# A Multi-Objective Integrated Model of Relief Chain Logistics Planning for Commodity Supply and Injured Peoples' Service

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# A Multi-Objective Integrated Model of Relief Chain Logistics Planning for Commodity Supply and Injured Peoples' Service

**BY**
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A thesis submitted to the Department of Industrial & Production Engineering, Bangladesh University of Engineering & technology, in partial fulfillment of the requirements for the degree of Master of Science in Industrial & Production Engineering

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# CERTIFICATE OF APPROVAL

The thesis titled **“A Multi-Objective Integrated Model of Relief Chain Logistics Planning for Commodity Supply and Injured Peoples’ Service”** submitted by Himangshu Kumar Paul**,** Student no: 1014082006 P has been accepted as satisfactory in partial fulfillment of the requirements for the degree of Master of Science in Industrial & Production Engineering on July 11, 2017.

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Himangshu Kumar Paul

***To the Almighty***

***To my family***

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# ABSTRACT

The unpredictable nature and global impact of natural and man-made disasters enforce governments of disaster-prone regions to provide practical response plans to minimize damage, ecological disruption and loss of human life. Humanitarian logistics management is one of the key issues that should be considered for an appropriate response, in particular, the planning of the transport of commodities required during response and the evacuation of injured people. This study proposes a multi-objective stochastic programming model for relief chain logistics planning that integrates location, inventory, and routing decisions considering logistics flow of both commodities and injured people. The model features five objectives: minimizing weighted sum of unserved demand and unserved injury, minimizing travel time for flow of commodities and injured people and minimizing total costs associated with flow of commodities. The first two objectives pursue fairness – expending the best effort to ensure delivery of relief commodities and evacuation of injured people. The other objectives pursue the efficiency goal. The proposed model is solved as a mixed-integer programming model applying the augmented ε-constraint method. A case study is presented to illustrate the potential applicability of this model for disaster planning. The findings demonstrate that the proposed model can benefit making decisions on facility location, resource allocation, and routing decisions in cases of disaster relief and evacuation efforts.

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# ABBREVIATIONS

| | |
|---|---|
| LRP | location–Routing Problem |
| SCM | Supply Chain Management |
| FLP | Facility Location Problem |
| VRP | Vehicle Routing Problem |
| MIP | Mixed-Integer Programming |
| EMC | Emergency Medical Center |
| RDC | Regional Distribution Center |
| AA | Affected Area |
| MOMP | Multi-Objective Mathematical Programming |
| AUGMECON | The Augmented ε-constraint Method |
| GAMS | General Algebraic Modeling System |
| MOOP | Multi-Objective Optimization Problem |

# Chapter 1

# INTRODUCTION

The World Health Organization defines a disaster as any occurrence that causes damage, destruction, ecological disruption, loss of human life, human suffering, deterioration of health and health services on a scale sufficient to warrant an extraordinary response from outside the affected community or area. Earthquakes, hurricanes, tornadoes, volcanic eruptions, fire, floods, blizzard, drought, terrorism, chemical spills, nuclear accidents are included among the causes of disasters, and all have significant devastating effects in terms of human injuries and property damage.

The rapid growth in world population and increased human concentrations in dangerous environment have led to rises in both the frequency and severity of natural disasters; consequently, the number of people affected by natural disasters continues to rise. For example, between 2000 and 2007, the number of reported natural disasters was approximately 460 disasters per year, indicating a dramatic increase, and also the number of victims is generally between 100 million and 400 million per year around the world [1].

The enormous scale of these disasters has called attention to the need for effective management of the relief supply chains. Emergency management is a discipline that involves preparing for disaster before it occurs, responding to disasters immediately, as well as supporting and rebuilding societies after the disasters have struck [2]. In a world where resources are stretched to the limit and the question of humanitarian relief seems too often to be tied with economical consideration, better designs and operations are urgently needed to help safe thousands of lives and millions of dollars. Well-planned logistical support operations contribute significantly in reducing losses and damages and in sustaining survivors in the aftermath of a disaster [3].

