solution algorithm both heuristic and exact methods seem to be popular. While the number of studies developing models for facilities without specific mentioning of its state is quite huge, the number of studies focusing on temporary facilities are quite small. Similarly, the number of studies adopting multi-criteria approach to FLP is also limited.

From the literature review we can conclude that only a limited number of studies focus on modeling temporary nature of disaster response facilities. Moreover, none of the studies focusing on temporary facilities have incorporated multiple objectives for FLP in humanitarian logistics; decision aid models that involve multiple actors are rarely used to address temporary FLP; the uncertain nature of parameters has not been taken into account; and the need for determining their order of establishment when the resources are limited. According to Kovacs and Spens (2007), the typical actors involved in disaster response operations include aid agencies, donors, governments, the military, logistics providers, and other non-governmental organizations, which makes the presence of multiple actors another distinctive feature of humanitarian logistics operations. From a practical perspective, the many actors involved in disaster management must thus be included in location selection.

CHAPTER 3 A multi-actor multi-objective optimization approach for locating temporary logistics hubs during disaster response

3.1 Introduction

Multiple objectives are a distinguishing feature of humanitarian logistics operations unlike in the commercial sector where the minimization of logistics costs is the primary motivation. Multi-objective optimization is capable of handling the non-commensurable nature of different types of objectives through three stages: model building, optimization, and decision-making (preference articulation). The decision-making step (involving either single or multiple actors) can happen either before the optimization (a priori articulation of preferences) or thereafter (a posteriori articulation of preferences). Multiple actors are another differentiating feature of disaster response operations. The typical actors involved in disaster response operations ranges from large scale aid agencies, donors, governments, the military, logistics providers, other non-governmental organizations, to very small local community groups. From a practical perspective, the many actors involved in disaster management must thus be included in location selection.

Humans are unsuccessful in making quantitative predictions, whereas they are comparatively efficient in qualitative forecasting. Further, humans are more prone to interferences from biasing tendencies if they are forced to provide numerical estimates since the elicitation of numerical estimates forces an individual to operate in a mode which requires more mental effort than that required for less precise verbal statements (Karwowski and Mital, 1986; Kahraman et al. 2003). Fuzzy linguistic models permit the translation of verbal expressions into numerical ones, thereby dealing quantitatively with imprecision in the expression of the importance of each criterion. While decision-making under conditions of risk and uncertainty have been modeled by probabilistic decision theories and by game theories, fuzzy decision theories attempt to deal with the vagueness or fuzziness inherent in subjective or imprecise determination of preferences, constraints and goals (Yager 1982).

The vagueness and ambiguity that surrounds decision-making during emergencies often increases the complexity of the location selection problem. Hence, different approaches must be employed. Among the approaches capable of incorporating multiple actors into the decision-making process, the fuzzy factor rating system (FFRS), which is applicable to both individual and group decision-making (GDM) (Chou et al., 2008), is an effective method for solving problems in a fuzzy group decision environment (Ou and Chou, 2009). Such a fuzzy approach is suitable for GDM problems under uncertainty because of the vagueness and imprecision inherent in decision-making during emergencies.

Based on the foregoing, the existing literature on temporary facilities fails to take account of the (1) temporary nature, (2) multi-objective nature, or (3) multi-actor nature of disaster response facilities. Therefore, to address the gaps in the literature, we develop a multi-actor, multi-period multi-objective optimization model with multi-sourcing and a short operational horizon to determine the location of temporary logistics hubs (TLHs) in the post-disaster stage. The objectives are minimizing total costs and minimizing total unsatisfied demand. We use the weighted sum method to solve the multi-objective optimization model and an FFRS under GDM to determine the weight of the objectives under the a priori articulation of preferences. The FFRS under the GDM condition enables combining the decision opinions of a multitude of actors prevalent in disaster relief operations.

3.2 Fuzzy factor rating system under group decision making

The factor rating system, which is also known as a multi-factor rating system or scoring method, is a popular and easily applied subjective decision-making method under the multi-attribute decision-making approach (Heragu, 1997; Chou et al., 2008). The chaotic and often turbulent nature of disaster management necessitates a simple yet efficient method that includes decision-makers' preferences. Although conventional factor rating system approaches have been successfully applied for rating different criteria, these approaches are less effective when dealing with the inherent imprecision of linguistic valuation in the decision-making process (Liang and Wang, 1991; Chen, 2001; Kahraman et al., 2003; Chou et al., 2008). To overcome the shortcomings of traditional approaches, fuzzy set theory, which allows for vague and/or imprecise boundaries, provides a mechanism to use fuzziness in the subjective or imprecise determination of preferences, constraints, goals, and group decisions (Kahraman et al., 2003; Yager, 1982; Ou and Chou, 2009) is integrated with the factor rating system in this study.

The review of the literature reveals the integration of many concepts and approaches with fuzzy set theory to enhance its capability of handling multi-attribute decision-making problems with imprecise attributes. While existing studies have used statistical approaches, scaling approaches, and multi-attribute approaches, the weights obtained through multi-attribute methods are considered to be more stable than those produced by direct evaluations (Maggino and Ruviglioni, 2009). Additionally, a fuzzy approach is more suitable for GDM problems given the uncertainty inherent in disaster management operations. The FFRS is thus an effective method for solving problems in a fuzzy group decision environment (Ou and Chou, 2009).

3.3 Problem description

The problem under consideration is determining the location of TLHs. Figure 1.4 shows the structure of a typical humanitarian supply chain and the positioning of TLHs within. The supplies from permanent warehouses or entry points typically come in larger vehicles, which might be unable to access affected areas because of partial or complete damage to roads and bridges. In the absence of logistics hubs, the congestion created by larger vehicles using vulnerable road networks may cause delivery times to increase significantly. In particular, the temporary nature of hubs is important in developing countries where infrastructure facilities are poor and disaster preparedness usually falls short. The major two decisions regarding temporary hubs are to determine (1) their optimal number and (2) location while considering the length of their operational horizon.

Determining the location of TLHs in the immediate aftermath of a disaster is a complicated task because of the multi-actor and multi-objective nature of the decision-making process. The two objectives considered in this study are minimizing total costs and minimizing total unsatisfied demand, which are non-commensurable. The choice of objectives represents an attempt to minimize total unsatisfied demand of affected people within the confines of limited budget. Our interview with the decision-makers revealed that the humanitarian organization's operations are often carried out within the confines of a limited budget therefore requiring cost to be minimized for the entire length of operation while also minimizing total unsatisfied demand. Moreover, cost is a function of distance and transportation cost per vehicle per kilometer and time is a function of distance and vehicular speed. Although we do not explicitly consider time minimization as the model objective, we are basically minimizing distance to reach affected areas within the current model formulation. Besides, lack of vehicular speed data during the immediate aftermath of disaster prevents using time as an objective. Under the given circumstances cost minimization has been used as a proxy for time minimization.

Typically, it is impossible for a single organization to meet the demand of all affected people in need, as such no single organization can be the sole decision-maker. Therefore, involving multiple humanitarian organizations in the disaster response is crucial for making location selection decisions. Furthermore, it is also important to consider the time-varying nature of cost attributes and demand of affected areas. The time-varying nature of demand is a common feature of humanitarian operations, in which, within the operational horizon, costs, available resources, and demand may vary (either increase or decrease) in each time period. Several factors affect the short operational horizons of TLHs such as the number of people affected or injured, location of the demand points, pattern of relief demand, number of houses damaged or destroyed, socioeconomic situation of the affected areas, type of disaster, and accessibility conditions within and outside the affected area. The main goal here is to identify how long it will take for society to return to normal functioning so that the TLHs can be decommissioned and made ready for their next disaster response mission.

How to prioritize the demand points in the affected area is another aspect of the location selection problem that arises because of the nature of disaster impact. Disaster impacts are non-uniform: some areas are highly affected, while other receive only mild effects. This variation necessitates the allocation of emergency relief materials to affected areas' demand points based on the severity of disaster impact. Multi-sourcing ensures that the number of TLHs assigned to serve an affected area depends on the severity of the disaster impact in that area. The higher the disaster impact, the larger is the number of TLHs assigned. The main decision is to determine the number of hubs required to supply emergency relief materials, select their locations, and allocate demand to open hubs in such a way that the total objective is minimized without exceeding the capacity of facilities over the entire planning horizon.

3.4 Methodology

3.4.1 Mathematical model formulation

The proposed multi-period multi-objective TLH location model with multi-sourcing and a short operational horizon allows us to accurately capture the changing levels of relief demand and costs over the planning horizon. Multi-sourcing helps ensure agility while addressing priority needs, which means that even if one of the hubs fails to meet the demand of affected areas, another hub will be able to fulfill this demand without distress. Multi-sourcing thus refers to the situation where demand in each affected area can be split between open facilities. The operational horizon refers to the length of time the TLH will be functioning.

We formulate a multi-objective optimization problem that minimizes total costs and total unsatisfied demand under time-varying demand, costs, and available units of emergency relief. Each district or demand point has an associated demand for emergency relief materials. Along the discrete time horizon, demand from the affected zone changes in a known way related to changes in the number of affected people and recovery of affected people, as a result of which demand can either increase or decrease or be stable.

The establishment of logistics hubs is required to meet the demand of affected people over the entire relief time horizon. Each logistics hub has a known threshold of emergency relief supplies that can be supplied. This threshold depends upon the available units of emergency relief supplies, which in turn depends on factors such as resource availability, the quality of the disaster response, and in addition to the capacity of TLHs. The amount of emergency relief materials available in TLHs can be either less than or equal to the capacity of TLHs but cannot exceed their capacity.

Each demand point can be served from one or more TLHs, a decision determined based on the severity of the disaster impact and that the demand can exceed supply. The shipment of emergency relief materials between supply points, TLHs, and demand points incurs a variable transportation cost proportional to the quantity, distance, capacity of vehicles, and time period. Further, the establishment of a new facility incurs a fixed opening cost, which represents the initial investment for the mobile storage units, procurement cost, cost of leasing land, and cost of transporting the mobile storage units from the supply sources to the candidate TLHs. Our model is deterministic in that the location of the disaster and affected areas are known before the decision to open a TLH is made. A single commodity emergency relief package is considered for distribution purpose. The model formulation epitomizes situation more prevalent in developing countries where demand usually exceed supply. The following subsection provides the mathematical model and its notations, parameters, and variables.

3.4.1.1 Model assumptions

- The location of supply points, candidate TLHs, and PODs and the distance between them are known.

- Two types of vehicle are used. One for relief transportation and other for relief delivery.
- The updated information in terms of disaster-induced damage conditions and casualties associated with each affected area can be obtained during the crucial rescue period.
- The total demand of affected people is assumed to be changing by time in a known way, and can be split or served by one or more facilities.
- All parameters of the model including cost, relief availability, and demand are variable during the planning horizon.
- Relief materials are limited in availability.
- TLHs have maximum available units of relief goods at a certain time period.
- Multiple decision-makers are considered for determining the weight of objectives only.

3.4.1.2 Nomenclature

The notations used in the mathematical model are as follows:

Sets

T set of time periods

I set of supply points

J set of temporary logistic hubs (TLHs)

K set of affected area demand points

Parameters

TC_{ijt} transportation cost of shipping one unit of the relief package from supply point *i* to TLH *j* in period *t* [USD per unit]

TC_{jkt} transportation cost of shipping one unit of relief package from TLH *j* to the affected area's demand point *k* in period *t* [USD per unit]

FC_j Fixed cost of opening a TLH in the candidate location [USD]

QS_{it} maximum available quantity of emergency relief materials at supply point $i \in$ I in period *t* [kg]

QH_{jt} maximum available quantity of emergency relief materials at TLH $j \in$ J in period *t* [kg]

d_{kt} demand of the affected area's demand point *k* in period *t* [kg]

P total number of TLHs

n_{kt} number of TLHs allocated for demand point k in period t

M a very large number

Variables

r_{ijt} amount of emergency relief materials shipped from supply point $i \in$ I to TLH $j \in$ J in period $t \in$ T

q_{jkt} amount of emergency relief materials shipped from TLH $j \in$ J to the affected area's demand points $k \in$ K in period $t \in$ T

y_j binary variable that equals 1 if the facility at j is selected as a TLH and 0 otherwise

z_{jkt} binary variable that equals 1 if TLH j serves demand point k in period $t \in$ T and 0 otherwise

3.4.1.3 Formulation

The multi-objective optimization problem is formulated as follows:

Minimize,

$$Objective\ 1: \mathrm{O}_1 = \sum_j FC_j y_j + \sum_i \sum_j \sum_t TC_{ijt} r_{ijt} + \sum_j \sum_k \sum_t TC_{jkt} q_{jkt} \qquad (3.1)$$

$$Objective\ 2: \mathrm{O}_2 = \sum_k \sum_t d_{kt} - \sum_j \sum_k \sum_t q_{jkt} \qquad (3.2)$$

Constraints,

$$\sum_k q_{jkt} = \sum_i r_{ijt} \qquad \forall j \in \mathrm{J}, t \in \mathrm{T} \qquad (3.3)$$

$$\sum_j r_{ijt} \leq QS_{it} \qquad \forall i \in \mathrm{I}, t \in \mathrm{T} \qquad (3.4)$$

$$\sum_i r_{ijt} \leq QH_{jt} \qquad \forall j \in \mathrm{J}, t \in \mathrm{T} \qquad (3.5)$$

$$\sum_k q_{jkt} \leq QH_{jt} \qquad \forall j \in \mathrm{J}, t \in \mathrm{T} \qquad (3.6)$$

$$\sum_j y_j \leq P \qquad (3.7)$$

$$\sum_j q_{jkt} \leq d_{kt} \qquad \forall k \in \mathrm{K}, t \in \mathrm{T} \qquad (3.8)$$

$$z_{jkt} \leq y_j \qquad \forall j \in \mathrm{J} \qquad (3.9)$$

$$\sum_j z_{jkt} \leq n_{kt} \qquad \forall\, k \in \mathrm{K}, t \in \mathrm{T} \qquad (3.10)$$

$$q_{jkt} \leq M z_{jkt} \qquad \forall j \in \mathrm{J}, t \in \mathrm{T} \qquad (3.11)$$

$$r_{ijt} \geq 0 \qquad \forall i \in \mathrm{I}, j \in \mathrm{J}, t \in \mathrm{T} \qquad (3.12)$$

$$q_{jkt} \geq 0 \qquad \forall j \in \mathrm{J}, k \in \mathrm{K}, t \in \mathrm{T} \qquad (3.13)$$

$$y_j \in \{0,1\} \qquad \forall j \in \mathrm{J} \qquad (3.14)$$

$$z_{jkt} \in \{0,1\} \qquad \forall j \in \mathrm{J},\ k \in \mathrm{K}, t \in \mathrm{T} \qquad (3.15)$$

The objective function (3.1) minimizes total costs, which include the fixed cost of opening a TLH, transportation cost from the supply point to the TLH, and transportation cost from the TLH to the affected area’s demand points. Objective function (3.2) minimizes total unsatisfied demand.

Constraint (3.3) ensures that the flow of emergency relief materials from the supply points to TLHs should be equal to the flow from the TLHs to the affected area’s demand points. Constraints (3.4) – (3.6) are the availability constraints. Constraint (3.4) ensures that the quantity of emergency relief materials moved from the supply points to the TLHs should be less than or equal to the maximum available quantity of emergency relief materials in the supply point in each period. Similarly, constraints (3.5) and (3.6) ensure that the quantity of emergency relief materials moved from the supply points to the TLHs and from the TLHs to the affected area’s demand points should be less than or equal to the maximum available quantity of emergency relief materials in the TLHs in each period. Constraint (3.7) limits the number of opened hubs to P. Constraint (3.8) ensures that the quantity of emergency relief delivered to each demand point does not exceed its demand. Constraint (3.9) ensures that a demand point is served by the TLH only if that TLH is open. Constraint (3.10) enforces multi-sourcing, ensuring that each demand point is served by a prespecified number of TLHs. Constraints (3.11) ensures emergency relief distribution only between the assigned TLH and the demand point. Constraints (3.12) – (3.15) express the nature of the decision variables used in the model.

3.4.2 Solution strategy for the multi-objective TLH location model

In our study, we use a priori method for solving multi-objective optimization problem. This involves priori articulation of preference of the decision-makers using FFRS under GDM which involves four decision-makers. This solution methodology is especially suitable for decision-making during the disaster response phase when a decision that is acceptable to all the parties involved is essential. Often the decision-makers have to make myriad of reactive decisions in response to the disaster in a very short period of time with little information. When the preference in terms of weight of the objectives can be elicited from all the decision-makers involved, one Pareto optimal solution can be obtained. This helps in minimizing the overall decision-making time and building a sense of ownership of the established TLHs.

The weighted sum approach is a frequently used method for combining different objective functions in a multi-objective optimization problem. This approach, also known as the scalarization method, minimizes the positively weighted convex sum of the objectives that represents a new optimization problem with a unique objective function. The theorem of the weighted sum method states that "if x^* is a Pareto-optimal solution of a convex multi-objective optimization problem, then there exists a non-zero positive weight vector w such that x^* is a solution." This theorem suggests that for a convex multi-objective optimization problem, any Pareto solution can be found by using the weighted sum method (Miettinen, 1998). The solutions obtained by using different weight settings represent the points on the Pareto front, meaning that the solutions are Pareto-optimal. The only requirement is the weight factors w_i>= 0 and sum of w_i=1. Therefore, we use the weighted sum method in this study.

The simplicity of using this method to solve multi-objective optimization problems is often complicated by the difficulty in determining the weight of the objectives. The weights used represent decision-makers' preferences and priorities, while the relative value of the weight reflects the relative importance of the objectives. Typically, infinitely many Pareto-optimal solutions exist for a multi-objective problem. Thus, it is often necessary to incorporate decision-makers' preferences for these objectives to determine a single suitable solution. By employing methods that incorporate the a priori articulation of such preferences, the user indicates his or her preferences before running the optimization algorithm and this subsequently allows the algorithm to determine a single solution. Alternatively, with a posteriori articulation of preferences, one manually selects a single solution from a representation of the Pareto-optimal set (Marler and Arora, 2010). This study focuses on the use of the weighted sum method that incorporates the a priori articulation of preferences.

Given the multi-actor nature of disaster management, it is necessary that the weight assigned to the objectives comply with the preference of multiple decision-makers. When decisions made by more than one person are modeled, two differences from the case of a single decision-maker can be considered: first, the goals of the individual decision-makers may differ such that each places a different ordering on the alternatives; second, the individual decision-makers may have access to different information upon which to base their decision. Theories known as n-person game theories deal with both these considerations, team theories of decision-making deal only with the second, and group decision theories deal only with the first (Kahraman et al. 2003). This study focuses on GDM to determine the weight of the objectives.

A GDM process can be defined as a decision situation where (1) there are two or more individuals' different preferences but the same access to information, each characterized by his/her own perceptions, attitude, motivations, and personalities; (2) all recognize the existence of a common problem; and (3) all attempt to reach a collective decision (Bui, 1987). The concept of GDM is used to incorporate multiple decision-makers' decision opinions. Fuzzy multi-attribute methods are often coupled with GDM to address the vagueness and imprecision inherent in location decisions. We use the FFRS under the GDM condition to determine the weight of the objectives in the a priori articulation state. This allows us to incorporate multiple decision-makers' decision opinions.

3.4.3 Fundamentals of fuzzy set theory

Zadeh (1965) pioneered the use of fuzzy set theory to address problems involving fuzzy phenomena. Fuzzy set theory uses approximate rather than precise reasoning (Saaty and Tran, 2007) and can process data by using partial set membership functions. Fuzzy logic allows impersonating ambiguous and uncertain linguistic knowledge and offers a robust framework for model designers dealing with systems that contain high uncertainty (Aguilar-Lasserre et al., 2009). Triangular, trapezoidal, and Gaussian are among the three simplest and most commonly used shapes to represent fuzziness. Researchers have proven that triangular and trapezoidal shapes perform slightly better than the Gaussian shape because of their computational efficiency and the ease of data acquisition (Zimmerman, 2001). While triangular shapes represent fuzzy numbers, trapezoidal shapes represent fuzzy intervals. Trapezoidal fuzzy numbers are therefore the most widely used form of fuzzy numbers because they can be handled arithmetically and interpreted intuitively (Chou et al., 2008). Hence, the linguistic terms assessing scarcely quantifiable variables are represented by trapezoidal fuzzy numbers in this study.

A fuzzy set $\tilde{A} = (a, b, c, d)$ on R, $a \leq b \leq c \leq d$, is called a trapezoidal fuzzy number if its membership function is

$$\mu_{\tilde{A}}(x) = \begin{cases} \frac{(x-a)}{(b-a)}, & a \leq x \leq b, \\ 1, & b \leq x \leq c, \\ \frac{(x-d)}{(c-d)}, & c \leq x \leq d, \\ 0, & otherwise, \end{cases} \tag{3.16}$$

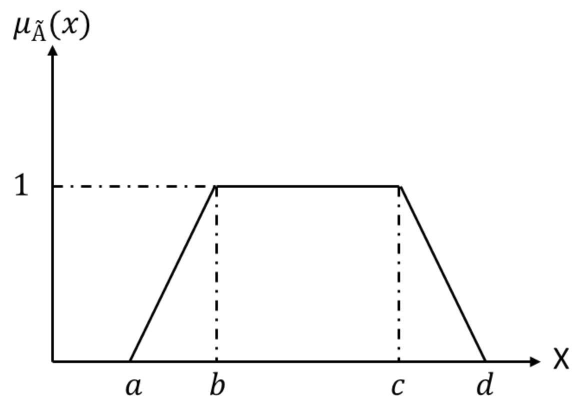


Figure 3.1: A trapezoidal fuzzy number

where a, b, c, d are real numbers (Dubois and Prade, 1978; Keufmann and Gupta, 1991). As shown in Figure 3.1, the trapezoidal fuzzy number can be denoted by (a, b, c, d). The x in the interval $[b, c]$ gives the maximal grade of $\mu_{\tilde{A}}(x)$i.e., $\mu_{\tilde{A}}(x)$=1; this is the most probable value of the evaluation data. The constants c and d are the lower and upper bounds of the available areas of the evaluation data, respectively. These constants reflect the fuzziness of the evaluation data (Liang, 1999).

Given two trapezoidal fuzzy numbers, $\tilde{A}$= (a, b, c, d) and $\tilde{B}$= (e, f, g, h), the four main operations of these two fuzzy numbers can be expressed as follows (Keufmann and Gupta, 1991**;** Liang and Wang, 1991**;** Chen and Hwang, 1992**;** Chiou *et al.*, 2005):

1. Addition of two trapezoidal fuzzy numbers $\oplus$

$\tilde{A} \oplus \tilde{B} = (a+e, b+f, c+g, d+h), a \geq 0, e \geq 0$ (3.17)

2. Multiplication of two trapezoidal fuzzy numbers $\otimes$

$\tilde{A} \otimes \tilde{B} = (ae, bf, cg, dh), a \geq 0, e \geq 0$ (3.18)

3. Multiplication of any real number k and a trapezoidal fuzzy number $\otimes$

$k \otimes \tilde{B} = (ka, kb, kc, kd), a \geq 0, k \geq 0$ (3.19)

4. Division of two trapezoidal fuzzy numbers /

$\frac{\tilde{A}}{\tilde{B}} = (\frac{a}{h}, \frac{b}{g}, \frac{c}{f}, \frac{d}{e}), a \geq 0, e \geq 0$ (3.20)

3.4.3.2 Linguistic variables and fuzzy numbers

In fuzzy set theory, conversion scales are applied to transform linguistic terms into fuzzy numbers. Determining the number of conversion scales is generally intuitive: while too few conversion scales reduce analytical discrimination capability, too many conversion scales make the system overly complex and impractical (Chou et al., 2008). In this study, a scale of 1–5 is used for the importance weight following Liang (1999). Given the fuzzy nature of this weight selection problem, the importance weights of the individual objectives are used as the linguistic variables in this study. Table 3.1 lists the linguistic variables and fuzzy numbers used.

Determination of the conversion scale for the linguistic variables is generally assumed to be intuitive: while too few conversion scales reduce analytical discrimination capability, too many conversion scales make the system overly complex and impractical. The current study uses a scale of 1-5 for the importance weight in the manner employed by Liang and Wang (1991), Liang (1999), Yong (2006) and Chou et al. (2008).

Table 3.1: Linguistic variables and fuzzy numbers

Linguistic variables	**Fuzzy numbers**
Very Low (VL)	(0,0,0,3)
Low (L)	(0,3,3,5)
Medium (M)	(2,5,5,8)
High (H)	(5,7,7,10)
Very High (VH)	(7,10,10,10)

3.4.4 Algorithm of an FFRS under the GDM condition

In the following section, we explain the algorithm of the proposed method by using the concepts of fuzzy set theory and factor rating system under the GDM condition. The decision-makers are assumed to act in the best interests of the affected people. The proposed method derives its insights from Chou et al. (2008) and Ou and Chou (2009).

Step 1: Selection of decision-makers

Under the GDM scenario, multiple decision-makers can be chosen. The choice of decision-maker also varies case-to-case and country by country. However, the effectiveness of GDM is influenced by group size. Yetton and Botter (1983) point out that a group of five, and to a lesser extent, seven, is the most effective. A committee of decision-makers can be formed based on their overall role in the disaster management activity. The nature of these decision-makers and their decision opinions can lead to the generation of four situations: (1) when the decision-makers are homogeneous and their decision opinions are also homogeneous; (2) when the decision-makers are homogeneous but their decision opinions are heterogeneous; (3) when the decision-makers are heterogeneous but their decision opinions are homogeneous; and (4) when the decision-makers are heterogeneous and their decision opinions are also heterogeneous.

Step 2: Collecting decision opinions and establishing decision matrices

The next step is to collect their decision opinions and determine if decision-makers are homogeneous or heterogeneous. If the degree of the importance of decision-makers is equal, then the group of decision-makers is deemed to be a homogeneous group.

In a committee of k decision-makers (D_t, t = 1,2,…, k) responsible for assessing n objectives (O_j, $j=1,2,\dots,n$), the degree of the importance of the decision-makers is I_t, $t = 1,2,\dots,k,$ where $I_t \in [0,1]$ and $\sum_{t=1}^{k} I_t = 1$. If $I_1 = I_2 = \ldots = I_k = \frac{1}{k}$, the group of decision-makers is called a homogeneous group; otherwise the group is called a heterogeneous group.

Step 3: Constructing the aggregated fuzzy rating of the individual objectives

Subsequently, we construct the aggregated fuzzy rating of the individual objectives. Table 3.1 shows the linguistic variables and corresponding fuzzy numbers for the decision-makers to access the importance of the objectives. Let $\widetilde{W}_{jt} = (a_{jt}, b_{jt}, c_{jt}, d_{jt})$, $j = 1, 2, \dots, n;\ t = 1, 2,$

....,k, be the linguistic rating given to objectives O_1, O_2,…., O_n by decision-maker D_t. The aggregated fuzzy rating, $\widetilde{W}_j = (a_j, b_j, c_j, d_j)$, of objective O_j assessed by the committee of k decision-makers is defined as

$$\widetilde{W}_j = (I_1 \otimes \widetilde{W}_{j1}) \oplus (I_2 \otimes \widetilde{W}_{j2}) \oplus \ldots \oplus (I_k \otimes \widetilde{W}_{jk}), \quad (3.21)$$

where $a_j = \sum_{t=1}^{k} I_t a_{jt}$, $b_j = \sum_{t=1}^{k} I_t b_{jt}$, $c_j = \sum_{t=1}^{k} I_t c_{jt}$, $d_j = \sum_{t=1}^{k} I_t d_{jt}$.

