PLANNING AND OPTIMIZATION OF A STOCHASTIC MULTI-PHASE MULTI- CRITERIA MULTI-ECHELON HUMANITARIAN LOGISTICS NETWORK

BY

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Dissertation

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ABSTRACT

Disasters, may that be anthropogenic or natural, cause much havoc to vast area and population. Property and infrastructures get destroyed. People are often in need of urgent relief like dry foods and water to survive. In a country which is in the underdeveloped part of the world, relief and evacuation activities are usually carried out by local government run aid agencies. Most of the time, the local decision makers do the coordination or planning of these humanitarian activities largely based on either past experience or sometimes just pure hunch, which is neither efficient nor economic. Proper planning and coordination in the humanitarian activities in the pre and post disaster planning period can save many human lives and property, while saving money to the local relief agencies as well.

In an agricultural country like Bangladesh, rivers are usually important assets. But in a District like Sylhet, Bangladesh, these rivers can sometimes cause serious problems. During monsoon season, there are often too much rain in neighboring Indian up-steam hilly region, where most of these rivers are originated. This leads to a deluge of water abruptly surging through, mostly Surma and Kushiara rivers, in the down-steam regions of Sylhet district, which inundates the vast surrounding areas close to the riverbanks. Due to heavy river-bed sedimentation, these narrow rivers can't always hold this sudden deluge of water and hence the flash flooding occurs. These floods are called "flash" floods as they stay for a short period of time, but cause large economical damage and human suffering to the surrounding areas. Most of the people living on those affected areas are usually farmers. Heavy inundation causes the crops of those agricultural area to get washed away, on which people of those region mostly subsist on. In such situations, people in that area will starve to death, if the relief agencies don't promptly respond to their needs for relief.

These flash flood problems in that area of Bangladesh is recurrent in nature. So, good working pre and post disaster planning models can really help the local relief agencies to be better prepared for the disaster relief activities, in order to minimize casualties. Keeping that in mind, this research has developed three multi-criteria multi-echelon pre and post disaster planning models, which will help the incumbent agencies with various important pre and post disaster decision making activities.

In our study, the first pre-disaster planning model tends to minimize the travelling distances from the tentative supplier to tentative regional warehouse location sites as well as distances from the warehouses to the affected locations. The model picks maximum allowed number of best suppliers from a pool of suppliers, based on their total performance ratings on several evaluation criteria for multiple relief items, as well as other issues like their location distances and available capacities. The model also picks the optimum locations for setting up the warehouses, along with their expected capacities. Quantity of necessary relief goods that needs to be transported under different scenarios will be also obtained as output from this model, which has later been used to determine the appropriate level of prepositioned inventories that we can hold at the selected distribution center locations in the third post-disaster model, to reduce the load on the logistics system in the post disaster period. Once the warehouses have been set up at the selected locations, they are then ready to be used as permanent storage infrastructures. We have used scenario-based approach here to make sure that the facilities are built in such a way that it can accommodate moderate fluctuations in demand that might happen in near future. The second pre-disaster planning model is a bi-objective model that finds appropriate routes to be used among different relevant network nodes considering both the actual path distance and the route reliability under each partially observed scenario. The third post-disaster model manages the prepositioning of relief goods, the distribution of relief goods and medical supplies, evacuation of people who needs medical attention, ensuring the equity of the service provided at each affected node and optimizes the use of available transportation facilities by minimizing the number of trips required. These three models are designed to be solved sequentially to provide the users all the necessary information to design the desired efficient aid logistics network.

This research has used the recurrent flash flood problem of Sylhet, Bangladesh as the test case to check the effectiveness of the model that intends to assist in the development an effective relief logistics network. Use of this proposed research will mitigate this recurrent problem that is causing misery to a vast population. To solve the developed MILP models, CPLEX version 12.8 has been used, which has utilized a Branch and Cut algorithm to solve the problems. Obtained results has been demonstrated both numerically and graphically in the result and discussion section of this dissertation for the better visual understanding by the decision maker, which can help them to plan an efficient and economic humanitarian logistics network. In summary , the author of this dissertation is hopeful that this research will provide the aid management authorities with necessary decision making models that will help them effectively in disaster mitigation, which will not only reduce human suffering and wastage of relief goods but also will minimize the overall operational cost at the same time.

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Dedicated

To my family

TABLE OF CONTENT

LIST OF FIGURES

LIST OF TABLES

ABBREVIATIONS

Abbreviation	Description/Meaning
S	Supplier location nodes
DC	Distribution Centers (Regional Warehouse Facility)
AA	Affected Areas (Actual Demand Points)
SME	Subject Matter Expert
DM	Decision Makers
MOOP	Multi-Objective Optimization Problem
LP	Linear Programming
MIP	Mixed Integer Programming
MILP	Mixed Integer Linear Programming
OR	Operation Research

Chapter 1

Introduction

Climate change is an undeniable fact that has already affected a large population of the world. It has already caused much irreversible damage and will continue to cause much more in near future. Some of the most devastating consequences of climate change are the occurrence of the barrage of natural disasters of various kinds in the recent years. Natural disasters like floods, earthquakes, cyclones, tornedoes, land slides etc. have become very common occurrences now a days. In most cases, these disasters are very unpredictable in nature. We don't exactly know when and where they might strike or the degree of severity of the strike. This unpredictability makes these natural disasters more dangerous as they usually cause much more havoc when people are unprepared. Developed western countries often have very well-organized disaster response strategies, which usually results in less havoc. But underdeveloped countries are still lagging behind in this area. Very often, disasters strike them in a more or less off-guard, under-prepared state and thus create utmost havoc and devastation. Hence, proper disaster planning and response system development is very crucial for them to minimize the damages caused by these disasters on their already poverty-stricken population.

Besides natural disasters, man-made or anthropogenic disasters, like conflagration or forest fires, viral or bacterial outbreak or epidemics, catastrophic transportation or structural failures, explosion from mining or terrorist activities etc. can also cause much havoc on human life and property. Sometimes they are not any less dangerous than natural disasters, because the unpredictability element is still present here, just like the natural ones. We can neither be hundred percent prepared for all these natural and anthropogenic disasters nor fully prevent them from happening. But what we can do, is to mitigate the catastrophic effects of these disasters by carefully tailoring an effective disaster management system. This dissertation aims to provide necessary efficient decision-making models to aid management authorities in disaster mitigation.

Supply chain management, which is one of the very important areas of OR, has been widely used to serve as an effective tool to design business logistics as well as humanitarian logistic networks for a long time, since the advent of OR during World War II. A well-designed humanitarian logistic network can greatly reduce human suffering in case of a catastrophic events.

There are several parts of an effective disaster management system. But in general, we can divide the disaster management activities in to two parts- pre-disaster planning activities and post-disaster evacuation and relief activities. This research will focus on both of those two areas to ensure better integration and coordination between pre and post disaster activities by designing an effective humanitarian logistics network.

1.1 Motivation

In the case of sudden onset of any unpredictable disaster, may that be natural or anthropogenic, quick and sufficient response is the only thing that can really make a big difference (since in most cases, we can't really prevent disasters from happening, but can take prompt actions to mitigate the casualties after they happen). Here the term 'response' is being used to indicate a broad spectrum of activities like supply of food, water or medicine, quickly evacuating wounded people, transportation of people to temporary or permanent shelters for medical attention, pre-positioning non-perishable relief goods in the pre-disaster periods, vehicle management for post-disaster operations etc. Not only do we have to make sure there is availability of these relief goods and services, but also that they reach the affected area as quickly as possible and they are sufficient enough to tackle the situation.

There are a good number of researchers who have worked in this area before. But most of the models that previous researchers have developed so far, have not addressed the entire integrated aid operation and all the associated activities in a coordinated way. Many previous works in this area were focused predominantly on pre-disaster planning, but did not address post disaster actives or vise-versa. That opens up a good opportunity to develop a complete research methodology that can address both pre and post disaster activities seamlessly, while making sure they are properly integrated. Proper integration in pre and post disaster activity is important to minimize mismanagement and maximize the operational efficiency. This research intends to address these issues.

Also, the fact that the author of this research, originally came from an under-developed part of the world where many disastrous event (many of whom are also recurrent in nature) occurs very frequently and author has noticed previously that the authorities incumbent for carrying out the aid operation there often struggle to properly manage and plan the operation (which only makes the situation worse and increases casualties), motivated him to pick disaster planning and management as an important research area to focus on. Author of this research sincerely feels that, there are much more improvement and deeper research that needs to be done in this area to minimize human suffering and mismanagement to a greater extent.

1.2 Scope and rationale of the study

Humanitarian logistics systems have several characteristics that make it distinct, from other supply chain systems. Planning an effective humanitarian logistics system is hence quite difficult due to these distinct characteristics. Uncertain demand of relief commodities, uncertain working condition, weather, geography, difficulty to obtain data from the actual affected areas etc. are only some of the unique problems that are faced in this area. In many cases where data is unavailable, the only thing we can do then is just to make reasonable assumptions to develop an effective plan. Moreover, like any other supply chain, humanitarian logistics networks can also be multi echelon. To optimize network performance, it is important to make sure supply chain activities are well coordinated within different levels of the network.

This research intends to address these various issues, to design and optimize an effective logistics network while considering different uncertainties, that a catastrophic event might often poses. Developing a method which will address all these issues of an aid network in a single research is still a minimally explored issue and thereby yields the rationale of this proposed research.

This research intends to develop an effective plan that includes all levels of humanitarian logistics network, including appropriate supplier and facility location selection, prepositioning of commodity in the pre-disaster phase, making sure the adequate amounts of aids reaches the demand points and the wounded people are properly evacuated from the affected area, vehicle management, ensuring equity of distribution, maximizing route reliability, while trying to minimize the overall cost as much as possible.

In short, it can be stated that this dissertation will be able provide us a way to effectively minimize the expense and human suffering that is inflicted upon us by disasters, while aiding the decision makers with powerful insights about the management of the overall humanitarian logistics network under disastrous situations.

1.3 Outline of the Study

The proposed research can be outlined as below:

- The research will comprise of two planning stages of relief operations. The pre-disaster planning stage and the post-disaster planning stage. The pre-disaster stage of this research comprises of two stochastic linear programming models. Post disaster stage contains just one model. All these models are related to each other.
- In Pre-disaster planning stage, first model is regarding facility location selection. Its objective is to minimize the travelling distances of the tentative warehouse sites from both the suppliers and affected locations. The second model of the pre-disaster stage intends to select the appropriate routes to travel to and from warehouses, based on historical reliability data on different available routes under different disaster scenarios. This second model uses the information outputs obtained from first model as inputs.
- To deal with the demand and supply uncertainty of the disastrous situation, scenario-based approach will be used in all the models.
- The third and final model is under post-disaster planning stage, which is in fact a distribution and evacuation model. Outputs obtained from the first and second model will be used as inputs to the third and final model to get the final results.
- At the later stage of this research, a sample test case will be introduced to show the effectiveness of the developed model.
- All these three models together, once solved using appropriate optimization method, can provide decision makers all the information decision makers need to design a complete and effective humanitarian logistics network.

Chapter 2
Literature Review

Natural calamities or other catastrophic events wreak havoc to developed and under-developed regions alike, mostly because of their abrupt or unpredictable nature. Another very important issue that plays into intensifying the casualties caused by these events is lack of proper management in pre and post-disaster period. Proper planning is an important key issue in time sensitive cases like these where timely response can make a world of difference. In this dissertation, in an effort to develop an effective mathematical model to aid these pre and post disaster planning activities, the author reviewed a number of relevant literatures to familiarize himself with the history, backgrounds and also the recent works performed in this arena. Literature reviewed for this purpose can be divided into three major groups. First group is 'Review on pre-disaster planning and distribution'. The second group is 'Review on post-disaster planning and evacuation", while the third group is 'Review on solution methodologies'. They will be discussed in the following sections.

2.1 Review on pre-disaster planning and distribution

Since the advent of Operation Research (OR) and Management Science (MS) during second world war, researchers are finding new areas where OR/MS techniques can make significant impact. Supply chain was one of the primary areas where application of OR/MS techniques made huge differences. Now specialized areas of supply chain, like humanitarian logistics, started drawing the attention of researchers and other stakeholders (like government entities, non-government relief/aid organizations etc.) in early 1960s'. Before 60s', even after World War II, when principles of OR were invented, stakeholders and managers of relief operation mostly used rely on their intuitions while planning for aid via a logistics network due the absence of good quantitative research on this issue.

Pre-disaster planning phase usually involves issues like supplier selection, facility location selection, inventory management, and distribution. In this section of the literature review, we will focus on these issues one by one.

Supplier Selection is a very important issue when it comes to planning an efficient logistics network, to optimize it's the overall performance. Often many real-life problems involve consideration of multiple criteria, where Multiple Criteria Decision Making (MCDM) techniques can play important roll to find viable economic and efficient solutions in a shorter time. Supplier selection process is one of those cases where we must consider multiple selection criteria for the candidate suppliers for evaluation purpose. Analytical Hierarchy Process (AHP), which is one of the vastly used MCDM techniques, can be used successfully in cases like these.

In the AHP method, decision makers usually assign ranking weightage to different selection criteria and then also grade suppliers in those specific criteria. Then finally, appropriate supplier(s) are selected based on their respective total weighted performance scores under different selection criteria. AHP is often considered to be very efficient pre-selection tool to eliminate underperforming suppliers at the early planning stage. This way decision makers can save a lot of money and time in the later stage of the planning process.

Ghodsypour and O'Brien [1998] proposed a supplier selection and order allocation model, which was based on AHP method. The model considered various qualitative and quantitative selection criteria like buyer's budget, quality, service, pricing etc. In their study they found that the number and weight of the supplier selection criteria are largely dependent on the respective companies purchasing strategy. Muralidharan, et al. [2002] developed a multi-step supplier selection model, based on AHP method. In their model, the decision makers used to rate the prospective suppliers on nine different evaluation criteria. The model also tried to involve various departments of the company, like purchase, storage, quality control etc. with the supplier selection process to ensure more accurate evaluation. Rouyendegh and Erkan [2012] proposed a supplier selection model for procurement of different items required for a commercial supply chain, which was based on AHP technique. The model considered various important selection criteria like cost, quality, flexibility, delivery and variety to ensure efficient supplier selection.

Hou and Su [2007] also developed a supplier selection model, based on AHP technique as a decision support system for the managers. In their model, they incorporated different external and internal factors along with the evaluation criteria to make more efficient decision. Chan [2003] developed a supplier selection model which uses AHP technique to select appropriate suppliers for business industries. In their model, they used a method called “Chain of Interaction” to determine the importance of each selection criteria, which is required to generate the overall supplier score. Asamoah, et al. [2012] also utilized AHP technique for supplier selection for pharmaceutical manufacturing industries. They used the three selection criteria for their evaluation, which includes product quality, price offering and reliability of the suppliers. The result obtained from the study indicates that the AHP technique makes it easier to evaluate, rank and select efficient suppliers for manufacturing firms in a relatively shorter time period and in a reliable way.

Facility location selection is a very important part of designing the logistics network as it effects the overall performance of the network and directly influences the response time and costing of the operation [Haghani,Oh 1996]. Usually in the facility selection models, researchers give the model multiple tentative locations as inputs, from which the model choses n-number of most appropriate locations to set up distribution centers while complying to all the given constraints and decision makers pre-determined preferences (if there is any). Inventory management is another important issue in any supply chain which needs proper planning as well. We should not bring in such small quantity of goods that it fails to satisfy the demands at the affected area. On the other hand, if we bring too much goods, large amount items will remain unused, which will incur holding cost and spoilage and when this adds up to the total operational expense, it drives up. So, both of these inventory situations are undesirable. What we need to do to minimize the inventory cost, is to bring items in quantities which is as close to our actual needs as possible. This will drive down both unsatisfied demand and holding and spoilage cost. It will be our objective in this research, to develop model(s) in such a way so that we can minimize these undesirable situations and expenses. Another important part of pre-disaster inventory management is ‘pre-positioning’. Pre-positioning involves stocking up some portion of the non-perishable relief goods to the DC locations in the pre-disaster period, to reduce the logistical load on the transportation network in the post disaster period. Problem is, if we pre-position too much and the disaster doesn’t strike soon, a good portion of those relief items will get either wasted or expired. If we pre-position too little, it might not have any significant effect or any logistical advantage at all. These situations must be kept in mind when modelling an efficient relief network.

In recent years the field of emergency management was reviewed by many researchers. Kovacs and Spens [2007], keeping in mind the needs of both academics and practitioners, described the unique characteristics of humanitarian logistics. They also acknowledged the need of humanitarian logistics to learn from business logistics on various issues. Different areas of humanitarian logistics, like preparation, prompt response, reconstruction of affected infrastructures and other related studies were explored in this review. Altay and Green [2009] performed a comprehensive study of different stages of disaster operation management in the light of OR/MS. According to them, public and private agencies should coordinate and integrate their logistics activities to properly achieve the performance objectives at the various phases of the disaster relief operation. Later, Özdamar and Ertem [2015] presented a survey that focuses mainly on the response and recovery planning phases of the disaster lifecycle. Different mathematical models related to this area were explored in this study in terms of vehicle and network structures. The study also provides details on goals, constraints and structures of those mathematical models and different solution methodologies used to optimize those models. Gutjahr and Nolz [2016] performed a review on multicriteria optimization in Humanitarian logistics. The study discusses different recent literatures on the application of multi-objective optimization in the management of disastrous events and humanitarian crises situations. Different optimization criteria applied in this field for efficient management of the aid operations were also discussed and examined here. Beamon and Balcik [2008] performed a study comparing the performance measurements criteria of humanitarian logistics chain with that of a commercial supply chain. They highlighted on various performance measures like ability to change output level, change in variety of product, delivery time flexibility etc. in their study.

Knott [1987] developed a single commodity linear programming model for the bulk food transportation to ensure the efficient use of the truck fleet to minimize the transportation cost while maximizing the amount of food delivered. In another article later [1988], Knott developed a linear programming model for vehicle scheduling, to transport bulk relief goods to a disaster affected area. Guelat, et al. [1990] developed a multi-commodity, multi-modal network assignment model for strategic planning of freight transportation. It wasn't a humanitarian logistics model, but it can provide valuable insight on routing and transportation.

The objective of the proposed model was to minimize the sum of total routing cost and total transfer costs.

Haghani and Oh [1996] proposed a multi-commodity, multi-modal network flow model for disaster relief operations. Their mixed pickup and delivery model could determine detailed routing and scheduling plans for multiple transportation modes for carrying various relief commodities from multiple supply points to various demand points or affected area, with in specific time window. Their model intended to minimize the sum of the vehicular flow costs, commodity flow costs, supply or demand carry-over costs and the inter-modal transfer costs over all time periods. They used two heuristic solution approach to solve their model, both of whom was done using LINDO. The first method was a Lagrangian relaxation approach and the second method was an iterative fix-and-run process.

Afshar and Haghani [2012] also developed a mathematical model for controlling the flow of relief goods through the supply chain under disastrous situation. The model aimed at minimizing the total amount of weighted unsatisfied demand over all commodities to optimize their model. They used branch and bound algorithm of CPLEX solver to solve their MIP model.

Barbarosoglu, et al. [2002] worked on developing an efficient planning model for scheduling of transportation trips via helicopter for a disaster relief operation. Their developed two-stage model addresses various issues of the disaster logistics activity. The first stage of the model works on vehicle (helicopter) assignment, crew assignment and number of trips required during the relief operation. The second stage of the model addresses other operational issues, like helicopter travel route selection, the loading and unloading time management, delivery, refueling schedule for the helicopters, etc.