Response is defined as the set of actions conducted during the initial impact of these emergency situations, including those to save lives and prevent further property damage providing emergency relief to victims of natural or manmade disasters [4]. Immediately after a disaster has struck, efforts are mainly focused on searching for and rescuing survivors. This requires logistics support by means of transporting injured people from affected areas to hospitals or other emergency medical centers. It is furthermore necessary to dispatch commodities (such as food or tents) and equipment to the affected areas. These commodities may either come from designated warehouses or directly from suppliers. The timely and effective mobilization of resources is essential in aiding people who are made vulnerable by natural disasters. The supply shortage may render emergency response ineffective and result in increased suffering [5, 6].

Under circumstances of considerable uncertainty in conditions, dispatching and transporting commodities from a variety of places to a variety of areas can lead to considerable complexities in planning.

Since it is almost impossible to speculate the timing and the intensity of any disaster, it is highly demanding to exactly estimate the impact, damage, and the resource needs in advance. Thus, the planning problem should be naturally addressed as a stochastic problem where randomness arises not only from demand but also from supply, cost, and travel time.

In real humanitarian operations, it is often seen that demand, supply, and cost are uncertain during the first stage of disaster response [7].Uncertainty in supply is caused by the variability brought about by how the supplier operates because of the faults or delays in the supplier's deliveries. It is often unknown which resources are available, and even the involvement and contribution of suppliers is unpredictable [8]. On the other hand, per-positioned assets can be destroyed by a disaster. Uncertainty in the cost of the operations generally happens because of the uncertainty associated with routes, suppliers, etc. Travel times between two locations can be uncertain due to the damaged infrastructure and unreliable information regarding the road conditions. Finally, demand uncertainty, according to Davis [9], is the most important of the three and is presented as demand volatility or inaccurate assessments.

The motivation behind this study that differentiates this paper from the existing ones in the related literature can be summarized as follows:

- Achieving a model which integrates strategic, tactical, and operational decisions. Although there is a strong relation between the locations of facilities; the allocation of suppliers, vehicles, and customers to the facilities; and the design of routes around the facilities, the interrelations between those are often ignored. Separating different level decisions will lead to suboptimal outcomes.

- Considering both the uncertain and dynamic features of disaster relief operation. Most of the available location–routing problem (LRP) literature focuses on the development of purely deterministic models. For real-world applications, however, various sources of uncertainty (demand, cost, travel times, etc.) have to be considered. It would thus be of high practical and academic relevance to consider stochastic to a greater extent with respect to LRP models.
- Applying the model to a real-world disaster relief chain. Actually applying LRP models to real-world decision problems not only broadens the spectrum of considered location–routing options but also provides evidence of their efficacy and practicality. While LRPs are generally a very well-researched class of decision problems, the academic contributions to this stream of research are too rarely applied and adapted to actual real-world problem settings. Closing the gap between theory and practice offers many appealing research opportunities.

## 1.1 Rationale of the Study

Humanitarian logistics is a branch of logistics which specializes in organizing the warehousing and delivery of supplies to the affected area, and transportation of the injured person from the affected area during or after natural disasters or complex emergencies. With a focus on disaster-related issues, humanitarian logistics research is becoming a key factor in devising improved ways of managing multi-stakeholder relief operations. Based on recent papers calling for more research in humanitarian logistics and a number of literature reviews, several authors (e.g. Wassenhove 2006; Chandraprakaikul 2010; Tatham and Pettit 2010; Caunhye, Nie, and Pokharel 2012; Celik et al. 2012; Galindo and Batta 2013; Day 2014) suggest that there is a need for operations research and management science (OR/MS) specialists to transfer more techniques from commercial SCM into humanitarian logistics research [10-16]. Beamon and Balcik [17] have compared commercial and humanitarian SCM and suggested that the ultimate goal to deliver the right supplies in the right quantities to the right locations at the right time is similar. They also discuss the differences based on revenue sources, goals, stakeholders and performance measurement between the two. Additionally, while high market incentive and low risk are associated with commercial SCM, low market incentive and high risk can be observed in humanitarian logistics [18].