Step 4: Computing the weight of objectives

To compute the weight of objectives, defuzzify the fuzzy rating of the individual objectives; compute the normalized weights, and construct the weight vector. To defuzzify the rating of the fuzzy objectives, the signed distance is adopted. The defuzzification of $\widetilde{W}_j$, denoted as $d(\widetilde{W}_j)$ is therefore given by

$$d(\widetilde{W}_j) = \frac{1}{k}(a_j + b_j + c_j + d_j) \quad (3.22)$$

The crisp value of the normalized weight for objectives O_j, denoted by W_j, is given by

$$W_j = \frac{d(\widetilde{W}_j)}{\sum_{j=1}^{n} d(\widetilde{W}_j)}, \quad (3.23)$$

where $\sum_{j=1}^{n} W_j = 1$. The weight vector W = $[W_1, W_2, \ldots, W_n]$ is therefore formed.

This crisp value of the normalized weight of the objectives O_j can therefore be used as the weight of the objectives in the weighted sum approach.

3.5 Model discussion

The applicability of the methodology developed in section 3.4 in real life problems is discussed here. The methodology was developed being inspired by a real world humanitarian supply chain design problem, a mixed integer linear program for a three-echelon, multi-capacitated humanitarian supply chain network design is developed. The methodology developed herein takes account of several significant factors (1) multiple objectives; (2) multiple actors; (3) prioritization of affected areas; (4) short operational horizon for designing the post-disaster relief distribution network. Our model captures both the fixed opening cost of establishing a TLH and the variable transportation cost of supplying the emergency relief to TLHs and distributing them to the affected area PODs. Scalarization is adopted to solve the multi-objective optimization model. It is a simple yet effective method which guarantees a Pareto optimal solution. Scalarization involves priori articulation of preferences. A FFRS under GDM is developed to determine the weight of the objectives.

There are supply sources, TLHs and affected area PODs in the relief network which is a typical network setting. The methodology developed herein is applicable to any situation which requires establishment related decision-making involving multiple decision-makers, prioritization needs, while considering trade-off between non-commensurable objectives. In particular, the proposed methodology can be applied to establishment decision-making related to SAR centers, emergency medical centers, general logistics hubs etc. Numerical illustration and analysis in Section 3.6 further highlights on the applicability of the methodology for a real life disaster case of Nepal earthquake 2015.

3.6 Numerical illustration and analysis

To support the usefulness of the proposed model as a decision-making tool for selecting the location of TLHs, we evaluate the performance of the model by using disaster data from the April 2015 Nepal earthquake.

3.6.1 April 2015 Nepal earthquake

On 25 April 2015, a 7.8 magnitude earthquake occurred in Barpak in the Gorkha district, which is approximately 78 km northwest of the capital city, Kathmandu. Aftershocks occurred for weeks after the initial earthquake. The earthquake resulted in roughly 8,790 deaths and 22,300 injuries, while some 773,174 houses were destroyed (501,783) or damaged (271,391) (NPC, 2015). At the height of the emergency, some 188,900 people were temporarily displaced. Of Nepal’s 75 districts, 39 were affected and 14 of those were declared severely affected. The 14 districts prioritized are located in Kathmandu, Bhaktapur, Lalitpur, Makwanpur, Nuwakot, Rasuwa, Dhading, Gorkha, Kavrepalanchok, Sindhupalchok, Sindhuli, Dolakha, Ramechhap, and Okhaldhunga. Approximately 5.4 million people live in these 14 districts, which are located in the western and central regions of Nepal. Of these, 2.8 million people were estimated to need assistance.

The government of Nepal declared a state of emergency in the country on 25 April and called upon the international humanitarian community for support. More than 450 aid organizations responded to the emergency (UNOCHA, 2015) by facilitating rescue, evacuation, relief distribution, rehabilitation, and recovery. A number of governmental, non-governmental, national, and international organizations conducted large-scale operations in the 14 most affected districts. The humanitarian supply chain during the immediate aftermath of the earthquake faced many challenges such as the lack of vehicles, congestion in the airport, the lack of coordination and cooperation, and operational and location issues related to the use of regional logistics hubs. Disaster response proved extremely difficult due to the large scale of the devastation, huge number of responders, manifold objectives of multiple organizations, infrastructural difficulties in accessing affected zones, and poor weather conditions. Apart from the inevitable challenges, many criticized the Nepalese government for its lack of preparedness, which caused relief supplies to pile up at the airport (The New York Times 2015, Disaster Recovery Journal 2015).

3.6.2 Nature of the data

In this example, the supply points are the points of entry to Nepal from neighboring countries via land and air. We did not consider seaports because Nepal is a landlocked country. We selected seven entry points: The Mechi customs office, Jhapa; Biratnagar customs office, Morang; Bhairawa customs office, Kapilbastu; Kodari customs office, Sindhupalchok; Nepalgunj customs office, Banke; Birgunj customs office, Parsa; and Tribhuwan international airport, Kathmandu. We ensured the selected entry points had warehouses in place to handle the sudden upsurge in emergency relief materials. The amount of emergency relief materials available in the supply points was assumed to be known. Eleven candidates in Dhading, Dolakha, Gorkha, Kathmandu, Kavrepalanchok, Makwanpur, Nuwakot, Okhaldhunga, Ramechhap, Sindhuli, and Sindhupalchok were selected for locating TLHs. The opening of a TLH incurs a fixed opening cost. The capacity of a candidate TLH is restricted by the available units of emergency relief materials.

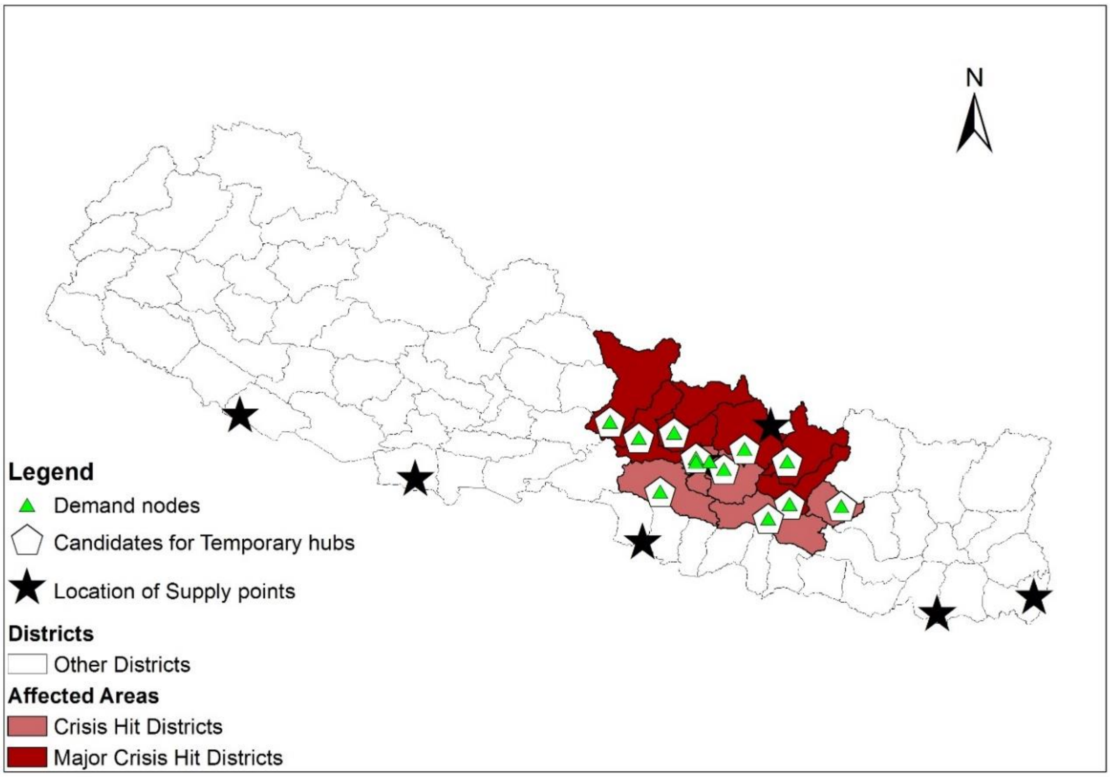


Figure 3.2: Location of supply points, candidate TLHs, and demand points

Among the 14 severely affected districts, 13, namely Bhaktapur, Dhading, Dolakha, Gorkha, Kathmandu, Kavrepalanchok, Lalitpur, Makwanpur, Nuwakot, Okhaldhunga, Ramechhap, Sindhuli, and Sindhupalchok, were used as the demand points in this study. One district in Rasuwa was not considered because of the lack of distance-related data. Figure 3.2 shows the spatial location of the supply points, candidate TLHs, and affected areas' demand points. The demand points represent the location of the aggregated demand arising in each district. The demand points and candidate hubs overlap with each other. Demand was estimated based on the severity of the disaster impact. According to Salmeron and Apte (2010), the degree of severity differentiates the demand in each zone. A larger proportion of the population is assumed to require relief in major crisis-hit areas compared to crisis-hit areas. Rasuwa, Gorkha, Nuwakot, Dhading, Sindhupalchok, Dolakha, and Ramechhap were identified as major crisis-hit areas and Kavrepalanchok, Sindhuli, Okhaldhunga, Makwanpur, Lalitpur, Bhaktapur, and Kathmandu as crisis-hit areas. Similarly, major crisis-hit districts were allocated two TLHs, whereas crisis-hit districts were assigned a single TLH. The nature of the demand is assumed to be increasing initially and then stagnating after a while. This assumption is in reference to the numerical results of Sheu (2010).

As discussed earlier, the operational horizon of TLHs is affected by many factors; as such, the operational horizon was assumed to be five weeks in this numerical example. We considered a single package relief delivery system. A single emergency relief package was assumed to weigh 10 kg and include essential items such as meals, a basic medical kit, blankets, baby supplies, and clothing. We assumed that a single emergency relief package was sufficient to sustain an individual for a week.

3.6.3 Results

In this section, we first calculate the weight of the objectives by using an FFRS under the GDM condition and then present the results of the optimization model. We ignore the first 72 hours of critical importance, acknowledging the reality of real-life emergency responses. Assuming that TLHs could be established within 72 hours is unrealistic because of the time needed and complexity of finding an appropriate location. Hence, our model is valid for the response situation after the first 72 hours. The distribution planning is considered for 35 days divided into five weekly periods.

3.6.3.1 Calculating the weight of the objectives

Step 1: A committee of four decision-makers, D_1, D_2, D_3, and D_4, from four humanitarian organizations active in disaster management in Nepal is formed. Objective O_1 represents minimizing total costs and O_2 represents minimizing total unsatisfied demand.

Step 2: Table 3.2 shows homogeneous and heterogeneous decision opinions of the decision-makers from different humanitarian organizations. From this, two situations can be generated: when the decision-makers are homogeneous and when they are heterogeneous. However, in this study, we only explore the situation when the decision-makers are homogeneous because of the complexity of determining their importance without bias.

Table 3.2: Importance ratings of the objectives

Objectives	**Decision-makers (Homogeneous)**			
	D_1	**D_2**	**D_3**	**D_4**
O_1	H	M	H	M
O_2	VH	VH	VH	H

Step 3: The importance rating of each objective is assessed by using the linguistic variables and their respective fuzzy numbers. The aggregated fuzzy rating of the individual objective when the decision-makers are homogeneous is constructed (see Table 3.3) by using equation (3.21).

Table 3.3: Aggregated fuzzy ratings of the objectives

Objectives	**Decision-makers**				**Aggregated fuzzy rating**
	D_1	**D_2**	**D_3**	**D_4**	
O_1	(5, 7, 7, 10)	(2, 5, 5, 8)	(5, 7, 7, 10)	(2, 5, 5, 8)	(3.5, 6, 6, 9)
O_2	(7, 10, 10, 10)	(7, 10, 10, 10)	(7, 10, 10, 10)	(5, 7, 7, 10)	(6.5, 9.25, 9.25, 10)

Step 4: The defuzzified values of the aggregated fuzzy rating (Table 3.4) are obtained by using equation (3.22) and the crisp value of the normalized weight is calculated by using equation (3.23).

Table 3.4: Defuzzified values of the aggregated fuzzy rating and normalized weights of the objectives

Objectives	**O_1**	**O_2**
Defuzzified value of aggregated fuzzy rating	6.125	8.750
Normalized weight	0.411	0.588

3.6.3.2 Optimization results

The model was coded in Lingo 17.0 Optimization modeling software. All the experiments were run on a personal computer with an Intel (R) Core (TM) i3-3220 CPU (3.30 GHz) and 8 GB of RAM. All the test problems were computed in under 10 minutes.

To determine the optimal number of TLHs, the model was run without constraint (3.7). The model results in eight optimal TLHs with locations in Gorkha, Kathmandu, Kavrepalanchok, Makwanpur, Nuwakot, Ramechhap, Sindhuli, and Sindhupalchok to meet the time-varying demand over the entire planning horizon. The eight selected TLHs result in the minimum value of both objectives over the entire planning horizon. Figure 3.3 shows the spatial location of the eight selected TLHs in Nepal.

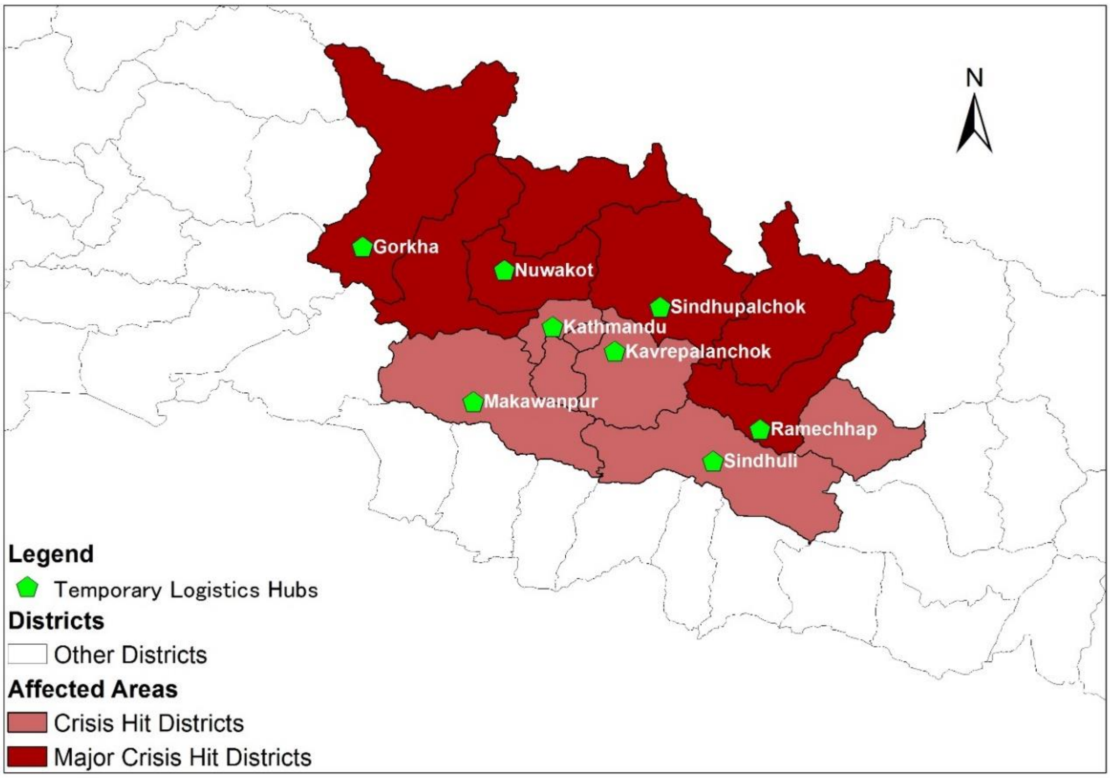


Figure 3.3: Spatial location of the optimal TLHs

Furthermore, calculations were carried out to understand the impact of the number of TLHs on both the cost and the unsatisfied demand objectives. The results in Figure 3.4 show the change in cost attributes and total unsatisfied demand with a change in the number of TLHs. Irregular nature of results can be observed from the figure when the number of TLH is 5. This might be attributed to (1) high transportation cost from TLHs to the PODs; (2) time-varying nature of the transportation cost; The study considers transportation cost to be time-varying, therefore an initially increasing, then stagnating and gradual decrease in transportation cost is assumed as an impact of the disaster. This nature is reflective of the real life situation after Nepal earthquake 2015; (3) high level of demand satisfaction with minimum number of TLHs as a result of which both the upstream and the downstream transportation cost from TLHs to PODs is quite high at this point. High transportation cost at this point may be attributed to high level of demand satisfaction with minimum number of TLHs. When the number of TLHs is 5, the unsatisfied demand is almost close to its minimum value as a result of which both the upstream and the downstream transportation cost from SPs to TLHs and from TLHs to PODs is quite high at this point.

Figure 3.4 shows that eight TLHs provides the minimum total cost and minimum unsatisfied demand; increasing the number of TLHs beyond eight raises the total cost, whereas total unsatisfied demand remains the same, perhaps owing to the limited availability of relief materials in the TLHs and supply points. Thus, we performed a sensitivity analysis to examine the extent to which the available quantity of emergency relief in the TLHs and supply points affects costs and demand satisfaction.

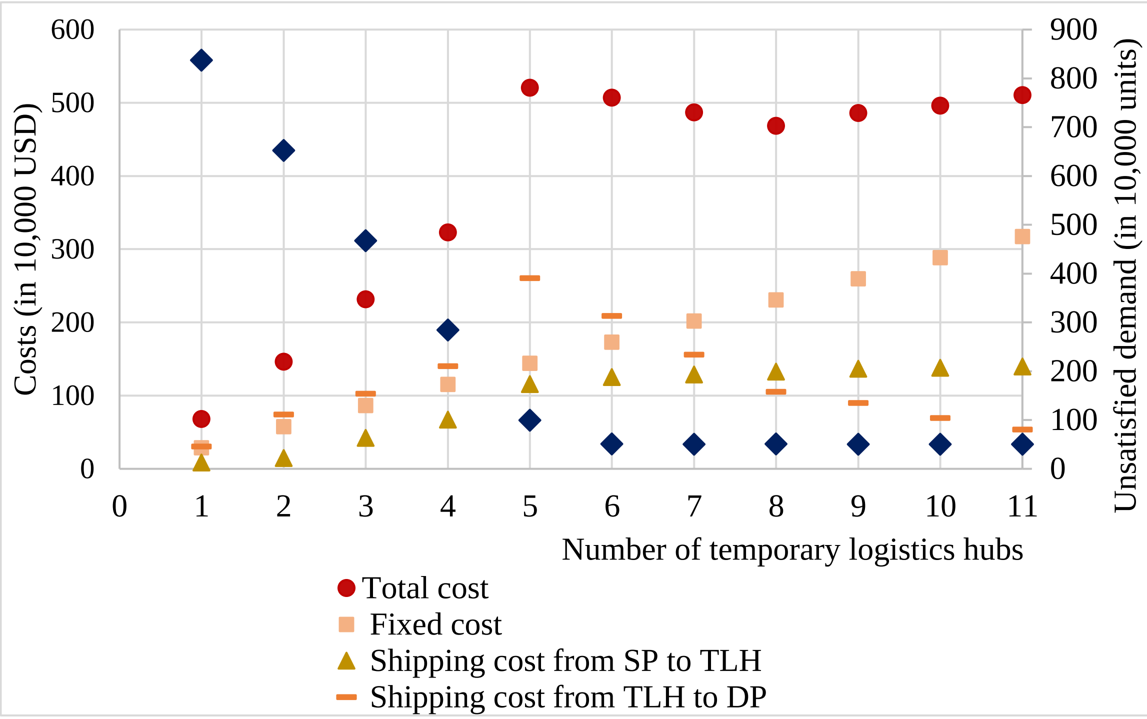


Figure 3.4: Change in the cost attributes and unsatisfied demand with a changing number of TLHs

Figure 3.5 shows the location choices when varying the number of TLHs. From the figure we can observe that, TLH candidate located in Nuwakot is the most important location as it is common to all the solutions which is followed by TLH candidate in Sindhupalchok, Kavrepalanchok, Makwanpur, Kathmandu, Gorkha, Sindhuli, Ramechhap, Dhading, Okhaldhunga and Dolakha.

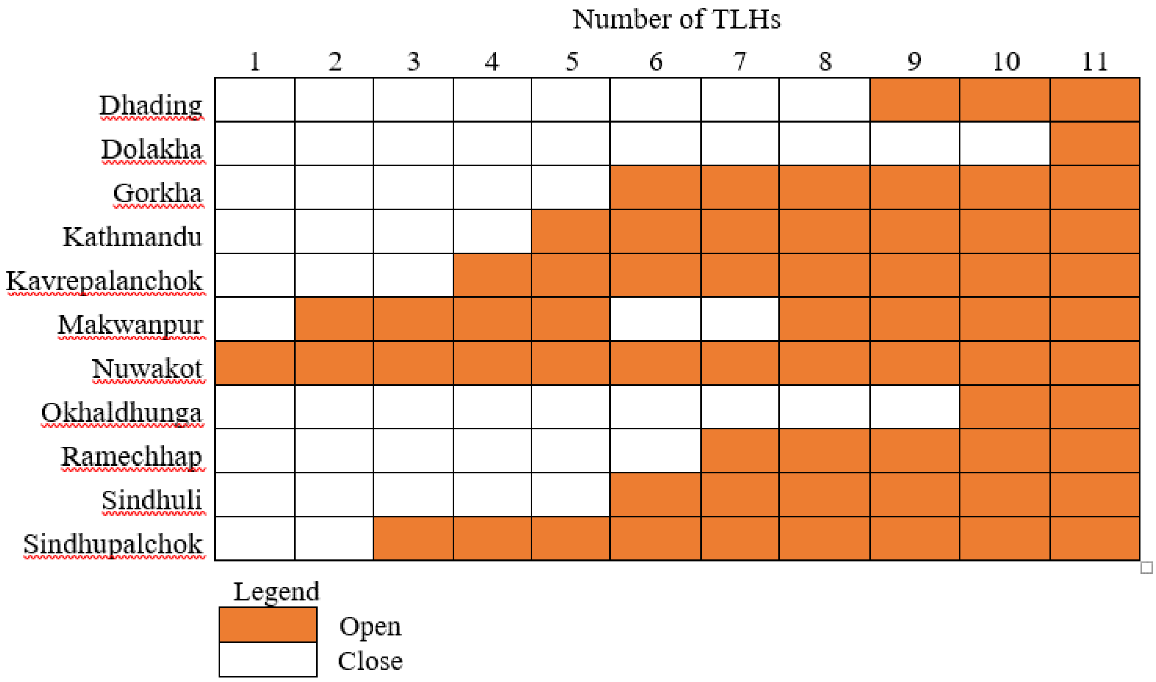


Figure 3.5: Change in location choices with changing number of TLHs

Table 3.5: Sensitivity of the available quantity of relief materials in the TLHs

Scenarios	**Total unsatisfied demand (in 1000 units)**	**Total cost**	**Shipping cost from SP to TLH**	**Shipping cost from TLH to DP**
		(in 1000 USD)		
Original case	512.10	4686.68	1325.65	1053.84
Scenario I	482.10	4691.15	1324.66	1059.30
Scenario II	452.10	4693.32	1336.61	1049.52
Scenario III	422.10	4697.68	1348.48	1042.01
Scenario IV	392.10	4697.82	1361.19	1029.43
Scenario V	362.10	4701.76	1375.49	1019.09

Table 3.5 shows the results of the sensitivity analysis over the available quantity of emergency relief materials in the TLHs. The table illustrates the cost attributes and total unsatisfied demand. Each scenario represents an increase in the available units of relief materials by 10,000 units in each step. In each scenario, the model resulted in eight optimal TLHs. With an increase in the availability of emergency relief materials in the TLHs, the results show that total unsatisfied demand decreases at the cost of increased total costs, while the fixed cost remains the same. This sensitivity analysis allows us to conclude that keeping the locations

the same, an increase in the availability in the TLHs decreases total unsatisfied demand and increases total cost. This cost can be attributed to increases in downstream transportation costs. The sensitivity analysis of the model over the varying quantity of emergency relief materials available in the supply points shows no significant reduction in total costs or unsatisfied demand upon increasing the available units.

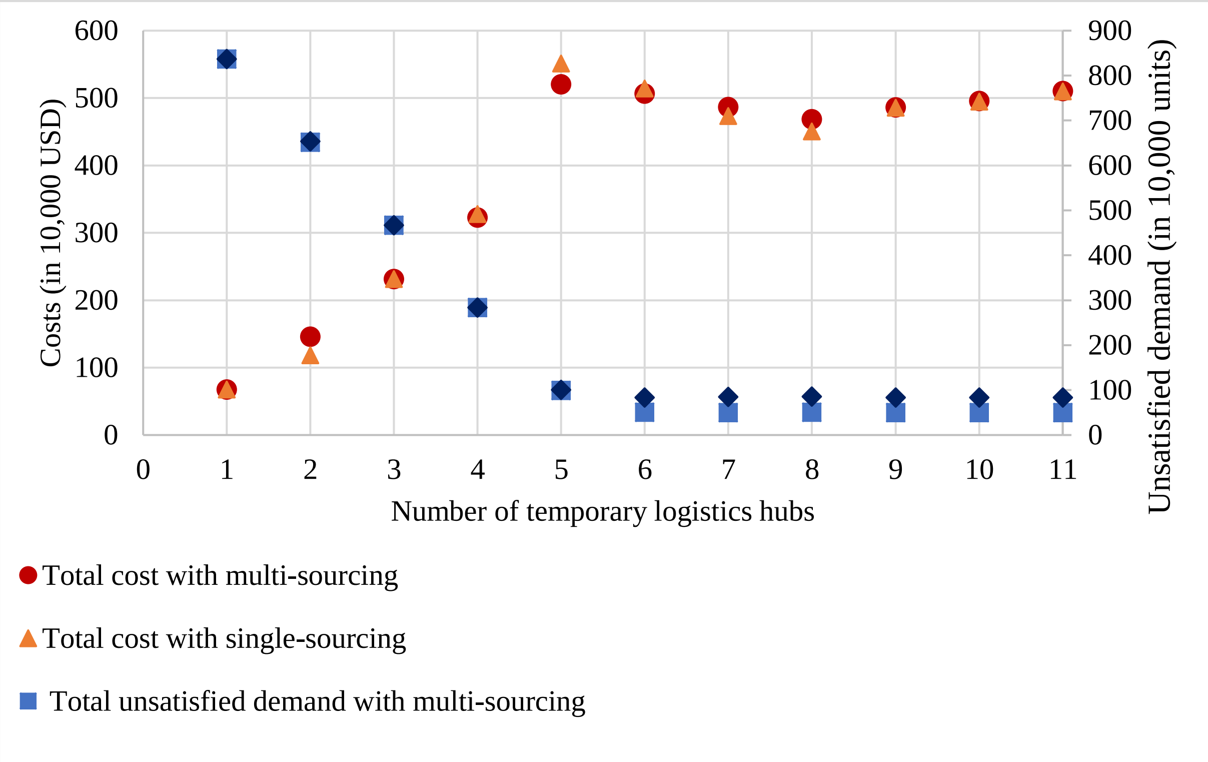


Figure 3.6: Comparison of single-sourcing with multi-sourcing

Additionally, we investigated the model performance over the multi-sourcing constraint. Figure 3.6 shows the model results with and without the multi-sourcing constraint. In both cases, the optimal number of TLHs remains the same. While the other input parameters remain the same, the results highlight that multi-sourcing reduces total unsatisfied demand with a slightly higher cost compared with single-sourcing. This finding indicates the importance of multi-sourcing for minimizing total unsatisfied demand. However, the difference seems to be not that significant. For the case of the numerical study, we consider the need for multi-sourcing only for six major crisis hit affected area PODs located in Gorkha, Nuwakot, Dhading, Sindhupalchok, Dolakha, and Ramechhap. Only two TLHs are assigned for major crisis hit areas and one for the crisis hit areas as the model setting for first time period which is gradually changing over time. This small number of TLH assigned within the concept of multi-sourcing might be the reason behind not that significant difference.