Barbarosoglu and Arda [2004] again developed a two-stage stochastic programming model later, for transportation planning in disaster response. In this study of theirs', they did not address some very important issues, like facility location selection or vehicle route selection, but did addressed some other crucial issues like uncertainties in supply, route capacities and meeting demand requirements etc. They developed nine earthquake scenarios to test their models' efficacy to deal with real-world disastrous situations.

Ozdamar, et al. [2004] developed a multi-modal multi-commodity transportation network model for emergency situations. This dynamic time dependent transportation model addresses the distribution multiple commodities from a number of suppliers, to different distribution centers near the affected areas, along with the planning of vehicle fleet for the required transportation works. The objective of the study was to minimize the total amount of unsatisfied demands over all time periods. The proposed model was formulated in such a way that the model can be effective even under changing demand, supply quantities or available vehicle fleet size. They used an iterative Lagrangian relaxation algorithm, implemented via GAMS solver, to solve their proposed model.

Viswanath and Peeta [2003] formulated a multi-commodity maximal covering network design model to aid the selection of appropriate routes for earthquake response. The model had two objectives, to minimize the total travelling-routing expense and to maximize the total demand covered. The solved the integer programming model using branch-and-cut algorithm in CPLEX.

Beamon and Balcik [2008] worked on a facility location decision model that can help the decision makers to respond promptly in case of sudden onset of a disastrous situation. Their model, which is basically a variant of the maximal covering location model, could determine the number and locations of the relief distribution centers and the amount of relief goods to be stocked at each distribution center to meet the needs of affected people. The model objective was to maximize the total expected demand covered by the established distribution centers. The model integrates facility location and inventory decisions for multiple product and can work with in the user defined budgetary and capacity constraints. They later developed a numerical case to show how the proposed model works on a realistic problem. At the end, they also discussed the managerial implications of their model.

Nolz, et al. [2010] developed a multi criteria covering model for planning the water delivery system in a disaster affected area. The model tends to optimize the physical location of the portable relief water reservoirs. The model also selects the appropriate routes to take to get to those water reservoir locations at the minimum time. They used a metaheuristic search algorithm called Non-dominating Sorting Genetic Algorithm-II (NSGA-II) to solve their model.

Vitoriano, et al. [2011] performed a reliability analysis for the disaster relief operation. They developed their model based on this reliability analysis. The mixed integer programming model was developed to address the uncertain elements of the relief operation and address issues like transportation network management, goods flow, vehicular availability, budgeting, route reliability etc. the specific objective of the model was to minimize the total operational cost , the total time required for logistics activity and to maximize the equity and reliability of the operation. They used a goal programming approach to solve the multi-criteria model. They used the earthquake incident in Haiti as a sample case to check the effectiveness of their model. They solved their developed model by CPLEX via GAMS platform.

Mete and Zabinsky [2010] developed a two-staged stochastic programming model for the planning of storage and distribution of medical supplies after a disastrous situation. They used the incident of Seattle earthquake as test case to check the effectiveness of their model. In the study they mentioned that the balance of risk and preparedness is possible in spite of the presence of the uncertain components in the logistics system. They used the CPLEX via GAMS solver to solve their proposed MIP model.

Rawls and Turnquist [2010] developed a two stage stochastic mixed integer programming model to address the pre-disaster planning issues like facility location selection, preposition of relief goods etc. they kept pre-disaster decisions like locating and prepositioning goods in the warehouses in the first stage while In the second stage, they mainly focused on routes selection and distribution, after obtaining information about demand and remaining supply. They subdivided the second stage of their model in to two smaller models later for the ease of calculation. They used a Lagrangian L-shaped method (LLSM) to solve the model, implemented via CPLEX. They used the hurricane incidents in Gulf coast of USA as test cases to check the effectiveness of their model.

Lin, et al. [2011] developed a multi depot mixed integer programming model which uses split delivery system to transport relief goods to the disaster affected area within a given time limit. A two-phased heuristics approach were used to solve the developed model. First phase uses Dantzig's Greedy Algorithm, where second phase uses a Random Re-start Hill Climbing Algorithm. They used CPLEX with C to implement the heuristics to solve the model. They used the earthquake incidents in Northridge, CA as test cases to check their model. They used

HAZUS-MA earthquake simulation software to generate the demand data for the earthquake scenarios.

Doerner, et al. [2009] developed a multi criteria optimization model for finding appreciate locations to set up public facilities close to the coastal area, so that the effect of tsunami on them is minimized. They dealt their developed model in two stages. In the first stage, the algorithm developed multiple pareto optimal solutions and later in the second stage the decision maker can chose an appropriate one from the group of available solutions, whichever is best for their planning process.

As for distribution, Tzeng, et al. [2007] developed a multi-objective relief distribution model to address the earthquake situation in Taiwan. The model aimed at the reduction of human suffering and damages by minimizing total cost of the logistics activity, minimizing the total time requirement for the operation and maximizing the minimal satisfaction during the planning period. In their case study, they used a TransCAD software, to find the quickest route. The quickest travel time, travel distance, number of victims in need of care in each area, mode of demand for every item of relief etc. required information was obtained from the model as output after solving the case. Authors used LINGO as analysis tool for their model.

Rottkemper, et al. [2012] proposed a bi-objective mixed-integer programming model for coordinating the relief distribution operation in case of onset of a disastrous event. The objective of their research was to minimize the total unsatisfied demands and the cost of operation. In their model they split their total demands in two parts; the certain demands and the uncertain demands. They solved their model by a Rolling Horizon method which was implemented in CPLEX.

Abouncer and Rekik [2012] developed a multi-objective location-transportation model for post-disaster planning. The objectives of the model were to minimize the total transportation time, minimize total number of stuffs or operatives required to properly carry-out the relief operation and minimize total amount of the unsatisfied demands across all demand points. They proposed an Epsilon-constraint method, implemented via CPLEX solver, to solve this mixed integer programming model.

J B Sheu [2007] developed a hybrid fuzzy clustering optimization approach to solve their three layers emergency logistics model. The proposed method had two recursive mechanism; the demand points in affected area grouping and relief co-distribution. They used an earthquake incident in Taiwan as a test case to check the effectiveness of their model.

Barzinpour and Esmaeili [2014] formulated a multi-objective mixed integer location selection and allocation model for post-disaster relief operation. The model tried to maximize the total covered population by the relief operation and minimize the total cost of operation which includes facility set up cost, transportation cost, inventory management cost etc. they used an urban earthquake incident in Iran as a test case to demonstrate the effectiveness of their proposed model. A goal programming approach was used to solve their multi-objective model.

Bozorgi, et al. [2013] developed a robust stochastic multi-objective logistics planning model for efficient disaster response. Their stochastic model took in consideration of various important issues of the relief logistics network, like the uncertainty and fluctuation of demand in the affected areas, possibility that some portion of the pre-positioned relief goods might not be usable at post-disaster period and so on. The objective of their model was to minimize the total cost of the relief operation and maximizing the total satisfaction level by minimizing the total unsatisfied demands at the affected area. They used an earthquake incident in Tehran, Iran as a test case to check the effectiveness of their model. Their mixed integer multi-objective model was solved using a ξ-constraint method in GAMS platform via CPLEX solver.

Tofighi, et al. [2016] developed a two-stage stochastic humanitarian logistics planning model. At the first stage of the model, locations of the central warehouse and the local distribution centers are determined. Amount of goods that is needed to be pre-positioned at the pre-disaster planning phase are also determined at this stage. Later on, in the second stage, they tried to minimize the total distribution time, total cost of unused inventories of relief goods and total weighted shortage cost of the unsatisfied demands. The model mainly aimed at developing an efficient inventory pre-position plan, not at developing a detailed post-disaster relief distribution plan. They also developed a tailored differential algorithm to solve the model they proposed. They used an earthquake incident in Tehran, Iran as a test case to check the effectiveness of their model.

Caunhey, et al. [2016] proposed a stochastic two-stage mixed integer location-routing model for disaster preparedness and response. They solved the two-stage model by converting it to a single stage model afterwards. The objective of the first stage model was to minimize the total cost of setting up warehouses and minimize the worst second stage cost. In the second stage, the model objective was to minimize the total transportation cost, total transportation time, total transshipment time and total unfulfilled demand. They used CPLEX solver, to solve their final single stage model.

Rath and Gutjahr [2014] developed a multi-objective mixed integer location-routing model for relief operation. The objective of the model was to minimize the total facility set up cost, minimize total operational cost and maximize the total covered demand. They used a heuristic search algorithm (Non-dominating Sorting Genetic Algorithm- II or NSGA-II) and MILP solver (CPLEX) to solve their model.

Moreno, et al. [2016] developed a bi-objective location selection and distribution model for relief operation. The objective of the model was to minimize the total logistics cost and minimize total unsatisfied demands at the demand locations. The model was developed to help the decision makers to make logistics decisions like relief center locations, amount of relief goods that needs to be distributed and required fleet size to transport the relief goods. The used a 2011 disaster event at Rio-De- Jeniro, Brazil as a test case to check the effectiveness of their model.

Salmeron and Apte [2010] proposed a stochastic two-stage optimization model for humanitarian logistics operation. The model objective was to minimize the total expected causalities and minimize total number of unserved people at different demand locations. The first stage of the model aims at facility expansion, while the second stage of the model involves resource allocation and relief transportation.

Rennemo, et al. [2014] developed a stochastic three-stage mixed integer linear programming model for disaster response. The model objective was to minimize the total operational cost while ensuring fairness in reception of relief goods. They used an earthquake incident in Haiti as a test case to check the effectiveness of their model.

Ahmadi, et al. [2015] proposed a two-stage stochastic multi-depot location-routing model for disaster response. The model aimed to help the decision makers to determine appropriate locations to set up warehouse facilities and appropriate routes to take for last-mile logistics for relief operation. The model objective was to minimize the total distribution time, minimize the total facility set up cost and minimize total amount of unsatisfied demands at different demand locations. They used a combination of a variable neighborhood search algorithm and GAMS solver to solve their model.

2.2 Review on post disaster planning and evacuation

Pre-disaster planning phase usually involves issues like post disaster distribution, vehicle planning and evacuation. In this section of literature review, we will focus on these issues one by one.

Yi and Ozdamar [2007] proposed a dynamic mixed integer multi-commodity network flow model for coordinating the relief activity along with the evacuation of wounded people from the affected areas. They tried to plan vehicular transportation for moving both the relief goods and the wounded people. In the model they tried to minimize both the amount of unserved demand and the number of unserved wounded people. The model plans the establishment of temporary emergency facilities in order to serve the medical needs of wounded affected people. They later developed a custom algorithm called “Route” to solve their mixed integer problem. Facility location selection was not a part of their network flow model.

Yi and Kumar [2007] developed a model to coordinate disaster management planning activities, which mainly involves transporting relief commodities to the distribution centers and evacuation of the wounded people to the medical facilities. They decomposed the original logistics problem into two phases for ease of handling, which are: the vehicle route construction and the multi-commodity dispatch. Later, they used a greedy search algorithm called Ant Colony Optimization (ACO) to solve their proposed model. The performance of the algorithm was also tested on a number of randomly generated test cases and the results indicated a satisfactory performance in terms of both solution quality and run time.

Ozdamar and Dimir [2012] developed a capacitated network flow model for post disaster relief logistics activity. The model aimed at minimizing the total time required for the relief goods distribution and wounded people evacuation. To solve the model, they developed a hierarchical cluster and route procedure (HOGCR) for coordinating vehicle routing for large-scale post-disaster relief logistics activities. They described this method ‘HOGCR’ as a multi-level clustering algorithm which groups the demand nodes into smaller clusters at each planning level and by doing this the algorithm derives the optimal solution to the cluster routing problems. To implement HOGCR to solve the model, they used CPLEX on a parallel computing platform and found satisfactory results.

Goerigk, et al. [2015] proposed a bi-objective robust mixed integer programming model to address the uncertainty involved in the relief operation after a disastrous event. Their model considers important design issues like unpredictable evacuation schedule change and constrained evacuation time. The developed model was iterative in nature. That means, once it is solved for a certain scenario, it keeps adding that to the model to improve the model accuracy. They used an evacuation incident occurred in Kaiserslautern, a German town, as a test case to check the effectiveness of their model. CPLEX solver was used to solve their model by an Iterative Algorithm.

Coutinho-Rodrigues, et al. [2012] developed a multi-objective model for evacuation path selection and location selection for evacuation shelter. The model had six objectives like risk minimization, minimization of total travel distance, total evacuation time etc. The developed mixed integer programming model was tested using a test case of a simulated incident that takes place in the city of Coimbra, Portugal.

Trivedi and Singh [2017] developed a multi-criteria decision making model for efficient management of evacuation operation in case of an emergency situation. They used a Fuzzy Analytical Hierarchy Process (AHP) and Goal programming approach for their model. The objectives of the model include minimization of total distance travelled for relief operation, total unsatisfied demands, associated risk, number of shelter setup and so on. They used the earthquake incident in Nepal as a test case to check the effectiveness of their developed model. GUROBI solver was used to solve the Mixed Integer Programming (MIP) model.

Kongsonaksaku, et al. [2005] developed a bi-level optimization model for flood evacuation planning. The model aimed to help the decision makers to select appropriate locations to set up the shelters, minimizing the total evacuation time and choose appropriate route to take to get to those shelter in quickest possible time. They used a flooding incident at Logan, Utah as a test case to check the effectiveness of their proposed model. A Genetic Algorithm approach was used to solve their model.

Ghasemi, et al. [2019] proposed a stochastic multi-objective, multi-period post-disaster response planning model. Their scenario-based model aimed to help the decision makers to determine appropriate locations for setting up the relief centers and the hospitals, flow of injured people and commodities to the facilities etc. The model objective was to minimize the total facility set up cost, minimize the total distribution cost and minimize total amount of unsatisfied demands at different demand locations. They used an earthquake incident in Tehran, Iran as a test case to check the effectiveness of their model. They their model in three different ways. They used a Modified Multi- objective Particle Swarm Optimization (MMOPSO) method, a Non-dominating Sorting Genetic Algorithm- II or NSGA-II method and an Epsilon-constraint method to solve their model. At the end they found out that the MMOPSO method performed the best in solving their specific model.

Pillac, et al. [2015] developed a mixed integer programming evacuation model to help the decision makers in case of large-scale evacuation and related mobilization of resources. The model objective was to maximize the total number evacuees who reached to safety and minimize the total time required for evacuation. They used an earthquake incident in Istanbul, Turkey as a test case to check the effectiveness of their model. The model aimed to help the decision makers on issues like selection of appropriate route for evacuation, allocation of resources among affected areas and so on. They used a column generation algorithm to solve their model.

Baryam and Yaman [2018] developed a scenario based stochastic two-stage post-disaster evacuation planning model. Their model aimed to help the decision makers to determine appropriate locations to set up the shelters, assigning evacuees to the nearest shelter, selecting the shortest route to get to those shelters etc. The model objective was to minimize the total evacuation time. They used an earthquake incident in Istanbul, Turkey as a test case to check the effectiveness of their model.

Bish, et al. [2014] found out that at post disaster period, when panic stricken people try to evacuate the affected area in a massive number too quickly, causes intense congestion in the transportation system, which in turns slows down the entire evacuation process. Understanding this problem, they developed a mixed integer evacuation planning model whose main objective was to minimize the total network clearance time. They used an emergency incident Virginia Beach as a test case to check the effectiveness of their model.

Navazi, et al. [2018] developed a robust emergency service network planning model that discusses issues like, inventory management, transportation planning via ground and air, how to deal with the fluctuation of demands at the affected areas etc. Their multi-facility, multi-modal disaster response planning model aimed at minimizing the total operational cost and minimizing total time required for the emergency operation. They used an augmented ξ- constraint method to solve their model.

Swamy, et al. [2017] developed a stochastic two-stage hurricane evacuation planning model using public transportation. The model assumed that the evacuation zone, shelter locations and time of disaster strike are pre-determined. The first stage of the model involves determining appropriate pick up location selection, assignment of shelters and selection of appropriate routes to get to those shelters, while the second stage of the model involves assignment of trip numbers to each of those transportation routes.

Chiu and Zheng [2007] developed a multi-priority emergency response model for evacuation and other post-disaster activities. The model aims at minimizing the total prioritized time required for effective evacuation operation, where different groups of evacuees have different priority level and all of them need to be moved through same route simultaneously after the occurrence of a disastrous event.

Yao, et al. [2009] developed a linear evacuation network planning model which was based on a concept called modified Cell Transmission Model (CTM). The model could deal with the demand uncertainty, which is associated with the evacuation planning. Evacuation was done based on spatio-temporal priorities of different evacuation candidate locations.

Abdelgawad, et al. [2010] developed a multi-objective transportation-evacuation network planning model for using public transportation during mass evacuation. It was a variant of a pick-up and delivery model. The model objective was to minimize the total evacuation time, waiting time and minimization of total operational cost.

Kulshreshtha, et al. [2011] developed a robust bi-level optimization model for evacuation planning. The model aims at assignment of shelters to the evacuees based their proximity and selection of appropriate routes to get to those shelters. The model objectives are to minimize the total cost of setting up the shelters and minimize the total operational cost. The model also consider the uncertainty of the demands at affected locations under three different scenarios. They used an approximation based cutting plane algorithm to solve their model.

Yuan and Wang [2009] developed two mathematical optimization models for evacuation and other post-disaster planning activities. First model is a multi-objective path selection model that aims at minimizing the total travel time during the relief operation, considering the fact that the travel speed on different arc at post-disaster period might be impacted by the disastrous event. They used a Modified Dijkstra algorithm to solve their first model. The second model aims at minimizing the total travel time again, along with minimizing the path complexity during the relief operation, considering issues like chaos, panic and congestion during post-disaster period. They used an Ant Colony Optimization algorithm to solve their second model.

Manopiniwes and Irohara [2014] developed a stochastic multi-objective mixed integer linear programming model for efficient disaster preparedness and post-disaster response. The objective of the model was to minimize the total cost associated with facility set up, stock pre-positioning, evacuation and vehicular planning etc. The model also tried to ensure equity in the relief operation. A weighted sum approach was used to solve the multi-objective model. They used a flooding incident in Thailand as a test case for their model.

Kimms and Maiwald [2018] developed a resilient bi-objective urban evacuation planning and disaster response model. The model objective was to minimize the overall hazards associated with the emergency situation and to maximize the network capacity. The model was based on the assumptions of the Cell Transmission Model (CTM). They used ε- constraint method to solve their bi-objective model.

2.3 Review on solution methodologies

Operations research approaches used in natural disasters management can be of different types. Mixed integer programming algorithms (like Branch and Bound or Branch and Cut), shortest-path algorithm, heuristic methods etc. are some of the most common solution approaches that has been being used in this area. What approach will be used to solve a specific model depends mostly on the nature of the problem that we are dealing with, such as whether the problem is mixed or pure integer programming problem, linear or non-linear programming problem, stochastic or deterministic programming problem etc. Stochastic programming models, in general, are relatively difficult to solve compared to the deterministic ones, due to their larger scale and complexity.

Among the reviewed literature, it has been seen that a large number of the developed models were solved using either exact or heuristic method, in this field of emergency logistics. In most linear cases, exact methods can usually guarantee that a global optimal solution will be found, if the method is given sufficiently time, whereas heuristics are solution methods that typically are relatively quick to find a viable solution, but can't always guarantee the solutions' global optimality [Ropke and Pisinger [2006]].

Many researchers have successfully used Branch and Cut algorithm before for their integer or mixed integer programming models. For instance, Gendreau, et al. [1998] used a Branch and Cut algorithm for their mixed integer Travelling Salesman Problem. The objective of their model was to construct tours for the salesman in such a way so that it maximizes company's total profit. According to their study, the algorithm was able to solve instances involving up to 300 vertices. They used CPLEX to implement the Branch and Cut algorithm for the model. Perez and Gonzalez [2003] also developed a Travelling Salesman Problem with pickup and delivery option. They used Branch and Cut algorithm to solve their proposed binary-integer programming model via CPLEX.