Performance measurement in humanitarian logistics is not necessarily similar to commercial logistics [14, 17-18]. Celik et al. [14] point that not only effectiveness, but also efficiency of post-disaster logistics activities are needed to capture performance. Christopher and Tatham [18] also discuss the need for developing appropriate performance metrics for humanitarian operations that capture the aid recipient's viewpoint. Performance in humanitarian relief chains is very difficult to measure because of some distinct characteristics that humanitarian operations have, such as very unpredictable demand, difficulty to obtain data from operations, unpredictable working environment, impact of unknown variables, like geography, political situations or weather etc. This research attempts to measure and optimize the performance of relief network considering the uncertainty that a disastrous event poses.

A relief supply chain has three echelons or levels where decision making is required: supplier level, regional distribution center level and finally at the affected areas. So far very few works have considered the decision making in all three echelons of humanitarian logistics network including logistics flow of both commodities and injured people. Again, none of them considered multi-objective model to minimize weighted sum of unserved demand and unserved injury, travel time for flow of commodities and injured people, and total costs associated with flow of commodities. So, developing a multi-objective model considering supply of commodities and service of injured people is still an open problem and thereby yields the scope of this thesis.

## 1.2 Objectives of the Study

The specific objectives of this research are:

- To develop a constrained Mixed Integer Programming (MIP) model for relief chain logistics planning that integrates location, inventory, and routing decisions considering logistics flow of both commodities and injured people.
- To optimize the formulated multi-objective MIP model by minimizing weighted sum of unserved demand and unserved injury, travel time for flow of commodities and injured people and total costs associated with flow of commodities.

So, in short the research will benefit making decisions on facility location, resource allocation, and routing decisions in case of disaster relief efforts.

There are some limitations associated with this study. In this research, augmented ε-constraint method has been used to solve the multi-objective MIP model. Augmented ε-constraint method can efficiently solve any small scale model with two or three objective functions. But, it is not very efficient and cannot produce pareto optimal solutions in large scale model like the one discussed in this research. Heuristic algorithms can be used instead of ε-constraint method to obtain satisfactory result. Moreover, most data used in numerical example to validate the model are hypothetical data collected from published papers. Actual data could produce more realistic result in this case.

### 1.3 Outline of the Methodology

The research methodology is outlined below:

- Appropriate locations for establishing Emergency Medical Centers (EMC) and Regional Distribution Centers (RDC) has been selected by using binary variables.
- Appropriate routes for dispatching injured person and relief commodities are determined.
- Optimal number of injured person dispatched from affected areas (AA) has been determined based on the capacity of EMCs and optimal quantity of relief commodities dispatched from RDCs are determined based on demand.
- To deal with the uncertainty on demand, supply and cost parameters; a scenario based approach is used considering multiple disaster scenarios.
- The objective functions are developed for unserved demand, unserved injury, travel time and cost.
- The model has been optimized and illustrated for an example problem.

# Chapter 2

# LITERATURE REVIEW

The operation research community has been investigating the field of humanitarian logistics since the 1990s; however, recent disasters have called for increased attention to these kinds of logistical problems. The related academic literature in this context falls into five streams: facility location, vehicle routing, inventory management, network flow, and combination of them (location–routing, location–allocation, allocation–routing, network flow routing, etc.). In this section, the literature on disaster relief logistics problems is reviewed. This review is divided into two contrasting categories: literature on facility location, inventory management, vehicle routing, and location–routing deterministic problems in disaster relief logistics and the one on the management of uncertainties in disaster relief logistics. Some of the key studies are discussed in each category.

## 2.1 Facility Location, Inventory Management, Vehicle Routing, and LRPs

Facility location decisions affect the performance of relief operations since the number and locations of the distribution centers directly influence the response time and costs incurred throughout the relief chain [19]. The classical FLP selects the best p sites among a range of possible locations with the objective of minimizing total demand-weighted travel distance between demand nodes and facilities (p-median problem) while other objectives considered for FLP are minimizing fixed costs of selected facilities (set covering problem), maximizing the coverage of demand (maximal covering problem), and minimizing maximum distance between demand-facility pairs (p-center problem) [20-25].

In FLP, facilities might have fixed capacities or their sizes might have to be optimized [26]. Extensions to FLP also include the allocation problem where facilities are located simultaneously with the flows between demand nodes and facilities (location–allocation problem). Salhi and Rand [27] show that when tours are not explicitly considered in this model, distribution costs may increase. Owen and Daskin [28] provide an extensive survey on FLP and its extensions.