3.7 Chapter summary

Deciding on the best location for TLHs to aid humanitarian relief distribution often involves more than one decision-maker and the trade-off between multiple objectives. In this study, we developed a mathematical model to determine the optimal location for TLHs by using a multi-objective optimization model with multi-sourcing as well as time-varying demand, cost, and capacities. We also proposed an FFRS under the GDM condition to take account of the decision opinions of multiple decision-makers. This consideration is important to avoid issues with the ownership of the TLHs that may arise because of monopolistic decision-making. The results of the questionnaire with humanitarian organizations show the heterogeneous nature of decision opinions. Although the humanitarian code dictates that minimizing human suffering should be given utmost priority during disaster response, this alone does not necessarily hold true. Indeed, humanitarian organizations often have to work under a tight budget, resulting in many trade-offs.

The model proposed herein was implemented by using data obtained from the Nepal earthquake in 2015. The results of the optimization model clearly highlight the trade-off relationship between minimizing total costs and unsatisfied demand. Emphasizing on minimizing costs results in decreased demand satisfaction, whereas emphasizing minimizing unsatisfied demand leads to increased costs. Significant TLH locations can be identified by varying the number of TLHs. The sensitivity analysis shows the extent to which the available quantities of emergency relief items in the TLHs and the supply points influences costs and unsatisfied demand. Higher availability in the TLHs increases demand satisfaction at the price of increased costs. Additionally, the model was found to be less sensitive to increases in the availability of relief materials in the supply points. Further, the analysis of the multi-sourcing constraint reveals the reduction in total unsatisfied demand at the cost of increased costs in the multi-sourcing setting compared with single-sourcing under the same availability restrictions. However, multi-sourcing enables supply chain agility, which is essential during disaster response.

CHAPTER 4 A credibility based multi-objective temporary logistics hub location-allocation model for relief supply and distribution under uncertainty

4.1 Introduction

In the recent years, the world has witnessed several devastating disasters and a significant growth in human life losses, economic losses, and material damages caused by the sudden-onset natural disasters. Given their unpredictable nature, disasters and its impacts are generally characterized by a high level of uncertainty. Humanitarian operations concerning sudden onset disasters are inherently uncertain both in the disaster preparedness phase and disaster response phase. In such case, depending on the scale of the disaster, preparedness alone may not always be sufficient which makes response phase one of the most important and critical components of disaster management. The main focus in the response phase is on meeting the basic needs of the people until more permanent and sustainable solutions can be found. In doing so selecting where and when to locate response facilities and how to allocate demand to the open facilities is an important task.

Disaster response operations are inherently complicated. Several factors contributes to the complexity faced during the response period; time-varying and uncertain nature of the disaster impact, presence of multiple objectives, qualitative attributes, existence of multiple actors are some of the major factors. These factors can significantly affect the overall performance of the relief chain network. Uncertainty has been one of the biggest challenges faced in humanitarian operations. Uncertainty may arise due to randomness or/and impreciseness. Uncertainty may relate to knowing the exact location of the disaster or in the values of the parameters like cost, transportation time, and demand. Uncertainty in this study refers to epistemic uncertainty arising due to lack of knowledge of decision-maker about the actual value hence contributing to impreciseness. Multiple objectives are a distinguishing feature of humanitarian operation where a balance is always sought between the humanitarian and cost based objectives. Additionally, location decision requires evaluation of qualitative attributes like transportation accessibility, open space availability, manpower to name a few of them.

Despite these complexities related to the post-disaster conditions and lack of sufficient information about the extent of the damages, disaster response facilities must be set up quickly because of the urgency of the situation. The decision on whether to open a facility or not, where to locate them, and how to allocate the demand to the opened facility is purely based on the amount and the quality of information available during the decision-making time. The lack of sufficient historical data for the uncertain parameters as well as the high computational complexity of stochastic programming models make the use of this approach somehow impossible and at the same time unreasonable especially in the real life cases (Pishvaee et al. 2011). On the contrary, fuzzy mathematical programming is a flexible tool for handling epistemic uncertainty that comes from lack of knowledge of decision maker about the actual value of parameters.

As the related literature shows, previous works addressing the issue of temporary facility location problem do not take account of the time-varying and uncertain nature of the parameters, presence of multiple objectives, qualitative attributes, and existence of multiple actors simultaneously during the response phase.

In contrast to conventional approach, where post-disaster challenges are accounted in the pre-disaster phase (i.e. before the actual occurrence of the disaster) using the scenarios of disasters, in this study we focus on determining the location of TLHs by considering actual post disaster challenges occurring after the disaster using a credibility based fuzzy chance constrained programming while minimizing total cost and maximizing total demand coverage. The essential idea of fuzzy chance constrained programming is to optimize some critical value with a given confidence level subject to some chance constraints, in a fuzzy environment. Essentially, it does not contribute additional uncertainty but requires information on the confidence interval and the spread of the symmetrical triangular fuzzy number which in turn provides a better way to account for epistemic uncertainty.

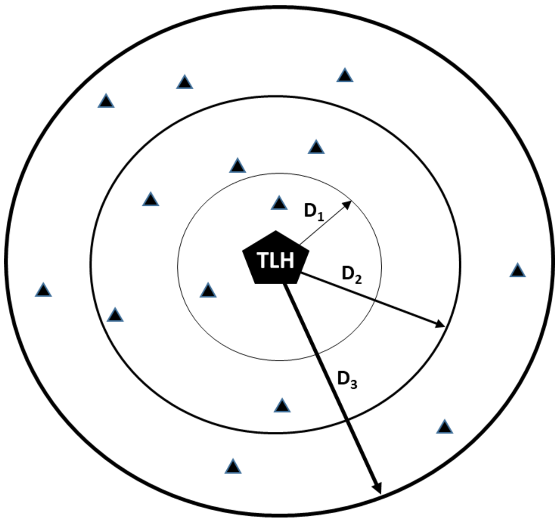
The TLHs considered in this study operate on a tactical level. Therefore, it is important to make sure it can cover PODs within the desired proximity while minimizing the total costs. Moreover, the TLH location selection model incorporates qualitative aspects like transportation accessibility and availability of open space into consideration. The evaluation of these qualitative aspects are purely based on the judgement provided by the experts (or decision-makers) which is often the case in the post-disaster phase. A fuzzy factor rating system under group decision-making condition is applied to illicit information from the experts. In summary, this study contributes to the existing literature by developing a credibility based multi-objective temporary logistic hub location model for post-disaster relief network design under uncertainty which captures both quantitative and qualitative aspects of location modeling.

4.2 Problem description

The relief chain network presented in this study is of multi-echelon, single product consisting of three layers: (1) supply points which represents all the points of entry to the affected country and permanent warehouses, (2) TLHs which acts an intermediator between the supply points and the point of distribution (POD), and (3) PODs which represents the aggregate demand location for demands arising from one district on a geographical region. Figure 1.4 shows the underlying structure of the humanitarian relief chain and positioning of the TLH within. The relief supplies enter the country via various points of entry (eg: sea, air, land) which are handled and arranged at TLHs and finally distributed to the PODs. Therefore, the decision to be made is on tactical level. The location of supply points and PODs are known in the post-disaster phase.

The establishment of TLH is required to distribute emergency relief to the PODs over the entire planning horizon. Each TLH has a known limit in the amount of emergency relief that can be delivered. Each POD is allowed to receive relief from only one TLH. The shipment of emergency relief between supply point, TLH, and POD incurs a variable transportation cost proportional to type of vehicle used, the quantity, distance, and the time period of operation. Further, establishment of a TLH incurs a fixed operation cost which can represent the cost of manpower, utilities, and rent needed to keep the facility operational. Establishment of TLH takes place in the beginning of each period. In the immediate aftermath of disaster it is almost impossible to determine the precise values of the parameters due to the impreciseness. Therefore, these parameters are assumed to be uncertain. Along the discrete and finite time horizon, these parameters are changing in a known way. An increase or decrease in especially total demand for emergency relief in a particular geographical region may require establishment of TLHs to be demand responsive.

The decisions to be addressed under the given circumstances include determining the locations, numbers, their capacities, the sequence of establishment of TLHs and allocation of POD’s to open TLHs as well as aggregate relief flow between them. Moreover, when designing a humanitarian relief chain it is important to make sure the established facilities can cover the demand areas within stipulated coverage distance while also minimizing total cost. We have implemented the concept of time-varying coverage provided by the TLHs. Figure 4.1 shows an illustration of the concept of time-varying coverage. For humanitarian operations, as important as it is to follow humanitarian code of conduct, one has to acknowledge the fact that these operations often operate within the confines of a limited budget. Moreover, qualitative aspects like transportation accessibility and open space availability should be considered to ensure operational sustainability of the established TLHs. The model formulation epitomizes situation more prevalent in developed countries where relief supplies are abundant to meet the demand.



Where,

D_t time varying coverage distance of TLHs in each period

▲ location of PODs

Figure 4.1: Illustration of concept of time-varying coverage

4.3 Mathematical model formulation

4.3.1 Assumptions

- The demand points, supply points, and the candidate temporary logistic hubs and the distance between them are known.
- The weight capacity of the vehicles used for carrying relief are known.

- Different types of relief are allowed to be loaded in a vehicle to serve the affected areas.
- Information in terms of disaster-induced damage conditions and casualties associated with each affected area, can be obtained during the response period but are imprecise.
- Costs, demand, and available relief parameters are assumed imprecise/fuzzy in nature and changing by time in a known way during the entire planning horizon.
- Relief supplies are available abundantly.

4.3.2 Nomenclature

The notations used in the mathematical model are as follows:

Sets

T	set of time periods {t|t= 1, 2, …, e}
I	set of supply points {i|i= 1, 2, …, f}
J	set of temporary logistic hubs {j|j= 1, 2, …, g}
K	set of affected area demand points {k|k= 1, 2, …, h}

Parameters

$\tilde{C}_{ijtm}$	unit transportation cost of shipping emergency relief package from supply point to temporary logistics hub in period t for vehicle type m ($/kmcar)
$\tilde{C}_{jktm}$	unit transportation cost of shipping emergency relief package from temporary logistics hub to point of distribution in period t for vehicle type m ($/kmcar)
$\tilde{F}_j$	a constant operational cost of having a TLH open (operating) in location j during period t
$\tilde{Q}_{it}$	available quantity of relief at supply point i ∈ I in period t
$\tilde{Q}_{jt}$	available quantity of relief at TLH j ∈ J in period t
a_{jkt}	a binary parameter equal to 1 if s_{jk}<=D_{max}, 0 otherwise
s_{jk}	distance between TLH and POD
D_{max}	the maximum coverage distance of TLH j in period t
$\tilde{d}_{kt}$	demand at each point of distribution j ∈ J in period t
P	total number of temporary logistic hubs

α confidence level

T_{jt} a value representing transportation accessibility in candidate location j in period t

O_{jt} a value representing availability of open spaces in candidate location j in period t

N_T threshold value for transportation accessibility in candidate j

N_O threshold value for availability of open spaces in candidate j

Variables

r_{ijt} amount of relief packages shipped from supply points i ∈ I to temporary logistics hubs j ∈ J in period t ∈ T

q_{jkt} amount of relief packages shipped from temporary logistics hubs j ∈ J to affected area points of distribution k ∈ K in period t ∈ T

y_{jt} binary variable that equals 1 if TLH is open in location j at the beginning of period t and 0 otherwise

x_{jkt} binary variable that equals 1 if POD k is served by TLH j in period t and 0 otherwise

z_{kt} binary variable that will be 1 if TLH j covers POD at k in time period t and 0 otherwise

4.3.3 Formulation

Minimize,

$$\mathrm{O}_1 = \sum_j \tilde{F}_j y_{jt} + \sum_i \sum_j \sum_t \tilde{C}_{ijtm} r_{ijt} + \sum_j \sum_k \sum_t \tilde{C}_{jktm} q_{jkt} \qquad (4.1)$$

Maximize,

$$\mathrm{O}_2 = \sum_k \tilde{d}_{kt} z_{kt} \qquad (4.2)$$

Constraints,

$$\sum_j a_{jkt} y_{jt} \geq z_{kt} \qquad \forall k \in K,\ t \in T \qquad (4.3)$$

$$\sum_j x_{jkt} = 1 \qquad \forall k \in K,\ t \in T \qquad (4.4)$$

$$h y_{jt} - \sum_k \sum_t x_{jkt} \geq 0 \qquad \forall j \in J,\ t \in T \qquad (4.5)$$

$$x_{jkt} \leq y_{jt} \qquad \forall j \in J,\ k \in K,\ t \in T \qquad (4.6)$$

$\sum_k q_{jkt} = \sum_i r_{ijt}$ $\quad \forall j \in J,\ t \in T$ (4.7)

$\sum_i r_{ijt} \leq \tilde{Q}_{it}$ $\quad \forall j \in J,\ t \in T$ (4.8)

$\sum_j r_{ijt} \leq \tilde{Q}_{jt}$ $\quad \forall i \in I,\ t \in T$ (4.9)

$\sum_k q_{jkt} \leq \tilde{Q}_{jt}$ $\quad \forall j \in J,\ t \in T$ (4.10)

$\sum_j y_{jt} \leq P$ $\quad \forall j \in J,\ t \in T$ (4.11)

$\sum_j q_{jkt} \geq \tilde{d}_{kt}$ $\quad \forall k \in K,\ t \in T$ (4.12)

$y_{jt} = 0,\ \exists\, j \in \{j: T_{jt} \leq N_T\}$ (4.13)

$y_{jt} = 0,\ \exists\, j \in \{j: O_{jt} \leq N_O\}$ (4.14)

$r_{ijt} \geq 0$ $\quad \forall i \in \mathrm{I},\ j \in \mathrm{J},\ t \in \mathrm{T}$ (4.15)

$q_{jkt} \geq 0$ $\quad \forall j \in \mathrm{J},\ k \in \mathrm{K},\ t \in \mathrm{T}$ (4.16)

$z_{kt} \in \{0,1\}$ $\quad \forall\, k \in K,\ \ t \in T$ (4.17)

$y_{jt} \in \{0,1\}$ $\quad \forall j \in \mathrm{J}$ (4.18)

$x_{jkt} \in \{0,1\}$ $\quad \forall j \in \mathrm{J},\ k \in \mathrm{K},\ t \in \mathrm{T}$ (4.19)

The objective function (4.1) minimizes the total cost which includes a fixed operating cost of open TLHs and the transportation cost from supply points to TLHs and from TLHs to the PODs. The objective function (4.2) maximizes the total demand coverage.

Constraint (4.3) is the coverage constraint, it ensures that a POD is covered only when one or more TLHs are located within D_{max} distance units of POD. Constraint (4) ensures that POD's are served by only one TLH. Constraint (4.5) guarantee that each selected TLH can deliver to several PODs. Constraint (4.6) make sure that demand is allocated to open facilities only. Constraint (4.7) is the flow conservation constraint. Constraints (4.8), (4.9), and (4.10) are the availability constraints. Constraint (4.11) limits on the maximum number of TLHs that can be opened. Constraint (4.12 ensures that all the demand is met. Constraint (4.13) and (4.14) are the subjective constraints. These constraints prevent allocating facilities in the neighborhoods whose transportation accessibility, open space availability and disaster vulnerability is below the required level. Constraints (4.15), (4.16), (4.17), (4.18), and (4.19) depict the nature of decision variables.

4.4 Solution strategy

4.4.1 Determine the values of qualitative attributes

Availability of open spaces and transportation accessibility plays an important role in ensuring establishment and operational sustainability of the TLHs. However, determining its values to enable quantitative evaluation is a cumbersome task. We use modified version of fuzzy multi-attribute group decision-making approach to determine the values of the qualitative attributes. The methodology includes five sequential steps starting with (1) selection of decision-makers, (2) determining the degree of importance of decision-makers, (3) computing the importance weight of the attributes (4) collecting decision opinions to assess candidate TLHs with respect to individual attributes and computing the aggregated fuzzy ratings, (5) constructing a fuzzy rating matrix, (6) deriving the total fuzzy scores for candidate TLHs and (7) computing the crisp values of attributes. The crisp values of the attributes thus computed are therefore used as the value representing open space availability and transportation accessibility in candidate location j in period t.

4.4.2 Convert the multi-objective possibilistic model to single objective model

One of the most popular approach to solving multi-objective optimization involves formulating a single objective optimization problem that is related to the multi-objective problem by means of a real-valued scalarizing function. Besides the weighted sum method, the epsilon constraint method is probably the best known technique to solve multi-objective optimization problems (Ehrgott, 2005). The epsilon-constraint method has several advantages over the weighing method (for a detailed explanation of the advantages please refer to Mavrotas (2009)). In the epsilon constraint method, one of the objective function is optimized using the other objective functions as constraints, incorporating them in the constraint part of the model. In the ideal situation, the value of the epsilon is determined by the decision-maker. Another alternative is to obtain the upper bound by solving the single objective optimization model. By parametrical variation in the right hand side of the constrained objective function the efficient solution of the problem can be obtained. For the mathematical model formulated in section

4.3.3, epsilon constraint method can be applied either to minimize total cost or to maximize total demand coverage while subjecting other objective as a constraint.

4.4.3 Apply fuzzy chance constrained programming approach to the possibilistic model and obtain its crisp equivalent

The essential idea of fuzzy chance constrained programming is to optimize some critical value with a given confidence level subject to some chance constraints in a fuzzy environment. Among the three different credibility-based fuzzy mathematical programming models i.e. expected value model; chance constrained programming model; and dependent chance constrained programming model (see Yang and Liu (2007) for details of three models), we employ chance constrained programming model in this study. Chance-constrained programming, which was initiated by Charnes and Cooper (1959), offers a powerful means for modeling uncertain decision systems. Chance constrained programming is able to control the satisfaction degree of chance constraints by adding a constraint for each objective function. However, it needs additional information on the ideal value of the objective function to determine the right hand side of the added constraints. Inclusion of fuzzy concept in chance constrained programming provides a means of allowing the decision-maker to consider objectives and constraints in terms of the possibility of their attainment (Liu and Liu, 2002) while accounting for the epistemic uncertainty in parameter values. In doing so, a constraint is added for each objective function where the ideal value of the objective function can be obtained from the decision-makers involved in the location decision making or by obtaining the optimal value of the objective.

Based on the existing literature there are generally three prominent fuzzy measures to deal with the possibilistic chance constraints (Liu, 2009). These include possibility, necessity, and credibility measure. The main advantage of these measures is to specify an occurrence degree for each fuzzy (i.e. possibilistic) event in the interval [0, 1] with varying optimistic and pessimistic attitudes. The possibility measure indicates the possibility (i.e. the most optimistic) level of an uncertain event's occurrence that involves possibilistic parameters. The necessity measure shows the corresponding minimum possibility level under the most pessimistic view. Meanwhile, the credibility measure represents the certainty degree of occurring an uncertain event. Liu (2008) extended the chance-constrained programming to fuzzy decision systems using the credibility measure, which is called credibility–based fuzzy chance-constrained programming. Credibility measure is self-dual, meaning that if a credibility value of a fuzzy event achieves 1, decision-maker believes the fuzzy event will surely happen. Therefore, it has been used to convert the possibilistic chance constraints into their crisp counterparts as it can provide results that would be more reliable than possibility and necessity measures (Tofighi et al. 2016).

The possibilistic model developed in Section 4.3.3 can be reformulated by employing credibility based fuzzy chance constrained programming in two ways depending on the choice of objective. Here we present the reformulation when minimizing total cost as:

$$\text{Max} \quad \bar{f} \tag{4.20}$$

$$(4.1) \equiv \text{Cr}\left\{\textstyle\sum_j \tilde{F}_j y_{jt} + \sum_i \sum_j \sum_t \tilde{C}_{ijt} r_{ijt} + \sum_j \sum_k \sum_t \tilde{C}_{jkt} q_{jkt} \geq \bar{f}\right\} \geq \alpha_1 \tag{E1}$$

$$(4.2) \equiv Cr\left(\textstyle\sum_k \tilde{d}_{kt} z_{kt} \geq \varepsilon\right) \geq \alpha_2 \tag{E2}$$

$$(4.8) \equiv \text{Cr}\left(\textstyle\sum_i r_{ijt} \leq \tilde{Q}_{it}\right) \geq \alpha_3 \qquad \forall j \in J,\ t \in T \tag{E3}$$

$$(4.9) \equiv \text{Cr}\left(\textstyle\sum_j r_{ijt} \leq \tilde{Q}_{jt}\right) \geq \alpha_3 \qquad \forall i \in I,\ t \in T \tag{E4}$$

$$(4.10) \equiv \text{Cr}\left(\textstyle\sum_k q_{jkt} \leq \tilde{Q}_{jt}\right) \geq \alpha_3 \qquad \forall j \in J,\ t \in T \tag{E5}$$

$$(4.11) \equiv \text{Cr}\left(\textstyle\sum_j q_{jkt} \geq \tilde{d}_{kt}\right) \geq \alpha_4 \qquad \forall k \in K,\ t \in T \tag{E6}$$

⇒ (4.3) – (4.7), (4.11), and (4.13) - (4.19)

In the above formulation, Cr(.) Denotes the credibility of the event in (.) and α_1, α_2, α_3, and α_4 are the predetermined confidence levels within which chance constraints should be fulfilled.

Application of fuzzy measures constitutes conversion of the original possibilistic chance constraints to their crisp counterparts. Defuzzification is a method that can be used to covert the possibilistic chance constraints to their crisp counterparts. In defuzzification, the fuzzy chance constraints are converted to their respective crisp equivalents with respect to the predetermined confidence level. Then the equivalent crisp model can be solved using traditional solution process. Let us consider a triangular fuzzy parameter $\zeta = (\zeta_1, \zeta_2, \zeta_3)$ and a real number r. From the definition of possibility, necessity, and credibility measures on fuzzy event, these measures about two events, $\zeta \leq r$ and $\zeta \geq r$ are expressed as:

$$\mathrm{Pos}\{\zeta \geq \mathrm{r}\} = \begin{cases} 1, & \text{if } r \leq \zeta_2, \\ \frac{\zeta_3 - r}{\zeta_3 - \zeta_2}, & \text{if } \zeta_2 \leq r \leq \zeta_3, \\ 0, & \text{if } r \geq \zeta_3, \end{cases} \tag{4.21}$$

$$\mathrm{Pos}\{\zeta \leq \mathrm{r}\} = \begin{cases} 1, & \text{if } r \geq \zeta_2, \\ \frac{r - \zeta_1}{\zeta_2 - \zeta_1}, & \text{if } \zeta_1 \leq r \leq \zeta_2, \\ 0, & \text{if } r \leq \zeta_1, \end{cases} \tag{4.22}$$

$$\mathrm{Nec}\{\zeta \geq \mathrm{r}\} = 1 - \mathrm{Pos}\{\zeta \geq \mathrm{r}\} \tag{4.23}$$

$$\mathrm{Nec}\{\zeta \geq \mathrm{r}\} = \begin{cases} 1, & \text{if } r \leq \zeta_1, \\ \frac{\zeta_2 - r}{\zeta_2 - \zeta_1}, & \text{if } \zeta_1 \leq r \leq \zeta_2, \\ 0, & \text{if } r \geq \zeta_2, \end{cases} \tag{4.24}$$

$$\mathrm{Nec}\{\zeta \leq \mathrm{r}\} = \begin{cases} 1, & \text{if } r \geq \zeta_3, \\ \frac{r - \zeta_2}{\zeta_3 - \zeta_2}, & \text{if } \zeta_2 \leq r \leq \zeta_3, \\ 0, & \text{if } r \leq \zeta_2, \end{cases} \tag{4.25}$$

$$\mathrm{Cr}\{\zeta \geq \mathrm{r}\} = \frac{1}{2}(\mathrm{Pos}\{\zeta \geq \mathrm{r}\} + \mathrm{Nec}\{\zeta \geq \mathrm{r}\}) \tag{4.26}$$

$$\text{i.e. } \mathrm{Cr}\{\zeta \geq \mathrm{r}\} = \begin{cases} 1, & \text{if } r \leq \zeta_1, \\ \frac{2\zeta_2 - \zeta_1 - r}{2(\zeta_2 - \zeta_1)}, & \text{if } \zeta_1 \leq r \leq \zeta_2, \\ \frac{\zeta_3 - r}{2(\zeta_3 - \zeta_2)}, & \text{if } \zeta_2 \leq r \leq \zeta_3, \\ 0, & \text{if } r \geq \zeta_3, \end{cases} \tag{4.27}$$

Similarly, we can also obtain,

$$\mathrm{Cr}\{\zeta \leq \mathrm{r}\} = \begin{cases} 0, & \text{if } r \leq \zeta_1, \\ \frac{r - \zeta_1}{2(\zeta_2 - \zeta_1)}, & \text{if } \zeta_1 \leq r \leq \zeta_2, \\ \frac{r - 2\zeta_2 + \zeta_3}{2(\zeta_3 - \zeta_2)}, & \text{if } \zeta_2 \leq r \leq \zeta_3, \\ 1, & \text{if } r \geq \zeta_3, \end{cases} \tag{4.28}$$

$\mathrm{Pos}\{\zeta \leq \mathrm{r}\}$, $\mathrm{Nec}\{\zeta \leq \mathrm{r}\}$, and $\mathrm{Cr}\{\zeta \leq \mathrm{r}\}$show the possibility, necessity, and credibility degrees to what extent ζ is not greater than r respectively. Similarly, $\mathrm{Pos}\{\zeta \geq \mathrm{r}\}$, $\mathrm{Nec}\{\zeta \geq \mathrm{r}\}$, and $\mathrm{Cr}\{\zeta \geq \mathrm{r}\}$ show the possibility, necessity, and credibility degrees to what extent ζ is not less than r respectively. Based on (4.27) and (4.28), it can be proven that that for $\alpha \geq 0.5$ (see Zhu and Zhang, 2009),

$$\mathrm{Cr}\{\zeta \geq \mathrm{r}\} \geq r \Leftrightarrow r \leq (2\alpha - 1)\zeta_1 + (2 - 2\alpha)\zeta_2) \tag{4.29}$$

$$\mathrm{Cr}\{\zeta \leq \mathrm{r}\} \geq \mathrm{r} \Leftrightarrow \mathrm{r} \geq (2 - 2\alpha)\zeta_2) + (2\alpha - 1)\zeta_3 \tag{4.30}$$

Based on equation (4.29) and (4.30), the above credibility-based fuzzy chance constrained model can be converted to the following crisp equivalent model.

$$\text{(E1)} \equiv (\textstyle\sum_j((2-2\alpha_2)F_{j(2)} + (2\alpha_2 - 1)F_{j(3)})y_{jt} + \sum_i\sum_j\sum_t((2-2\alpha_2)C_{ijt(2)} + (2\alpha_2 - 1)C_{ijt(3)})r_{ijt} + \sum_j\sum_k\sum_t((2-2\alpha_2)C_{jkt(2)} + (2\alpha_2 - 1)C_{jkt(3)})q_{jkt}) \geq \bar{f} \tag{4.31}$$

$$\text{(E2)} \equiv \textstyle\sum_k((2-2\alpha_1)d_{kt(2)} + (2\alpha_1 - 1)d_{kt(3)})z_{kt} \geq \varepsilon \tag{4.32}$$

$$\text{(E3)} \equiv \textstyle\sum_i r_{ijt} \leq ((2\alpha_3 - 1)Q_{it(1)} + (2-2\alpha_3)Q_{it(2)}) \qquad \forall j \in J,\ t \in T \tag{4.33}$$

$$\text{(E4)} \equiv \textstyle\sum_j r_{ijt} \leq ((2\alpha_3 - 1)Q_{jt(1)} + (2-2\alpha_3)Q_{it(2)}) \qquad \forall i \in I,\ t \in T \tag{4.34}$$

$$\text{(E5)} \equiv \textstyle\sum_k q_{jkt} \leq ((2\alpha_3 - 1)Q_{jt(1)} + (2-2\alpha_3)Q_{jt(2)}) \qquad \forall j \in J,\ t \in T \tag{4.35}$$

$$\text{(E6)} \equiv \textstyle\sum_j q_{jkt} \geq ((2-2\alpha_4)d_{kt(2)} + (2\alpha_4 - 1)d_{kt(3)}) \qquad \forall k \in K,\ t \in T \tag{4.36}$$

⇒ (4.3) – (4.7), (4.11), and (4.13) - (4.19)

Taking into account the nature of the problem, all the uncertain parameters are modelled as symmetric triangular fuzzy numbers. Use of symmetrical fuzzy numbers allows decision-makers to choose the spread of the fuzzy number which in turn enables accounting for epistemic uncertainty prevalent in predicting the values of the parameters. Symmetric triangular fuzzy number can be uniquely defined by $\tilde{A}$ = (ζ^s, ζ^c) where, ζ^s is the spread value, and ζ^c is the center value of $\tilde{A}$. If all the fuzzy parameters are considered as symmetric triangular numbers, equivalent crisp model can be reformulated as,

$$\text{(E1)} \equiv (\textstyle\sum_j((2-2\alpha_2)F_j^c + (2\alpha_2 - 1)(F_j^c + F_j^s))y_{jt} + \sum_i\sum_j\sum_t((2-2\alpha_2)C_{ijt}^c + (2\alpha_2 - 1)(C_{ijt}^c + C_{ijt}^s))r_{ijt} + \sum_j\sum_k\sum_t((2-2\alpha_2)C_{jkt}^c + (2\alpha_2 - 1)(C_{jkt}^c + C_{jkt}^s))q_{jkt}) \geq \bar{f} \tag{4.37}$$

(E2) , (E3), (E4), (E5), and (E6) can be formulated similarly.