Similarly, Ku and Beck [2016] developed a mixed integer Job Shop Scheduling problem. They were able to solve the problem successfully both in CPLEX and GUROBI solvers, using the default integer programming algorithm that was built into those platforms. Again, Cordeau, et al. [2010] developed a Travelling Salesman Problem with First-In-First-Out (FIFO) loading option. They also used Branch and Cut algorithm to solve the Mixed-integer programming model, which appeared to have performed better that any other existing exact algorithm. The algorithm was able to solve instances up to 50 nodes in a reasonable computing time. Branch and Bound algorithm was used by Gkonis, et al. [2007], who developed an mixed integer linear programming emergency response model for oil spill problem in natural water bodies. Wohlgemuth, et al. [2012] developed a stochastic pickup and delivery problem, which was solved by using a Tabu search approach.

Besides these, many researchers have also used various meta-heuristic algorithms to solve their humanitarian logistics models. For instance, Yi and Kumar [2007] used an ant colony optimization technique to solve their relief distribution problem. Hamedi, et al. [2012] used a genetic algorithm based heuristic technique, to solve a humanitarian response planning model, for a fleet of vehicles with reliability considerations. Berkoune, et al. [2012] developed a genetic algorithm based method as well to solve their multi-commodity and multi-depot routing problem, which aims to minimize the total duration of all trips. Song, et al. [2009] formulated a transit evacuation model as a location-routing problem with stochastic demands, which was solved using shortest path algorithm.

Ozdamar, et al. [2004] used a Lagrangian relaxation method to solve their multi-period multi-commodity network flow model, which was basically integer programming problem. Sheu, et al. [2005] formulated a grouped affected area model to associate the respective distribution priorities with them. The model was solved using a fuzzy clustering method. Adıvar and Mert [2010] developed a fuzzy linear programming model to design a plan for transporting aid from international donor countries to the disaster affected countries. A Fuzzy clustering technique was used to solve that problem. Ozdamar and Demir [2012] presented a hierarchical clustering and routing procedure to deal with large scale relief networks by using a k-means partitioning heuristic. Kristianto, et al. [2014] used the fuzzy shortest path algorithm to convert a complex shortest path problem with time windows and capacity constraint to the original simpler shortest path problem and thus making the problem relatively easier to solve.

So as we can see, different researchers have used different techniques here to solve their problems, which mainly appears to depend on the type of research models that they have formulated and the level of flexibility and accuracy they desired in the output.

Chapter 3

Model Development

Disasters are unpredictable catastrophic occurrences that truly test the endurance and resilience of a state or community, whether they can effectively recover from it to resume their normal operations in the quickest way possible. Any disaster, may that be manmade like conflagration, terrorist incident or natural disasters like flood, earthquakes, cyclones etc., have been proven to be undeniable challenge to any state or nation due to their unpredictable nature and potential ability to wreak havoc and fatalities. These disastrous incidents have long lasting social, environmental and economic consequences. Overcoming these consequences are where the challenge lies. The best way to minimize the impact of these disastrous incidents is proper pre and post disaster planning, which can truly help in rapid recovery process. The randomness of the points of impacts and their scale has always been a big problem. But luckily, with the help of OR/MS research techniques, we can develop models which can deal with these uncertainties to the nearest margins. The objective of this research is to assist decision makers to develop an efficient relief logistics network that can aid in the rapid recovery process.

3.1 Problem Identification

Due to the increase in industrialization and accompanying pollutions and climate change, the number and magnitude of natural disasters have grown exponentially in last several decades. the number of affected people has also grown in proportion (about 300 million persons per annum on the average since the 1990s) and so does the annual damage costs (about 0.17 percent of the world GDP) (Guha-Sapir, Hoyois, & Below, 2014). Developing proper plan and strategies in the pre and post disaster period can help to keep these casualty numbers down.

To design an efficient humanitarian logistics network, several logistics issues need to be addressed with utmost importance. Some of those issues include the determination of the number and appropriate locations of the prospective regional Distribution Centers (DCs), the amount of relief goods that need to be transported from supplier locations to DCs and from DCs to the affected locations, with in the capacity constraints. Besides these, we will also need efficient route planning to minimize associated travel risks where possible. We will need to preposition some of the non-perishable relief goods in advance in the DC locations at the pre-disaster planning phase, to reduce load on the logistics network during the post-disaster phase. Evacuation of the wounded or sick people from the affected area to the medical center location is another crucial logistics issue. We have to make plans to provide appropriate manpower to the medical centers to ensure quality treatment and also have to try to minimize the amount of unserved demands and unserved wounded people to minimize human casualties and sufferings. To perform all these required logistics activities, we must manage an adequate size fleet of vehicle. Planning and managing trips with the available number of vehicles of different kind is also a challenge.

Fortunately, this research work addresses all these aforementioned issues of a relief logistics network. Previous researches performed in this area mostly focus on specific area of the humanitarian logistics network, instead of dealing it as an integrated system as a whole. In this dissertation, three inter-related models will be developed that will solved sequentially to obtain all the necessary information that the decision maker needs to complete the design of the entire humanitarian logistics network. A scenario-based approach will be used here for first two pre-disaster model to deal with the relevant uncertainties. But the final post-disaster evacuation and distribution model will be based on just one scenario, since in the post-disaster period we will already know which scenario we are in. More details about these models will be discussed in the next section of this chapter.

3.2 Problem description

The research comprises of two planning stages of the disaster relief operation. The pre-disaster planning stage and the post-disaster planning stage. Now **pre-disaster planning stage comprises of two models** who are related to each other. **Post disaster planning stage contains just one model** that addresses most of the post disaster activities that requires planning and is dependent on the outputs obtained from the pre-disaster models.

Pre-disaster planning stage

This stage has two models. **First pre-disaster model** is a supplier and facility location selection model, which tends to minimize the travelling distance of the tentative warehouse sites from both supplier and affected locations. In this model we give the positions of the several tentative locations as inputs where a warehouse of a certain capacity options can be set up. Complying to the budgetary constraint, the model usually picks a few locations out of the several given options, along with their expected capacities. For supplier selection, a multiple criteria decision making process is followed in the model, where the model picks maximum allowed number of best suppliers from a pool of suppliers, based on their total ratings (ratings are usually based on decision makers best judgement) on several evaluation criteria for multiple relief items, as well as other issues like their location distances and available capacities. Scenario based transported goods quantity data will be also obtained as output from this model, which can be used later to determine the appropriate level of prepositioned inventories that we can hold at the selected DC locations, to reduce the load on logistics system in the post disaster period. Output variables are either integers or binary here. Once we set up the warehouses, they are then ready to be used as permanent infrastructures, i.e. their location or capacity won't change over time, once built. We have used scenario-based approach here to make sure that the facilities are built in such a way that it can accommodate moderate fluctuations in demand in near future. The model itself will be a MILP model.

The second pre-disaster model is later used to select the appropriate routes to travel to and from warehouses, based on historical reliability data on different available routes under different disaster scenarios. We have already determined the locations where the Distribution facility/warehouse going to be in the first model. In this second model, those information output obtained from first model will work as inputs. For obvious reason this second model is also scenario based. Route reliability values will be calculated from available historical data. Our objectives here are both to maximize the total reliability, while trying to minimize the travelling distances. Outputs here are the appropriate routes to follow under different scenarios in different stages of the supply chain. Output variables obtained in this model are all binary.

Post-disaster planning stage

3rd and final model is in the post disaster stage, which is basically a distribution and evacuation model. We have already obtained the information about the location and capacity of the distribution center (DC) warehouse, tentative amounts of the prepositioned goods from the first model and which path or route to take under different scenarios to travel from supplier to distribution center to the affected locations from the second model. Now we can use these information as input to the 3rd and final model in the post disaster stage (distribution and evacuation model). This 3rd (post-disaster) model will contain only one scenario, since at that point of the post-disaster period, decision makers will obviously know which scenario they are in and they can plan accordingly. Amount of different types of relief commodities to be transported from the suppliers to the DC and the from DC to the affected areas, number of wounded peoples to be transported to different medical tents set up at DC locations, Amounts of medical supplies brought from suppliers to DCs, required number of medical personnel at DCs to serve the wounded people, number of trips required between different nodes to do these transportations of goods and wounded people, etc. information will be obtained from this 3rd model as integer outputs. The output information from these three models are basically what is needed to design an effective humanitarian logistics network. There are several assumptions associated with each of these three models.

3.3 Model Details

3.3.1 Model 1: Pre-disaster Supplier and Facility location selection model

3.3.1.1 Assumptions, Sets, Parameters and Variables

Assumptions

1. Suppliers and the DC facility locations will be determined at the beginning of the planning process using this model. Once built, the DC facilities will act as permanent structures with adequate capacity to accommodate moderate fluctuations in demand in future times.
2. Budgetary constraint will dictate how many DC warehouse facilities of different capacity can be constructed. Whatever locations and capacities are chosen for these DC warehouses, will remain unchanged in future times.

3. For supplier selection, we will need to rate the suppliers on different criteria and for different commodities. There is no establisher best way to do these ratings, other than using the best judgement of decision maker on this. Same goes for determining the importance rating for each supplier selection criteria.
4. All scenarios used in the model are partially observable scenarios **
5. The supplier rating values are defined by the decision makers and does depend on the judgement and point of view of the decision makers. If the priority of any of the selection criteria changes in later period of logistics planning, this model has to be modified and run again to reflect those changes in final output.
6. Facility setup cost is dependent not only on the capacity, but also on the location. Because land acquisition expense is different at different regions.
7. At the beginning of planning (at the first model), we don't know which route to follow in different scenarios as route selection comes later in the second model. So, in the first model (facility location selection model), as the distance between nodes, we will use the shortest distance of all available routes between those respective nodes.
8. Primarily, in this model, the tentative affected locations (demand points -DPs) will be selected based on historical record. These DP locations might change later, if necessary, in the post-disaster stage.

****** The concept of the "partially observable scenario" comes from the concept of "partially observable system". In a partially observable system, the entire state of the system is not always and fully visible to an external observer. In such case, the observer may use a memory system to add information to the his/her understanding of the system, since the entire system is not clearly visible to him/her [Thrun, and Norvig (2012)]. In other words, a system can be called as "fully observable" only when the observer can always see the entire state of the system, otherwise the system is called "partially observable". Hence, in case of disaster scenarios in this model, they are all "partially observable scenarios".

Sets

$s \in S \rightarrow$ Set of possible scenarios

$i \in I \rightarrow$ Set of supplier nodes

$j \in$ J → Set of Distribution Center (DC) nodes

$k \in$ K → Set of Affected Area (AA) nodes

$m \in$ M → Set of relief items type

$h \in$ H → Set of capacity types of warehouses

$c \in$ C → Set of supplier selection criteria

Parameters

All volume/capacity parameters are given in cubic meter (m^3) and all money amounts are in unit of $1000

Deterministic parameters

BL = Budget limit to cover the fixed cost for setting up the regional DCs.

F_{hj} = set up cost for a facility of capacity *h* at location *j*

LS_{ij} = Shortest available path distance from supplier node *i* to DC node *j*.

LS_{jk} = Shortest available path distance from DC node *j* to affected area node *k*.

WC_h = Capacity of a warehouse of type *h*.

T1 = Cost of pre disaster transportation per km for per unit of relief commodities transported from supplier *i* to DC *j*.

T2 = Cost of pre disaster transportation per km for per unit of relief commodities transported from DC *j* to affected area *k* .

U_m = Unit volume in (cubic meter) of one pallet of commodity of type *m*.

SR_{cim} = Rating for supplier *i* at selection criteria *c* , for commodity *m*.

G_{cm} = Weight rating for the supplier selection criteria *c* in case of commodity *m*.

θ_{km} = Maximum allowable ratio of unsatisfied demands at affected area *k* for relief commodity *m* (it is a very small fractional number; usually defined by the decision maker).

Ω = An user defined parameter for prepositioning relief goods (in percentage).

Stochastic parameters

ρ_s = Probability of occurrence of scenario *s* (partially observable scenarios).

W_s = User defined weightage for scenario *s* (probability of occurrence of scenario *s* (ρ_s) can be used in place of W_s as well).

D_{kms} = Demand of commodity type *m* at affected area *k* at scenario *s*.

C_{ims} = Capacity limit of supplier *i* for commodity type *m* at scenario *s*.

Decision variables

Integer variables

S_{ijms} = Amount (in units) of commodity of type *m* needed to be transported from supplier node *i* to DC node *j* under scenario *s*.

R_{jkms} = Amount (in units) of commodity of type *m* needed to be transported from DC node *j* to affected area node *k* under scenario *s*.

$\triangle_{kms}$ = Amount of unserved demand or shortage (in units) of commodity type *m* at affected location *k* under scenario *s*.

IN_{jms} = Amount of prepositioned commodity of type *m* at DC node *j* under scenario *s*.

Non-integer variable

IN_{jm} = Amount of prepositioned commodity of type *m* at DC node *j*.

Binary variables

μ_{hj} = 1 if a warehouse of capacity *h* is established at node *j*, '0' otherwise.

Sup_i = 1 if supplier at node *i* is selected, '0' otherwise.

3.3.1.2 Model and Description

Model

Objective functions,

1. Max $\Sigma_h \Sigma_j WC_h \cdot \mu_{hj}$
2. Max $\Sigma_m \Sigma_i \Sigma_c Sup_i \cdot SR_{cim} \cdot \mathrm{G}_{cm}$
3. Min $\Sigma_s \ \rho_s \ (T_1 \cdot \Sigma_i \Sigma_j \Sigma_m \mathrm{LS}_{ij} \cdot S_{ijms} + T_2 \cdot \Sigma_j \Sigma_k \Sigma_m \mathrm{LS}_{jk} \cdot R_{jkms})$
4. Min $\Sigma_s \ \rho_s \ (\Sigma_k \Sigma_m \frac{\triangle_{kms}}{D_{kms}})$

Subject to,

Supplier and Facility location selection constraints

$\Sigma_h \Sigma_j F_{hj} \cdot \mu_{hj} \leq \mathrm{BL}$

$\Sigma_h \mu_{hj} \leq 1 \qquad \forall j$

$\Sigma_i \ Sup_i \leq \mathrm{NS}$

Relief goods flow constraints

$\Sigma_i S_{ijms} \geq \Sigma_k R_{jkms} \qquad \forall j, m, s$

Capacity constraints

$\Sigma_j S_{ijms} \leq \mathrm{C}_{ims} \cdot Sup_i \qquad \forall i, m, s$

$\Sigma_i \Sigma_m \ S_{ijms} \cdot \mathrm{U}_m \leq \Sigma_h \mathrm{WC}_h \cdot \mu_{hj} \qquad \forall j, s$

Shortage/Unsatisfied demand constraints

$\triangle_{kms} = \mathrm{D}_{kms} - \Sigma_j R_{jkms} \qquad \forall k, m, s$

Equality constraints for prepositioning of relief commodities at DC nodes

$IN_{jms} = \Sigma_k \mathrm{R}_{jkms} \qquad \forall j, m, s$

$$IN_{jm} = \Omega \, . \frac{\sum_s \mathrm{W}_s \, . \, IN_{jms}}{\sum_s \mathrm{W}_s} \qquad \forall j, m$$

Equity constraint

$$\frac{\triangle_{kms}}{D_{kms}} \leq \theta_{km} \qquad \forall k , m , s$$

Non-negativity constraints

μ_{hj} , $Sup_i \in (0,1)$

S_{ijms} , R_{jkms} , $\triangle_{kms}$, $IN_{jms} \geq 0$ (Integer variables)

$IN_{jm} \geq 0$ (non-integer variable)

Model description

Model 1 has four objectives. First objective tends to maximize the available warehouse capacity for storage of relief goods by setting up warehouses of appropriate capacity at appropriate location while staying with in the budgetary limit. The second objective maximizes total supplier ratings. The third objective aims to minimize the total transportation cost of different relief goods across different network nodes, across all scenarios. The fourth objective minimizes the ratio of total unsatisfied demand, to the total demand, for all relief goods, in different affected area nodes, across all scenarios.

There is a total of 18 constraints in this model. The first two constraints, constraint 1 and 2, are suppler and facility location selection constraints. Constraint 1 ensures that the total cost of setting up the warehouses across the network don't exceed the available budget. Constraint 2 ensures that any prospective Distribution Center (DC) location don't get to have more than one facility of any capacity. Constraint 3 ensures that the total number of suppliers selected by the model does not exceed the maximum allowable number of supplier limit.

Constraint 4 is a relief goods flow constraint. Constraint 4 ensures that the total amount of goods that are being transported from a particular DC location to different affected nodes, is not more than the total amount of goods that the DC location is receiving from different suppliers. Constraint 5 and 6 are capacity constraints. Constraint 5 ensures that the amount of goods or commodity transferred from different suppliers to the DC locations, stays within the capacity limit of that supplier for that specific good. Constraint 6 ensures that the total amount of goods that are being received in different DC locations, does not exceed the capacity of that specific Distribution Center facility.

Constraint 7 to 10 are equality constraints. Constraint 7 basically defines the amount of unsatisfied demand variables for each affected area node. Constraint 8 explains how the prepositioned goods amount under each scenario will be defined. Constraint 9 explains how the actual prepositioned goods amount will be defined, which is not based on any specific scenario. Constraint 10 explains that the total weightage used for prepositioning must sum up to one.

Constraint 11 is an equity constraint for unsatisfied demand at each demand point, which makes sure that each affected area node gets equal priority. Constraint 12 and 13 identifies the binary variables in this model, which are the facility location and capacity selection variables and the supplier selection variables. Constraint 14 to 17 declares that all the integer variables in this model are positive numbers. Constraint 18 declares that the only non-integer variables in this model is also a positive number. The model hence itself is a mixed integer linear programming problem.

3.3.2 Model 2: Pre-disaster Stochastic Travel route selection model

3.3.2.1 Assumptions, Sets, Parameters and Variables

Assumptions

1. Tentative locations selected in the previous model for setting up warehouses and the selected supplier locations will be given in this route selection model as inputs.
2. Route lengths between different nodes will be measured using google maps. Route reliability under a certain scenario, is the probability that the route will be functional or operational under that certain scenario.
3. All scenarios used in the model are partially observable scenarios.
4. Probability of path fractions (RN_{ijpfs} , $\text{RN}_{jkp'f's}$) staying operational will be considered as independent of each other given each scenario.

5. The route selected via this second pre-disaster planning model will be assumed to be operational in the post-disaster period.

Sets

$i \in$ I → Set of supplier nodes

$j \in$ J → Set of Distribution Center (DC) nodes

$k \in$ K → Set of Affected Area (AA) nodes

p ϵ P → Set of possible routes to go from one supplier node *i* to another DC node *j*

p′ ϵ P′ → Set of possible routes to go from one DC node *j* to another AL node *k*

f ϵ F→ Set of possible fractions of routes to go from one supplier node *i* to another DC node *j*

f ‘ϵ F’→ Set of possible fractions of routes to go from one DC node *j* to another AL node *k*

s ϵ S → Set of possible scenarios.

Stochastic Parameters

ρ_s = Probability of occurrence of scenario *s* (partially observable scenarios).

RN_{ijps} = Probability that path *p* will be functional between node *i* and *j* under scenario *s*.

$\mathrm{RN}_{jkp's}$ = Probability that path *p'* will be functional between node *j* and *k* under scenario *s*.

RN_{ijpfs} = Probability that path fraction *f* of route *p* will be functional between node *i* and *j* under scenario *s*.