Ray [29] presented a single-commodity, multi-modal network flow model for a capacitated network over a multi-period planning horizon. In this model the sum of incurred costs for the transportation and storage of food in West Africa is minimized.

Parentela and Nambisan [30] developed emergency response plans that combined all the information in connection with the location and capacities of resource suppliers, the spatial distribution of the victims, the environment and the economy. Brotcorne et al. [31] classified the location and relocation models of ambulances and other emergency vehicles into three categories: deterministic models, probabilistic queuing models, and dynamic models.

Akkihal [32] considered optimal locations for warehousing non-consumable inventories required for the initial aid deployment. Tzeng et al. [33] developed a multi-objective relief-distribution model for designing relief delivery systems using a real-life case. The model featured three objectives including minimization of total costs, minimization of the total travel time, and maximization of the minimal satisfaction of fairness during the planning horizon.

Ukkusuri and Yushimito [34] developed a model for selecting the optimal locations for the pre-positioning of supplies in such a way to maximize the probability that demand points can be reached from a single supply facility in the presence of transportation network disruptions.

Tofighi et al. [35] addressed a two-echelon humanitarian logistics network design problem for joint stock prepositioning and relief distribution involving multiple central warehouses (CWs) and local distribution centers (LDCs) and developed a novel two-stage scenario-based possibilistic-stochastic programming (SBPSP) approach. Golabi et al. [36] investigated a combined mobile and immobile pre-earthquake facility location problem. They developed a mathematical model which minimizes the aggregate traveling time for both people and UAVs over a set of feasible scenarios.

Research on inventory management focuses on determining the item quantities required at various RDCs along the relief chain, procurement quantities, and order frequency; it also identifies the appropriate amount of safety stock to maintain. Whybark [37] argued that disaster planning is centered on disaster inventories and, therefore, acquisition, storage, and the distribution of products are significant. However, little research is known on the inventory in disaster relief logistics. Ozbay and Ozguven [38] developed a time-dependent inventory control model for safety stock levels that could be used for the development of efficient pre- and post-disaster plans. Beamon and Kotleba [39] formulated a stochastic inventory control model that determined optimal order quantities and reorder points for a pre-positioned warehouse during the course of a long-term emergency relief response. Peng et al. [40] proposed a system dynamics disruption analysis approach for inventory and logistics planning and developed model which will analyze the behaviors of disrupted disaster relief supply chain by simulating the uncertainties associated with predicting post-seismic road network and delayed information. Toyasaki et al. [41] focused on horizontal cooperation in inventory management which is currently implemented in the United Nations Humanitarian Response Depot (UNHRD) network. Their work follows a two-step research approach, which involves collection of empirical data and quantitative modeling to examine and overcome the coordination challenges of the network.

Similar to FLP, VRP has posed a challenge to researchers and practitioners for a long time. The classical standard vehicle routing problem (VRP) generates a set of routes which visit each customer exactly once. It aims at minimizing the total travel time and/or the operational cost. The problem was first introduced by Dantzig and Ramser [42] to solve a real-world application concerning the delivery of gasoline to service stations. A comprehensive overview of the VRP can be noticed in Toth and Vigo [43], and other general surveys on the deterministic VRP also can be found in Laporte [44]. Balcik et al. considered a vehicle-based last mile distribution system, in which an LDC stores and distributes emergency relief supplies to a number of demand locations. They proposed a mixed integer programming model that determines delivery schedules for vehicles and equitably allocates resources, based on supply, vehicle capacity, and delivery time restrictions, with the objectives of minimizing transportation costs and maximizing benefits to aid recipients [45]. Afsar et al. [46] developed exact and heuristic algorithms for solving the generalized vehicle routing problem with flexible fleet size. The problem aims at minimizing the total cost for a set of routes, such that each cluster is visited exactly once and its total demand is delivered to one of its nodes.

Mosterman et al. [47] presented an automated emergency response system and an experimental framework for its design and validation. The system consists of a high-level mission optimization and a fleet of heterogeneous autonomous vehicles.