⇒ (4.3) – (4.7), (4.11), and (4.13) - (4.19)

4.5 Numerical illustration and analysis

Numerical illustration aims at demonstrating the utility and relevance of the model and solution methodology developed above in real life disaster cases. In doing so, this study uses April 2015 Nepal earthquake for the numerical illustration. Details of the impacts of the earthquake can be referred from chapter 3 section 3.6.1.

4.5.1 Relief chain configuration

The study considers seven points of entry (6 land and 1 air) to the country as the supply points. A total of 12 districts are selected as candidates for TLH establishment. All the 14 districts severely affected by the earthquake are considered as the location of PODs. Figure 4.2 shows the spatial location of the supply points, candidate TLHs, and PODs. An operational horizon of 7 periods with each period lasting for a week is considered for conducting the response operations. A single package relief delivery system is considered. A single emergency relief package is assumed to weigh 10 kg and include essential items such as meals, a basic medical kit, blankets, baby supplies, and clothing. It is assumed that a single emergency relief package is sufficient to sustain an individual for a week.

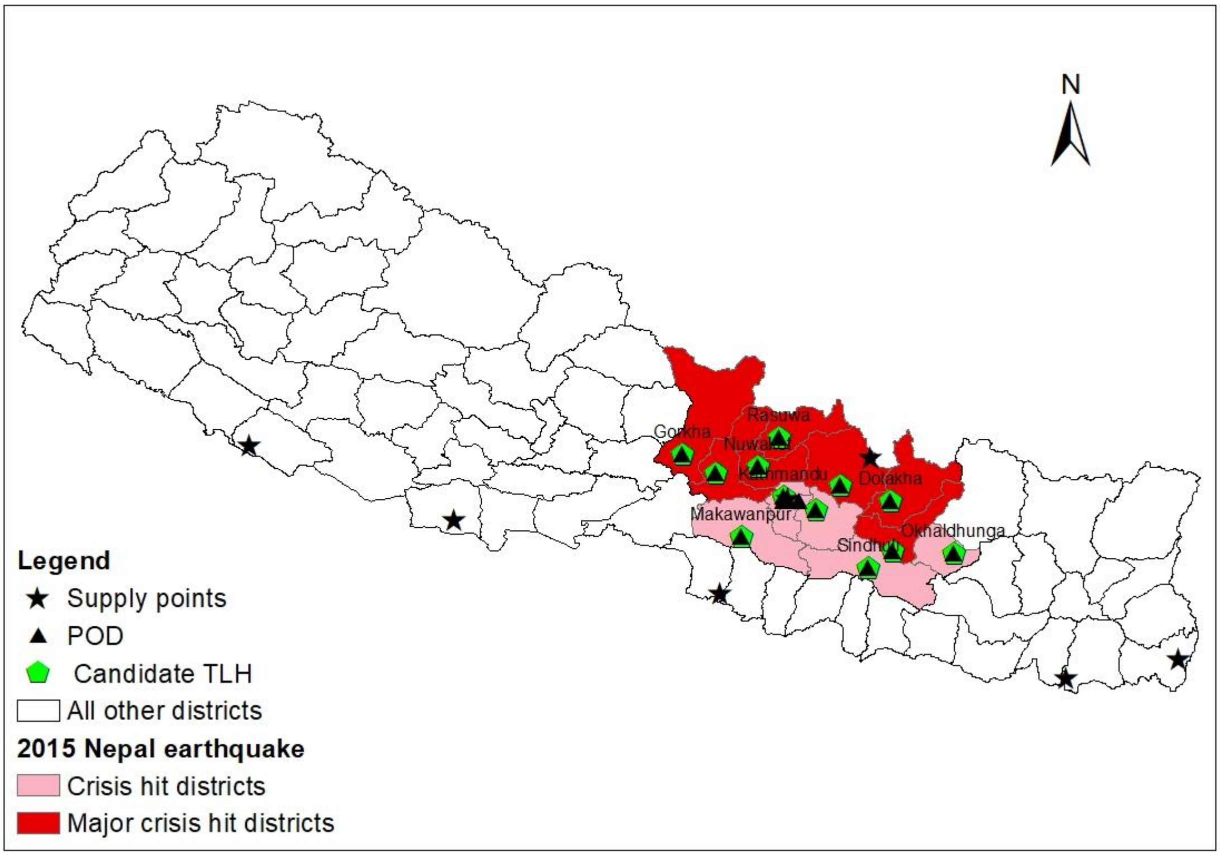


Figure 4.2: Spatial location of supply points, candidate TLHs, and PODs

4.5.2 Nature of input parameters

In the case of humanitarian relief chain design after disaster, there is an inherent impreciseness (i.e. epistemic uncertainty) in the data. This type of uncertainty includes those data such as demand of relief item, cost of transportation, accessibility issues, availability issues, and situation of road network. Moreover, these data are also time dependent as a result of which its value changes based on the changes in response environment. Table 4.1 shows the nature of input parameters used in this study. Transportation cost, relief demand, available relief in TLHs, and available relief in supply points, and fixed operation costs are considered to be changing with time while also enduring uncertainty in its value. The imprecise parameters are considered as symmetric triangular fuzzy numbers for which the provided data represents the central value of the associated fuzzy number. The fuzzy numbers can then be constructed by considering desired spread, whereas the spread itself can be determined by close consultation with the experts in decision making. The experts may rely either on available data or on their own knowledge or both. And the symmetric triangular fuzzy numbers were constructed by considering 15 percent spread in both sides of the central value. For the purpose of this numerical illustration the confidence level is considered to be 80 percent within which the chance constraints are to be fulfilled. The coverage distance is assumed to gradually increase from 100km in the first period to 200km in the seventh period within the operational horizon. The operational horizon is considered to be finite and deterministic and coverage is assumed to gradually change over time but in a known fashion.

Table 4.1: Nature of input parameters

Parameters	**Nature**	
Transportation cost	Dynamic (Time varying)	Uncertain
Relief demand		
Available relief in TLHs		
Available relief in Supply points		
Fixed operation cost		
Operational horizon	Finite	Deterministic
Coverage	Dynamic (Time varying)	

4.5.3 Results

We ignore the first 72 hours of disaster response acknowledging the reality of real-life emergency response operation. Because of the time needed and complexity of finding an appropriate location, assuming that TLHs could be established within 72 hours is unrealistic. Hence, our model is valid for the response situation after the first 72 hours. The model was coded in Lingo 17.0 Optimization modeling software. All the experiments were run on a personal computer with an Intel (R) Core (TM) i5-7500 CPU (3.40 GHz) and 16 GB of RAM. All the test problems were computed in under 10 minutes.

The result shows the optimal number of TLHs that need to be operational in each period along with their spatial location for the entire planning horizon and the allocation of the selected TLHs to the PODs when minimizing total cost. The values of the qualitative parameters (availability of open space and transportation accessibility) is obtained using FMAGDM. A comparison of the results of multi-objective optimization with uncertainty in parameters and deterministic parameters is also presented. Sensitivity analysis brings light on the impact of the parameters on the overall results.

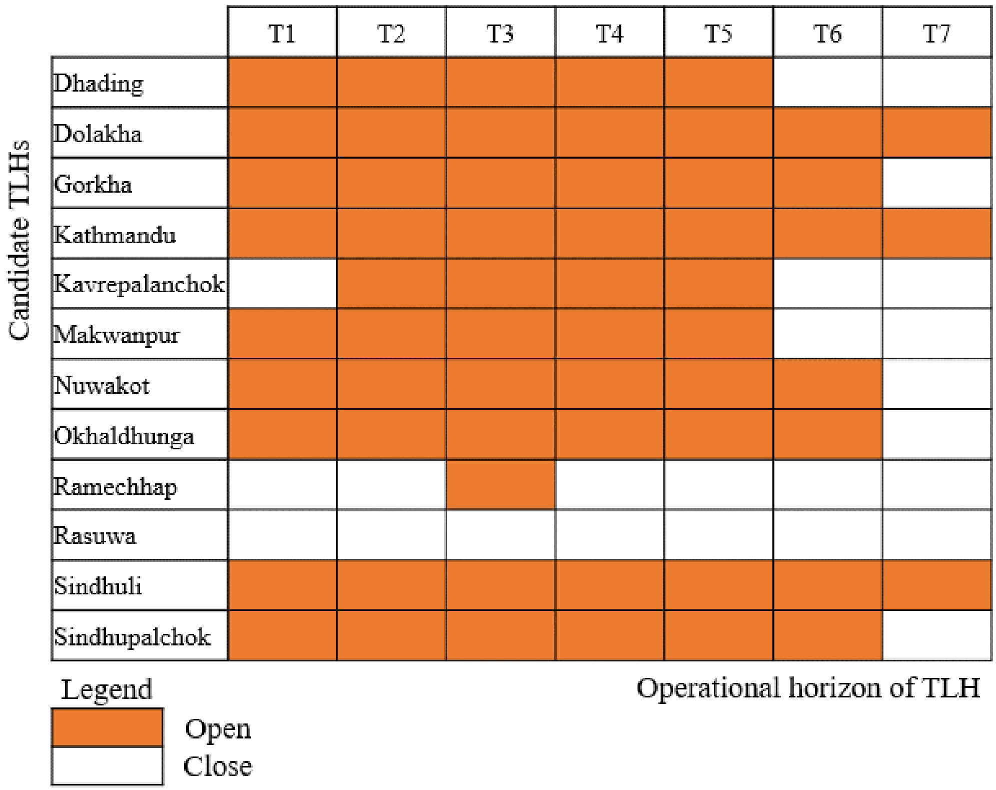


Figure 4.3: Optimal location of TLHs considering multiple objectives with uncertainty in parameters when minimizing total cost

Figure 4.3 shows the number, the spatial location, and the sequence of establishment of TLHs considering objective of minimizing total cost under uncertainty in relief demand, cost, and available relief. In the figure, T1…T7 represents time period of the operational horizon. Among the twelve candidates, TLH in Dolakha, Kathmandu, and Sindhuli is selected to operate for seven periods and Gorkha, Nuwakot, Okhaldhunga, and Sindhupalchok is selected to operate for six periods. Similarly, TLH in Dhading and Makwanpur is selected to operate for five periods and TLH in Kavreplanchok is selected to operate for four periods starting from second period ending in fifth period. Finally, TLH in Ramechhap is selected to be operational in fourth period. The candidate TLH location in Rasuwa is the only candidate that is not selected to be operational. One of the possible reasons could be the limited transportation accessibility of Rasuwa within and outside the district in real life. A total of 13.76 million demands are covered with total cost of 1.058 million USD.

Table 4.2: Allocation of relief supplies from supply points to TLHs (in 10,000 kg)

Supply points	TLH	T1	T2	T3	T4	T5	T6	T7
Tribhuwan international airport	Dhading	164.8	143.8	81.9	54.6	54.6		
	Kathmandu	632.0	675.2	737.1	764.4	764.4	759.8	415.8
	Okhaldhunga	22.2					33.9	
	Sindhuli						25.3	30.5
Biratnagar	Ramechhap			169.0				
Bhairahawa	Gorkha	133.0	186.1	226.0	212.7	199.4	139.6	
Tatopani	Dhading		87.0	194.4	147.2	192.7		
	Dolakha	190.9	267.3	155.6	305.4	286.4	200.4	60.1
	Kavrepalanchok		209.5	330.6	246.8	183.6		
	Makwanpur	91.7	128.3	155.8	146.7	137.5		
	Okhaldhunga	10.1	45.2	54.8	51.6	48.4		
	Sindhuli	64.6	90.4	109.8	103.3	96.9	42.5	
Inarwa	Dhading			3.9	61.9			
	Nuwakot	157.3	220.3	267.5	251.7	236.0	338.3	
	Sindhupalchok	141.2	197.6	240.0	225.9	211.7	148.2	

Table 4.2 shows the allocation of the emergency relief from supply point to TLHs and Table 4.3 shows the allocation of TLHs to different PODs in different periods of operation. Given the same limit on the available quantities of emergency relief in all the supply points which is gradually increasing over time, from Table 4.2 it can be observed that out of seven supply points five supply points located in Tribhuwan international airport, Biratnagar, Bhairahawa, Tatopani, and Inarwa is selected under the given circumstances to minimize total cost while ensuring maximum demand coverage under uncertainty in parameters. Similarly, from Table 4.3 it can be observed that among twelve candidate TLHs, eleven of them are selected to be operational in different periods. Among all the TLHs selected, the one located in Kathmandu is serving many PODs. With Kathmandu being the capital of the country it has ease of accessibility to many of the affected areas and the results closely approximates reality.

Table 4.3: Allocation of relief supplies from TLHs to POD (in 10,000 kg)

TLH	POD	T1	T2	T3	T4	T5	T6	T7
Dhading	Dhading	164.8	230.8	280.2	263.7	247.3		
Dolakha	Dolakha	91.5	128.1	155.6	146.4	137.3	96.1	28.8
	Ramechhap	99.4	139.2		159.0	149.1	104.4	31.3
Gorkha	Gorkha	133.0	186.1	226.0	212.7	199.4	139.6	
Kathmandu	Bhaktapur	66.4				41.0	69.7	20.9
	Dhading							51.9
	Gorkha							41.9
	Kathmandu	380.2	532.3	646.4	608.4	570.4	399.3	119.8
	Kavrepalanchok	83.3					87.4	26.2
	Lalitpur	102.1	142.9	90.7	156.0	153.1	107.2	32.1
	Makwanpur						96.2	28.9
	Nuwakot							42.9
	Rasuwa							6.7
	Sindhupalchok							44.5
Kavrepalnchok	Bhaktapur		93.0	106.3	106.3	58.7		
	Kavreplanchok		116.6	141.5	133.2	124.9		
	Lalitpur			82.8	7.3			
Makwanpur	Makwanpur	91.7	128.3	155.8	146.7	137.5		
Nuwakot	Dhading						173.1	
	Nuwakot	136.1	190.5	231.4	217.8	204.1	142.9	
	Rasuwa	21.2	29.7	36.1	34.0	31.9	22.3	
Okhaldhunga	Okhaldhunga	32.3	45.2	54.8	51.6	48.4	33.9	
Ramechhap	Ramechhap			169.0				
Sindhuli	Okhaldhunga						10.2	
	Sindhuli	64.6	90.4	109.8	103.3	96.9	67.8	20.3
Sindhupalchok	Sindhupalchok	141.2	197.6	240.0	225.9	211.7	148.2	

To illustrate the significance of considering uncertainty in parameter values when modeling TLH location-allocation problem, Figure 4.4 shows the model results when minimizing total cost while ensuring maximum demand coverage with deterministic parameters. The deterministic model results in a total cost of 0.912 million USD with a total coverage of 12.626 million demands. Comparison of Figure 4.3 and Figure 4.4 revels the dynamics in terms of the number and location of TLHs and that incorporation of uncertainty in parameter value leads to difference in the number and spatial location of the TLHs. A difference can be seen in the total number of TLHs operational in period one, two, four, and five. An increase in hub number can be observed in the case with uncertainty in parameters compared to the deterministic parameter case.

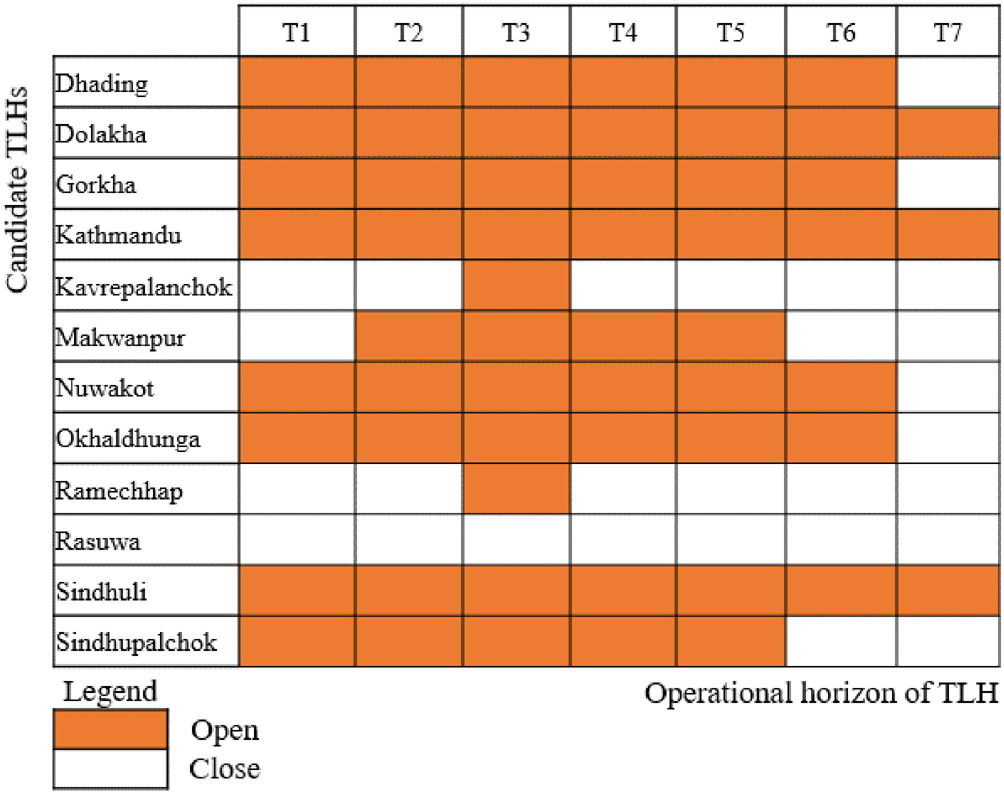


Figure 4.4: Optimal location of TLHs considering multiple objectives with deterministic parameters when minimizing total cost

Table 4.4 elucidates the difference in the number of TLHs operational with and without the consideration of uncertainty in parameters. In the figure, T1…T7 represents time period. From Table 4.4, it can be observed that the total number of TLHs that should be operational under consideration of epistemic uncertainty is larger than the deterministic case. The increase in the number of TLHs may be attributed to the demand uncertainty and time-varying nature and may as well be pertinent to actual needs in the affected areas. Irrespective of the consideration of uncertainty, a gradual growth and then respective decline in the number of TLHs operational can also be observed. From this comparison, it can be concluded that inclusion of uncertainty in parameter plays an important role in location selection process.

Table 4.4: Comparison of the results of multi-objective model with uncertainty in parameters and deterministic parameters

Model objective	Nature of parameters	Demand coverage (1000 units)	Total cost (100 USD)	TLH operational periods	T1	T2	T3	T4	T5	T6	T7
Minimize total cost	Uncertain	13763.06	10583.46	60	9	10	11	10	10	7	3
	Deterministic	12626.66	9120	56	8	9	11	9	9	7	3

Sensitivity analysis has been performed to understand the impact of number of TLHs on total cost and demand coverage and the overall network structure. Table 4.5 shows the sensitivity of the model results to the number of TLHs. It can be observed that increasing the number of TLHs leads to both increase in demand coverage and increase in total cost. Maximum demand coverage is obtained with ten hubs operating for seventy periods with a demand coverage of 13.76 million units and a total cost of 0.112 million USD. If we compare the results of the maximum coverage under limit on number of TLHs and under the optimal condition where model decides the number and the operational periods, we can observe that total demand is covered with lesser number of TLHs and at lower total costs under the optimal condition. However, it is worth to note that under the optimal condition the number of TLHs operating is varying in each period unlike a fixed number under the constrained situation. This signifies the time-varying nature of the TLH establishment and need for time-varying sequencing of the establishment process.

Table 4.5: Sensitivity analysis on the number of TLHs

TLHs		Demand coverage (1000 units)	Total cost (100 USD)	Fixed operating cost	Transportation cost from supply point to TLH	Transportation cost from TLH to POD
Number	Operational periods					
4	28	13496.91	14150.95	4578	1856.184	5151.725
5	35	13310.77	12434.37	3815	1594.346	7025.028
6	42	13496.91	11585.91	4578	1856.184	5151.725
7	49	13496.91	11260.45	5341	1934.512	3984.941
8	56	13496.91	11175.34	6104	2248.004	2823.336
9	63	13656.6	11146.92	6867	2290.011	1989.913
10	70	13763.06	11188.95	7630	2419.268	1139.677
11	77	13763.06	11384.63	8393	2590.631	401
12	84	13763.06	12083.61	9156	2653.928	273.6777

To further understand the impact of confidence level and spread of the symmetric triangular fuzzy numbers on the attainment of objectives, sensitivity analysis was performed. Figure 4.5 shows the sensitivity analysis on confidence level (α) with 15 percent spread on the symmetrical triangular fuzzy number and epsilon constraint for demand coverage at greater than or equal to 10 million units. Figure 4.6 shows the sensitivity on the spread of the symmetric triangular fuzzy number with 80 percent confidence level and epsilon constraint for demand coverage at greater than or equal to 10 million units. From figure 4.5 it can be observed that increase in the confidence level leads to increase in both total cost and demand coverage. This confidence level ensures the attainment level of the constraints with given degree of confidence. Similar trend can be observed from figure 4.6 as well, an increase in the spread of the triangular fuzzy number leads to increase in both total cost and total demand coverage.

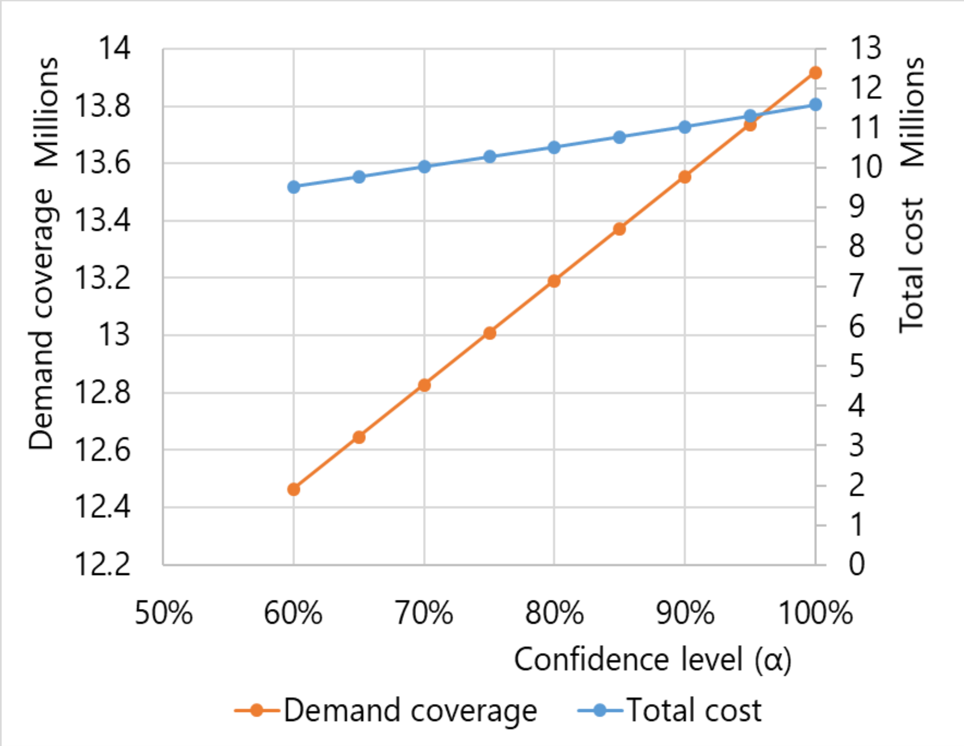


Figure 4.5: Sensitivity analysis on confidence level (α)

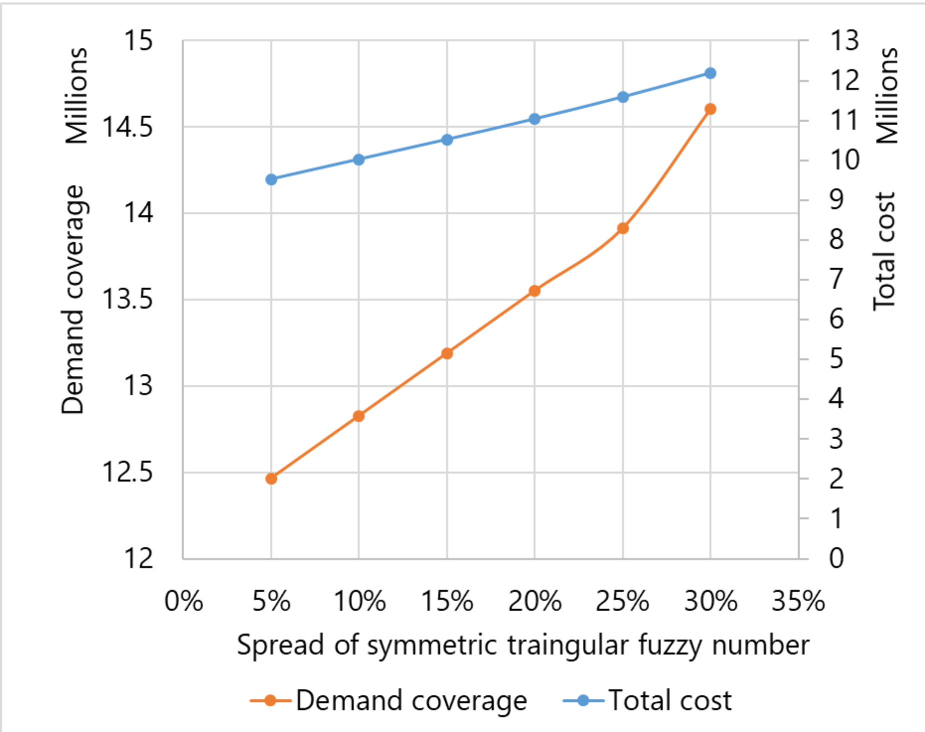


Figure 4.6: Sensitivity analysis for spread of symmetric triangular fuzzy number

4.5 Chapter summary

Uncertainty and time-varying nature are the two key features of disaster response operations. This time-varying and uncertain nature of the demand and other parameters during the disaster response period plays an important role in the overall location selection process and the corresponding allocation decisions. Additionally, the time-varying nature of these parameters demands the corresponding variation in the location and allocation decisions as well. In this study, we have developed a multi-objective mathematical model considering uncertain and time-varying nature of parameters while also including the qualitative parameters in the quantitative modeling to determine the time-varying locations and the corresponding allocation of the TLHs within the operational horizon of seven periods. The mathematical model minimizes total cost (operational and transportation cost) while maximizing the demand coverage under time-varying coverage distance. Each TLH's demand coverage is assumed to be gradually changing depending on the time of operation which in turn depends on the factors like transportation accessibility and available relief.