$\mathrm{RN}_{jkp'f's}$ = Probability that path fraction *f'* of route *p'* will be functional between node *j* and *k* under scenario *s*.

$\mathrm{RN}_{ijps} = \prod_{f=1} \mathrm{RN}_{ijpfs}$

$\mathrm{RN}_{jkp's} = \prod_{f'=1} \mathrm{RN}_{jkp'f's}$

Deterministic parameters

L_{ijp} = Path distance from supplier node *i* to DC node *j* using route p.

$\mathrm{L}_{jkp'}$ = Path distance from DC node *j* to affected area node *k* using route p'.

Decision variables (Binary)

α_{ijps} = 1 if path *p* is chosen to transport commodity between supplier node *i* and DC node j, under scenario *s*, '0' otherwise.

$\beta_{jkp's}$ =1 if path *p'* is chosen to transport commodity between DC node *j* and affected area node k, under scenario *s*, '0' otherwise.

3.3.2.2 Model and Description

Model

Objective functions,

1. Min $\Sigma_s \Sigma_i \Sigma_j \Sigma_p L_{ijp} \cdot \alpha_{ijps} + \Sigma_s \Sigma_j \Sigma_k \Sigma_{p'} L_{jkp'} \cdot \beta_{jkp's}$
2. Max $\Sigma_s P_s \left(\Sigma_i \Sigma_j \Sigma_p RN_{ijps} \cdot \alpha_{ijps} + \Sigma_j \Sigma_k \Sigma_{p'} RN_{jkp's} \cdot \beta_{jkp's} \right)$

Subject to,

$\Sigma_p \alpha_{ijps} = 1 \qquad \forall i, j, s$

$\Sigma_{p'} \beta_{jkp's} = 1 \qquad \forall j, k, s$

$\alpha_{ijps}, \beta_{jkp's} \in (0,1)$

Model Description

Model 2 is a bi-objective model, since it has only two objectives. First objective tends to minimize the total travelling distances between different network nodes, across all scenarios. The second objective maximizes the total reliability of all the transportation arcs between different network nodes, across all scenarios. The reliability data for a certain route will be calculated from the historical records of that particular routes' condition after disastrous events.

There are total four constraints in this model. The first constraint ensures that exactly one route is selected to transport goods between any specific supplier node and any specific DC node. Constraint 2 ensures that exactly one route is selected to transport goods between any specific DC node and any specific affected area node. Constraint 3 and 4, indicate that both of the variables in this model are binary. So, this model is also an integer programming problem like the first pre-disaster model. From the nature of the formulation, it can be said that this model is actually a variant of a set partitioning problem.

3.3.3 Model 3: Post-disaster distribution and evacuation model

3.3.3.1 Assumptions, Sets, Parameters and Variables

Assumptions

1. This post-disaster distribution and evacuation model will contain only one scenario in it since the decision maker already know what scenario they are in at this point.
2. Tentative facility location, capacity data and the amount of prepositioned goods at DC locations data have been obtained in the first pre-disaster model, while appropriate routes to use for the transportation of goods was determined in the second pre-disaster model. All this output information will be given as input in this final post-disaster model.
3. Suppliers will be available under all scenarios. However, availability of different commodities might be different under different scenarios. Besides relief commodities, medical supplies will also be available from supplier locations.
4. Transportation of medical personnel has not been considered in the model, as they might not come to the service location together from some specific location. In fact, they might come from anywhere. That's why only the number of medical personnel required to carry out the medical services in different DC locations will only be in quested in the model, not their transportation.

5. A reasonable assumption will be made to determine the desired Patient-to-medical personnel ratio (λ) in the model. This parameter will be user defined.
6. Although some of the most vulnerable places were chosen as the possible affected locations at the pre-disaster period for the selection of appropriate facility location and selection of appropriate travelling routes, the actual affected location can change in the post disaster period. The post disaster model will still be applicable none the less. But in that case, before running the post disaster model, we have to run the pre-disaster route selection model to find the new appropriate routes to be used for transportation, which will be a required as input to the post-disaster model.
7. The final model also determines the number of trips required from vehicles of different capacity to transport relief goods and wounded people. In case of the transportation of medical supply, volume of medical supplies is difficult to assume, and they are usually not in large volume (as they are not used for serious treatment here, just for primary care). So, usually this small volume of medical supplies can be transported along with the relief goods without significant changes in the network design. Only the weight of the medical supplies is considered during transportation consideration.
8. From the output of the number of trips required for transportations, the model user or planning authority can decide on how many vehicles of different capacity they are going to use, depending on their economic capability.
9. Time required for all these relief activities has not been considered here. Time requirement has been assumed to be non-crucial here in this model.
10. Prepositioning of some relief goods in the pre-selected warehouses will be done to reduce load on transportation system at post-disaster period. The quantity of prepositioned goods will be determined using the scenario-based output data that we obtained in the first model and it will be given as input to this final post-disaster model. A user defined multiplier will be used to determine the final prepositioned amount of goods.
11. Unit transportation cost per kilometer is assumed to be higher in case of transportation to and from the effected locations due to the remoteness of those regions, compared to transportation from supplier to DCs.

12. Relief goods are assumed to be non-perishable in nature. However, when they are stored in DC location for prepositioning for a long time, a proportion of them might become unusable. This proportion will also be determined by the users as well.
13. Different types of relief goods will have different priority level and so does different types of injured people. Because of their different priority level, the amount of penalty associated with different types of unsatisfied demands or unserved wounded people, will be different.
14. If a new load of relief goods becomes available in the later stage of operation (like arrival of a new batch of aids from a foreign government later), they won't be able to directly send this aid to the affected area in this model. The new batch of aids must be sent to the supplier locations first and from there the relief goods will flow through the planned supply chain and thus make it to the affected locations eventually.
15. No vehicle can carry both commodities and injured people at the same time. As a matter of fact, the types of vehicles that carries commodity and the types of vehicles that carries people are different.
16. The transportation capacity, in terms of both weight and volume, for each vehicle types are known, both in case of transportation of commodities as well as for the transportation of injured people.
17. Each vehicle can complete multiple deliveries and each demand location can be visited multiple times with the same or different types of vehicles, if necessary.
18. An injured person is only considered served when he/she has been delivered to an emergency medical center, which situated at any of the DC locations.
19. Demand, available supplier capacity and usable fraction of that capacity will be obtained from the historical data. If required data is absent in any case, reasonable assumptions will be made to estimate those values.
20. Relief goods will be transported and distributed as unit loads. Broken case or split case/carton transportation will not be allowed here.

Sets

$i \in I \rightarrow$ Set of supplier nodes

$j \in J \rightarrow$ Set of Distribution Center (DC) nodes

$k \in$ K → Set of Affected Area (AA) nodes

$m \in$ M → Set of relief items type

$n \in$ N → Set of types of people who need medical evacuation

$h \in$ H → Set of capacity types of warehouses

$q \in$ Q → Set of vehicle capacity type required for relief items transportation

$e \in$ E → Set of vehicle capacity type required for people transportation

Parameters

All volume units are in cubic meter (m^3) and all money amounts are in unit of $1000

SL = Remuneration for each temporary medical personnel.

MC_n = Cost of each unit of medical supply to serve type n wounded people, who will be served in temporary medical facilities in DC nodes.

AMS_{in} = Available medical supply at supply node *i* to treat type *n* wounded people.

λ = Acceptable patient to medical personnel ratio.

TEV = Available number of total voluntary unpaid medical first aid workers.

T1 = Cost of post disaster transportation per km for per unit of medical supplies of type *n* transported from supplier *i* to DC *j*.

T2 = Cost of post disaster transportation per km for per unit of relief commodities transported from supplier *i* to DC *j*.

T3 = Cost of post disaster transportation per km for per unit of relief commodities transported from DC *j* to affected area *k* .

T4 = Cost of post disaster transportation per km for wounded people transferred from affected area *k* to DC *j* .

LE_{ij} = Actual pre-selected path distance from supplier node *i* to DC node *j*.

LE_{jk} = Actual pre-selected path distance from DC node *j* to affected area node *k*.

AV_q = Maximum allowable number of trips via type *q* vehicle.

AV_e = Maximum allowable number of trips via type *e* vehicle.

WH_j = Warehouse capacity at DC location *j*.

D_{km} = Estimated demand of aid commodity of type *m* at affected area *k*.

D_{kn} = Estimated demand of transporting wounded people of type *n* from affected area *k*.

Cap_q = volume capacity of cargo vehicle type *q*.

Cap_e = volume capacity of vehicle type *e*.

WL_q = Weight capacity (in kg) for type *q* vehicle.

WL_e = Weight capacity (in kg) for type *e* vehicle.

U_m = volume of commodity of type *m*.

W_m = weight of commodity of type *m*.

W_n = Average weight wounded people of type *n*..

C_{im} = Available capacity of supplier *i* for commodity *m* at post disaster period

SFR_{im}= Fraction of the commodity *m* remains usable at supplier *i* at post disaster period

FR_{jm} = Fraction of the prepositioned commodity *m* remains usable (unspoiled) at DC node *j* at post disaster period

IN_{jm} = Amount of prepositioned commodity of type *m* at DC node *j* (obtained from model 1)

WM_n = Unit weight of medical supply type *n* in kg.

VF_q , VF_e = Fixed cost associated with each trip made via vehicle type *q* and *e* respectively

θ_1 , θ_2 = Very small fractional numbers to ensure service equity at the affected areas; usually defined by the decision maker

τ_1 , τ_2 = These are the penalty cost values for unsatisfied relief goods demand and unserved wounded people, respectively.

Decision variables (all integers)

EV_j = Number of voluntary (unpaid) medical personnel at DC location *j*.

E_j = Number of paid medical personnel at DC location *j*.

MS_{jn} = Number of units of medical supplies to serve type n wounded people, who will be served in temporary medical facilities in DC node j.

S_{ijm} = Amount (number of pallets) of commodity of type *m* needed to be transported from supplier node *i* to DC node *j*

X_{jkm} = Amount (number of pallets) of commodity of type *m* needed to be transported from DC node *j* to affected area node *k*

Y_{kjn} = Number of wounded people of type *n* needed to be transported from affected area node *k* to DC node *j*

Z_{km} = Amount of shortage (in units) of commodity type *m* at affected area *k*

Z_{kn} = Number of unserved wounded people of type *n* at affected area *k*

V_{ijq} = Number of trips required by vehicle type *q* for commodity transportation from supplier node *i* to DC node *j*

V_{jkq} = Number of trips required by vehicle type *q* for commodity transportation from DC node *j* to affected area node *k*

V_{kje} = Number of trips required by vehicle type *e* for transportation of people from affected location node *k* to DC node *j*.

3.3.3.2 Model and Description

Model

Objective functions,

1. Max $\Sigma_j\ EV_j$
2. Min SL . $\Sigma_j\ E_j$ + T1. $\Sigma_i\ \Sigma_j\ \Sigma_n$ LE_{ij} . MS_{ijn}
3. Min T2. $\Sigma_i\ \Sigma_j\ \Sigma_m$ LE_{ij} . S_{ijm} + T3. $\Sigma_j\ \Sigma_k\ \Sigma_m$ LE_{jk} . X_{jkm} + T4. $\Sigma_j\ \Sigma_k\ \Sigma_n$ LE_{jk} . Y_{kjn}
4. Min $(\tau_1 .\ \Sigma_k\ \Sigma_m \frac{Z_{km}}{D_{km}} + \tau_2\ .\ \Sigma_k\ \Sigma_n\ \frac{Z_{kn}}{D_{kn}})$
5. Min $\Sigma_i\ \Sigma_j\ \Sigma_q\ VF_q . V_{ijq} + \Sigma_j\ \Sigma_k\ \Sigma_q\ VF_q . V_{jkq} + \Sigma_k\ \Sigma_j\ \Sigma_e\ VF_e . V_{kje}$

Subject to,

Medical supply and staffing constraints

$\Sigma_i\ MS_{ijn} \geq \Sigma_k\ Y_{kjn}$ $\quad \forall\ j, n$

$\Sigma_j\ MS_{ijn} \leq AMS_{in}$ $\quad \forall\ i, n$

$\lambda\ (EV_j + E_j) \geq \Sigma_k\ \Sigma_n\ Y_{kjn}$ $\quad \forall\ j$

$\Sigma_j\ EV_j \leq$ TEV

Capacity constraints

$\Sigma_j\ S_{ijm} \leq C_{im} . SFR_{im}$ $\quad \forall\ i, m$

$\Sigma_k\ X_{jkm} \leq \Sigma_i\ S_{ijm} + IN_{jm} . FR_{jm}$ $\quad \forall\ j, m$

$\Sigma_i\ \Sigma_m\ S_{ijm} . U_m + \Sigma_m\ IN_{jm} . U_m \leq WH_j$ $\quad \forall\ j$

Demand constraints

$\Sigma_j\ X_{jkm} \leq \mathrm{D}_{km}$ $\quad \forall k , m$

$\Sigma_j\ Y_{kjn} \leq \mathrm{D}_{kn}$ $\quad \forall k , n$

Unsatisfied demand and unserved people constraints

$Z_{km} = D_{km} - \Sigma_j X_{jkm}$ $\forall k, m$

$Z_{kn} = D_{kn} - \Sigma_j Y_{kjn}$ $\forall k, n$

Vehicular capacity constraints

$\Sigma_q \; V_{ijq} \,.\, \mathrm{WL}_q \geq \Sigma_m \; S_{ijm} \,.\, \mathrm{W}_m + \Sigma_n \; MS_{ijn} \,.\, \mathrm{WM}_n$ $\forall i, j$

$\Sigma_q \; V_{jkq} \,.\, \mathrm{WL}_q \geq \Sigma_m \; X_{jkm} \,.\, \mathrm{W}_m$ $\forall j, k$

$\Sigma_e \; V_{kje} \,.\, \mathrm{WL}_e \geq \Sigma_n \; Y_{kjn} \,.\, \mathrm{W}_n$ $\forall k, j$

$\Sigma_q \; V_{ijq} \,.\, \mathrm{Cap}_q \geq \Sigma_m \; S_{ijm} \,.\, \mathrm{U}_m$ $\forall i, j$

$\Sigma_q \; V_{jkq} \,.\, \mathrm{Cap}_q \geq \Sigma_m \; X_{jkm} \,.\, \mathrm{U}_m$ $\forall j, k$

Maximum availability constraints

$\Sigma_i \Sigma_j \; V_{ijq} + \Sigma_j \Sigma_k \; V_{jkq} \leq AV_q$ $\forall q$

$\Sigma_k \Sigma_j \; V_{kje} \leq AV_e$ $\forall e$

Equity constraints

$\frac{Z_{km}}{D_{km}} \leq \theta_1$ $\forall k, m$

$\frac{Z_{kn}}{D_{kn}} \leq \theta_2$ $\forall k, n$

Non-negativity constraints

EV_j , E_j , MS_{ijn} , S_{ijm} , X_{jkm} , Y_{kjn} , Z_{km} , Z_{kn} , V_{ijq} , V_{jkq} , $\mathrm{V}_{kje} \geq 0$

All variables are integers here

Model Description

Model 3 has five objectives. First objective aims to maximize the use of the volunteer medical personnel within the available limit. The second objective minimizes the total amount of salary paid to the non-volunteer medical personal and the total transportation cost of medical supplies to different DC nodes, across all scenarios. The third objective minimizes the total transportation cost of all relief goods and wounded people, across all scenarios. The fourth objective minimizes the total unsatisfied demands for all relief goods and the total number of unserved wounded people in different affected area nodes, across all scenarios. The fifth objective minimizes the fixed cost associated with total number of trips required for the transportation of all relief goods and wounded people to and from different network nodes, across all scenarios.

There are a total of 31 constraints in this model. The first four constraints, constraint 1 to 4, are medical supply and staffing constraints. Constraint 1 ensures that the total amount of medical supplies brought to a particular DC medical center is adequate to serve all the wounded people, who are coming in there from different affected areas. Constraint 2 ensures that the total amount of medical supplies brought to the DC medical centers, don't exceed the available supplier capacity limit. Constraint 3 ensures that each DC medical center location has sufficient number of medical staffs, volunteer or non-volunteer, to serve all the wounded people who are being transported into that particular DC location for medical attention. Constraint 4 ensures that the total number of volunteer medical staffs assigned to different DC medical centers, do not exceed the total available volunteer limit.

Constraint 5, 6 and 7 are capacity constraints. Constraint 5 ensures that the amount of goods or commodity transported in from different suppliers to the DC locations, stays within the capacity limit of that supplier for that specific good. Constraint 6 ensures that the amount of goods or commodity transported from a DC location to the affected are locations, do not exceed the amount of goods or commodity that has been brought in from different suppliers to that DC location, plus the amount of relief goods that has already been prepositioned in that DC location, during the pre-disaster planning phase. Constraint 7 ensures that the total amount of goods that are being received in different DC locations, does not exceed the capacity of that specific Distribution Center facility.

Constraint 8 and 9 are demand constraints. Constraint 8 ensures that the total amount of goods that are being transported from any DC locations to the affected area locations, is not more than the reported demand for that goods in that specific affected location, in order to avoid wastage of relief goods. Constraint 9 ensures that the total number of wounded people that are being transported into the different DC medical center locations for medical attention, from a particular affected area, is not more than the reported number of wounded people in that specific affected node.

Constraint 10 and 11 are equality constraints. Constraint 10 basically defines the amount of unsatisfied demand variables for each affected area node, while Constraint 11 defines the number of unserved wounded people variables for each affected area node.

Constraint 12 to 16 are vehicular capacity constraints. Constraint 12 ensures that the weight of the total amount of goods that are being transported from any supplier locations to any of the DC locations, using a specific vehicle type, does not exceed the safe weight carrying limit of that specific vehicle types in each respective cases. Constraint 13 ensures that the weight of the total amount of goods that are being transported from any DC locations to any of the affected area locations, using a specific vehicle type, does not exceed the safe weight carrying limit of that specific vehicle types in each respective cases. Constraint 14 ensures that the weight of the total number of wounded people who are being transported from any affected area locations to the DC locations for medical attention, using a specific vehicle type, does not exceed the safe weight carrying limit of that specific vehicle types in each respective cases.

Constraint 15 ensures that the volume of the total amount of goods that are being transported from any supplier locations to any of the DC locations, using a specific vehicle type, does not exceed the safe volumetric carrying limit of that specific vehicle types in each respective cases. Constraint 16 ensures that the volume of the total amount of goods that are being transported from any DC locations to any of the affected area locations, using a specific vehicle type, does not exceed the safe volumetric carrying limit of that specific vehicle types in each respective cases.

Constraint 17 and 18 are called maximum availability constraints. Constraint 17 ensures that the total number of trips that are being performed using a certain type of vehicles for transporting relief goods to different nodes of the network, does not exceed the maximum allowable number of trips that are permitted by using that specific type of vehicle. Similarly, constraint 18 ensures that the total number of trips that are being performed using a certain type of vehicles for transporting wounded people, from different affected area to different DC medical center nodes, does not exceed the maximum allowable number of trips that are permitted by using that specific type of vehicle.

Constraint 19 and 20 are equity constraints for unsatisfied demand and unserved wounded people respectively at various demand points, which makes sure that each affected area node gets equal priority. Constraint 21 to 31 declares that all the variables in this model are positive numbers and integers. The model hence itself is an integer programming model.