LRP models have been investigated in detail resulting in an abundant literature. These models integrate the discrete facility location (FLP) and vehicle routing problems (VRP). Both FLP and VRP are NP-Hard, however, VRP is usually considered to be more inhibiting for exact methods. As for modeling techniques, Haghani and Oh [19] proposed a formulation and solution of a multi-commodity, multi-modal network flow model for disaster relief operations. Their model could determine detailed routing and scheduling plans for multiple transportation modes carrying various relief commodities from multiple supply points to demand points in a disaster area. They formulated the multi-depot mixed pickup and delivery vehicle routing problem with time windows as a special network flow model over a time-space network. The objective was minimizing the sum of the vehicular flow costs, commodity flow cost, supply/demand storage cost and inter-modal transfer costs over all time periods. They developed two heuristic solution algorithms; the first was a Lagrangian relaxation approach and the second was an iterative fix-and-run process. Their work is one of the few studies that can be implemented at the operational level.

Barbarosoglu et al. [48] proposed a bi-level modeling framework to address the crew assignment, routing, and transportation issues during the initial response phase of disaster management in a static manner. Ozdamar et al. [49] addressed an emergency logistics problem for distributing multiple commodities from a number of supply centers to distribution centers near the affected areas. They formulated a multi-period multi-commodity network flow model to determine pickup and delivery schedules for vehicles as well as the quantities of loads delivered on these routes, with the objective of minimizing the amount of unsatisfied demand over time. The structure of the proposed formulation enabled them to regenerate plans based on changing demand, supply quantities, and fleet size. They developed an iterative Lagrangian relaxation algorithm and a greedy heuristic to solve the problem.

Lin et al. [50] designed a logistics model for delivery of prioritized items for logistics operations that is applicable to a disaster relief effort. Their model considered multi-items, multi-vehicles, multi-periods, soft time windows, and split delivery strategy scenario and is formulated as a multiobjective programming model. Najafi et al. [51] devised a dynamic model for dispatching and routing vehicles in response to an earthquake. They considered two hierarchical objective functions that are concerned with minimizing transit times for both goods and the injured people.

LRP models integrate the discrete FLP and VRP and optimize the locations and capacities of facilities as well as vehicle routes and schedules. A classification of LRP models is presented by Min et al. [52].

Yi and Ozdamar [3] proposed a model that integrated the supply delivery with evacuation of wounded people in disaster response activities. They considered establishment of temporary emergency facilities in disaster area to serve the medical needs of victims immediately after disaster. They used the capacity of vehicles to move wounded people as well as relief commodities. Their model considered vehicle routing problem in conjunction with facility location problem. The proposed model is a mixed integer multi-commodity network flow model that treats vehicles as integer commodity flows rather than binary variables. That resulted in a more compact formulation but post processing was needed to extract detailed vehicle routing and pick up or delivery schedule. They reported that post processing algorithm was pseudo-polynomial in terms of the number of vehicles utilized.

Rath and Gutjahr [53] developed a three-objective warehouse location–routing problem in disaster relief. The problem encompasses strategic costs, operative costs, and uncovered demand as objectives. The authors recommended an exact solution method as well as a meta-heuristic technique building on an MILP formulation with a heuristically generated constraint pool. Lin et al. [54] proposed the location of temporary depots around the disaster-affected area identifying tours for vehicles to deliver items from each located temporary depot. They set forth a two-phase heuristic approach. It locates temporary depots and allocates covered demand areas to an open depot in phase I and explores the best logistics performance under the given solution from phase I in phase II.

Barzinpour and Esmaeili [55] developed a multi-objective location allocation model for preparation planning phase of disaster management. Rezaei-Malek et al. [56] aimed at developing a new integrated model in order to determine the optimum location-allocation and distribution plan, along with the best ordering policy for renewing the stocked perishable commodities at the pre-disaster phase. Caunhye et al. [57] proposed a two-stage location-routing model with recourse for integrated preparedness and response planning under uncertainty. The model is used for risk management in disaster situations where there are uncertainties in demand and the state of the infrastructure.