The model proposed herein was implemented by using data obtained from the April 2015 Nepal earthquake. The results of the optimization model shows the total cost, associated demand coverage, number, and spatial location of the TLHs and their corresponding allocations. The results of the optimization model also shows that, while the time-varying nature of relief demand and the coverage levels of TLH remaining the same, the time periods when the TLHs are operational are different under different circumstances of multi-objective uncertain model and multi-objective deterministic model. Changes in the location of TLHs was observed with the introduction of uncertainty in parameters when compared to the deterministic model. The results also show the allocation of emergency relief from supply points to TLHs and from TLHs to PODs varying based on time periods and highlights the role of selected supply points and TLHs for emergency relief supply and delivery. Inclusion of qualitative attributes in the optimization model makes sure that minimum standards are met to enable establishment and operation of TLHs in the selected locations.

Sensitivity analysis provided us with a wider understanding of the impact of limiting number of TLHs, confidence level within which objectives and constraints must be fulfilled, the spread of the symmetrical triangular fuzzy number on the coverage and cost objectives. It can be concluded that increase in these parameters lead to increase in both the demand coverage and total cost. Additionally, the fuzzy factor rating system used under group decision-making condition also enables accommodating multiple decision-makers in the decision-making process. Often during the chaotic response period a single decision-maker may not have all the information regarding various parameter. Therefore, inclusion of multiple decision-makers in obtaining the values of these parameters plays an important role.

CHAPTER 5 Fuzzy multi-attribute group decision-making for ordering the establishment of temporary logistics hubs

5.1 Introduction

A typical location problem includes determining how many, where, and how to locate and allocate the demand for open facilities. However, disaster response operation in most emerging countries is often resource constrained and requires the effective allocation of resources (mobile storage units) to ensure their effective utilization. In location decision-making, traditional network models take into account quantitative factors and aim to minimize the total cost or to maximize profitability or coverage. Non-quantitative criteria—such as, manpower qualifications, geographical characteristics, disaster vulnerability, availability of open spaces, and road accessibility issues—are also important in deciding location. While optimization approaches can be used for evaluating quantitative factors, this evaluation of qualitative factors is often accompanied by ambiguity and vagueness (Önüt et al. 2010). This is particularly so in the aftermath of a disaster, when the environment is chaotic, and there is limited information and time. Moreover, Montibeller and Yoshizaki (2011) state that intangible factors can change a network configuration resulting from a mathematical model.

Furthermore, in the aftermath of a disaster the decision-making process typically involves multiple decision-makers with varying interests and opinions. Indeed, the growing complexity and uncertainty of decision situations make it less and less possible for a decision-maker to consider all relevant aspects of a problem, thereby necessitating the participation of multiple experts in the decision-making process (Ben-Arieh and Chen, 2006). As such, achieving a proper balance among them is a significant challenge. Essentially, disaster managers have to make myriad reactive operational decisions to solve complex dilemmas with little to no information under immensely stressful conditions as they respond to emergencies. This highlights the need for a simple and inclusive methodology. Under these circumstances, an appropriate decision-making strategy would require that the resolutions and opinions of a group of decision-makers be taken into account when evaluating the subjective and objective attributes in the TLH selection process.

Within the extant literature, however, there is a general lack of studies that amalgamates optimization with a multi-criteria decision-making approach, which enables assessing both qualitative and quantitative aspects, to model location problem. On the one hand, studies using an optimization approach to the problem of location selection hardly include qualitative attributes. On the other hand, studies focusing on location selection by incorporating qualitative attributes barely focus on the temporary nature of disaster response facilities and the need to incorporate optimization techniques. There is also a scarcity of studies that concentrate on issues related to ordering the establishment of TLHs in addition to their location and allocation strategies when the resources are limited. Moreover, few studies focus specifically on temporary facilities for relief distribution. Indeed, while the study of Maharjan and Hanaoka (2018) has incorporated multiple decision-makers in a multi-objective optimization for TLH location selection, it does not consider the order of its establishment.

In this chapter we address the gaps in the existing literature and aid in the decision-making process by developing a methodology that determines the order of establishment of TLHs, and which considers location problems in doing so. The proposed methodology operates in three stages. The first stage uses an optimization model to determine the number and spatial location of the TLHs. In the second stage, a fuzzy factor rating system under group decision-making is used to rate the importance of attributes. Finally, in the third stage, a fuzzy multi-attribute group decision-making approach is used to determine the order of establishment of selected TLHs. As such, this study aims to develop a methodology that determines the order of establishment of TLHs that incorporates an optimization model and a multi-criteria decision-making approach. The methodology allows evaluating quantitative aspects and several qualitative attributes while considering the temporary nature of disaster response facilities under the presence of multiple-actors.

5.2 Fuzzy multi-attribute group decision-making

Known for its utility in evaluating imprecise attributes, the fuzzy multi-attribute group decision-making approach uses fuzzy set theory to deal with the vagueness and imprecision in decision-making. It also uses the logic and principle of the simple additive weighing method in factor rating systems to derive total scores for individual alternatives, which allows ranking by order of preference (Heragu, 1997; Heizer and Render, 2004) in GDM conditions. This approach has been proven to be simple but efficient in dealing with qualitative dimensions of alternative selection problem by Chou et al. (2008). Furthermore, while we are unsuccessful in making quantitative predications, we are comparatively efficient at qualitative forecasting. Fuzzy decision theories attempt to deal with the vagueness—that is, fuzziness—inherent in the subjective or imprecise determination of preferences, constraints, and goals (Yager and Filey, 1994). In addition to its abundant application in commercial logistics, fuzzy group decision making is a popular approach used for facility location problems (cf. Kahraman et al., 2003; Chou et al., 2008; Ertuğrul, 2011). However, their application in humanitarian logistics is nominal.

5.3 Model formulation

Consider the occurrence of a large-scale disaster that causes significant infrastructural damage and injury and results in large number of affected people. The scale of the disaster will attract responses from different humanitarian, governmental and non-governmental organizations, as well as local community groups, thereby creating a multi-actor scenario. Depending on the scale of the disaster, the number of humanitarian actors can range from a few dozens to several hundred. Effective disaster response requires the establishment of TLHs that can manage, sort, and store incoming emergency relief materials intended for distribution to affected people in different geographical locations immediately after the disaster. In large-scale disasters, we can assume a situation where the mobile storage units used as TLHs are limited in number in the immediate aftermath. To facilitate the response to urgent emergency relief demands in affected areas while enabling the effective utilization of scarce mobile storage units, this study develops a mechanism to determine the order of establishment of TLHs.

Based on the aforementioned prerequisites, the methodology for determining the order of establishment of TLHs involves: an optimization model, to calculate the number and the spatial location of TLHs; a mechanism establishing the importance weight of the subjective attributes; and a fuzzy multi-attribute group decision-making approach, to ascertain their order of establishment. In the first stage, the optimization model calculates the location alternatives for TLHs by minimizing total unsatisfied demand over the entire planning horizon. Moreover, to select an appropriate location, several qualitative attributes—including the availability of manpower, basic infrastructure facilities, security, and accessibility issues—need to be evaluated immediately after a disaster has occurred. While quantitative factors can be modeled using optimization techniques, qualitative factors are often difficult to incorporate and evaluate. As such, the main purpose of the second mechanism is to synthesize the importance weight of the attributes that will be used to evaluate the resulting location alternatives when multiple decision-makers exist. Finally, in the third step, the results obtained from the first stage optimization model are used as alternatives for subjective evaluation. The last two steps can be operated recursively to accommodate the varying numbers and opinions of decision-makers. This methodology is thus a development of that of Maharjan and Hanoaka (2018), and is intended to assist decision-makers in the design of emergency logistics plan. The next subsection provides the details of each mechanism.

5.3.1 Selection of location alternatives for TLHs

This mechanism aims to determine the number and spatial location of TLHs. We have formulated an optimization model with the objective of minimizing total unsatisfied demand under time-varying demand and changing level of available emergency relief. The proposed approach allows us to accurately capture the changing levels of relief demand and supplies over the planning horizon. Within this optimization model, the establishment of TLHs is required to meet the demand of affected people over the entire relief time horizon. Each district or demand point has an associated demand for emergency relief materials. A demand point represents the aggregated demands of one district. Along the discrete time horizon, demands from the affected zone changes in a known way related to information availability, changes in the number of affected people, and the recovery of affected people—and demand can increase, decrease, or stagnate as a consequence. The amount of emergency relief materials available in TLHs is affected by its capacity, as well as external availability issues. This amount can be less than or equal to the capacity of TLHs—that is, it cannot exceed the capacity of TLHs. Our model is deterministic—the location and the affected areas of the disaster are known before the decision to open a TLH is made. The following section provides further detail of the mathematical model, notations, parameters, and variables.

Nomenclature

T Set of time periods.

I Set of supply points.

J Set of temporary logistic hubs (TLHs).

K Set of affected area demand points.

QS_{it} Maximum available quantity of emergency relief materials at supply point $i \in$ I in period t [kg].

QH_{jt} Maximum available quantity of emergency relief materials at TLH $j \in$ J in period t [kg].

d_{kt} Demand of the affected area's demand point k in period t [kg].

n_{kt} Number of TLHs allocated to demand point k in period t.

M A very large number.

r_{ijt} Amount of emergency relief materials shipped from supply point $i \in$ I to TLH $j \in$ J in period $t \in$ T.

q_{jkt} Amount of emergency relief materials shipped from TLH $j \in$ J to the affected area's DP $k \in$ K in period $t \in$ T.

y_j Binary variable that equals 1 if the facility at j is selected as a TLH and 0 otherwise.

z_{jkt} Binary variable that equals 1 if TLH j serves demand point k in period t and 0 otherwise.

The optimization problem is formulated as follows:

Minimize the unmet demand,

$$\sum_k \sum_t \mathrm{d_{kt}} - \sum_j \sum_k \sum_t \mathrm{q_{jkt}} \tag{5.1}$$

Constraints,

$$\sum_k \mathrm{q_{jkt}} = \sum_i \mathrm{r_{ijt}} \qquad \forall \mathrm{j} \in J, \mathrm{t} \in T \tag{5.2}$$

$$\sum_j \mathrm{r_{ijt}} \leq \mathrm{QS_{it}} \qquad \forall \mathrm{i} \in I, \mathrm{t} \in T \tag{5.3}$$

$$\sum_i \mathrm{r_{ijt}} \leq \mathrm{QH_{jt}} \qquad \forall \mathrm{j} \in J, \mathrm{t} \in T \tag{5.4}$$

$$\sum_k \mathrm{q_{jkt}} \leq \mathrm{QH_{jt}} \qquad \forall \mathrm{j} \in J, \mathrm{t} \in T \tag{5.5}$$

$$\sum_j \mathrm{y_j} \leq \mathrm{P} \tag{5.6}$$

$$\sum_j \mathrm{q_{jkt}} \leq \mathrm{d_{kt}} \qquad \forall \mathrm{k} \in K, \mathrm{t} \in T \tag{5.7}$$

$$\mathrm{z_{jkt}} \leq \mathrm{y_j} \qquad \forall \mathrm{j} \in J \tag{5.8}$$

$$\sum_j \mathrm{z_{jkt}} \leq \mathrm{n_{kt}} \qquad \forall \mathrm{k} \in K, \mathrm{t} \in T \tag{5.9}$$

$$\mathrm{q_{jkt}} \leq \mathrm{Mz_{jkt}} \qquad \forall \mathrm{j} \in J, \mathrm{t} \in T \tag{5.10}$$

$$\mathrm{r_{ijt}} \geq 0 \qquad \forall \mathrm{i} \in I, \mathrm{j} \in J, \mathrm{t} \in T \tag{5.11}$$

$$\mathrm{q_{jkt}} \geq 0 \qquad \forall \mathrm{j} \in J, \mathrm{k} \in K, \mathrm{t} \in T \tag{5.12}$$

$$y_j \in \{0,1\} \qquad \forall j \in J \tag{5.13}$$

$$z_{jkt} \in \{0,1\} \qquad \forall j \in J,\ k \in K, t \in T \tag{5.14}$$

The objective function (5.1) minimizes total unsatisfied demand. Constraint (5.2) is the flow conservation constraint. Constraints (5.3) – (5.5) are the availability constraints. Constraint (5.3) ensures that the quantity of emergency relief materials moved from the supply points to the TLHs should be less than or equal to the maximum available quantity of emergency relief materials in the supply point in each period. Similarly, constraints (5.4) and (5.5) ensure that the quantity of emergency relief materials moved from the supply points to the TLHs and from TLHs to the demand points of affected areas should be less than or equal to the maximum available quantity of emergency relief materials in the TLHs in each period. Constraint (5.6) limits the total number of TLHs. Constraint (5.7) ensures that the quantity of emergency relief delivered to each demand point does not exceed its demand. Constraint (5.8) ensures that a demand point is served by TLH only if the TLH is open. Constraint (5.9) enforces multi-sourcing, ensuring that each demand point is served by a pre-specified number of TLHs. Constraint (5.10) obligates emergency relief distribution only between the assigned TLH and the demand point. Constraints (5.11) – (5.14) express the nature of the decision variables used in the model.

5.3.2 Determining the importance weight of attributes

The main purpose of this stage is to determine the importance weight of the subjective attributes used in evaluating TLH location alternatives. In this study, we adapted the "fuzzy factor rating system under group decision making condition" to accommodate the calculation of the importance weights of subjective attributes. The fuzzy factor rating system under group decision-making uses fuzzy logic to account for the inherent vagueness and uncertainty associated with decision-making during disaster response. The modified mechanism is composed of six sequential steps, explained hereunder.

Step 1: Selection of attributes.

Several attributes play an important role in determining the order of establishment of TLHs. In this study, the term "attribute" is used to refer to subjective attributes only. The attributes can be selected based on a variety of criteria, including the socio-economic situation of the country, the geo-climatic situation, a literature survey, and a review of lessons learned from the reports of past disasters. The attributes should be selected so as to ensure the sound utility and operational sustainability of the TLHs.

Step 2: Selection of decision-makers.

Under the GDM scenario, multiple decision-makers can be chosen. The choice of decision-makers also varies from case-to-case and country by country. A committee of decision-makers can be formed based on their overall role in the disaster management activity. The nature of these decision-makers and their decision opinions can lead to the generation of different scenarios: (1) when the decision-makers are homogeneous (1.1) their decision opinions are homogeneous, or (1.2) their decision opinions are heterogeneous; (2) when the decision-makers are heterogeneous (2.1) their decision opinions are homogeneous, or (2.2) their decision opinions are heterogeneous.

Step 3: Determining the degree of importance of decision-makers.

As such, the next step is to determine if decision-makers are homogeneous or heterogeneous. If the degree of the importance of decision-makers is equal, then the group of decision-makers is deemed to be a homogeneous group; otherwise the group is deemed heterogeneous.

In a committee of k decision-makers (D_t, $t = 1, 2, \ldots, k$) responsible for assessing m alternatives (A_i, $i=1, 2, \ldots, m$), under each of the n attributes (C_j, $j=1, 2, \ldots, n$), as well as importance of attributes, the degree of importance of the decision-makers is I_t, $t = 1, 2, \ldots, k$, where $I_t \in [0,1]$ and $\sum_{t=1}^{k} I_t = 1$. If $I_1 = I_2 = \ldots = I_k = \frac{1}{k}$, the group of decision-makers is called a homogeneous group; otherwise the group is called heterogeneous group. The importance of each decision-maker can be determined by interviewing the final decision-maker or based on their role in overall disaster management activities.

Step 4: Collecting decision opinions and computing the aggregated fuzzy weight of individual attributes.

The decision opinions of decision-makers can be obtained using a questionnaire interview or in person. The questionnaire uses the linguistic variables outlined in Table 5.1 to enable decision-makers to assess the importance of the attributes. The current study uses a scale of 1-9 for rating in the manner employed by Liang and Wang (1991), Liang (1999), Yong (2006) and Chou et al. (2008). Subsequently, to compute the aggregated fuzzy rating of the individual attributes, let $\widetilde{W}_{jt}$= $(a_{jt}, b_{jt}, c_{jt}, d_{jt}), j = 1, 2, ..., n; t = 1, 2, ..., k,$ be the linguistic rating given to attributes C_1 , C_2 ,…., C_n by decision-maker D_t . The aggregated fuzzy rating, $\widetilde{W}_j$ = (a_j, b_j, c_j, d_j), of attribute C_j assessed by the committee of k decision-makers is defined as

$$\widetilde{\mathrm{W}}_{\mathrm{j}} = (\mathrm{I}_1 \otimes \widetilde{\mathrm{W}}_{\mathrm{j}1}) \oplus (\mathrm{I}_2 \otimes \widetilde{\mathrm{W}}_{\mathrm{j}2}) \oplus \ldots \oplus (\mathrm{I}_{\mathrm{k}} \otimes \widetilde{\mathrm{W}}_{\mathrm{jk}}), \tag{5.15}$$

where $a_j = \sum_{t=1}^{k} I_t a_{jt}$, $b_j = \sum_{t=1}^{k} I_t b_{jt}$, $c_j = \sum_{t=1}^{k} I_t c_{jt}$, $d_j = \sum_{t=1}^{k} I_t d_{jt}$.

Table 5.1: Linguistic variables and fuzzy numbers for ratings

Linguistic variables	**Fuzzy numbers**
Very poor	(0, 0, 0, 20)
Between very poor and poor	(0, 0, 20, 40)
Poor	(0, 20, 20, 40)
Between poor and fair	(0, 20, 50, 70)
Fair	(30, 50, 50, 70)
Between fair and good	(30, 50, 80, 100)
Good	(60, 80, 80, 100)
Between good and very good	(60, 80, 100, 100)
Very good	(80, 100, 100, 100)

Step 5: Computing the importance weight of attributes.

To compute the importance weight of attributes, defuzzify the fuzzy rating of the individual attributes, compute the normalized weights, and construct the weight vector. To defuzzify the rating of the fuzzy attributes, the signed distance is adopted. The defuzzification of $\widetilde{W}_j$, denoted as $d(\widetilde{W}_j)$, is therefore given by

$$\mathrm{d}(\widetilde{\mathrm{W}}_{\mathrm{j}}) = \frac{1}{\mathrm{k}}(\mathrm{a}_{\mathrm{j}} + \mathrm{b}_{\mathrm{j}} + \mathrm{c}_{\mathrm{j}} + \mathrm{d}_{\mathrm{j}}) \tag{5.16}$$

The crisp value of the normalized weight for attributes C_j, denoted by W_j, is given by

$$\mathrm{W}_{\mathrm{j}} = \frac{\mathrm{d}(\widetilde{\mathrm{W}}_{\mathrm{j}})}{\sum_{\mathrm{j}=1}^{\mathrm{n}} \mathrm{d}(\widetilde{\mathrm{W}}_{\mathrm{j}})}, \tag{5.17}$$

where $\sum_{j=1}^{n} W_j = 1$. The weight vector W = $[W_1, W_2, . . . , W_n]$ is therefore formed.

The crisp value of the normalized weight of the attributes C_j can thus be used as the importance weight of the attributes.

5.3.3 Identifying the order of establishment of TLHs

To facilitate the establishment of TLHs, this stage aims to determine the order in which TLHs should be established. To do so, a fuzzy multi-attribute group decision-making approach uses the qualitative attributes selected in the second stage to evaluate each TLH location alternative obtained from the first stage. The following summarizes the main steps involved in this fuzzy multi-attribute group decision-making method.

Step 1: Obtain the decision-opinions of decision-makers to assess alternatives with respect to individual attributes, and obtain aggregated fuzzy ratings.

To assess the fuzzy ratings of location alternatives with respect to individual attributes, obtain the decision-opinions of decision-makers using the linguistic variables outlined in Table 5.1, and pool them together to obtain the aggregated fuzzy ratings. An interview questionnaire can be used for the rating of alternatives.

Let $\tilde{x}_{ijt}= (o_{ijt}, p_{ijt}, q_{ijt}, r_{ijt})$, $i = 1, 2, \ldots, m; j = 1, 2, \ldots, n; t = 1, 2, \ldots, k$, be the linguistic suitability rating assigned to alternatives A_i for attributes C_j by decision-maker D_t. The aggregated fuzzy rating $\tilde{x}_{ij}$ of alternative A_i for attribute C_j assessed by the committee of k decision-makers is defined as

$$\tilde{x}_{ij} = (I_1 \otimes \tilde{x}_{ij1}) \oplus (I_2 \otimes \tilde{x}_{ij2}) \oplus \ldots \oplus (I_k \otimes \tilde{x}_{ijk}) \tag{5.18}$$

This can subsequently be represented and computed as

$\tilde{x}_{ij}= (o_{ij}, p_{ij}, q_{ij}, r_{ij})$, $i = 1, 2, \ldots, m,\ j = 1, 2, \ldots, n$

where $o_{ij} = \sum_{t=1}^{k} I_t o_{ijt}$, $p_{ij} = \sum_{t=1}^{k} I_t p_{ijt}$, $q_{ij} = \sum_{t=1}^{k} I_t q_{ijt}$, $r_{ij} = \sum_{t=1}^{k} I_t r_{ijt}$.

Step 2: Construct a fuzzy rating matrix.

The fuzzy rating matrix $\widetilde{M}$ can be constructed based on fuzzy ratings, and expressed concisely in the matrix format

$$\widetilde{M} = \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdot & \cdot & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \vdots & \vdots & \tilde{x}_{2n} \\ \vdots & \vdots & & & \vdots \\ . & . & \cdot & \cdot & . \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \cdot & \cdot & \tilde{x}_{mn} \end{bmatrix}$$

where $\tilde{x}_{ij}, \forall i, j$ is the aggregated fuzzy rating of alternative A_i with respect to attribute C_j.

Step 3: Derive the total fuzzy scores for individual alternatives by multiplying the fuzzy rating matrix by its respective weight vectors.

Obtain the total fuzzy score vector by multiplying the fuzzy rating matrix $\widetilde{M}$ by the corresponding weight vector *W*, *i.e.*,

$$\tilde{F} = \widetilde{M} \otimes W^T = \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdot & \cdot & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \vdots & \vdots & \tilde{x}_{2n} \\ \vdots & \vdots & & & \vdots \\ . & . & \cdot & \cdot & . \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \cdot & \cdot & \tilde{x}_{mn} \end{bmatrix} \otimes \begin{bmatrix} W_1 \\ W_2 \\ \vdots \\ . \\ W_n \end{bmatrix} \tag{5.19}$$

$$= \begin{bmatrix} \tilde{x}_{11} \otimes W_1 \oplus \tilde{x}_{12} \otimes W_2 \oplus \cdots \oplus \tilde{x}_{1n} \otimes W_n \\ \tilde{x}_{21} \otimes W_1 \oplus \tilde{x}_{22} \otimes W_2 \oplus \cdots \oplus \tilde{x}_{2n} \otimes W_n \\ \cdot \\ \vdots \\ \tilde{x}_{m1} \otimes W_1 \oplus \tilde{x}_{m2} \otimes W_2 \oplus \cdots \oplus \tilde{x}_{mn} \otimes W_n \end{bmatrix} = \begin{bmatrix} \tilde{f}_1 \\ \tilde{f}_1 \\ \cdot \\ \vdots \\ \tilde{f}_m \end{bmatrix} = [\tilde{f}_i]$$

where $\tilde{f}_i = (s_i, t_i, u_i, v_i)$.

Step 4: Compute the crisp values using a defuzzification method.

Defuzzify the fuzzy scores $\tilde{f}_1, \tilde{f}_2, \ldots, \tilde{f}_m$ by using signed distance method. The following defuzzification equation is used to determine the crisp total scores of individual locations.

$$d(\tilde{f}_i) = \frac{1}{4}(s_i + t_i + u_i + v_i) \qquad i = 1, 2, \ldots, m \tag{5.20}$$

where $d(\tilde{f}_i)$ gives the defuzzified value (crisp value) of the total fuzzy score of location alternative A_i.

Step 5: Determine the order of establishment of the TLHs.

Finally, to determine the order of establishment of TLHs, rank the location alternatives based on the crisp values. The location alternatives with larger crisp values should be established first, followed by the location alternatives with lower values. The higher crisp value indicates the better performance of alternatives over the selected attributes.

5.4 Numerical illustration and analysis

To support the usefulness of this methodology, a numerical experiment was performed using disaster data from April 2015 Nepal earthquake. The detail of the impacts can been referred from chapter 3.

5.4.1 Optimal number and the spatial location of TLHs

To determine the optimal number and location of TLHs, we considered seven supply points, eleven candidate TLHs, and 13 demand points. The optimal solution was achieved by minimizing total unsatisfied demand over the entire planning horizon. An operational horizon of five weeks was considered with each period lasting one week. We accounted for a single package relief delivery system. A single emergency relief package was assumed to weigh 10 kg and to include essential items such as meals, a basic medical kit, blankets, baby supplies, and clothing. We estimated that a single emergency relief package is sufficient to sustain an individual for a week. The demand, cost, and available units of relief supplies are assumed to be time-varying.