Chapter 4

Multi Criteria Optimization and Mixed Integer Programming Methods

4.1 Multi Criteria Optimization

A Multi criteria or Multi-objective optimization problem is quite different from a single objective ones' in many ways. There are several popular ways to handle multi-objective optimization problems, like

- The Scalarization (weighted sum) Technique
  In this method a multi objective problem can be handled like a single objective one by multiplying each objective with a suitable and reasonable weight and then adding them together. This technique of handling a multi-objective is often preferred by many researchers because of its simplicity and ease of prioritization of any specific objective(s). Weights are usually defined by the user or decision makers. Users are free to manipulate weights in this method based on the relative importance of the objectives from their point of view.

- ε-Constraints Method
  In this method of handling multi-objective problem, usually all the objectives, except one, is converted to constraints. The objectives that are turned into constraints are restricted within some user specified values (ε). That's where the name of the method comes from. This method can be used for both convex or non-convex problems. But this method doesn't have as much flexibility as the scalarization technique when it comes to prioritizing objective(s).

- Goal Programming

  In goal programming method, all the objectives of a multi-objective problem are turned into a goal constraint and a penalty cost is associated with not achieving each goal. The only objective of the problem becomes the maximization/minimization of the total penalty cost depending on the type of problem we are trying to solve. It does give users freedom to better manipulate the objective priority by manipulating the corresponding penalty cost. But in terms of simplicity, scalarization techniques is simpler.

Since in this research we want to give the decision makers or users better freedom to choose the priority of each of the objectives, and also considering the reality that not all our users/decision makers of this research might not always be mathematically or technically proficient, we decided to use the Scalarization technique for all three of the multi-objective models in this research, since Scalarization technique uses a simpler approach when it comes to setting up objective priorities and easier handling of their relative weights.

In a multi-objective optimization problem, a solution may be optimal with respect to one objective or sometimes, even in terms of the total fitness, but may be a poor candidate for a particular objective. For a minimization problem, even if a certain solution set has the minimum total combined objective function value, it may not be the best solution, with respect to all the objectives of the model, simultaneously. Therefore, in multi-objective solution methods, we do not try to find one optimal solution, but often try to generate multiple trade off optimal solutions, which are more commonly known as ‘Pareto Optimal Solutions’. As none of these ‘Pareto optimal solutions’ can be declared as better than others, they are often also called as ‘Non-Dominated Pareto Optimal Solutions’.

In case of non-dominated Pareto optimal solutions, it eventually comes down to the decision makers (DMs), to choose solution that will work best for them. Usually this Pareto optimal solutions are generated by varying weights assigned to different objectives. So the DMs here usually tend to pick the solution that was generated with higher relative weight associated with the objective(s), which might be more important to them as decision makers.

4.2 Mixed Integer Programming Methods

When an optimization problem is desired to have different types of output values like decimal, integers or binary, that problem is then called a Mixed Integer Problem (MIP). In fact, most of the modern real-life optimization problems faced by researchers now a days are mostly MIP in nature. A Binary Integer Problem (BIP) is also a special type of MIP. In this research, all three developed models are either MIP, BIP or pure Integer Programming (IP) problem. Also, it needs to be mentioned that, in this research all the models in consideration are linear in nature. So, we will be focusing on MILP specifically.

There are many popular algorithms available to solve MILP problems. Branch and Bound (BB) is one of those very popular combinatorial optimization techniques, that is widely used for solving integer or mixed integer linear programs. The way BB works, that can often be compared to the looks of the branching of a tree. When solving an LP problem, when we get a non-integer value for a variable, which is supposed to be integer, the BB algorithm creates two branches, an upper branch and a lower branch , which are the closest upper and lower integer value of that recently obtained non-integer solution. This upper and lower branch is then added to the original problem as an additional constraint and solved. If the solution is infeasible or worse than the solution we already have, we discard them, otherwise they are kept. The algorithm keeps going this way. When we can't find any integer solution set which gives more desirable objective value than the current one, then we know that we have reached optimality.

Another widely used MILP solving method is Branch and Cut, which is basically a combination of Branch and Bound and Cutting Plane method. At the beginning this method, an LP problem is solved by using just the regular simplex method. Once an optimal solution is obtained for the LP problem, if a non-integer value is obtained for a certain variable(s), which is supposed to be integer, a cutting plane method is used, to impose or add more linear constraints in the problem. These additional constraints are satisfied by all feasible integer points only (non-integer solutions don't satisfy them). At this point, the branch and bound part of the algorithm kicks in and the process keeps going this way. A node can be pruned if an upper bound is lower than an existing lower bound. Further cuts can also be made later on if necessary. Because of the way it works, it is also known as an 'Exact Algorithm'.

Popular commercially available solver platforms like CPLEX and GUROBI often uses Branch and Cut algorithm to solve various real-life complex integer or mixed integer programming problems, like Job Shop Scheduling problem, Vehicle Routing Problem, Travelling Salesman Problem etc. In this research, since all of our model are either integer or mixed integer type, we will be using this Branch and Cut algorithm via CPLEX platform to solve the models. At chapter 6 (Results and Discussion), we will be demonstrating the outputs we obtained using the methods discussed in this chapter in details.

Chapter 5

Numerical Test Case

To test the effectiveness of the models developed in this research we need a numerical test case. Since the whole research was performed with an aim to help the decision makers of less developed part of the world to develop an effective humanitarian logistics networks to minimize cost, human casualty and suffering, the author of this research decided do pick a test case from his own home country which happen to be in the lesser developed part of the world.

In this numerical case we focused on developing an effective relief network at Sylhet District, Bangladesh to help the local decision makers to deal with the monsoon flash flood situations.

Figure 5.1: 2019 flash flood in Sylhet (Photo Credit: BDNEWS24.com)

Figure 5.2: 2017 flash flood in Sylhet (Photo Credit: The Daily Sun BD)

Figure 5.3: 2016 flash flood in Sylhet (Photo Credit: The Daily Star)

In mostly agricultural country like Bangladesh, rivers are usually important asset. But in a District like Sylhet, these rivers are both boon and a curse. In dry season the rivers like Surma, Kushiara and Shari-Goyain are of great help since they supply most of the water that is required for agricultural irrigation in the nearby mostly agricultural areas. Origin of all these rivers are from nearby hilly region of India. At monsoon, if there are too much rain in the Indian up-stream hilly region, this large amount of water rushes through these rivers, mostly through Surma and Kushiara, in the down-steam regions of Sylhet, Bangladesh. Being a lower area than the Indian up-stream and due to heavy sedimentation, these rivers can't always hold this sudden deluge of water and for obvious reason they inundate the surrounding, mostly agricultural areas. These floods are called "flash" floods as they stay for a short period of time, like less than 7 to 10 days, but causes large economical damage and human suffering to the surrounding areas. Crops in the nearby agricultural area get washed away, on which people of those area mostly subsists on. In such situations, people in that area will starve to death, if the relief agencies don't promptly respond to their needs for relief. These flash flood problems in that area of Bangladesh is recurrent in nature as it occurs in every one or two years in most cases.

In case of a disastrous situation, most underdeveloped counties don't usually have well developed alert system like the ones' developed countries have. Many people living in the countryside or rural region don't have proper access to internet and other modern communication facilities to stay updated on any local crisis situations that might develop within a very short notice. Most of them don't own private transportation (like cars or trucks), that might allow them to evacuate themselves quickly without any help from the local disaster management authorities. Hence, they mostly rely on local authorities to manage the relief distribution and evacuation, when necessary.

So a good working relief logistic model can be of great help to them and can reduce these casualties to a great extent. Because of the lack of an efficient, easy and inexpensive planning system, even at this decade, the local decision makers in those counties make most of their logistics decision based on pure hunch or sometimes based on previous experience, instead of using mathematical models to help them in every step of planning.

Figure 5.4: Geographical location of Bangladesh (Source: Wikipedia)

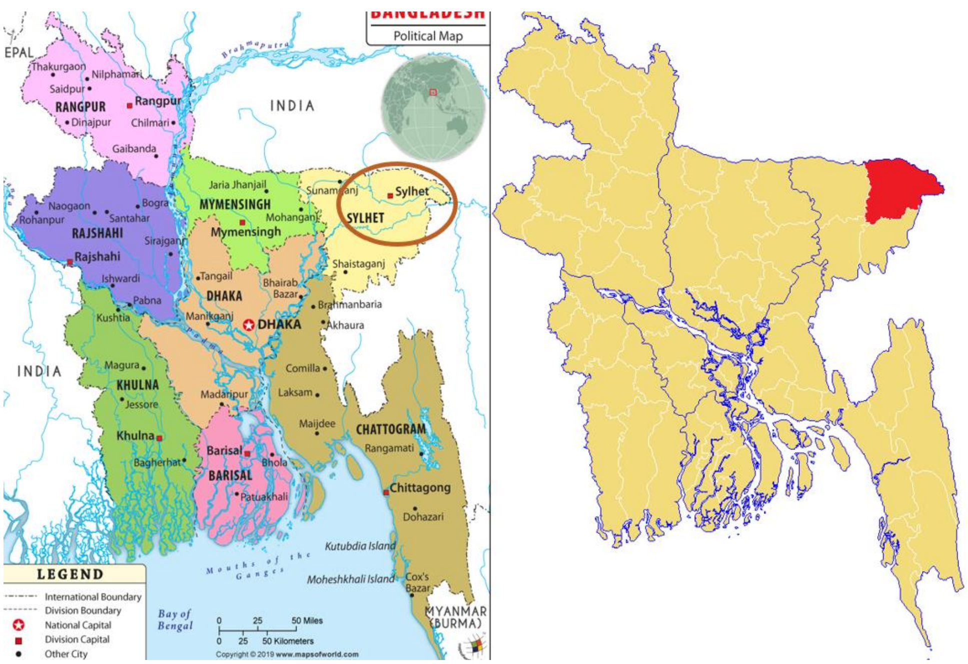


Figure 5.5: Focus region of our study in Bangladesh (Sylhet District Location) (Source: Wikipedia)

Figure 5.6: River networks in Bangladesh (Source: Banglapedia)

Literatures like Akkihal [2006] and Balcik and Beamon [2008] suggested using historical relief demand for disastrous incidents. But, one of the problems in working cases in under-developed countries like Bangladesh, is that their data collection process and extent of data collection is neither very efficient nor very comprehensive. It is sometimes difficult to collect data from the local government websites. Because, even at 2019, many of the local government offices have not yet computerized all the data that they have collected previously in cases of different humanitarian crisis situations. Due to this lack of computerization and sometimes lack of efficient and comprehensive bookkeeping, there are often many missing data. Author of this study was, however, able to collect majority of the required data from the local sources and domain experts (like Subject Matter Experts (SMEs) in the local administrative authorities). In some cases, for a few missing data here and there, author had to make reasonable assumptions based on the best judgement to construct the numerical case, which is necessary to check the effectiveness of the proposed models.

Tentative demand and supplier capacity data was collected from SMEs of the local relief authority. As mentioned previously, that proper information or historical demand records are not always available to the local relief authority due to lack of proper data management. So after collecting whatever data was available to the local offices, the rest of the missing data were estimated by using best judgement. Other parameter values like type and capacity of the vehicles used, vehicle rents, penalty cost for demand shortage etc. were reasonably estimated in perspective of the socio-economic situation of Bangladesh. All the parameter values are given in the following section.

There are three prospective Distribution Center (DC) warehouse facility capacity types (small, medium and large) that can be set up at candidate locations to store relief goods, before dispatching them to the affected areas:

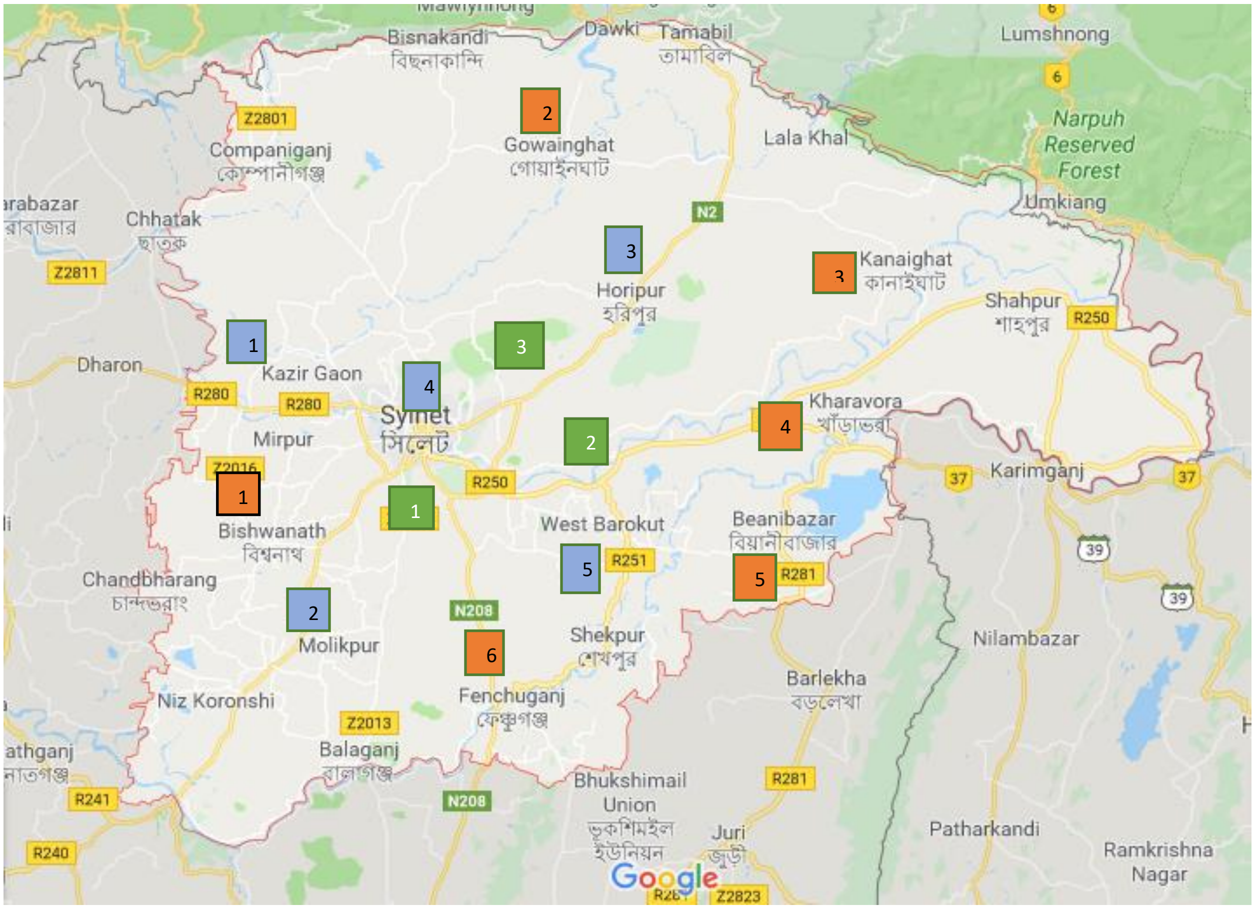
Table 5.1: DC warehouse capacity types

Obs. No.	Capacity type	Capacity (in cubic meter)
1	Small	200
2	Medium	400
3	Large	600

Five prospective locations have been selected for constructing DC warehouse facilities:

Table 5.2: Prospective DC facility locations

Position no.	Tentative location
1	Kazirgaon, Sylhet
2	Molikpur, Sylhet
3	Horipur, Sylhet
4	Sylhet Shadar, Sylhet
5	West Barokut, Sylhet



Prospective supplier location nodes

Prospective DC location nodes

Prospective Affected Area nodes

Figure 5.7: Sylhet District Map

There are three potential supplier locations, from which the model has to select at least two suppliers. Three prospective supplier locations are as following:

Table 5.3: Prospective Supplier locations	
location no.	Tentative locations
1	Bodikuna, Sylhet
2	Phulbari, Sylhet
3	Atgaon, Sylhet

Six locations have been selected based on historical deserter strike records as prospective affected areas for distributing relief goods directly to the affected population:

Table 5.4: Prospective Affected Area location	
location no.	Tentative location
1	Bishwanath, Sylhet
2	Gowainghat, Sylhet
3	Kanaighat, Sylhet
4	Kharavora, Sylhet
5	Beanibazar, Sylhet
6	Fenchuganj, Sylhet

There are two types of relief goods to be distributed– food and water. Unit description of each good are as following:

Table 5.5: Volume and weight of a single unit of relief goods			
Sl. No.	Item type	Unit volume in cubic meter	Unit weight in kg
1	Food	0.5	190
2	Water	0.5	130

Transportation costs from supplier to DC and from DC to Affected Area have not been considered equal. Transportation cost in former case is usually higher than the transportation cost in later case, because in the post disaster period transportation facility and road condition in the affected area are usually worse, due to the impact of the catastrophic incident.

Considering the local economy and pricing, per unit transportation cost from supplier to DC for all type of relief goods has been determined as 4$ per unit load/ km and per unit transportation cost from DC to Affected Area for all type of relief goods has been considered as 6.25 $ per unit load/ km. Per person transportation cost from AAs to the medical centers located at DCs for all type of wounded people has been considered as 12 $ per person/ km.

This test case has considered three disaster scenarios where scenario 1 represents the least severe situation and the severity increases in the later ones. The probability of occurrence of each scenario have been obtained using the available historical data. All scenarios considered here are partially observable scenarios. The calculated probability values are as following:

Table 5.6: Probability of occurrence for the partially observable scenarios	
Scenarios	Probability of occurrence
1	0.46
2	0.31
3	0.23

Under each scenario, the demand data for each type of relief goods in each affected area (in units) are as following:

Table 5.7: Demand data for Scenario 1 (in units)		
Affected Area No.	Relief good types	
	Type 1	Type 2
1	46	21
2	58	26
3	33	19
4	48	29
5	62	34
6	53	27

Table 5.8: Demand data for Scenario 2 (in units)		
Affected Area No.	Relief good types	
	Type 1	Type 2
1	57	31
2	69	35
3	43	28
4	58	40
5	72	43
6	65	38

Table 5.9: Demand data for Scenario 3 (in units)		
Affected Area No.	Relief good types	
	Type 1	Type 2
1	78	36
2	99	42
3	55	34
4	82	51
5	97	56
6	89	44

Under each scenario, the supplier capacity data for each type of relief goods (in units) are as following:

Table 5.10: Supplier capacity data for Scenario 1 (in units)		
Supplier No.	Relief good types	
	Type 1	Type 2
1	295	234
2	263	219
3	253	214

Table 5.11: Supplier capacity data for Scenario 2 (in units)		
Supplier No.	Relief good types	
	Type 1	Type 2
1	322	256
2	286	240
3	278	233

Table 5.12: Supplier capacity data for Scenario 3 (in units)		
Supplier No.	Relief good types	
	Type 1	Type 2
1	498	395
2	445	367
3	361	253

In this problem the initial budget for opening required number DCs has been assumed to be \$400,000. Facility setup costs at different tentative DC locations for three different capacity types are as following:

Capacity type / DC location	1	2	3
1	71	108	127
2	67	104	125
3	78	112	136
4	83	124	141
5	76	115	129

Table 5.13: Facility setup costs (in terms of $10,000)

All the distances among different nodes of the network have been collected from Google Map using car-route option. If there are multiple routes to choose from between nodes, then the multiple route distances are written with commas. Distance between different supplier nodes and DC nodes are given in km as following:

Supplier no. / DC location	1	2	3
1	17,22,19	30,28	72,87
2	33,27	46,52,58	49,47
3	34,30,32	25,27	15,11,13
4	16,14	28,32,29	24,22
5	22,20,24	9,12,14	24,19,21

Table 5.14: Distances between different supplier and DC nodes (in km)

Distance between different DC nodes and affected area nodes in km are as following;

DC location / Affected Area nodes	1	2	3	4	5
1	24,26	17,15	46,43	29,25,27	34,41,38
2	46,40	71,79,76	32,29,35	38,37	51,58
3	62,65,63	87,84	29,33	59,63,61	56,42,48
4	56,59	83,70	52,58,55	60,57,58	28,33
5	55,52	66,71,79	49,61,52	56,53	20,18,22
6	48,53,59	75,62	53,51,55	49,60,54	43,42

Table 5.15: Distances between different DC and AA nodes (in km)

Two types of vehicles are available for transportation. Their capacities are as following;

Vehicle type	Volume Capacity (in cubic meter)	Towing (weight) capacity in kg
1	4	1400
2	6	1700

Table 5.16: Vehicle types and capacities

Maximum available number of trips from different types of vehicles are as follows

Vehicle type	Maximum number of available trips
1	80
2	120

Table 5.17: Maximum available number of trips from vehicles

Notable that in this research work, we did not try to find the number of vehicles required. Instead we tried find out number of trips required to perform all the necessary logistics activity. We left it on decision makers to decide how many vehicles they are going to use to make the number of required trips.