The literatures mentioned above are based on the hypothesis that disaster information is deterministic. Since disaster response needs are not known with certainty at the moment of making a plan, a stochastic approach is thus needed to be applied in which uncertain data are used for planning the response.

## 2.2 Stochastic optimization approach for disaster relief logistics

The significance of uncertainty has motivated a number of researchers to address stochastic optimization in disaster relief planning involving the distribution of emergency commodities and necessity items by probabilistic scenarios representing disasters and their outcomes (e.g., Cormican et al. 1998; Barbarosoglu and Arda 2004; Beraldi et al. 2004; Chang et al. 2007; Beraldi and Bruni 2009; Mete and Zabinsky 2010; Rawls and Turnsquist 2010) [4, 58-63]. Research addressing the design of disaster planning is limited to those that modeled the stochastic situation under demand uncertainty and those that modeled it under demand and supply uncertainty (or demand/cost uncertainty).

Barbarosoglu and Arda [4] developed a two-stage stochastic programming model for transportation planning in disaster response. Their study expanded on the multi-commodity, multi-modal network flow problem of Haghani and Oh [19] by including uncertainties in supply, route capacities, and demand requirements. The inclusion of uncertainties is a prominent advance in the analysis. Chang et al. [60] modeled locating and distributing rescue resources in a flood emergency under possible flood scenarios using two-stage stochastic programming; the model could serve as a decision-making tool for the government agencies in the planning of flood emergency logistics under demand uncertainty. Salmeron and Apte [64] developed a two-stage stochastic optimization model for planning the allocation of budget for acquiring and positioning relief assets; in this model, the first-stage decisions represented the "aid pre-positioning" by the expansion of resources such as warehouses, medical facilities, ramp spaces, and shelters, whereas the second stage concerned the logistics of the problem under demand/cost uncertainty. Rawls and Turnquist [63] proposed a model for immediate post-disaster response under uncertainty in physical damage caused by the disaster. Here they included pre-disaster first stage decisions of locating and stocking warehouses which can be damaged by the disaster. In the second stage, routes are constructed after obtaining information about demand and remaining supply. Demand, transportation network and surviving stock of various commodities after an event are all subject to uncertainty. In a similar manner, Rawls and Turnquist [65] treat demand and infrastructure as stochastic elements, yet omitting potential deterioration of pre-positioned supply. Mete and Zabinsky [62] developed a stochastic programming model for the storage and distribution of medical supplies during the disasters while capturing the disaster specific information and possible effect of disasters through the use of disaster scenarios. With this methodology, they stated that balancing the risk and preparedness was possible in spite of the stochasticities associated with the disasters. They applied the model for possible earthquake scenarios in Seattle, Washington, USA. Bozorgi-Amiri et al. [66] designed a robust, stochastic programming model to simultaneously optimize the humanitarian relief operations in both the preparedness and response phases. Their model is composed of two stages; the first stage determines the location of RDCs and the required inventory quantities for each type of relief items under storage, and the second stage determines the amount of transportation from RDCs to affected areas (AAs). Their model is based on the hypothesis that disaster information is not time-variant and did not address routing of vehicles. To integrate strategic, tactical, and operational decisions, Bozorgi-Amiri and Khorsi [67] proposed a multi-objective dynamic stochastic programming model for a humanitarian relief logistics problem where decisions are reached for pre- and post-disaster. The model features three objectives: minimizing the maximum amount of shortages among the affected areas in all periods, the total travel time, and sum pre- and post-disaster costs. The proposed model is solved as a single-objective mixed-integer programming model applying the ε-constraint method. They did not address logistics flow of injured person in their model.

Najafi et al. [68] proposed a multi-objective, multi-modal, multi-commodity, multi-period stochastic model to manage the logistics of both commodities and injured people in the earthquake response and represented the data of uncertainty by interval data. The proposed stochastic model enjoys three hierarchical objective functions which, respectively, are as follows: minimization of total waiting time of unserved injured persons, minimization of total lead time of meeting the commodity needs, and minimization of total vehicles utilized in the response. It does not address the problem of determining the response facility locations and inventory levels of the relief supplies at each facility.