The model was coded using Lingo 17.0 Optimization modeling software. All the experiments were run on a personal computer with an Intel (R) Core (TM) i5-7500 CPU (3.40 GHz) and 16 GB of RAM. All the test problems were computed in under ten minutes. Under the given conditions, the model resulted in a total of six TLHs with locations in Dolakha, Gorkha, Kathmandu, Makwanpur, Okhaldhunga, and Sindhupalchok. Figure 5.1 shows the spatial location of the selected TLHs on a map of Nepal.

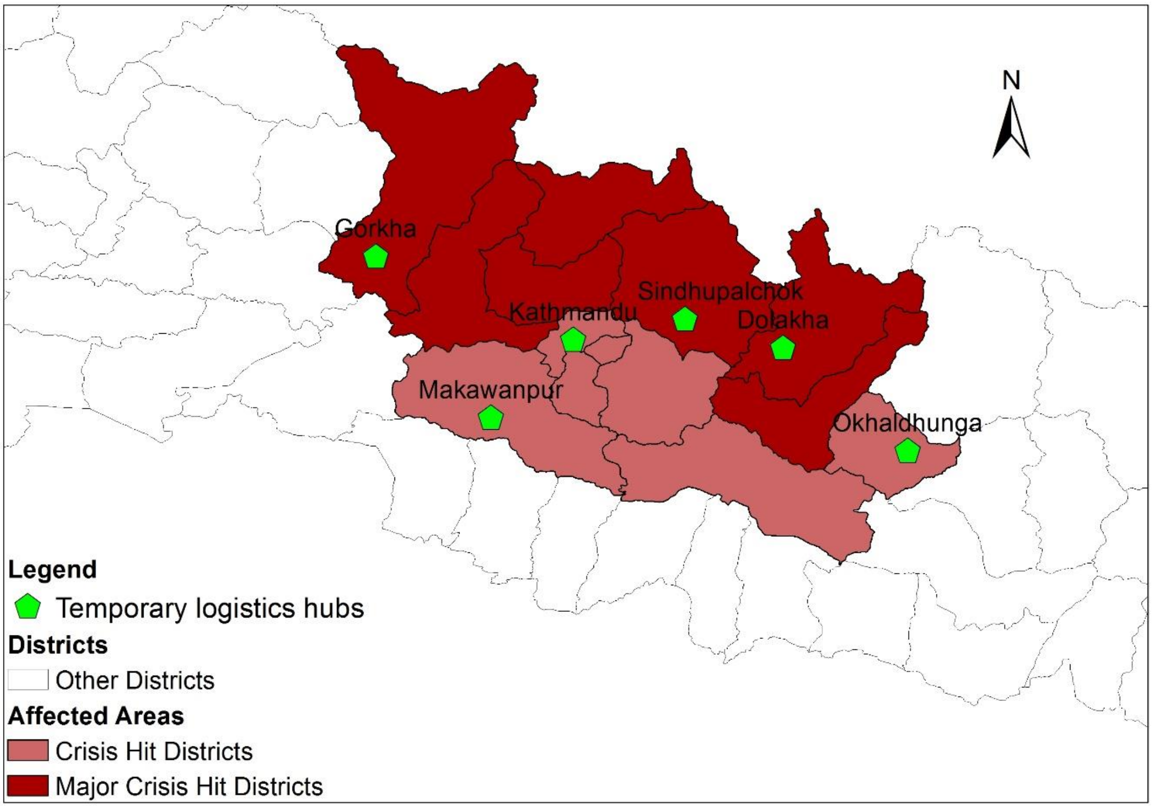


Figure 5.1: Spatial location of temporary logistics hubs

5.4.2. Determining the importance weight of attributes

Eight attributes were identified through a combination of a survey of the literature on the problem of facility location in humanitarian operations, the lessons learnt reports published by different entities, as well as information regarding the socio-economic and geo-climatic context of Nepal. Table 5.2 lists and describes the selected attributes.

Table 5.2: Description of the attributes

S.N.	Attribute		Description of the attribute
1	Availability of open spaces	C_1	Determines whether there are open spaces available to establish TLHs.
2	Accessibility via road	C_2	Refers to accessibility via road network, and determines the ease or difficulty in accessing the location by means of trucks, vans, etc.
3	Accessibility via air	C_3	Refers to accessibility issues via helicopters or planes.
4	Security	C_4	Denotes the security of the warehouse and related facilitates around the selected location.
5	Availability of necessary infrastructure	C_5	Refers to the availability of basic infrastructural facilities, like electricity, water supply, etc.
6	Availability of skilled manpower	C_6	Refers to the availability of the necessary manpower to support proper functioning of TLH in the candidate location.
7	Disaster vulnerability of selected locations	C_7	Refers to the disaster vulnerability of the selected location alternative—for example, whether the location is susceptible to secondary disasters.
8	Proximity to disaster affected areas	C_8	Describes how close or far the selected location is from the affected areas in need of emergency relief.

A committee of four decision-makers—D_1, D_2, D_3, and D_4—from four humanitarian organizations active in disaster management in Nepal was formed. The decision-makers involved in evaluating the qualitative attributes were assumed to be homogeneous—the degree of importance is thus equal for all of the decision-makers.

Table 5.3 shows the decision-opinions of four decision-makers using the linguistic weighing variables. The aggregated fuzzy rating of individual attributes was computed using equation (5.15) with reference to fuzzy numbers corresponding to each linguistic variable (Table 3.1). The importance weight of the attributes was calculated by defuzzifying the fuzzy numbers using the signed distance approach represented by equation (5.16), and the normalized weight was calculated using equation (5.17). The aggregated fuzzy weight, crisp values after defuzzification, and the normalized weight are shown in Table 5.3.

Table 5.3: The importance weight of attributes

Attributes	D_1	D_2	D_3	D_4	Aggregated fuzzy weight (AFW)	Defuzzified value of AFW	Normalized AFW
C_1	VH	VH	VH	H	(6.5, 9.25, 9.25, 10)	8.750	0.147
C_2	VH	VH	H	VH	(6.5, 9.25, 9.25, 10)	8.750	0.147
C_3	M	H	VH	VH	(5.25, 8, 8, 9.5)	7.687	0.129
C_4	H	M	H	H	(4.25, 6.5, 6.5, 9.5)	6.687	0.112
C_5	VH	H	VH	M	(5.25, 8, 8, 9.5)	7.687	0.129
C_6	M	VL	H	M	(2.25,4.25, 4.25, 7.25)	4.500	0.076
C_7	H	VH	H	H	(5.5, 7.75, 7.75, 10)	7.750	0.130
C_8	VH	VH	M	H	(5.25, 8, 8, 9.5)	7.687	0.129

5.4.3 Order of establishment of TLHs

To determine the order of establishment, we used the six TLHs obtained from the first stage as alternatives and evaluated them further using the attributes selected in the second stage by applying the fuzzy multi-attribute group decision-making method proposed in third stage.

Table 5.4: Decision-makers' evaluation and fuzzy rating matrix

Attribute	Alternative	D1	D2	D3	D4	Aggregated fuzzy ratings
C_1	Dolakha	F	B.P & F	B.P & F	P	(7.5, 27.5, 42.5, 62.5)
	Gorkha	B.G & V.G	P	B.P & F	V.G	(35, 55, 67.5, 77.5)
	Kathmandu	G	V.P	P	G	(30, 45, 45, 65)
	Makwanpur	V.G	P	G	G	(50, 70, 70, 85)
	Okhaldhunga	F	P	B.F & G	B.P & F	(15, 35, 50, 70)
	Sindhupalchok	B.F & G	V.P	B.P & F	G	(22.5, 37.5, 52.5, 72.5)
C_2	Dolakha	B.F & G	F	B.P & F	F	(22.5, 42.5, 57.5, 77.5)
	Gorkha	B.G & V.G	G	F	G	(52.5, 72.5, 77.5, 92.5)
	Kathmandu	V.G	P	G	G	(50, 70, 70, 85)
	Makwanpur	B.G & V.G	G	G	G	(60, 80, 85, 100)
	Okhaldhunga	F	B.P & F	B.P & F	P	(7.5, 27.5, 42.5, 62.5)
	Sindhupalchok	F	F	B.P & F	G	(30, 50, 57.5, 77.5)
C_3	Dolakha	B.P & F	V.P	B.P & F	F	(7.5, 22.5, 37.5, 57.5)
	Gorkha	V.P	P	P	P	(0, 15, 15, 35)
	Kathmandu	V.G	G	G	G	(65, 85, 85, 100)
	Makwanpur	G	B.P & F	G	B.F & G	(37.5, 57.5, 72.5, 92.5)
	Okhaldhunga	F	P	B.P & F	P	(7.5, 27.5, 35, 55)
	Sindhupalchok	P	V.P	P	B.P & F	(0, 15, 22.5, 42.5)
C_4	Dolakha	G	F	B.P & F	F	(30, 50, 57.5, 77.5)
	Gorkha	F	G	B.F & G	G	(45, 65, 72.5, 92.5)
	Kathmandu	B.G & V.G	G	G	G	(60, 80, 85, 100)
	Makwanpur	B.F & G	G	B.F & G	G	(45, 65, 80, 100)
	Okhaldhunga	F	P	F	B.P & F	(15, 35, 42.5, 62.5)
	Sindhupalchok	F	B.P & F	B.P & F	G	(22.5, 42.5, 57.5, 77.5)
C_5	Dolakha	G	F	F	B.P & F	(30, 50, 57.5, 77.5)
	Gorkha	B.F & G	B.P & F	P	F	(15, 35, 50, 70)
	Kathmandu	B.G & V.G	G	B.F & G	B.F & G	(45, 65, 85, 100)
	Makwanpur	G	G	F	G	(52.5, 72.5, 72.5, 92.5)
	Okhaldhunga	F	P	B.P & F	B.P & F	(7.5, 27.5, 42.5, 62.5)
	Sindhupalchok	B.P & F	P	P	B.F & G	(7.5, 27.5, 42.5, 62.5)
C_6	Dolakha	G	P	B.P & F	P	(15, 35, 42.5, 62.5)
	Gorkha	B.F & G	B.P & F	P	B.P & F	(7.5, 27.5, 50, 70)
	Kathmandu	V.G	G	B.F & G	B.F & G	(50, 70, 85, 100)
	Makwanpur	G	B.P & F	B.P & F	B.F & G	(22.5, 42.5, 65, 85)
	Okhaldhunga	F	B.V.P & P	B.P & F	P	(7.5, 22.5, 35, 55)
	Sindhupalchok	B.P & F	P	P	B.F & G	(7.5, 27.5, 42.5, 62.5)
C_7	Dolakha	B.G & V.G	F	B.P & F	B.P & F	(22.5, 42.5, 62.5, 77.5)
	Gorkha	F	B.F & G	B.P & F	G	(30, 50, 65, 85)
	Kathmandu	B.G & V.G	G	F	F	(45, 65, 70, 85)
	Makwanpur	F	G	F	G	(45, 65, 65, 85)
	Okhaldhunga	F	B.V.P & P	F	B.P & F	(15, 30, 42.5, 62.5)
	Sindhupalchok	P	B.P & F	B.P & F	G	(15, 35, 50, 70)

Table 5.4 (contd.): Decision-makers' evaluation and fuzzy rating matrix

Attribute	Alternative	D1	D2	D3	D4	Aggregated fuzzy ratings
C_8	Dolakha	B.G & V.G	F	B.P & F	B.P & F	(22.5, 42.5, 62.5, 77.5)
	Gorkha	G	B.F & G	F	B.G & V.G	(45, 65, 77.5, 92.5)
	Kathmandu	F	G	B.F & G	F	(37.5, 57.5, 65, 85)
	Makwanpur	P	G	F	B.F & G	(30, 50, 57.5, 77.5)
	Okhaldhunga	F	B.P & F	B.P & F	B.P & F	(7.5, 27.5, 50, 70)
	Sindhupalchok	B.G & V.G	B.P & F	F	V.G	(42.5, 62.5, 75, 85)

The decision-opinion of decision-makers in terms of fuzzy ratings for selected alternatives were obtained using the linguistic variables outlined in Table 5.1. Table 5.4 shows the decision-makers' evaluations and the aggregated fuzzy ratings computed for each alternative, as well as the respective criterion combination using equation (5.18). The fuzzy ratings matrix in Table 5.5 has been constructed using the aggregated ratings in Tables 5.3 and 5.4.

Table 5.5: Fuzzy rating matrix

Attributes	Dolakha	Gorkha	Kathmandu	Makwanpur	Okhaldhunga	Sindhupalchok
C_1	(7.5, 27.5, 42.5, 62.5)	(35, 55, 67.5, 77.5)	(30, 45, 45, 65)	(50, 70, 70, 85)	(15, 35, 50, 70)	(22.5, 37.5, 52.5, 72.5)
C_2	(22.5, 42.5, 57.5, 77.5)	(52.5, 72.5, 77.5, 92.5)	(50, 70, 70, 85)	(60, 80, 85, 100)	(7.5, 27.5, 42.5, 62.5)	(30, 50, 57.5, 77.5)
C_3	(7.5, 22.5, 37.5, 57.5)	(0, 15, 15, 35)	(65, 85, 85, 100)	(37.5, 57.5, 72.5, 92.5)	(7.5, 27.5, 35, 55)	(0, 15, 22.5, 42.5)
C_4	(30, 50, 57.5, 77.5)	(45, 65, 72.5, 92.5)	(60, 80, 85, 100)	(45, 65, 80, 100)	(15, 35, 42.5, 62.5)	(22.5, 42.5, 57.5, 77.5)
C_5	(30, 50, 57.5, 77.5)	(15, 35, 50, 70)	(45, 65, 85, 100)	(52.5, 72.5, 72.5, 92.5)	(7.5, 27.5, 42.5, 62.5)	(7.5, 27.5, 42.5, 62.5)
C_6	(15, 35, 42.5, 62.5)	(7.5, 27.5, 50, 70)	(50, 70, 85, 100)	(22.5, 42.5, 65, 85)	(7.5, 22.5, 35, 55)	(7.5, 27.5, 42.5, 62.5)
C_7	(22.5, 42.5, 62.5, 77.5)	(30, 50, 65, 85)	(45, 65, 70, 85)	(45, 65, 65, 85)	(15, 30, 42.5, 62.5)	(15, 35, 50, 70)
C_8	(22.5, 42.5, 62.5, 77.5)	(45, 65, 77.5, 92.5)	(37.5, 57.5, 65, 85)	(30, 50, 57.5, 77.5)	(7.5, 27.5, 50, 70)	(42.5, 62.5, 75, 85)

The normalized weight in Table 5.3 and fuzzy ratings in Table 5.5 were combined using equation (5.19) to obtain the total fuzzy scores for each location. Table 5.6 shows the resulting scores. The crisp values of the total fuzzy scores were obtained using the defuzzification equation (5.20), shown in Table 5.6. Finally, the alternatives were ranked based on the defuzzified total scores and used to determine the order of establishment of TLHs (Table 5.6).

Table 5.6: Aggregated fuzzy number, defuzzified total score, and order of establishment

Location alternatives	Aggregate fuzzy number	Defuzzified total score	Order of establishment
Kathmandu	(47.21, 66.48, 72.38, 88.76)	68.71	I
Makwanpur	(44.31, 64.31, 71.34, 89.87)	67.46	II
Gorkha	(30.16, 49.51, 60.14, 77.29)	54.27	III
Dolakha	(19.60, 38.96, 52.88, 71.58)	45.76	IV
Sindhupalchok	(19.23, 37.85, 50.46, 69.17)	44.18	V
Okhaldhunga	(10.42, 2940, 43.04, 63.04)	36.48	VI

The results of the interviews with the decision-makers in Table 5.3 reveals the differences in their decision-opinions. While three of the four decision-makers revealed that the availability of open spaces is of very high importance, one decision-maker placed comparatively lower importance on the same attribute. The decision-opinions of different decision-makers are heterogeneous in general—underscoring the importance of considering multiple decision-makers in the evaluation process. The normalized aggregated fuzzy weight in Table 5.3 shows that the "availability of open spaces" and "accessibility via roads" were perceived as highly important attributes, while the "availability of skilled labor" was deemed least important.

The order of establishment of TLHs can be determined with reference to the defuzzified total scores provided in Table 5.6. A higher value of a defuzzified total score means that the selected TLH performs better than its alternatives, and should thus be established first to achieve maximum effectiveness. Based on the decision-opinions of four decision-makers considered homogeneous, the final order of establishment should see the first TLH installed in Kathmandu, followed by Makwanpur, Gorkha, Dolakha, Sindhupalchok, and finally Okhaldhunga. The spider chart in Figure 5.2 illustrates the performance of the selected TLHs over the selected attributes. As seen in Figure 5.2, the location alternative of Kathmandu performs the best among the six selected TLHs, and therefore should be established first. While Kathmandu lags behind other alternatives in terms of open space availability, accessibility via roads, and proximity to disaster affected areas, it performs better overall.

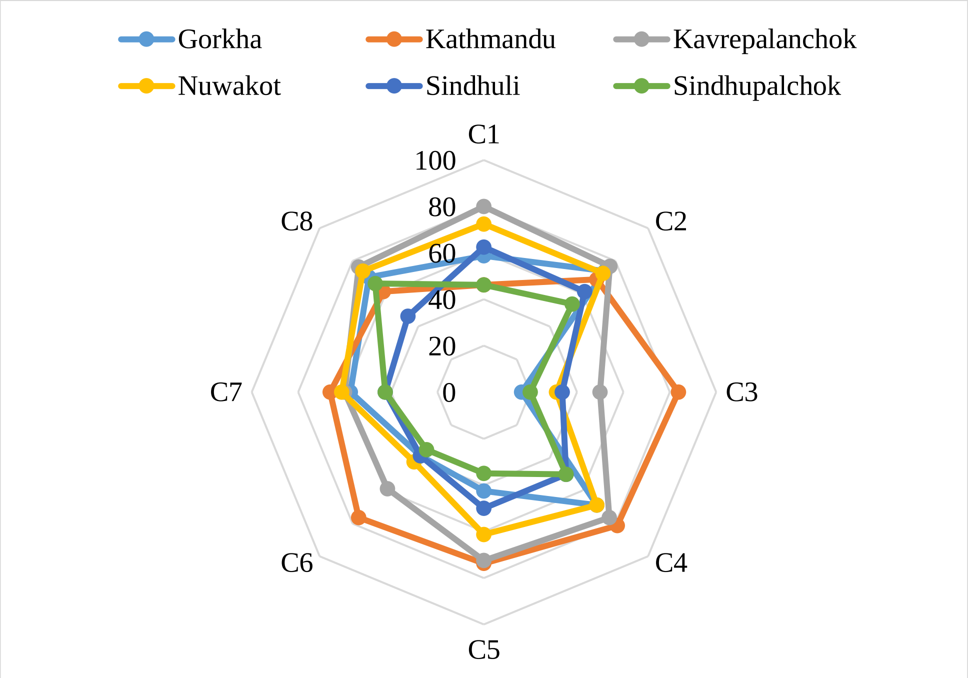


Figure 5.2: Performance of TLHs over all attributes

In order to understand the importance of including multiple actors and their impact on the overall decision-making process, we performed further calculations under different scenarios. Table 5.7 provides a comparison of the results in terms of variation in the order of establishment under three scenarios: single actor, multi-actor homogeneous, and multi-actor heterogeneous. When the decision-making process is conducted by only one decision-maker, the order of establishment is as follows: Kathmandu, Makwanpur, Dolakha, Gorkha, Okhaldhunga, and Sindhupalchok. In the homogenous multi-actor scenario, the order of establishment is: Kathmandu, Makwanpur, Gorkha, Dolakha, Sindhupalchok, and Okhaldhunga. Meanwhile, in a heterogeneous multi-actor scenario it the order is: Kathmandu, Makwanpur, Gorkha, Sindhupalchok, Dolakha, and Okhaldhunga. This highlights the importance of considering multiple decision-makers and their influence over the decision-making process—as is the case in reality.

Table 5.7: Comparison of single and multiple actor scenarios

Selected locations	**Order of establishment**		
	Single-actor	Multi-actor	
		Homogeneous	Heterogeneous
Dolakha	**III**	**IV**	**V**
Gorkha	IV	III	III
Kathmandu	I	I	I
Makwanpur	II	II	II
Okhaldhunga	**V**	**VI**	**VI**
Sindhupalchok	VI	V	IV

5.5 Chapter summary

Recently, temporary facilities for disaster response has been receiving growing attention from scholars and practitioners alike. However, location selection and ordering are immensely complex due to the lack of information, growing number of humanitarian responders, and the need to evaluate subjective attributes during the chaotic disaster response period. This study has combined an optimization model with fuzzy multi-attribute group decision-making to develop a methodology for determining the order of establishment of TLHs. This is a three-stage process: the multi-period optimization problem determines the number and spatial location of TLHs by minimizing the total unsatisfied demand, the fuzzy factor rating system calculates the importance weight of subjective attributes, and the fuzzy multi-attribute group decision-making method ascertains the order of establishment of the selected TLHs by considering eight subjective attributes.

The proposed methodology was implemented using data obtained from the April 2015 Nepal earthquake. Of the eleven candidate locations assumed to fulfill the time-varying demand over the entire planning horizon, the optimization model pinpointed six locations: Dolakha, Gorkha, Kathmandu, Makwanpur, Okhaldhunga, and Sindhupalchok. Interviews with decision-makers revealed the differences in their opinion regarding the prominence of different attributes. This difference in decision-opinion was also observed when evaluating the performance of selected locations versus the attributes. Further analysis showed that the order of establishment varies significantly when the locations are evaluated under different scenarios. In this study, the order of establishment under the three scenarios of single actor, homogeneous multiple actors, and heterogeneous multiple actors were found to differ considerably. This led us to conclude that it is essential to consider real life scenarios when making decisions regarding TLHs.

Though we have used a single objective optimization approach for generating the optimal TLH number and their spatial location alternatives in this chapter, the multi-objective optimization models both the deterministic one and the possibilistic one can also be used to generate alternatives. Depending on the actual need of the situation appropriate mathematical model can be used in the first phase.

CHAPTER 6 Summary and Conclusion

6.1 Facility location in perspective

Figure 6.1 shows the facility location problem in perspective. Through this dissertation we have addressed a temporary logistics hub establishment problem with a finite horizon with both single and multiple objectives considering time-varying uncertain and time-varying deterministic nature of parameters using both qualitative and quantitative modeling approach.

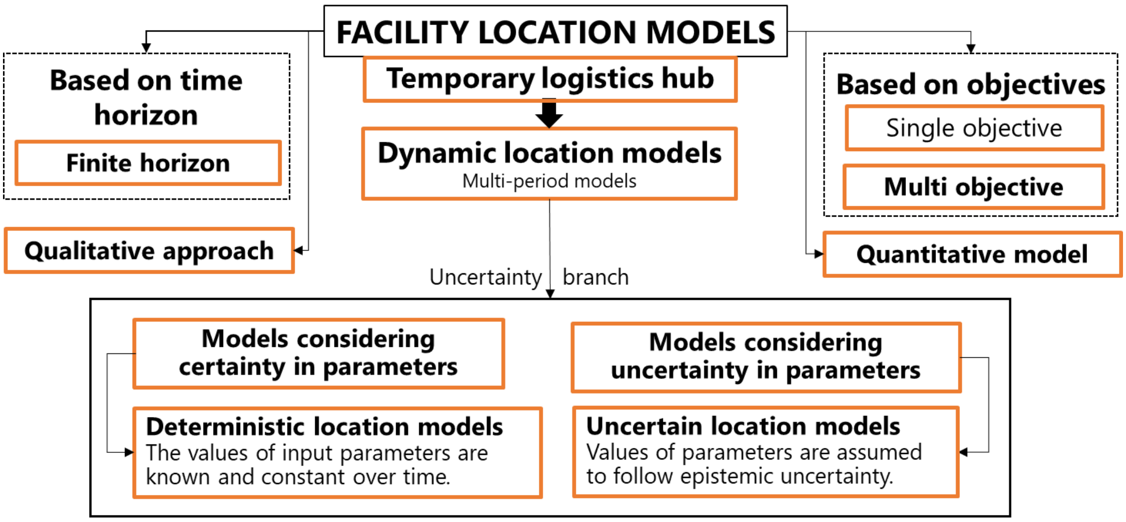


Figure 6.1: Facility location problem in perspective

6.2 Summary and Conclusion

In the recent years, the field of humanitarian logistics has been receiving burgeoning attention from both academics and practitioners. However, review of the extant of literature reveals a general lack of studies focusing on temporary logistical facilities that enables streamlining post-disaster operations to minimize suffering of affected people. This dissertation started with a broader aim of introducing the concept of temporary logistics hubs and its significance in post-disaster operation especially focusing on developing countries where preparedness lags behind actual needs. In doing so we studied different dimensions of TLHs ranging from determining their location, allocation, timing of establishment, and ordering of establishment and developed models and methodology for determining them. Furthermore, methodologies were also developed to enable evaluation of qualitative and quantitative attributes, and decision-making approaches which plays a vital role in enabling comprehensive analysis of multiple aspects of TLH location problem and its operational sustainability. The following sections summaries what has been achieved through each chapter in retrospective to the objectives of this study.

Chapter three – One of the key decisions to make regarding TLHs is to determine and decide on where to locate them to achieve desired objective/s. Unlike commercial operations, humanitarian operations often have more than one objective which necessitates use of multi-objective optimization. However, use of this approach requires knowing the weights assigned to different objectives which is often complicated. Furthermore, humanitarian response operations often requires engagement of wide range of actors ranging from government organizations to national and international non-governmental organization, and community organizations where the decision-makers have to make myriad of decisions under pressure and impreciseness while ensuring agility of relief chain. To address these issues in this chapter we developed a multi-objective location model with the objectives of minimizing total cost and unsatisfied demand with multi-sourcing feature and a FFRS under GDM. The FFRS under GDM is used to determine the weight of objectives which is capable of accommodating decision-opinion of multiple decision-makers. The results of the numerical illustration using April 2015 Nepal earthquake shows trade off relationship between the two objectives and varying decision-opinion of different decision-makers when the decision-makers were considered homogeneous. Sensitivity analysis shows higher availability of emergency relief in the TLHs increases demand satisfaction at the price of increased costs. Further, the analysis of the multi-sourcing constraint reveals the reduction in total unsatisfied demand at the cost of increased costs in the multi-sourcing setting compared with single-sourcing under the same availability restrictions. Despite the increased cost, multi-sourcing enables supply chain agility, which is essential during disaster response.

Chapter four – Disaster response operations are often carried out immediately after its occurrence, during which time the information regarding precise values of the parameters is still evolving. The entire decision-making ability/process is tainted with high degree of uncertainty. Under these circumstances, knowing not only where and how many TLHs to establish, but also when to establish them is necessary while taking account of the uncertainty in parameter value. In this chapter we develop a possibilistic multi-objective optimization model that determines the location of TLHs and allocation of open TLHs to the demand points. The model minimizes total cost while maximizing total demand coverage using epsilon constraint method. A credibility based fuzzy chance constrained programming approach is used to account for possibilistic parameters and FMAGDM is used to evaluate availability of open spaces and transportation accessibility during the immediate aftermath. The results of the numerical illustration shows the location, number of TLHs along with their sequence (timing) of establishment and allocation of the open facilities to PODs. Sensitivity analysis provided us with a wider understanding of the impact of limiting number of TLHs, confidence level within which objectives and constraints must be fulfilled, the spread of the symmetrical triangular fuzzy number on the coverage and cost objectives. It can be concluded that increase in these parameters lead to increase in both the demand coverage and total cost. Additionally, the fuzzy factor rating system used under group decision-making condition also enables accommodating multiple decision-makers in the decision-making process. Often during the chaotic response period a single decision-maker may not have all the information regarding various parameter. Therefore, inclusion of multiple decision-makers in obtaining the values of these parameters plays an important role.