Higher amount of unserved demands and unserved wounded people indicate higher amount of human suffering and reducing human suffering is very important to design an effective relief supply chain. To consider unserved demands and unserved wounded peoples at affected areas in monetary terms, we will assign penalty cost with them. So, there will be two types of penalty costs here – penalty for unserved demands at affected areas and penalty for unserved wounded peoples in the affected areas. To ensure the best performance of this logistics model, it is imperative to keep this total penalty cost as close to zero as possible. Penalty costs are as following;

Item type	Penalty for unserved demands (in US $)
1	80
2	65

Item type	Penalty for unserved wounded people (in US $)
1	75
2	90

Table 5.18: Penalty Costs

Evaluation criteria	Importance weight of the criteria for each commodities type (M1, M2)		Rating for each commodities type (M1, M2)					
			Supplier 1		Supplier 2		Supplier 3	
	M1	M2	M1	M2	M1	M2	M1	M2
Item cost	4	3	9	8	8	7	7	8
Quality	4	4	9	7	9	8	8	7
Delivery lead time	2	3	8	9	10	8	9	8

Table 5.19: Supplier rating data for supplier selection

Affected Area (AA) No.	Wounded People types	
	Type 1	Type 2
1	29	18
2	34	21
3	25	17
4	41	26
5	31	24
6	27	16

Table 5.20: Data for number of wounded people to be evacuated under scenario 1

Route reliability values (scenario 1)

Supplier no. / DC location	1	2
3	0.87,0.91,0.94	0.85,0.88
4	0.89,0.93	0.92,0.87,0.94
5	0.94,0.88,0.91	0.93,0.86,0.92

Table 5.21 : Supplier- DC route reliabilities under scenario 1

DC locations / Affected Areas location	3	4	5
1	0.91,0.88	0.86,0.89,0.87	0.84,0.87,0.91
2	0.86,0.92,0.95	0.92,0.88	0.82,0.87
3	0.81,0.86	0.87,0.89,0.88	0.89,0.85,0.91
4	0.88,0.84,0.90	0.91,0.95,0.89	0.88,0.92
5	0.92,0.87,0.96	0.89,0.94	0.91,0.86,0.92
6	0.83,0.88,0.93	0.90,0.87,0.85	0.93,0.91

Table 5.22 : DC-AA route reliabilities under scenario 1

Route reliability values (scenario 2)

Supplier no. / DC location	1	2
3	0.83,0.88,0.91	0.82,0.85
4	0.87,0.89	0.87,0.84,0.88
5	0.88,0.86,0.83	0.91,0.82,0.86

Table 5.23 : Supplier- DC route reliabilities under scenario 2

DC locations / Affected Areas location	3	4	5
1	0.89,0.85	0.84,0.86,0.83	0.82,0.81,0.86
2	0.84,0.87,0.92	0.89,0.85	0.78,0.84
3	0.79,0.83	0.82,0.86,0.83	0.86,0.81,0.87
4	0.85,0.82,0.85	0.89,0.91,0.84	0.85,0.88
5	0.87,0.85,0.91	0.84,0.89	0.87,0.82,0.87
6	0.81,0.85,0.89	0.87,0.84,0.81	0.89,0.86

Table 5.24 : DC-AA route reliabilities under scenario 2

Route reliability values (scenario 3)

Supplier no. / DC location	1	2
3	0.81,0.86,0.88	0.79,0.81
4	0.84,0.86	0.85,0.82,0.86
5	0.84,0.82,0.81	0.87,0.78,0.83

Table 5.25 : Supplier- DC route reliabilities under scenario 3

DC locations / Affected Areas location	3	4	5
1	0.86,0.82	0.79,0.82,0.81	0.79,0.76,0.82
2	0.81,84,88	0.83,0.82	0.76,0.81
3	0.75,0.79	0.76,0.80,0.82	0.78,0.75,0.83
4	0.83,0.74,0.81	0.85,0.87,0.79	0.81,0.83
5	0.84,0.79,0.87	0.81,0.87	0.82,0.78,0.83
6	0.76,0.82,0.86	0.83,0.80,0.78	0.84,0.77

Table 5.26 : DC-AA route reliabilities under scenario 3

There are some other parameter data as well which are required in model 3. Transportation cost for medical supplies in model 3 is considered higher than regular per unit/per km transportation cost, because they often need special packaging and handling to avoid any damage. Transportation cost for both type of medical supplies is $9 per unit /km. Weight of each unit of medical supplies (which includes mostly medicines, gauge/bandage, light medical equipment's like stethoscope, thermometer, blood pressure machine etc. primary care tools) of either type is considered as 4 kg. Acceptable patient to medical personnel ratio was taken as 3. Average weight of a wounded person was considered as 85 kg. Total available volunteer (un-paid) medical personnel was assumed as 35. It was assumed that supplier had 90% of their usual capacity available during the post disaster period. It was also assumed that about 94% of the prepositioned commodity was unspoiled during post disaster period. Fixed cost for each vehicle trip has been considered 1.2 times higher for the bigger category than the smaller one.

User defined parameters will vary depending on decision makers. For our research purpose, we considered all θ (equity constraints limit) as 0.10 or 10%. We considered the proportion of the goods to be pre-positioned as Ω = 16%. Salary for each paid (non-volunteer) medical personnel for a 10 days' work period, was considered as $1000 for per person. In some cases where actual data was not available, we made reasonable assumptions to run the models properly.

Chapter 6

Results and Discussions

In this research work, a multi-echelon humanitarian logistics network has been developed. The research comprises of three multi-criteria optimization models, which, together, helps the decision maker to design an effective and efficient relief logistics network. Since all disasters involves a noticeable degree of uncertainty, so scenario-based approach was used to deal with the stochastic parameters in all models. To show the effectiveness of the developed models, a numerical test problem has been developed in the last chapter and it is implemented in all three models and then they are solved by Branch and Cut Algorithm using CPLEX solver v12.8. The computer used to run the solver had a 2.65 GHz processor and 4 GB RAM. In this chapter we are going to discuss the results obtained from the CPLEX for all three models and their significance. Since all three of our models are multi-objective, we used a Scalarization or Weighted Sum approach to deal with those multi-objective problems. The weight we choose in each case here is quite important, as the weight value significantly influences the final optimized objective values and sometimes the optimized variable values as well.

6.1 Results from Model 1: Pre-disaster Supplier and Facility Selection Model

The first pre-disaster supplier selection and facility planning model is a MILP model with four objectives. In this attempt, we considered the weight values for the corresponding objectives as 10, 25, 35 and 190. Decision variables in this model are;

μ_{hj} = 1 if a warehouse of capacity *h* is established at node *j*, '0' otherwise. (**Binary Var.)**

Sup_i = 1 if supplier at node *i* is selected, '0' otherwise. (**Binary Var.)**

S_{ijms} = Amount (number of pallets) of commodity of type *m* needed to be transported from supplier node *i* to DC node *j* under scenario *s*. (**Positive Integer Var.)**

R_{jkms} = Amount (number of pallets) of commodity of type *m* needed to be transported from DC node *j* to affected area node *k* under scenario *s*. (**Positive Integer Var.)**

$\triangle_{kms}$ = Amount of unserved demand (in number of pallets) of commodity type *m* at affected location *k* under scenario *s*. (**Positive Integer Var.)**

IN_{jms} = Amount of prepositioned commodity of type *m* at DC node *j* under scenario *s*. (**Positive Integer Var.)**

IN_{jm} = Amount of prepositioned commodity of type *m* at DC node *j* (**Positive Non-integer Var.)**

The results obtained from CPLEX for this model and the test case are shown in the table below. Only the variable that returned any non-zero value has been displayed in the following table. If any variable(s) has not been displayed in the table, assume a 'zero' value for them. Since integer variable IN_{jms} doesn't carry any decision-making significance, so it won't be showed or discussed here either. But outputs obtained for IN_{jm} will be shown here, as it is an important non-integer output variable that will be used as inputs in model 3 later.

Facility No.	Variable µ jh	Variable value (binary)
1	µ 32	1
2	µ 43	1
3	µ 53	1

Supplier No.	Variable Sup i	Variable value (binary)
1	Sup 1	1
2	Sup 2	1

Arc Type	Variable (Integer)	Scenario 1	Scenario 2	Scenario 3
Supplier to DC	S ijm			
	S231	33	43	55
	S232	19	28	34
	S141	104	126	177
	S142	47	66	78
	S251	163	195	268
	S252	90	121	151
DC to AA	R jkm			
	R411	46	57	78
	R412	21	31	36
	R421	58	69	99
	R422	26	35	42
	R331	33	43	55
	R332	19	28	34
	R541	48	58	82

Arc Type	Variable (Integer)	Scenario 1	Scenario 2	Scenario 3
DC to AA	R jkm			
	R542	29	40	51
	R551	62	72	97
	R552	34	43	56
	R561	53	65	89
	R562	27	38	44

Table 6.1: CPLEX output/solutions for model 1

DC location Number (j)	IN_{jm} (non-integer positive variable) values for Ω =16% from model 1	
	m=1	m=2
3	20.4176	9.6032
4	6.5856	4.0384
5	31.5312	18.1824

Table 6.2: Pre-positioned relief commodity quantity results obtained from model 1 for storing in the DC nodes (to be used as inputs in model 3 **after adjustment for spoilage**)

DC location Number (j)	$IN_{jm} \cdot FR_{jm}$ (Rounded to the closest integer) values for Ω =16% and spoilage FR_{jm} = 94%	
	m=1	m=2
3	19	9
4	6	4
5	30	17

Table 6.3: Pre-positioned **unspoiled relief commodity** quantity (rounded to the nearest integer) to be available in the DC nodes at post disaster period (**to be used as inputs in model 3**)

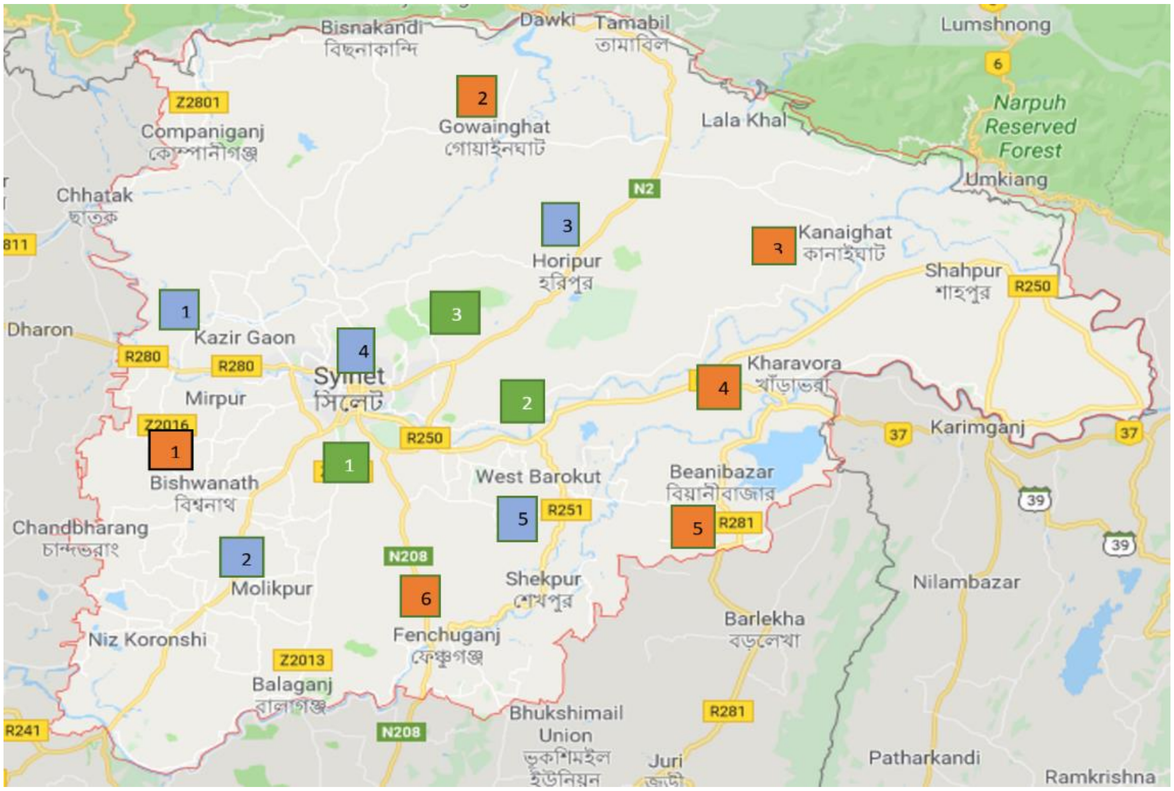
6.1.1 Pareto optimal solutions

Since this is a multi-objective optimization problem (MOOP), it can have multiple trade off optimal solutions, which are more commonly known as 'Pareto Optimal Solutions'. In case of non-dominated Pareto optimal solutions, it eventually comes down to the decision makers (DMs), which solution they want to pick. Usually they pick the solution that was generated with higher weightage associated with the objective(s), which is more important to them as decision makers. Some of the Pareto optimal solutions from our first model are shown in the table below:

Pareto solution number	Weights used for four objectives respectively	Objective 1 Facility Setup Cost (US $)	Objective 2 Suppliers' weighted rating (larger is better)	Objective 3 Transportation Cost (US $)	Objective 4 Total Penalty Cost (US $)
1	10, 25, 35, 190	3,820,000	8300	166,585	0
2	15, 20, 25, 125	3,590,000	6460	109,906	7750
3	20, 15, 30, 155	3,940,000	5025	124,876	4340

Table 6.4: Pareto optimal solutions obtained from model 1

From the table above, it is evident that, in this particular case, no single solution can be claimed as absolutely better than the others. Therefore, these Pareto optimal solutions can be called non-dominated. Here, the decision maker should choose the solution that suits him/her best. For example, if the decision maker thinks minimization of the total penalty cost for unsatisfied demands is more important, he/she should choose solution 1, or if he/she thinks minimization of the total transportation cost is more important, he/she should choose solution 2 and so on. Furthermore, an extensive sensitivity analysis can be performed in future (it has been mentioned in section 7.2 as future research recommendation), which can help decision maker to a greater extent to make the right decision by giving them more information regarding the influences of the different decision parameters and other inputs on the overall objectives.



0 Tentative Supplier locations
0 Tentative DC locations
0 Tentative Affected Areas

Figure 6.1: Preliminary Un-optimized network key locations

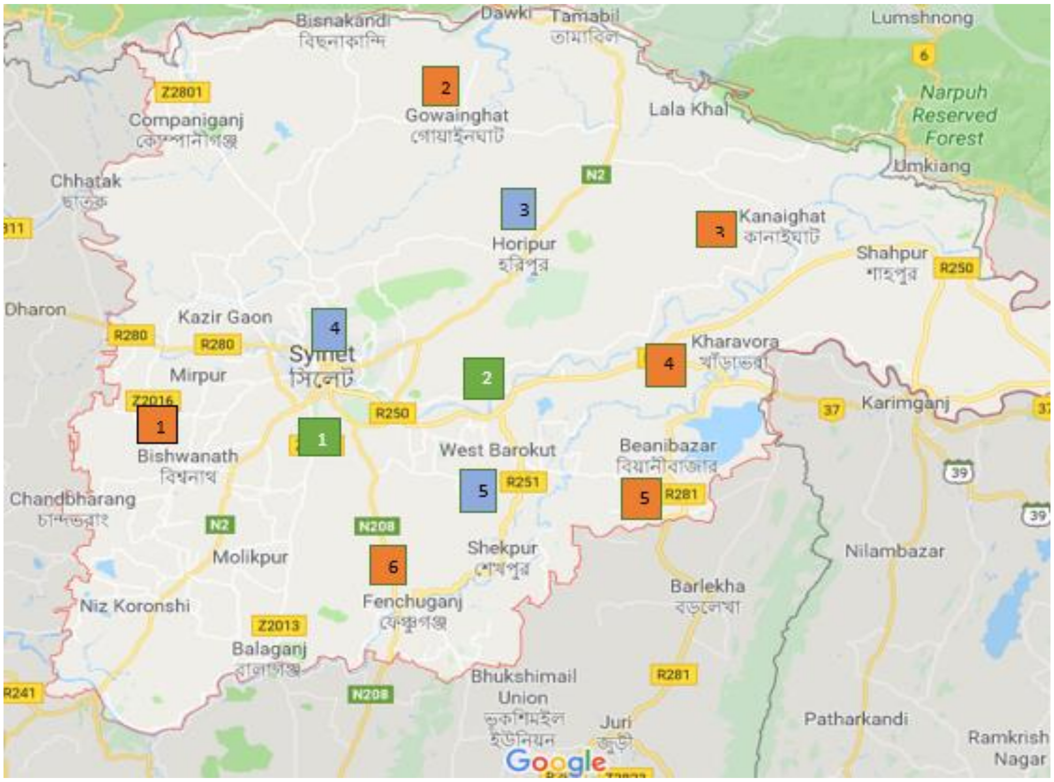


Figure 6.2: Optimized Locations (by model 1)