Chapter five – This chapter introduces the concept of the order of establishment of TLHs. Determining the order of establishment plays an important role in ensuring maximum utilization of the mobile storage units which are used as TLHs when they are in limited availability which is often true during the initial phase of post-disaster operation. Order of establishment can be determined after their optimal number, their corresponding spatial location and allocation strategies, and their timing of establishment have been determined. It is worth noting that the concept introduced in this chapter is almost non-existent in the existing literature. From the methodological point of view, often studies have used either optimization approach or multi-criteria decision-making approach to deal with location problems. In this chapter we attempt to take the benefit obtained by amalgamating an optimization approach with multi-criteria decision-making approach where the optimization model determines the optimal numbers and locations of TLHs and FMAGDM is used to determine their order of establishment. While both the mathematical models developed in chapter three and four can determine the optimal number and location of the TLHs we have developed a single objective optimization model with the objective of minimizing total unsatisfied demand to determine the initial results. FMAGDM approach employed here enables evaluation of qualitative attributes affecting the ordering decision while taking account of decision-opinion of multiple decision-makers in terms of fuzzy linguistic variables. In the numerical illustration, the decision-opinion of four decision-makers reveals availability of open spaces and transportation accessibility as the two most important attributes for determining the order of establishment of TLHs. The performance of the selected TLHs can also be observed from the results.

Generally speaking, humanitarian operations should focus on optimizing humanitarian objectives as dictated by the humanitarian code of conduct. However, discrepancy can be observed in the real life operations where minimizing cost becomes a significant objective. A thorough understanding of the impact of the choice of objectives on the location selection is desirable in this case. In this dissertation, we have developed three optimization models with different objectives with the aim of understanding this. Chapter three has developed a multi-objective optimization model with the objective of minimizing total cost and total unsatisfied demand. Similarly, in chapter four a possibilistic multi-objective model with the objectives of maximizing total demand coverage and minimizing total cost is developed. On the contrary, a single objective optimization model with the objective of minimizing total unsatisfied demand is developed in chapter five. As a summary, in terms of the choice of objectives this dissertation has explored location selection with wide range of objectives which can provide managerial insights on the impact of choice of objective function on TLH location selection decision.

In retrospect to the objectives of this dissertation we have developed three different models to determine the optimal number, their spatial location, allocation of selected TLHs, and their order of establishment while also accounting for features like multi-sourcing, incorporating multiple actors in the decision-making process, uncertainty arising due to impreciseness in this dissertation. While multi actor approach to optimization modelling is almost insignificant in the literature of humanitarian logistics, the interview with the logistics experts from different humanitarian organizations revealed difference in their decision opinion highlighting the significant of incorporating them in the decision-making process.

6.3 Comparison of results

In chapter three, model results of the numerical illustration has selected eight optimal TLHs with locations in Gorkha, Kathmandu, Kavrepalanchok, Makwanpur, Nuwakot, Ramechhap, Sindhuli, and Sindhupalchok to operate for the entire planning horizon of five periods. In chapter four, time-varying locations in eleven candidate TLH locations in Dhanding, Dolakha, Gorkha, Kathmandu, Kavrepalanchok, Makwanpur, Nuwakot, Okhaldhunga, Ramechhap, Sinduli, and Sindhupalchok are selected for establishment of TLHs within an operational horizon of seven periods. Among the twelve candidates, TLH in Dolakha, Kathmandu, and

Sindhuli is selected to operate for seven periods and Gorkha, Nuwakot, Okhaldhunga, and Sindhupalchok is selected to operate for six periods. Similarly, TLH in Dhading and Makwanpur is selected to operate for five periods and TLH in Kavreplanchok is selected to operate for four periods starting from second period ending in fifth period. Finally, TLH in Ramechhap is selected to be operational only in fourth period. In chapter five, a total of six TLHs with locations in Dolakha, Gorkha, Kathmandu, Makwanpur, Okhaldhunga, and Sindhupalchok are selected to operate for the entire planning horizon of five periods.

It is worth to note that, the features of the mathematical model and the objectives of concern are different in each chapter, consequently the optimal choice of TLH location and their numbers are also different. Although, chapter three and chapter five deals with static nature of TLHs and chapter four with time-varying nature, TLH candidate locations in Dolakha and Kathmandu are selected to operate for the entire planning horizon in all three chapters which signifies the importance of these locations in the overall humanitarian response operation irrespective of the choice of objectives and modelling features. However, from the results, it can also be concluded that, the choice of objective function and the solution methodology in addition to other model features has considerable impact on the location selection decision.

6.4 Practical implication and applicability

Based on the insights gained in the course of this dissertation, this section discusses what implications the research findings have for the actors/decision-makers for improving humanitarian operations.

- Large scale humanitarian operations usually see involvement of more than one actor/stakeholder/decision-maker in real life. However, an inability to accommodate the actors in the establishment decision-making may have its consequences. Therefore, practical implication of involving multiple decision- maker early in the decision-making process enables coordination by synthesizing a representative outcome from a decision-maker's judgements. This further helps to develop a sense of ownership of the established TLHs and its operations. This sense of ownership is important to maximize the utilization of the established hubs while enabling coordination.
- The application of group decision-making approach also enables minimizing discrepancy caused by lack of information of information asymmetry. When the decision is made by a group more accurate information can be obtained while reducing

redundancy in information and operation. The practical implication of involving multiple decision-makers early in the decision making process allows synthesis information from more than one decision-maker during the information scarce response phase.

- The trade-off between non-commensurable objectives provides decision-makers with ample alternatives and combinations from which to choose when deciding on the available quantity of emergency relief goods as well as the number and location of the TLHs.
- The methodology developed herein can provide disaster managers with an effective means to ascertain the location sequencing of TLHs under impreciseness in values of parameters which is often the case in real life response operations. Time-varying location sequencing allows the humanitarian relief chain network to be responsive to the changes in the factors pertinent to increasing the efficiency and effectiveness of humanitarian operations.
- When the resources for establishment of TLHs are limited and their effective utilization is vital which is often the case in the immediate aftermath of the disaster (eg: after April 2015 Nepal earthquake) particularly in developing countries where the investment on disaster preparedness is minimal, determining the order of establishment of TLHs especially useful of the decision-makers who have to make myriad of decisions with limited information and time.
- The evaluation of TLH location alternatives based on the qualitative attributes allows for ensuring operational sustainability of the established hubs. Based on the performance of TLH over the selected attributes, insightful suggestions can be made to strengthen the performance over the weaker attributes.
- Although, all the numerical illustrations have been performed with earthquake case, the models and methodologies developed within the scope of this dissertation have broader applicability in real life disaster cases. Especially, the methodology developed in Chapter 4 is applicable to moving disaster like floods where time-varying nature of TLHs are key to the effectiveness of humanitarian operation.

6.5 Recommendation for future establishment of TLHs

In response to Nepal earthquake 2015 nine storage hubs were made available in different parts of the country. Specific spatial location of the hubs can be observed in Figure 1.1. Table

6.1 shows the name/location of the hubs, date of identification, number of organizations using it, volume of relief stored in each hubs.

Table 6.1: Details of storage hubs during Nepal earthquake 2015

S.N.	Location of storage hubs	Date of identification	Number of organizations	Volume of relief (m^3)
1	Kathamndu	Pre-established	86	16,110
2	Gorkha (Deurali)	2015 May 1	47	6,278
3	Sindhupalchok (Chautara)	2015 May 8	19	3,511
4	Chitwan (Bharatpur)	2015 May 11	5	1,492
5	Kavrepalanchok (Dhulikhel)	2015 May 12	15	4175
6	Dhading (Dhading Besi)	NA	12	955
7	(Nuwakot) Bidur	NA	10	1,700
8	Rasuwa (Dhunche)	NA	4	183
9	Dolakha (Charikot)	NA	8	1,904

Recommendations made for future establishment of TLHs are in reference comparison with the actual logistics strategy adopted during Nepal earthquake 2015. Concisely translating the findings of this study to practical world and policy implications for future establishment of TLHs, the following points were found important to consider:

1. Response to Nepal earthquake 2015, saw establishment of transit hubs in Kavrepalanchok and Chitwan as the first response strategy which later acted as supply sources to regional storage hubs in Gorkha, Shindhupalchok, Dhanding, Nuwakot, Rasuwa, and Dolakha. In the ideal situation, these hubs should have been established as a part of preparedness phase. Doing this could have saved both time, effort, and money.

   Therefore, in the context of disaster response operation, special attention needs to be paid to strengthen disaster preparedness. This can translate to substantial reduction in transportation cost and improvement in overall relief delivery. Disaster preparedness can be strengthened by establishing warehousing facilities for storage of emergency relief, identifying reliable supply sources and open spaces etc.
2. The response to Nepal earthquake 2015 can be summarized (Table 6.2) as establishing storage hubs in major crisis hit districts except for hubs in Kathmandu, Kavrepalanchok,

and Chitawan. This may severely hinder effectiveness of the overall response operation. Therefore, future establishment decision-making should aim at avoiding ad hoc decision-making and adopt a systematic approach.

Table 6.2: Summary of the TLH selection

Candidate TLHs			Major crisis hit districts	Nepal earthquake	Model results		
Chapter 3	**Chapter 5**	**Chapter 4**			**Chapter 3**	**Chapter 5**	**Chapter 4**
Dhading	Dhading	Dhading	**Dhading**	Dhading			Dhading
Dolakha	Dolakha	Dolakha	**Dolakha**	Dolakha		Dolakha	Dolakha
Gorkha	Gorkha	Gorkha	**Gorkha**	Gorkha	Gorkha	Gorkha	Gorkha
Kathmandu	Kathmandu	Kathmandu		Kathmandu (Pre-existing)	Kathmandu	Kathmandu	Kathmandu
Kavrepalanchok	Kavrepalanchok	Kavrepalanchok		Kavrepalanchok (Transit hub)	Kavrepalanchok		Kavrepalanchok
Makwanpur	Makwanpur	Makwanpur			Makwanpur	Makwanpur	Makwanpur
Nuwakot	Nuwakot	Nuwakot	**Nuwakot**	Nuwakot	Nuwakot		Nuwakot
Okhaldhunga	Okhaldhunga	Okhaldhunga				Okhaldhunga	Okhaldhunga
Ramechhap	Ramechhap	Ramechhap	**Ramechhap**		Ramechhap		Ramechhap
Sindhuli	Sindhuli	Sindhuli			Sindhuli		Sindhuli
Sindhupalchok	Sindhupalchok	Sindhupalchok	**Sindhupalchok**	Sindhupalchok	Sindhupalchok	Sindhupalchok	Sindhupalchok
		Rasuwa	**Rasuwa**	Rasuwa			
				Chitawan (Transit hub)			

3. The significance of objective selection for distribution network design was demonstrated by the varying numbers and corresponding spatial locations of TLHs with the varying types of objectives (Table 6.2). Therefore, it is desirable to determine mutually acceptable objective/s in the preparedness phase. The choice of objectives may vary conditional to the nature of disaster and type of decision-making entities involved.
4. One of the main shortcoming faced in the operation of storage hubs during Nepal earthquake is the problem of ownership of the established hubs. Organizations were only found to be interested in using the storage hubs but not taking the responsibility of ensuring its operation. The interview with the decision-makers clearly illustrate difference in their decision-opinions. Therefore, future establishment decisions should focus on incorporating multiple decision-makers in location decision-making.
5. Future establishment of TLHs should focus on determining appropriate order of establishment. Nepal earthquake faced challenges with actual operation of established hub due to lack of sufficient and relevant equipment and handling capacities like forklifts. Although, detailed information on how long did it take for the problem to be solved, it determining the order of establishment of TLJs becomes instrumental in the successful operation of those established.

6. Establishment of TLHs needs be addressed in holistic view including quantitative and qualitative criteria incorporating multiple actors to ensure effective utilization and sustainable operation of TLHs. Depending on the scale of disasters, response operations are often beyond the capability of single entity. Moreover, response operations in developing countries frequently face epistemic uncertainty. Incorporation of multiple actors can lead to possible reduction in accuracy, information asymmetry with enhanced cooperation.

6.6 Scope of future work

The scope of the future work is geared towards addressing the limitation encountered in the conduct of this study. Though the concept, methodological development, and findings of this dissertation contribute to the body of the literature, based on the insights gained in the course of the study, the following specific topics lend themselves to future research.

Operational horizon: The length of disaster response operation plays an important role in determining the operational horizon of TLHs. However, determining the exact duration is a cumbersome task which depends on factors like economic status of the country/region, level of development, severity of disaster etc. Future research could focus on determining the exact length of operational horizon. This may enable efficient and effective utilization of mobile storage units in case of multiple disaster cases.

Importance of decision-makers: Real life decision-making involves active participation of more than one decision-makers. These decision-makers may have varying degree of importance based on their hierarchy and/or knowledge. Developing a method to determine the relative importance of decision-makers and incorporating it into the model is thus a possible extension.

Confidence level: As the complexity of the response operation is growing, determining the desired confidence level to ensure optimum service is of great value. Future researchers could examine in greater detail the nature of the confidence level used in chapter four and possible method to elicit its value.

Level of uncertainty: The level of uncertainty in the parameter values in our current study (chapter four) is represented by the spread of the symmetric triangular fuzzy number which has been assumed to be 15 percent. However, it is quite challenging to determine its precise value and its nature (time-varying or not). A coordinated approach with constant participation of decision-maker could be a possible avenue to further research on this topic.

Accounting for uncertainty: There is an extant of literature in humanitarian logistics using stochastic or robust approach to model uncertainty. However, the nature of uncertainty prevalent in post-disaster stage is often ignored. Through this study an attempt has been made to account for uncertainty arising due to impreciseness using possibility distribution. Future research could explore this avenue by developing/employing other approaches to account for this type of uncertainty.

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APPENDIX

APPENDIX A

Transportation cost from supply points to candidate TLHs per km per vehicle (in USD)

Supply points	Candidate TLHs	T1	T2	T3	T4	T5	T6	T7
TIA	DHA	0.167	0.167	0.155	0.149	0.143	0.143	0.143
	DOL	0.267	0.267	0.248	0.238	0.228	0.228	0.228
	GOR	0.290	0.290	0.269	0.259	0.249	0.249	0.249
	KTM	0.010	0.010	0.009	0.009	0.008	0.008	0.008
	KAV	0.051	0.051	0.047	0.046	0.044	0.044	0.044
	MAK	0.014	0.014	0.013	0.012	0.012	0.012	0.012
	NUW	0.163	0.163	0.151	0.145	0.139	0.139	0.139
	OKH	0.155	0.155	0.144	0.138	0.133	0.133	0.133
	RAM	0.414	0.414	0.384	0.369	0.354	0.354	0.354
	RAS	0.243	0.243	0.226	0.217	0.209	0.209	0.209
	SIN	0.257	0.257	0.238	0.229	0.220	0.220	0.220
	SIND	0.290	0.290	0.269	0.259	0.249	0.249	0.249
KAKAD	DHA	1.070	1.070	0.994	0.956	0.917	0.917	0.917
	DOL	0.831	0.831	0.772	0.742	0.712	0.712	0.712
	GOR	1.172	1.172	1.088	1.047	1.005	1.005	1.005
	KTM	0.937	0.937	0.870	0.837	0.803	0.803	0.803
	KAV	0.837	0.837	0.777	0.747	0.717	0.717	0.717
	MAK	0.933	0.933	0.866	0.833	0.800	0.800	0.800
	NUW	0.782	0.782	0.726	0.698	0.670	0.670	0.670
	OKH	1.058	1.058	0.983	0.945	0.907	0.907	0.907
	RAM	0.661	0.661	0.613	0.590	0.566	0.566	0.566
	RAS	1.154	1.154	1.071	1.030	0.989	0.989	0.989
	SIN	0.717	0.717	0.666	0.641	0.615	0.615	0.615
	SIND	0.600	0.600	0.557	0.536	0.514	0.514	0.514
BIRAT	DHA	0.925	0.925	0.859	0.826	0.793	0.793	0.793
	DOL	0.684	0.684	0.635	0.611	0.586	0.586	0.586
	GOR	1.027	1.027	0.954	0.917	0.880	0.880	0.880
	KTM	0.792	0.792	0.735	0.707	0.679	0.679	0.679
	KAV	0.692	0.692	0.642	0.618	0.593	0.593	0.593
	MAK	0.745	0.745	0.692	0.665	0.638	0.638	0.638
	NUW	0.635	0.635	0.590	0.567	0.544	0.544	0.544
	OKH	0.913	0.913	0.848	0.816	0.783	0.783	0.783
	RAM	0.514	0.514	0.477	0.459	0.440	0.440	0.440
	RAS	0.990	0.990	0.919	0.884	0.849	0.849	0.849
	SIN	0.570	0.570	0.530	0.509	0.489	0.489	0.489
	SIND;	0.453	0.453	0.420	0.404	0.388	0.388	0.388

BHAIRA	DHA	0.545	0.545	0.506	0.487	0.467	0.467	0.467
	DOL	0.937	0.937	0.870	0.837	0.803	0.803	0.803
	GOR	0.368	0.368	0.342	0.329	0.316	0.316	0.316
	KTM	0.541	0.541	0.502	0.483	0.464	0.464	0.464
	KAV	0.582	0.582	0.541	0.520	0.499	0.499	0.499
	MAK	0.531	0.531	0.493	0.474	0.455	0.455	0.455
	NUW	0.384	0.384	0.357	0.343	0.329	0.329	0.329
	OKH	0.610	0.610	0.566	0.544	0.522	0.522	0.522
	RAM	0.939	0.939	0.872	0.838	0.805	0.805	0.805
	RAS	0.592	0.592	0.550	0.529	0.508	0.508	0.508
	SIN	0.825	0.825	0.766	0.737	0.707	0.707	0.707
	SIND	0.708	0.708	0.657	0.632	0.606	0.606	0.606
TATOPANI	DHA	0.380	0.380	0.353	0.340	0.326	0.326	0.326
	DOL	0.192	0.192	0.178	0.172	0.165	0.165	0.165
	GOR	0.504	0.504	0.468	0.450	0.432	0.432	0.432
	KTM	0.227	0.227	0.211	0.203	0.195	0.195	0.195
	KAV	0.169	0.169	0.157	0.151	0.144	0.144	0.144
	MAK	0.221	0.221	0.206	0.198	0.190	0.190	0.190
	NUW	0.372	0.372	0.346	0.333	0.319	0.319	0.319
	OKH	0.367	0.367	0.340	0.327	0.314	0.314	0.314
	RAM	0.504	0.504	0.468	0.450	0.432	0.432	0.432
	RAS	0.457	0.457	0.425	0.408	0.392	0.392	0.392
	SIN	0.347	0.347	0.322	0.310	0.297	0.297	0.297
	SIND	0.380	0.380	0.353	0.340	0.326	0.326	0.326
NEPALGUNJ	DHA	0.994	0.994	0.923	0.887	0.852	0.852	0.852
	DOL	1.439	1.439	1.336	1.285	1.233	1.233	1.233
	GOR	0.868	0.868	0.806	0.775	0.744	0.744	0.744
	KTM	1.041	1.041	0.966	0.929	0.892	0.892	0.892
	KAV	1.084	1.084	1.006	0.968	0.929	0.929	0.929
	MAK	1.037	1.037	0.963	0.926	0.889	0.889	0.889
	NUW	0.884	0.884	0.821	0.789	0.758	0.758	0.758
	OKH	0.984	0.984	0.914	0.879	0.843	0.843	0.843
	RAM	1.439	1.439	1.336	1.285	1.233	1.233	1.233
	RAS	1.049	1.049	0.974	0.937	0.899	0.899	0.899
	SIN	1.325	1.325	1.230	1.183	1.136	1.136	1.136
	SIND	1.207	1.207	1.121	1.078	1.035	1.035	1.035
INARWA	DHA	0.447	0.447	0.415	0.399	0.383	0.383	0.383
	DOL	0.557	0.557	0.517	0.497	0.477	0.477	0.477
	GOR	0.398	0.398	0.369	0.355	0.341	0.341	0.341
	KTM	0.537	0.537	0.499	0.480	0.460	0.460	0.460
	KAV	0.557	0.557	0.517	0.497	0.477	0.477	0.477

	MAK	0.531	0.531	0.493	0.474	0.455	0.455	0.455
	NUW	0.116	0.116	0.107	0.103	0.099	0.099	0.099
	OKH	0.496	0.496	0.460	0.443	0.425	0.425	0.425
	RAM	0.680	0.680	0.632	0.607	0.583	0.583	0.583
	RAS	0.939	0.939	0.872	0.839	0.805	0.805	0.805
	SIN	0.443	0.443	0.411	0.396	0.380	0.380	0.380
	SIND	0.333	0.333	0.309	0.298	0.286	0.286	0.286

APPENDIX B

Transportation cost from TLHs to PODs per km per vehicle (in USD)

Candidate TLHs	PODs	T1	T2	T3	T4	T5	T6	T7
		1.4*G(T1)	1.4*C(T1)	1.3*C(T1)	1.2*C(T1)	1.2*C(T1)	1.2*C(T1)	1.2*C(T1)
DHA	BKT	1.386	1.305	1.468	1.223	1.223	1.223	1.223
	DHA	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	DOL	3.083	2.902	3.265	2.721	2.721	2.721	2.721
	GOR	1.273	1.198	1.348	1.123	1.123	1.123	1.123
	KTM	1.160	1.092	1.228	1.023	1.023	1.023	1.023
	KAV	1.669	1.571	1.767	1.473	1.473	1.473	1.473
	LTP	1.245	1.171	1.318	1.098	1.098	1.098	1.098
	MAK	2.263	2.130	2.396	1.997	1.997	1.997	1.997
	NUW	0.877	0.825	0.929	0.774	0.774	0.774	0.774
	OKH	6.308	5.937	6.679	5.566	5.566	5.566	5.566
	RAM	4.088	3.847	4.328	3.607	3.607	3.607	3.607
	RAS	1.559	1.468	1.651	1.376	1.376	1.376	1.376
	SIN	4.597	4.326	4.867	4.056	4.056	4.056	4.056
	SIND	2.404	2.263	2.546	2.122	2.122	2.122	2.122
DOL	BKT	1.697	1.597	1.797	1.498	1.498	1.498	1.498
	DHA	3.083	2.902	3.265	2.721	2.721	2.721	2.721
	DOL	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	GOR	5.276	4.965	5.586	4.655	4.655	4.655	4.655
	KTM	1.924	1.810	2.037	1.697	1.697	1.697	1.697
	KAV	1.414	1.331	1.498	1.248	1.248	1.248	1.248
	LTP	1.839	1.731	1.947	1.622	1.622	1.622	1.622
	MAK	2.999	2.822	3.175	2.646	2.646	2.646	2.646
	NUW	2.857	2.689	3.025	2.521	2.521	2.521	2.521
	OKH	7.058	6.643	7.473	6.228	6.228	6.228	6.228
	RAM	1.004	0.945	1.063	0.886	0.886	0.886	0.886
	RAS	3.542	3.333	3.750	3.125	3.125	3.125	3.125
	SIN	5.346	5.032	5.661	4.717	4.717	4.717	4.717
	SIND	1.386	1.305	1.468	1.223	1.223	1.223	1.223
GOR	BKT	2.164	2.037	2.291	1.909	1.909	1.909	1.909
	DHA	1.273	1.198	1.348	1.123	1.123	1.123	1.123
	DOL	5.276	4.965	5.586	4.655	4.655	4.655	4.655
	GOR	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	KTM	1.938	1.824	2.052	1.710	1.710	1.710	1.710
	KAV	2.447	2.303	2.591	2.159	2.159	2.159	2.159
	LTP	2.023	1.904	2.142	1.785	1.785	1.785	1.785
	MAK	2.037	1.917	2.157	1.797	1.797	1.797	1.797
	NUW	1.655	1.558	1.752	1.460	1.460	1.460	1.460
	OKH	6.096	5.737	6.455	5.379	5.379	5.379	5.379
	RAM	4.866	4.579	5.152	4.293	4.293	4.293	4.293
	RAS	2.342	2.204	2.479	2.066	2.066	2.066	2.066

	SIN	4.385	4.127	4.643	3.869	3.869	3.869	3.869
	SIND	3.182	2.995	3.370	2.808	2.808	2.808	2.808
KTM	BKT	0.226	0.213	0.240	0.200	0.200	0.200	0.200
	DHA	1.160	1.092	1.228	1.023	1.023	1.023	1.023
	DOL	1.924	1.810	2.037	1.697	1.697	1.697	1.697
	GOR	1.938	1.824	2.052	1.710	1.710	1.710	1.710
	KTM	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	KAV	0.509	0.479	0.539	0.449	0.449	0.449	0.449
	LTP	0.099	0.093	0.105	0.087	0.087	0.087	0.087
	MAK	1.103	1.038	1.168	0.973	0.973	0.973	0.973
	NUW	0.962	0.905	1.018	0.849	0.849	0.849	0.849
	OKH	5.177	4.872	5.481	4.568	4.568	4.568	4.568
	RAM	2.928	2.756	3.100	2.583	2.583	2.583	2.583
	RAS	1.756	1.653	1.859	1.549	1.549	1.549	1.549
	SIN	3.479	3.275	3.684	3.070	3.070	3.070	3.070
	SIND	1.245	1.171	1.318	1.098	1.098	1.098	1.098
KAV	BKT	0.283	0.266	0.300	0.250	0.250	0.250	0.250
	DHA	1.669	1.571	1.767	1.473	1.473	1.473	1.473
	DOL	1.414	1.331	1.498	1.248	1.248	1.248	1.248
	GOR	2.447	2.303	2.591	2.159	2.159	2.159	2.159
	KTM	0.509	0.479	0.539	0.449	0.449	0.449	0.449
	KAV	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	LTP	0.424	0.399	0.449	0.374	0.374	0.374	0.374
	MAK	1.584	1.491	1.677	1.398	1.398	1.398	1.398
	NUW	1.443	1.358	1.528	1.273	1.273	1.273	1.273
	OKH	5.643	5.311	5.975	4.980	4.980	4.980	4.980
	RAM	2.419	2.276	2.561	2.134	2.134	2.134	2.134
	RAS	2.129	2.004	2.254	1.879	1.879	1.879	1.879
	SIN	3.932	3.701	4.163	3.469	3.469	3.469	3.469
	SIND	0.735	0.692	0.779	0.649	0.649	0.649	0.649
MAK	BKT	1.301	1.225	1.378	1.148	1.148	1.148	1.148
	DHA	2.263	2.130	2.396	1.997	1.997	1.997	1.997
	DOL	2.999	2.822	3.175	2.646	2.646	2.646	2.646
	GOR	2.037	1.917	2.157	1.797	1.797	1.797	1.797
	KTM	1.103	1.038	1.168	0.973	0.973	0.973	0.973
	KAV	1.584	1.491	1.677	1.398	1.398	1.398	1.398
	LTP	1.160	1.092	1.228	1.023	1.023	1.023	1.023
	MAK	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	NUW	2.065	1.944	2.186	1.822	1.822	1.822	1.822
	OKH	4.059	3.821	4.298	3.582	3.582	3.582	3.582
	RAM	4.003	3.767	4.238	3.532	3.532	3.532	3.532
	RAS	2.741	2.580	2.902	2.418	2.418	2.418	2.418
	SIN	2.348	2.210	2.486	2.072	2.072	2.072	2.072
	SIND	2.320	2.183	2.456	2.047	2.047	2.047	2.047
NUW	BKT	1.160	1.092	1.228	1.023	1.023	1.023	1.023