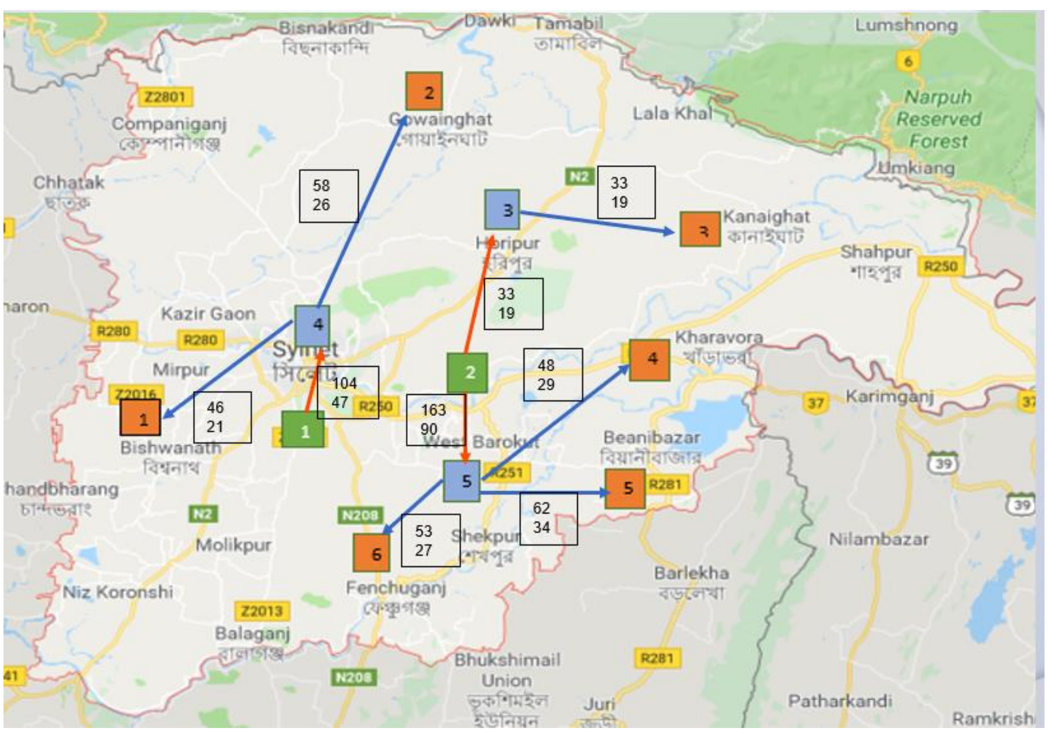


Figure 6.3: Optimized relief goods flow under scenario 1

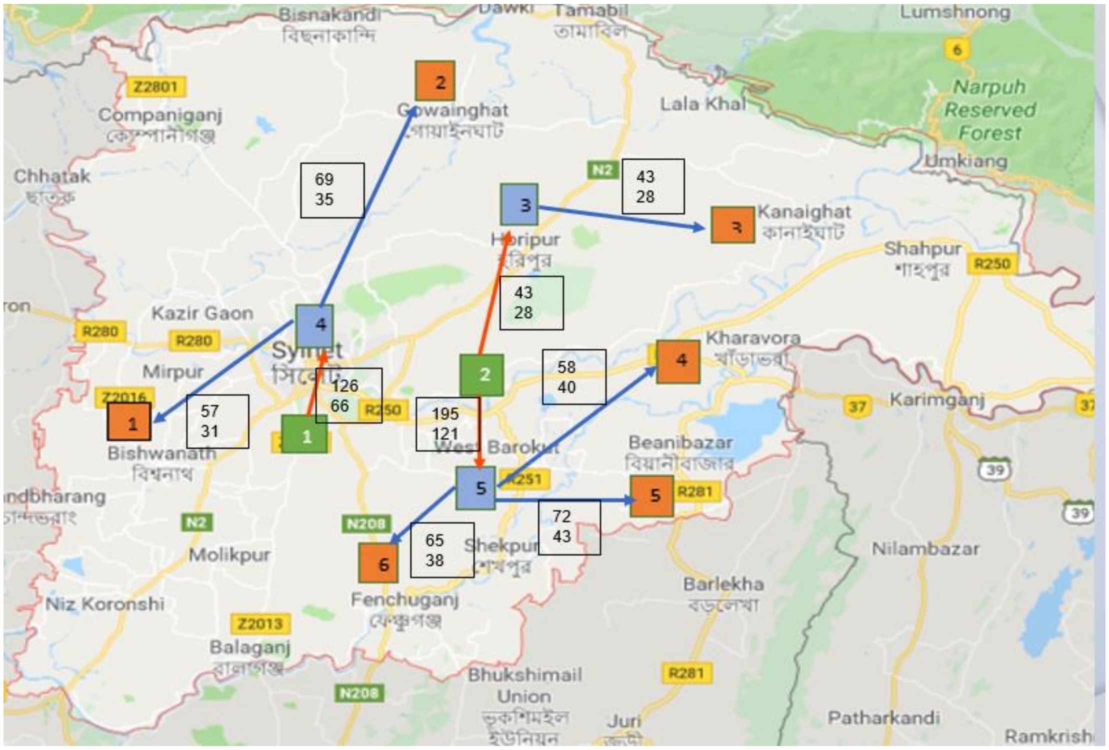


Figure 6.4: Optimized relief goods flow under scenario 2

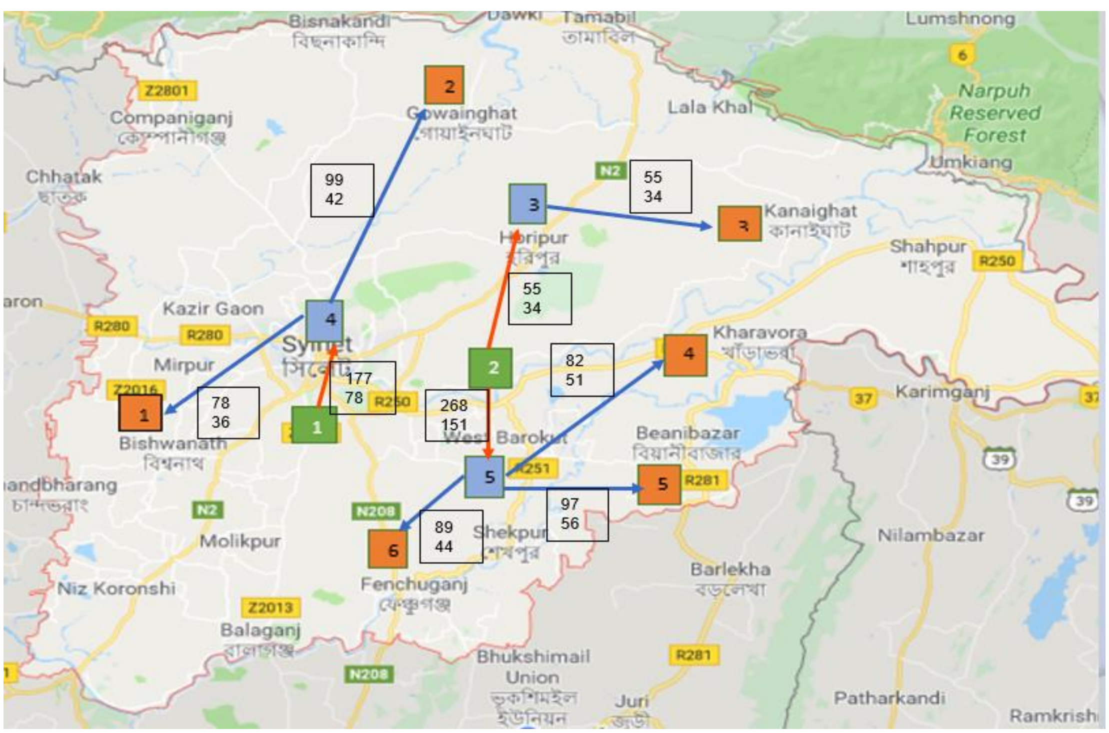


Figure 6.5: Optimized relief goods flow under scenario 3

6.2 Results from Model 2: Pre-disaster Route Selection Model

The second pre-disaster route selection model has also been solved by using CPLEX. Although, given the simplicity of this model, it can possibly be solved by other simpler solver platforms (like Microsoft Excel) as well. This model had two objectives. In this attempt, we considered the weight values for the corresponding objectives as 1 and 200. Decision variables in this model are;

α_{ijps} = 1 if path p is chosen to transport commodity between supplier node i and DC node j, under scenario s, '0' otherwise. (**Binary Var.)**

$\beta_{jkp's}$ =1 if path p' is chosen to transport commodity between DC node j and affected area node k, under scenario s, '0' otherwise. (**Binary Var.)**

The results obtained from CPLEX for this model and the test case are shown in the table below. Only the variable that returned any non-zero value has been displayed in the following table. If any variable(s) has not been displayed in the table, assume a 'zero' value for them;

Table 6.5: S-DC and DC- AA route selection results under different scenarios

α ij	Scenario 1	Scenario 2	Scenario 3		β jk	Scenario 1	Scenario 2	Scenario 3
13	3	2	2		31	2	2	2
23	2	1	1		41	2	2	2
14	2	2	2		51	3	1	1
24	1	1	1		32	2	2	2
15	2	2	3		42	1	1	1
25	1	1	1		52	1	1	1
					33	2	1	1
					43	1	1	3
					53	2	2	2
					34	1	1	1
					44	2	2	2
					54	1	1	1
					35	3	3	1
					45	2	2	2
					55	1	1	1
					36	3	2	2
					46	1	1	1
					56	1	2	1

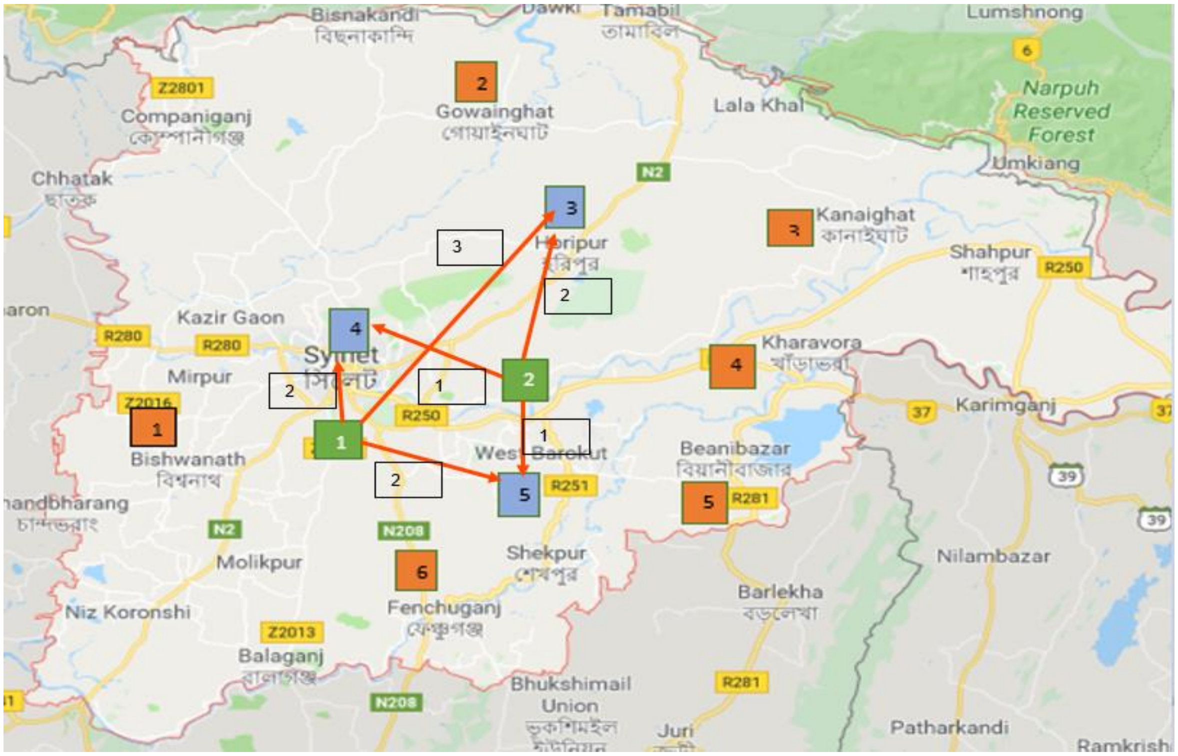


Figure 6.6: Optimized S-DC route/path selection under scenario 1

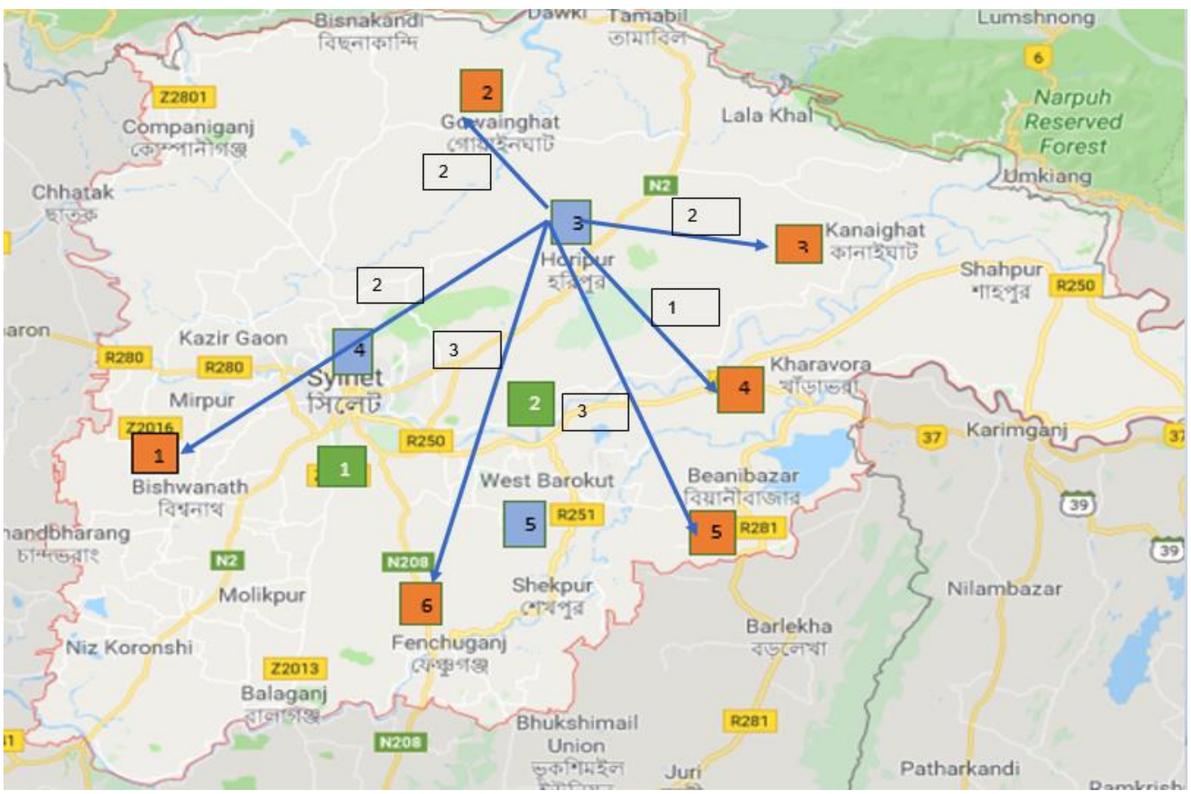


Figure 6.7: Optimized DC3- AAs route/path selection under scenario 1

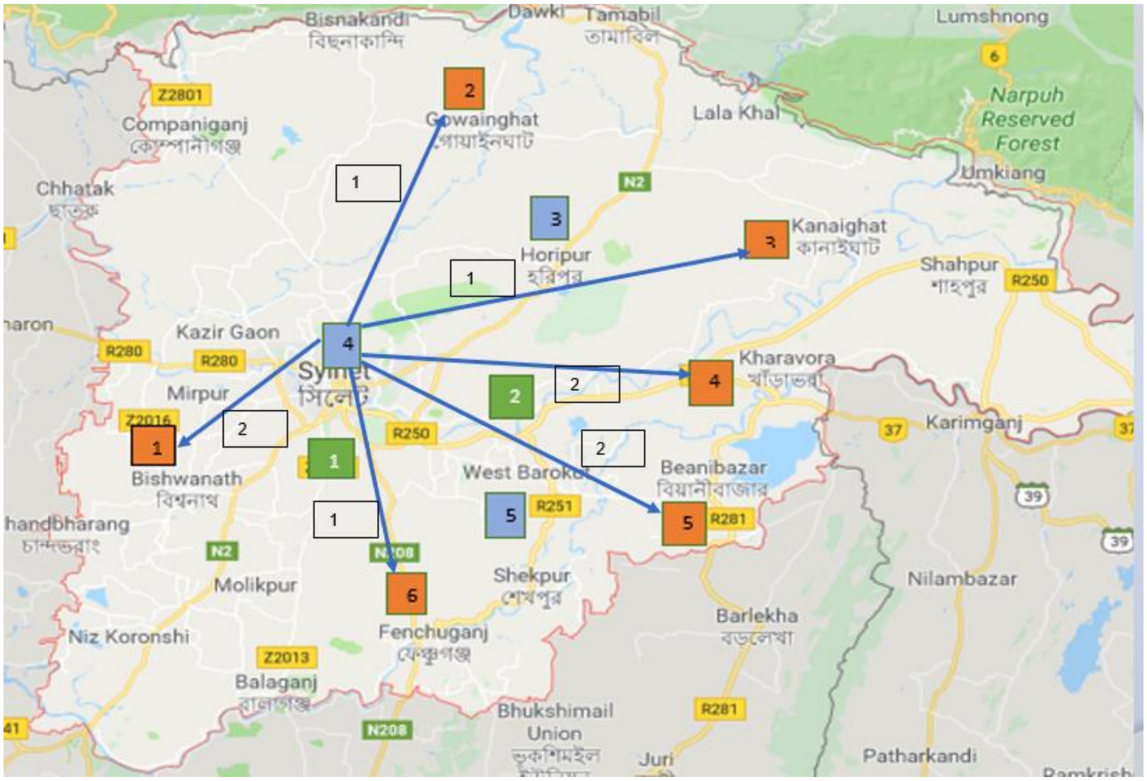


Figure 6.8: Optimized DC4- AAs route/path selection under scenario 1

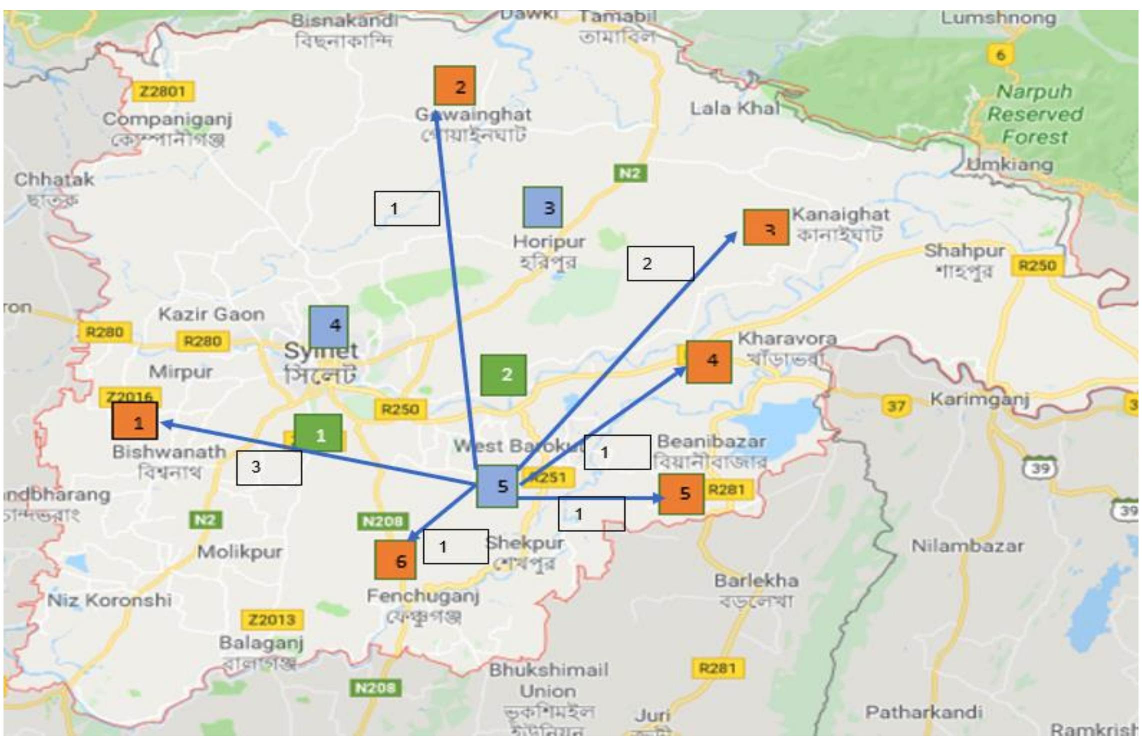


Figure 6.9: Optimized DC5- AAs route/path selection under scenario 1

6.3 Results from Model 3: Post-disaster Distribution and Evacuation Model

The third post-disaster distribution and evacuation model had five objectives. In this attempt, we considered the weight values for the corresponding objectives as 50, 15, 10, 190 and 75, for which the obtained objective values are 35, $106863, $220881, $0 and $110400 respectively. All decision variables are positive integers in this model, which are;

EV_j = Number of voluntary (unpaid) medical personnel at DC location j.

E_j = Number of paid medical personnel at DC location j.

MS_{jn} = Number of units of medical supplies to serve type n wounded people, who will be served in temporary medical facilities in DC node j.

S_{ijm} = Amount (number of pallets) of commodity of type *m* needed to be transported from supplier node *i* to DC node j

X_{jkm} = Amount (number of pallets) of commodity of type *m* needed to be transported from DC node *j* to affected area node k

Y_{kjn} = Number of wounded people of type *n* needed to be transported from affected area node *k* to DC node j

Z_{km} = Number of pallets of shortage of commodity type *m* at affected area *k*

Z_{kn} = Number of unserved wounded people of type *n* at affected area *k*

V_{ijq} = Number of trips required by vehicle type *q* for commodity transportation from supplier node *i* to DC node *j*

V_{jkq} = Number of trips required by vehicle type *q* for commodity transportation from DC node *j* to affected area node *k*

V_{kje} = Number of trips required by vehicle type *e* for transportation of people from affected location node *k* to DC node j.

The results obtained from CPLEX for this model and the test case are shown in the table below. Only the variable that returned any non-zero value has been displayed in the following table. If any variable(s) has not been displayed in the table, assume a ‘zero’ value for them;

Table 6.6: Outputs obtained from CPLEX for Model 3				
Variable	Output		Variable	Output
E j			Y kjn	
4	9		141	29
5	60		142	18
			241	34
EV j			242	21
3	10		331	25
4	25		332	3
			352	14
MS ijn			451	41
131	25		452	26
132	3		551	31
141	63		552	24
142	39		651	27
251	99		652	16
252	80			
			V jkq	
S ijm			411	1
141	98		412	5
142	43		422	7
251	147		331	2
252	83		332	1
			532	2
X jkm			541	1
411	46		542	6
412	21		552	8
421	58		561	1
422	26		562	6
331	19			
332	9		V kje	
531	14		142	3
532	10		241	2
541	48		242	2
542	29		331	1
551	62		332	1
552	34		352	1
561	53		451	4
562	27		452	1
			551	2
V ijq			552	2
131	1		651	1
142	12		652	2
251	2			
252	18			

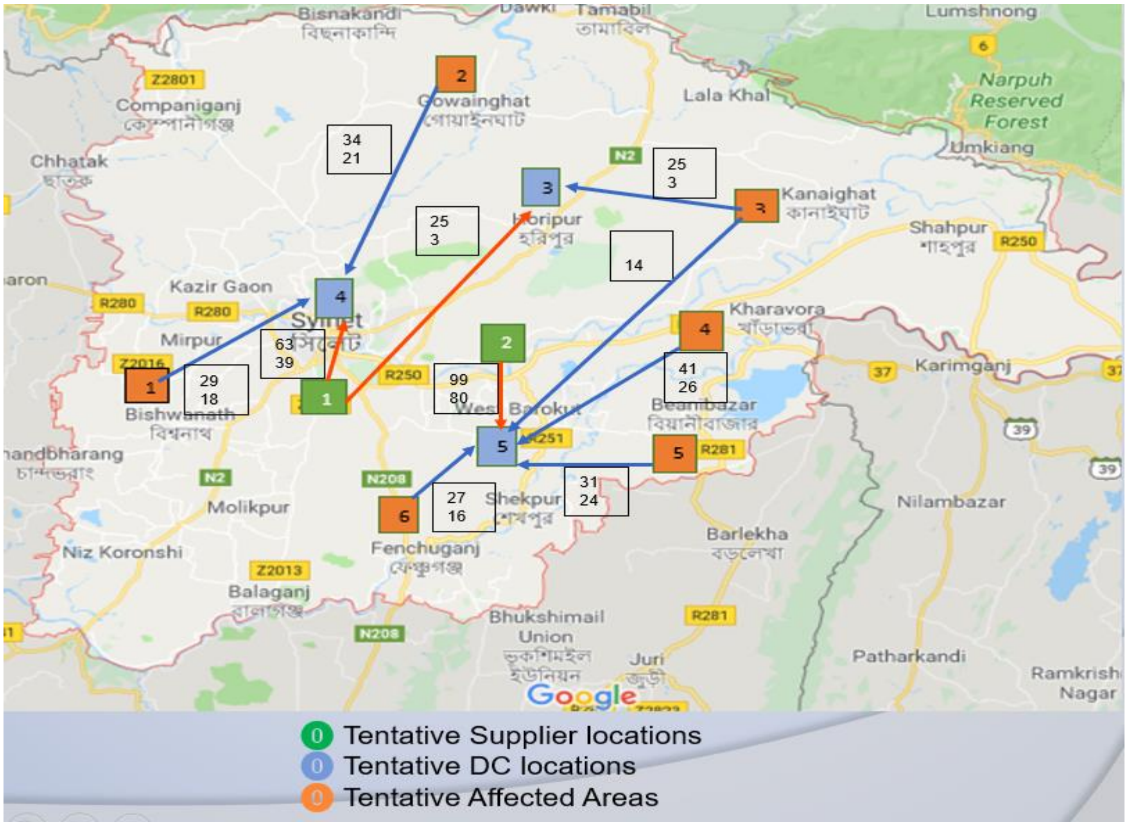


Figure 6.10: Medical supply and Medical Evacuation Flow result

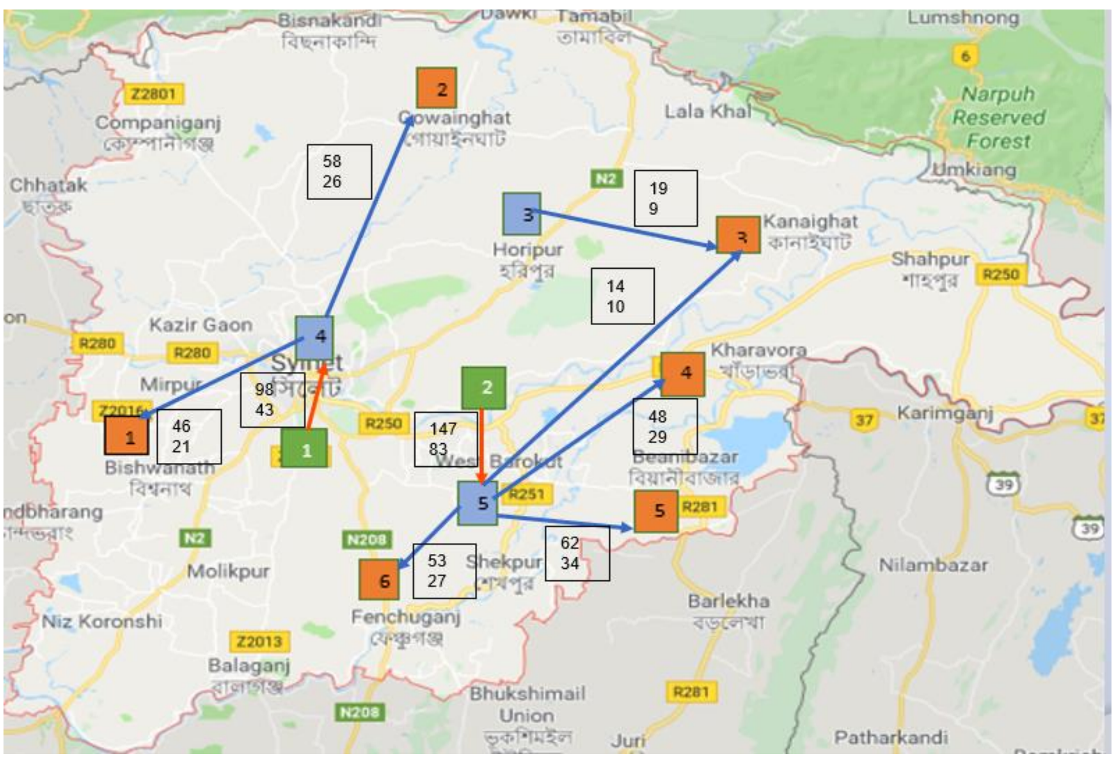


Figure 6.11: Relief goods Flow result

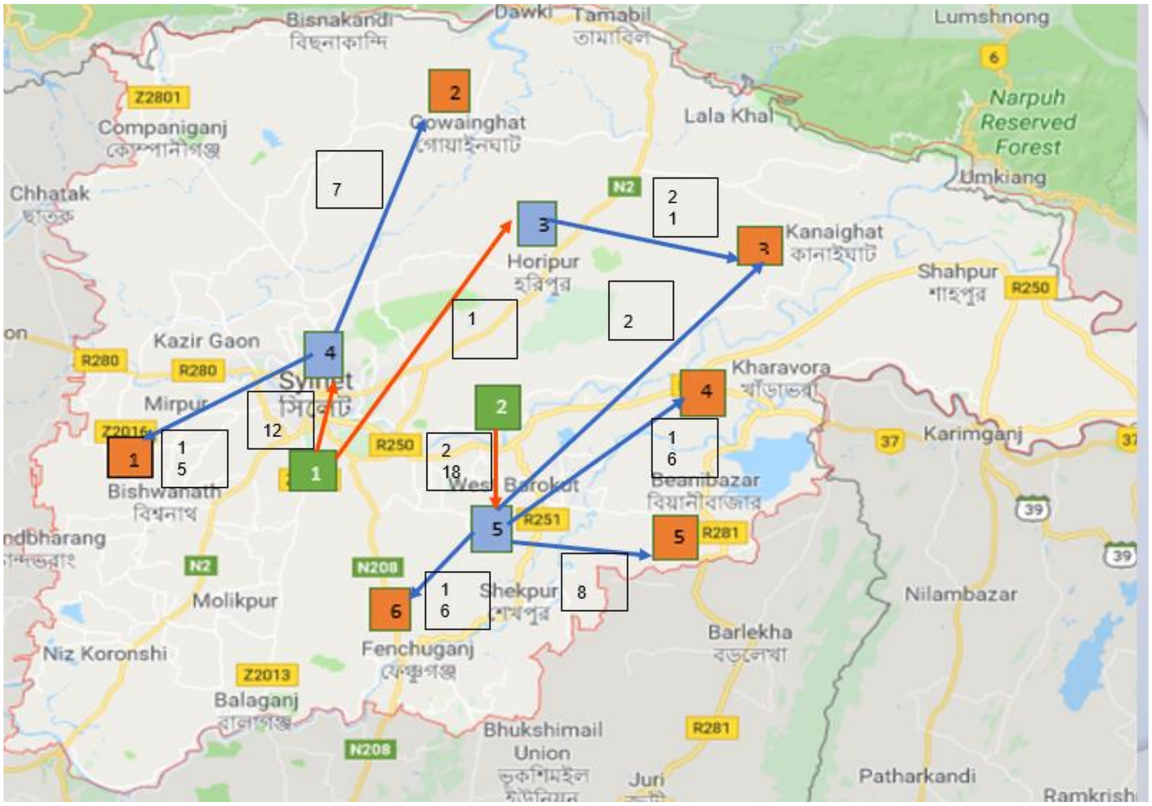


Figure 6.12: Relief goods and medical supplies carrying vehicle trips

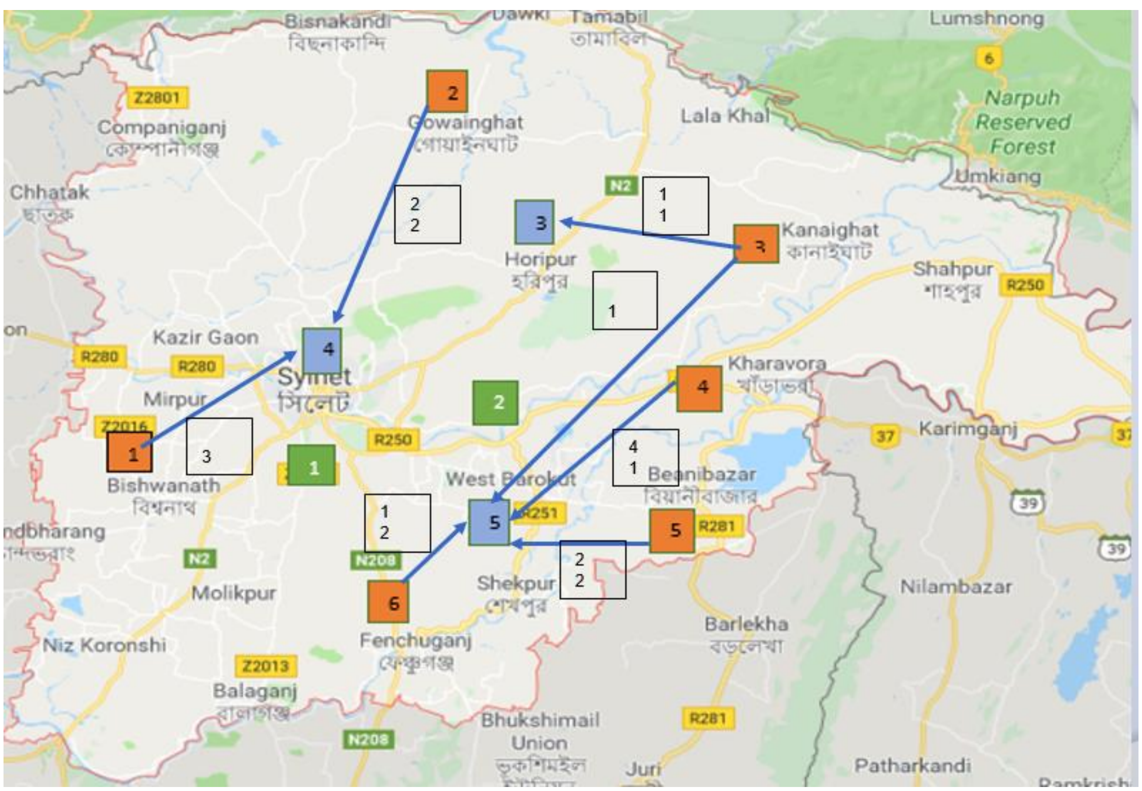


Figure 6.13: Medical evacuation (for wounded people evac.) vehicle trips

6.4 Discussions

In absence of well-integrated decision support systems like this research, decision makers in underdeveloped countries mostly rely on their intuition or past experience when it comes to designing aid logistics networks. This might work every now and then for smaller time period, but since various factors might change over time (like condition of any specific route or change in climate pattern or severity of disaster etc.), keep using this intuition-based system might not be a good idea in long term. Disaster planning is such a sensitive issue, where a very little mismanagement or miscalculation might cause serious loss of human lives or economical damage. But in case of mathematical model-based decision support system like this research, these changes in the factors and other information are properly reflected and regularly updated, which results in greater accuracy in planning. That’s where the practical contribution and benefit of this research lies.

In case of a disaster management system, it is difficult to exactly quantify its performance. But compared to traditional intuition-based system, it can be clearly seen in this research that here it is possible to drive the amount of total unsatisfied demand and unserved people at the affected area to an absolute ‘zero’, which cannot always guaranteed in case of traditional intuition-based panning. Moreover, decision makers will be able to significantly reduce the travel time and improve travel reliability at the same time using this proposed method as well, compared to the traditional intuition-based system.

In the result section of this chapter, results obtained from all three models were not only demonstrated numerically, but also graphically/pictorially to ensure better understanding of the output by its actual users, who are the decision makers of the aid operations and the management. In the less developed countries, the decision makers involved in managing the aid operations, often do not possess proper mathematical aptitude or have higher level of technical apprehension. On cases like those, graphically illustrated results can play important role for proper implementation.

Results obtained from all three models in this research, appear to be consistent with the expected outcome of this study. The outputs obtained here, can be used to develop an efficient humanitarian logistics network, which will be able to achieve all the objectives desired in all three models. Also note that, all the models in this research, being multi-objective in nature, gives decision makers more freedom to obtain the outputs that they aspire/require. Because all the multi-objective models in this research were solved by using Scalarization technique, which allows the decision makers to manipulate the objective weights very easily, even when they don’t possess much technical or mathematical skills. They can always assign higher weights to the objective(s) that matters to them most and thus can obtain outputs that can help them to develop the logistic network they desire, that will not only minimize operational cost, but also reduce human suffering, which is the main purpose of any aid operation as well as of this research.

Chapter 7

Conclusions and Recommendations

7.1 Conclusions

Underdeveloped countries often lack resources, infrastructures and management that developed countries usually have. Therefore, when a disastrous event occurs, in most cases, underdeveloped countries faces more casualties than the developed ones. Proper planning and management can make a large difference in situations like these when it comes to mitigating the overall casualties. This research focused on developing an integrated humanitarian logistics model which will help the decision makers in the underdeveloped part of the world to perform their aid operation in a more organized and efficient way that will not only minimize human suffering but also reduce the overall cost of operation. This research used the flash flooding problem of Sylhet, Bangladesh as test case to check the effectiveness of the model. One of the main reasons of choosing this incident as the test case is the recurrent nature of the disaster, which may not occur for a very long period but when it happens, it causes a significant damage to a large area and population over and over.

The research focused on both the pre and post disaster planning phase of the relief operation. In the pre-disaster planning phase, the research worked on selecting appropriate supplier locations, proper locations for setting up regional relief distribution centers, amount of goods that need to be prepositioned to reduce load on post-disaster logistics network, selecting appropriate routes to transport relief goods to the affected are and evacuate the wounded people etc. The post-disaster planning phase of the research worked on proper distribution of relief goods and medical supplies, evacuation of people to the temporary medical centers who needs medical attention, ensuring there is appropriate number of medical personnel available to serve those wounded people, ensuring equity of distribution and the service provided at the affected locations and minimizing the number of trips required for all the transportation activities required across all arcs. All of the three developed mathematical models in this research are MILP problems.

To solve the developed MILP models, CPLEX version 12.8 has been used. Branch and Cut algorithm was utilized to solve the problem via CPLEX. Obtained results has been demonstrated both numerically and graphically in the result and discussion section of this dissertation for the better understanding of the decision maker. The author of this research is hopeful that by utilizing this research, decision makers, in many underdeveloped part of the world, will be able to plan and develop humanitarian logistics networks, which will not only minimize human suffering and operational cost but also will improve the overall efficiency of the entire aid logistics operation.

7.2 Recommendations

There are several directions to which this research can be extended further in future, which are as following:

- More flexibility can be added to the model by using Robust optimization methodologies. Under robust optimization, the model will be more receptive changes, such as, sudden availability of a new batch of relief goods from foreign donation or change in decision makers' priorities on supplier evaluation criteria etc., even in the later stage of the model.
- An extensive sensitivity analysis can be performed in future on all three research models, to check the effect of different design parameters and other inputs used there and to identify their influences on the overall objectives, which can later be used to perform future modifications in the developed model, to make them more efficient and practical.
- Time element was not considered in this research (which was mentioned in the assumptions of the respective models). So, more realistic models can be developed from this research in future by incorporating the time element into it, which will improve models' responsiveness.
- A Fuzzy rule-based system can be introduced in the model to make the model more realistic and flexible.
- A dedicated algorithm can be developed to solve this model in a shorter time frame.
- For the ease of use of decision makers, who might not always be efficient in mathematical optimization or programming, a dedicated software with easy-to-use graphical user interface (GUI) can be developed, based on these research models. In the

developed software GUI, the user will just give the input data required and the software will provide them with desired graphical relief logistics network design along with necessary numerical outputs. The software can also be coupled with Arc-GIS platform to allow user to import and export required geographical data easily from a central server.

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