	DHA	0.877	0.825	0.929	0.774	0.774	0.774	0.774
	DOL	2.857	2.689	3.025	2.521	2.521	2.521	2.521
	GOR	1.655	1.558	1.752	1.460	1.460	1.460	1.460
	KTM	0.962	0.905	1.018	0.849	0.849	0.849	0.849
	KAV	1.443	1.358	1.528	1.273	1.273	1.273	1.273
	LTP	1.047	0.985	1.108	0.924	0.924	0.924	0.924
	MAK	2.065	1.944	2.186	1.822	1.822	1.822	1.822
	NUW	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	OKH	6.110	5.751	6.470	5.391	5.391	5.391	5.391
	RAM	3.861	3.634	4.088	3.407	3.407	3.407	3.407
	RAS	0.683	0.642	0.723	0.602	0.602	0.602	0.602
	SIN	4.413	4.153	4.673	3.894	3.894	3.894	3.894
	SIND	2.178	2.050	2.306	1.922	1.922	1.922	1.922
OKH	BKT	5.361	5.045	5.676	4.730	4.730	4.730	4.730
	DHA	6.308	5.937	6.679	5.566	5.566	5.566	5.566
	DOL	7.058	6.643	7.473	6.228	6.228	6.228	6.228
	GOR	6.096	5.737	6.455	5.379	5.379	5.379	5.379
	KTM	5.177	4.872	5.481	4.568	4.568	4.568	4.568
	KAV	5.643	5.311	5.975	4.980	4.980	4.980	4.980
	LTP	5.219	4.912	5.526	4.605	4.605	4.605	4.605
	MAK	4.059	3.821	4.298	3.582	3.582	3.582	3.582
	NUW	6.110	5.751	6.470	5.391	5.391	5.391	5.391
	OKH	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	RAM	8.062	7.588	8.536	7.114	7.114	7.114	7.114
	RAS	6.797	6.397	7.197	5.997	5.997	5.997	5.997
	SIN	2.758	2.596	2.920	2.434	2.434	2.434	2.434
	SIND	6.379	6.004	6.754	5.628	5.628	5.628	5.628
RAM	BKT	2.702	2.543	2.860	2.384	2.384	2.384	2.384
	DHA	4.088	3.847	4.328	3.607	3.607	3.607	3.607
	DOL	1.004	0.945	1.063	0.886	0.886	0.886	0.886
	GOR	4.866	4.579	5.152	4.293	4.293	4.293	4.293
	KTM	2.928	2.756	3.100	2.583	2.583	2.583	2.583
	KAV	2.419	2.276	2.561	2.134	2.134	2.134	2.134
	LTP	2.843	2.676	3.010	2.508	2.508	2.508	2.508
	MAK	4.003	3.767	4.238	3.532	3.532	3.532	3.532
	NUW	3.861	3.634	4.088	3.407	3.407	3.407	3.407
	OKH	8.062	7.588	8.536	7.114	7.114	7.114	7.114
	RAM	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	RAS	4.549	4.281	4.816	4.014	4.014	4.014	4.014
	SIN	6.351	5.977	6.724	5.604	5.604	5.604	5.604
	SIND	2.390	2.250	2.531	2.109	2.109	2.109	2.109
RAS	BKT	1.843	1.734	1.951	1.626	1.626	1.626	1.626
	DHA	1.559	1.468	1.651	1.376	1.376	1.376	1.376
	DOL	3.542	3.333	3.750	3.125	3.125	3.125	3.125
	GOR	2.342	2.204	2.479	2.066	2.066	2.066	2.066

	KTM	1.756	1.653	1.859	1.549	1.549	1.549	1.549
	KAV	2.129	2.004	2.254	1.879	1.879	1.879	1.879
	LTP	1.732	1.630	1.834	1.528	1.528	1.528	1.528
	MAK	2.741	2.580	2.902	2.418	2.418	2.418	2.418
	NUW	0.683	0.642	0.723	0.602	0.602	0.602	0.602
	OKH	6.797	6.397	7.197	5.997	5.997	5.997	5.997
	RAM	4.549	4.281	4.816	4.014	4.014	4.014	4.014
	RAS	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SIN	5.089	4.789	5.388	4.490	4.490	4.490	4.490
	SIND	2.865	2.696	3.033	2.528	2.528	2.528	2.528
SIN	BKT	3.649	3.434	3.864	3.220	3.220	3.220	3.220
	DHA	4.597	4.326	4.867	4.056	4.056	4.056	4.056
	DOL	5.346	5.032	5.661	4.717	4.717	4.717	4.717
	GOR	4.385	4.127	4.643	3.869	3.869	3.869	3.869
	KTM	3.479	3.275	3.684	3.070	3.070	3.070	3.070
	KAV	3.932	3.701	4.163	3.469	3.469	3.469	3.469
	LTP	3.508	3.301	3.714	3.095	3.095	3.095	3.095
	MAK	2.348	2.210	2.486	2.072	2.072	2.072	2.072
	NUW	4.413	4.153	4.673	3.894	3.894	3.894	3.894
	OKH	2.758	2.596	2.920	2.434	2.434	2.434	2.434
	RAM	6.351	5.977	6.724	5.604	5.604	5.604	5.604
	RAS	5.089	4.789	5.388	4.490	4.490	4.490	4.490
	SIN	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	SIND	4.668	4.393	4.942	4.118	4.118	4.118	4.118
SIND	BKT	1.018	0.958	1.078	0.899	0.899	0.899	0.899
	DHA	2.404	2.263	2.546	2.122	2.122	2.122	2.122
	DOL	1.386	1.305	1.468	1.223	1.223	1.223	1.223
	GOR	3.182	2.995	3.370	2.808	2.808	2.808	2.808
	KTM	1.245	1.171	1.318	1.098	1.098	1.098	1.098
	KAV	0.735	0.692	0.779	0.649	0.649	0.649	0.649
	LTP	1.160	1.092	1.228	1.023	1.023	1.023	1.023
	MAK	2.320	2.183	2.456	2.047	2.047	2.047	2.047
	NUW	2.178	2.050	2.306	1.922	1.922	1.922	1.922
	OKH	6.379	6.004	6.754	5.628	5.628	5.628	5.628
	RAM	2.390	2.250	2.531	2.109	2.109	2.109	2.109
	RAS	2.865	2.696	3.033	2.528	2.528	2.528	2.528
	SIN	4.668	4.393	4.942	4.118	4.118	4.118	4.118
	SIND	0.000	0.000	0.000	0.000	0.000	0.000	0.000

APPENDIX C

Distance from supply point to candidate temporary depots (in kilometers)

S.N.	Supply Points	Candidate temporary logistics hubs											
		Dhading	Dolakha	Gorkha	Kathmandu	Kavrepalanchok	Makwanpur	Nuwakot	Okhaldhunga	Ramechhap	Rasuwa	Sindhuli	Sindhupalchok
		DHA	DOL	GOR	KTM	KAV	MAK	NUW	OKH	RAM	RAS	SIN	SIND
1	TIA	85	136	148	5	26	83	79	211	131	124.15	148	83
2	Kakadbhitta, Jhapa	546	424	598	478	427	399	540	337	366	588.71	306	467
3	Biratnagar, Morang	472	349	524	404	353	324	466	262	291	505.16	231	393
4	Bhairahawa, Kapilbastu	278	478	188	276	297	196	311	479	421	302.09	361	354
5	Tatopani, sindhupalchok	194	98	257	116	86	190	187	257	177	233.37	194	83
6	Nepalgunj, Banke	507	734	443	531	553	451	502	734	676	535.33	616	609
7	Inarwa, Parsa	228	284	203	274	284	59	253	347	226	479.31	170	326

APPENDIX D

Distance from candidate temporary depots to point of distribution (in kilometers)

S.N.	Candidate temporary logistics hubs	Point of distribution													
		Bhaktapur	Dhading	Dolakha	Gorkha	Kathmandu	Kavrepalanc	Lalitpur	Makwanpur	Nuwakot	Okhaldhu	Ramechha	Rasuwa	Sindhuli	Sindhupalchok
1	Dhading	98	0	218	90	82	118	88	160	62	446	289	110.24	325	170
2	Dolakha	120	218	0	373	136	100	130	212	202	499	71	250.4	378	98
3	Gorkha	153	90	373	0	137	173	143	144	117	431	344	165.56	310	225
4	Kathmandu	16	82	136	137	0	36	7	78	68	366	207	124.15	246	88
5	Kavrepalanchok	20	118	100	173	36	0	30	112	102	399	171	150.54	278	52
6	Makwanpur	92	160	212	144	78	112	82	0	146	287	283	193.78	166	164
7	Nuwakot	82	62	202	117	68	102	74	146	0	432	273	48.26	312	154
8	Okhaldhunga	379	446	499	431	366	399	369	287	432	0	570	480.56	195	451
9	Ramechhap	191	289	71	344	207	171	201	283	273	570	0	321.6	449	169
10	Rasuwa	130.27	110.24	250.4	165.56	124.15	150.54	122.47	193.78	48.26	480.56	321.6	0	359.77	202.55
11	Sindhuli	258	325	378	310	246	278	248	166	312	195	449	359.77	0	330
12	Sindhupalchok	72	170	98	225	88	52	82	164	154	451	169	202.55	330	0

APPENDIX D

Coverage of PODs by TLHs

TLHs	PODs	Distance	T1	T2	T3	T4	T5	T6	T7
			100KM		150KM		175KM		200KM
DHA	Bhaktapur	98	1	1	1	1	1	1	1
	Dhading	0	1	1	1	1	1	1	1
	Dolakha	218	0	0	0	0	0	0	0
	Gorkha	90	1	1	1	1	1	1	1
	Kathmandu	82	1	1	1	1	1	1	1
	Kavrepalanchok	118	0	0	1	1	1	1	1
	Lalitpur	88	1	1	1	1	1	1	1
	Makwanpur	160	0	0	0	0	1	1	1
	Nuwakot	62	1	1	1	1	1	1	1
	Okhaldhunga	446	0	0	0	0	0	0	0
	Ramechhap	289	0	0	0	0	0	0	0
	Rasuwa	110.24	0	0	1	1	1	1	1
	Sindhuli	325	0	0	0	0	0	0	0
	Sindhupalchok	170	0	0	0	0	1	1	1
DOL	Bhaktapur	120	0	0	1	1	1	1	1
	Dhading	218	0	0	0	0	0	0	0
	Dolakha	0	1	1	1	1	1	1	1
	Gorkha	373	0	0	0	0	0	0	0
	Kathmandu	136	0	0	1	1	1	1	1
	Kavrepalanchok	100	1	1	1	1	1	1	1
	Lalitpur	130	0	0	1	1	1	1	1
	Makwanpur	212	0	0	0	0	0	0	0
	Nuwakot	202	0	0	0	0	0	0	0
	Okhaldhunga	499	0	0	0	0	0	0	0
	Ramechhap	71	1	1	1	1	1	1	1
	Rasuwa	250.4	0	0	0	0	0	0	0
	Sindhuli	378	0	0	0	0	0	0	0
	Sindhupalchok	98	1	1	1	1	1	1	1
GOR	Bhaktapur	153	0	0	0	0	1	1	1
	Dhading	90	1	1	1	1	1	1	1
	Dolakha	373	0	0	0	0	0	0	0
	Gorkha	0	1	1	1	1	1	1	1
	Kathmandu	137	0	0	1	1	1	1	1
	Kavrepalanchok	173	0	0	0	0	1	1	1
	Lalitpur	143	0	0	1	1	1	1	1
	Makwanpur	144	0	0	1	1	1	1	1
	Nuwakot	117	0	0	1	1	1	1	1
	Okhaldhunga	431	0	0	0	0	0	0	0
	Ramechhap	344	0	0	0	0	0	0	0

	Rasuwa	165.56	0	0	0	0	1	1	1
	Sindhuli	310	0	0	0	0	0	0	0
	Sindhupalchok	225	0	0	0	0	0	0	0
KTM	Bhaktapur	16	1	1	1	1	1	1	1
	Dhading	82	1	1	1	1	1	1	1
	Dolakha	136	0	0	1	1	1	1	1
	Gorkha	137	0	0	1	1	1	1	1
	Kathmandu	0	1	1	1	1	1	1	1
	Kavrepalanchok	36	1	1	1	1	1	1	1
	Lalitpur	7	1	1	1	1	1	1	1
	Makwanpur	78	1	1	1	1	1	1	1
	Nuwakot	68	1	1	1	1	1	1	1
	Okhaldhunga	366	0	0	0	0	0	0	0
	Ramechhap	207	0	0	0	0	0	0	0
	Rasuwa	124.15	0	0	1	1	1	1	1
	Sindhuli	246	0	0	0	0	0	0	0
	Sindhupalchok	88	1	1	1	1	1	1	1
KAV	Bhaktapur	20	1	1	1	1	1	1	1
	Dhading	118	0	0	1	1	1	1	1
	Dolakha	100	1	1	1	1	1	1	1
	Gorkha	173	0	0	0	0	1	1	1
	Kathmandu	36	1	1	1	1	1	1	1
	Kavrepalanchok	0	1	1	1	1	1	1	1
	Lalitpur	30	1	1	1	1	1	1	1
	Makwanpur	112	0	0	1	1	1	1	1
	Nuwakot	102	0	0	1	1	1	1	1
	Okhaldhunga	399	0	0	0	0	0	0	0
	Ramechhap	171	0	0	0	0	1	1	1
	Rasuwa	150.54	0	0	0	0	1	1	1
	Sindhuli	278	0	0	0	0	0	0	0
	Sindhupalchok	52	1	1	1	1	1	1	1
MAK	Bhaktapur	92	1	1	1	1	1	1	1
	Dhading	160	0	0	0	0	1	1	1
	Dolakha	212	0	0	0	0	0	0	0
	Gorkha	144	0	0	1	1	1	1	1
	Kathmandu	78	1	1	1	1	1	1	1
	Kavrepalanchok	112	0	0	1	1	1	1	1
	Lalitpur	82	1	1	1	1	1	1	1
	Makwanpur	0	1	1	1	1	1	1	1
	Nuwakot	146	0	0	1	1	1	1	1
	Okhaldhunga	287	0	0	0	0	0	0	0
	Ramechhap	283	0	0	0	0	0	0	0
	Rasuwa	193.78	0	0	0	0	0	0	1
	Sindhuli	166	0	0	0	0	1	1	1
	Sindhupalchok	164	0	0	0	0	1	1	1

NUW	Bhaktapur	82	1	1	1	1	1	1	1
	Dhading	62	1	1	1	1	1	1	1
	Dolakha	202	0	0	0	0	0	0	0
	Gorkha	117	0	0	1	1	1	1	1
	Kathmandu	68	1	1	1	1	1	1	1
	Kavrepalanchok	102	0	0	1	1	1	1	1
	Lalitpur	74	1	1	1	1	1	1	1
	Makwanpur	146	0	0	1	1	1	1	1
	Nuwakot	0	1	1	1	1	1	1	1
	Okhaldhunga	432	0	0	0	0	0	0	0
	Ramechhap	273	0	0	0	0	0	0	0
	Rasuwa	48.26	1	1	1	1	1	1	1
	Sindhuli	312	0	0	0	0	0	0	0
	Sindhupalchok	154	0	0	0	0	1	1	1
OKH	Bhaktapur	379	0	0	0	0	0	0	0
	Dhading	446	0	0	0	0	0	0	0
	Dolakha	499	0	0	0	0	0	0	0
	Gorkha	431	0	0	0	0	0	0	0
	Kathmandu	366	0	0	0	0	0	0	0
	Kavrepalanchok	399	0	0	0	0	0	0	0
	Lalitpur	369	0	0	0	0	0	0	0
	Makwanpur	287	0	0	0	0	0	0	0
	Nuwakot	432	0	0	0	0	0	0	0
	Okhaldhunga	0	1	1	1	1	1	1	1
	Ramechhap	570	0	0	0	0	0	0	0
	Rasuwa	480.56	0	0	0	0	0	0	0
	Sindhuli	195	0	0	0	0	0	0	1
	Sindhupalchok	451	0	0	0	0	0	0	0
RAM	Bhaktapur	191	0	0	0	0	0	0	1
	Dhading	289	0	0	0	0	0	0	0
	Dolakha	71	1	1	1	1	1	1	1
	Gorkha	344	0	0	0	0	0	0	0
	Kathmandu	207	0	0	0	0	0	0	0
	Kavrepalanchok	171	0	0	0	0	1	1	1
	Lalitpur	201	0	0	0	0	0	0	0
	Makwanpur	283	0	0	0	0	0	0	0
	Nuwakot	273	0	0	0	0	0	0	0
	Okhaldhunga	570	0	0	0	0	0	0	0
	Ramechhap	0	1	1	1	1	1	1	1
	Rasuwa	321.6	0	0	0	0	0	0	0
	Sindhuli	449	0	0	0	0	0	0	0
	Sindhupalchok	169	0	0	0	0	1	1	1
RAS	Bhaktapur	130.27	0	0	1	1	1	1	1
	Dhading	110.24	0	0	1	1	1	1	1
	Dolakha	250.4	0	0	0	0	0	0	0

	Gorkha	165.56	0	0	0	0	1	1	1
	Kathmandu	124.15	0	0	1	1	1	1	1
	Kavrepalanchok	150.54	0	0	0	0	1	1	1
	Lalitpur	122.47	0	0	1	1	1	1	1
	Makwanpur	193.78	0	0	0	0	0	0	1
	Nuwakot	48.26	1	1	1	1	1	1	1
	Okhaldhunga	480.56	0	0	0	0	0	0	0
	Ramechhap	321.6	0	0	0	0	0	0	0
	Rasuwa	0	1	1	1	1	1	1	1
	Sindhuli	359.77	0	0	0	0	0	0	0
	Sindhupalchok	202.55	0	0	0	0	0	0	0
SIN	Bhaktapur	258	0	0	0	0	0	0	0
	Dhading	325	0	0	0	0	0	0	0
	Dolakha	378	0	0	0	0	0	0	0
	Gorkha	310	0	0	0	0	0	0	0
	Kathmandu	246	0	0	0	0	0	0	0
	Kavrepalanchok	278	0	0	0	0	0	0	0
	Lalitpur	248	0	0	0	0	0	0	0
	Makwanpur	166	0	0	0	0	1	1	1
	Nuwakot	312	0	0	0	0	0	0	0
	Okhaldhunga	195	0	0	0	0	0	0	1
	Ramechhap	449	0	0	0	0	0	0	0
	Rasuwa	359.77	0	0	0	0	0	0	0
	Sindhuli	0	1	1	1	1	1	1	1
	Sindhupalchok	330	0	0	0	0	0	0	0
SIND;	Bhaktapur	72	1	1	1	1	1	1	1
	Dhading	170	0	0	0	0	1	1	1
	Dolakha	98	1	1	1	1	1	1	1
	Gorkha	225	0	0	0	0	0	0	0
	Kathmandu	88	1	1	1	1	1	1	1
	Kavrepalanchok	52	1	1	1	1	1	1	1
	Lalitpur	82	1	1	1	1	1	1	1
	Makwanpur	164	0	0	0	0	1	1	1
	Nuwakot	154	0	0	0	0	1	1	1
	Okhaldhunga	451	0	0	0	0	0	0	0
	Ramechhap	169	0	0	0	0	1	1	1
	Rasuwa	202.55	0	0	0	0	0	0	0
	Sindhuli	330	0	0	0	0	0	0	0
	Sindhupalchok	0	1	1	1	1	1	1	1

APPENDIX F

Lingo code for model in Chapter 5

```
!Two objective model, minimizing costs and mzximizing total demand
coverage;
!TIME = T1, T2, T3, T4, T5, T6, T7;

MODEL:

SETS:

      SUPPLY;

      TEMPDEPOT: F;

      DEMANDPT;

      TIME;

      SPXTP(SUPPLY, TIME): SCAP;

      TDXTP(TEMPDEPOT, TIME):TCAP, y;

      DPXTP(DEMANDPT, TIME):  DEM, z, NSUP;

      XLINK( TEMPDEPOT, DEMANDPT, TIME): x;

      ZLINK(TEMPDEPOT, DEMANDPT,TIME):COEFF;

      SPXTDXTP( SUPPLY, TEMPDEPOT, TIME):C1, R;

      TDXDPXTP(TEMPDEPOT, DEMANDPT, TIME):C2, Q;

ENDSETS


DATA:

   SUPPLY = TIA   Kakad Birat Bhaira      Tatopani    Nepalgunj   Inarwa;
! Supply Point capacities;
     SCAP = 900   900   900   900   900   900   900
            950   950   950   950   950   950   950
            1100  1100  1100  1100  1100  1100  1100
            1200  1200  1200  1200  1200  1200  1200
            1100  1100  1100  1100  1100  1100  1100
            1000  1000  1000  1000  1000  1000  1000
            1000  1000  1000  1000  1000  1000  1000;


TEMPDEPOT = DHA   DOL   GOR   KTM   KAV   MAK   NUW   OKH   RAM   RAS   SIN
      SIND; ! The distn centers;
        F = 100   100   100   100   100   100   100   100   100   100   100
      100;


      TCAP =750   750   750   750   750   750   750   750   750   750   750
      750
            810   810   810   810   810   810   810   810   810   810   810
      810
```

```
        840   840   840   840   840   840   840   840   840   840   840
    840
        840   840   840   840   840   840   840   840   840   840   840
    840
        830   830   830   830   830   830   830   830   830   830   830
    830
        820   820   820   820   820   820   820   820   820   820   820
    820
        820   820   820   820   820   820   820   820   820   820   820
    820;


! Shipping costs  from Supply point to Candidate temporary logistic hubs in
each period;
    C1= @OLE('E:\IJDRR_Credibility_2018.04.24.xlsx', '_CC1');

!Listing the name and number of PODs (Demand nodes) which is 13 in our
case;
 DEMANDPT=  BKT   DHA   DOL   GOR   KTM   KAV   LTP   MAK   NUW   OKH   RAM
    RAS   SIN   SIND;

    DEM=  @OLE('E:\IJDRR_Credibility_2018.04.24.xlsx', '_DD');

    COEFF=@OLE('E:\IJDRR_Credibility_2018.04.24.xlsx', '_COEFF1');

     C2=   @OLE('E:\IJDRR_Credibility_2018.04.24.xlsx', '_C22');

!Confidence level;
    a=0.8;

!Spread of Triangular fuzzy number;
    m=0.3;
ENDDATA


!The objective is to calculate maximum coverage attainable over the entire
planning horizon;
[OBJ] MIN = TCT;
    TCT = FXT + SPT + SPD;
    FXT = @SUM(TDXTP(J,P): (F(J)*(1-m+2*m*a)*y(J,P)));
    SPT = @SUM(SPXTDXTP( I,J,P): (C1(I,J,P)*(1-m+2*m*a)*R(I,J,P)));
    SPD = @SUM( TDXDPXTP( J,K,P): (C2(J,K,P)*(1-m+2*m*a)*Q(J,K,P)));


!CONSTRAINTS;
CVR>=10000;
CVR =@SUM(DPXTP(K,P): (DEM(K,P)*(1-m+2*m*a))*z(K,P));
!Coverage constraint;
@FOR(TIME(P):
 @FOR(DEMANDPT(K):
  @SUM(TEMPDEPOT(J):COEFF(J,K,P)*y(J,P))>=z(K,P)
    )
    );

! Supply Constraints at SP I;
 @FOR(TIME(P):
  @FOR(SUPPLY(I):
    @SUM(TEMPDEPOT(J): R(I,J,P)) <= (SCAP(I, P)*(1+m-2*m*a))
    )
    );
```

```
! Aggregate capacities at each TLH J;
@FOR(TIME(P):
 @FOR(TEMPDEPOT(J):
      @SUM(SUPPLY(I): R(I,J,P)) <= (TCAP(J,P)*(1+m-2*m*a)*y(J,P))
      )
      );

@FOR(TIME(P):
 @FOR( TEMPDEPOT(J):
      @SUM(DEMANDPT(K): Q(J,K,P)) <= (TCAP(J,P)*(1+m-2*m*a)*y(J,P))
      )
      );

! TD balance (inbound = outbound)constraints for Commodities at TLH J;
@FOR(TIME(P):
  @FOR(TEMPDEPOT(J):
      @SUM(SUPPLY(I): R(I,J,P)) = @SUM(DEMANDPT(K): Q(J,K,P))
      )
      );

!Demand constraints;
@FOR(TIME(P):
 @FOR(DEMANDPT(K):
      @SUM(TEMPDEPOT(J): Q(J,K,P)) >=(DEM(K,P)*(1-m+2*m*a))
      )
      );

! Ensures POD'S are served by only one TLH in time period P;
@FOR(TIME(P):
 @FOR(DEMANDPT(K):
  @SUM(TEMPDEPOT(J): x(J,K,P))= 1
      )
      );

!Ensure each TLH can deliver to several PODs;
@FOR(TIME(P):
 @FOR(TEMPDEPOT(J):
  @SUM(DEMANDPT(K):X(J,K,P))<=14*y(J,P)
      )
      );

!Ensure demand is allocated to open facilities only;
@FOR(TIME(P):
 @FOR(TEMPDEPOT(J):
  @FOR(DEMANDPT(K):x(J,K,P)<=y(J,P)
      )
      )
      );

@For( TDXTP(J,P):@BIN(y(J,P)));

@For( DPXTP(K,P):@BIN(Z(K,P)));

@FOR( XLINK(J,K,P): @BIN(x(J,K,P)));

@FOR (SPXTDXTP(I,J,P):R(I,J,P) >=0);

@FOR (TDXDPXTP(J,K,P):Q(J,K,P) >=0);

DATA:
@TEXT() = ' ';
```

```
@TEXT() = 'Solution to Uncertainty MOO Problem';
@TEXT() = "Total cost=    ", TOTCOST;

@TEXT() = ' ';
@TEXT() = "OPEN TLH: TLH Opened in Period";
@TEXT() = "TLH Period";
@TEXT() = @WRITEFOR(TDXTP(J,P)|y(J,P)#GT#0:'    ', TEMPDEPOT(J),' ',
TIME(P),'  ',y(J,P),@NEWLINE(1));

@TEXT() = ' ';
@TEXT() = "Shipment: SP to TLH";
@TEXT() = "SP TLH Period";
@TEXT() = @WRITEFOR(SPXTDXTP(I, J, P)|R(I, J, P)#GT#0:'    ',SUPPLY(I),'
', TEMPDEPOT(J),'   ', TIME(P),'   ',R(I, J, P),@NEWLINE(1));

@TEXT() = ' ';
@TEXT() = "Shipment: TLH to DP";
@TEXT() = "TLH DP Period";
@TEXT() = @WRITEFOR(TDXDPXTP(J,K,P)|Q(J,K,P)#GT#0:'    ',TEMPDEPOT(J),'
', DEMANDPT(K),'   ', TIME(P),'   ',Q(J,K,P),@NEWLINE(1));
@TEXT() = ' ';

ENDDATA

END
```