Rennemo et al. [69] presented a three-stage mixed-integer stochastic programming model for disaster response planning, considering the opening of local distribution facilities, initial allocation of supplies, and last mile distribution of aid. The vehicles available for transportation, the state of the infrastructure and the demand of the potential beneficiaries are considered as stochastic elements. Ahmadi et al. [70] proposed a two-stage stochastic programming multi-depot location-routing model considering network failure, multiple uses of vehicles, and standard relief time. The model determines the locations of local depots and routing for last mile distribution after an earthquake.

Safeer et al. [71] proposed a response planning stochastic model for humanitarian transportation operations. The objective of the proposed model is to minimize total transportation duration during emergency situations. The model aims to maximize satisfaction levels through attaining quick response which can help in making decisions on disaster relief logistics. Moreno et al. [72] developed a two-stage stochastic network flow model to help decide how to rapidly supply humanitarian aid to victims of a disaster considering factors such as budget allocation, fleet sizing of multiple types of vehicles, procurement, and varying lead times over a dynamic multiperiod horizon. Manopiniwes and Irohara [73] proposed a stochastic linear mixed-integer programming model for integrated decisions in the preparedness and response stages that considers three key areas of emergency logistics: facility and stock prepositioning, evacuation planning and relief vehicle planning.

Though these efforts have provided us different concepts for handling disaster relief operations efficiently, there is a paucity of research on integrating strategic, tactical, and operational decisions in the literature.

In the current study, a model is presented that integrates location, inventory, and routing decisions. To this end, a supply chain is considered including multiple suppliers, RDCs, EMCs, hospitals and demand points and addressing a multi-period, multi-modal transportation of relief commodity and injured person under uncertainty. Environmental uncertainty is described by discrete scenarios.

# Chapter 3

# COMPUTATIONAL OPTIMIZATION

Operations research approaches used in natural disasters management can be of various types. Mathematical programming, heuristic methods, probability theory and statistics, and simulations are some of them. Mathematical programming is entirely applied for problem formulation, such as mixed or pure integer programming, linear or non-linear programming, stochastic programming, etc.

As for deterministic problems, exact methods or heuristics are most commonly used. The branch and bound algorithm was used by Gkonis et al. [74] to solve linear mixed integer programming with oil spill response problem. Similarly, Sebbah et al. [75] presented this exact method to maximize the utility function of the relief plans of military logistics planning in humanitarian relief operations. Jia et al. [76] applied and evaluated three heuristic algorithms to solve maximal covering problem which are genetic algorithm, locate-allocate and Lagrangian relaxation. Lagrangian relaxation was also found in Ozdamar et al. [49] to compute linear and integer multi-period multi-commodity network flow problem. Yi and Ozdamar [3] gave suggestions on how to select the most appropriate heuristic to solve different location problem instances.

In Multi-Objective Mathematical Programming (MOMP) there are more than one objective functions and, in general, there is no single optimal solution that simultaneously optimizes all the objective functions. In these cases the decision makers are looking for the ‘‘most preferred” solution, in contrast to the optimal solution. In MOMP the concept of optimality is replaced with that of Pareto optimality or efficiency. The Pareto optimal (or efficient, non-dominated, non-inferior) solutions are the solutions that cannot be improved in one objective function without deteriorating their performance in at least one of the rest.

According to Hwang and Masud [77], the methods for solving MOMP problems can be classified into three categories, based on the phase in which the decision maker involves in the decision making process expressing his/her preferences: The a priori methods, the interactive methods and the a posteriori or generation methods. In a priori methods the decision maker expresses his/her preferences before the solution process (e.g. setting goals or weights to the objective functions). The criticism about the a priori methods is that it is very difficult for the decision maker to know beforehand and to be able to accurately quantify (either by means of goals or weights) his/her preferences. In the interactive methods phases of dialogue with the decision maker are interchanged with phases of calculation and the process usually converges, after a few iterations, to the most preferred solution. The decision maker progressively drives the search with his answers towards the most preferred solution. The drawback is that he/she never sees the whole picture (the Pareto set) or an approximation of it. Hence, the most preferred solution is ‘‘most preferred” in relation to what he/she has seen and compare so far. In the a posteriori methods the efficient solutions of the problem (all of them or a sufficient representation) are generated and then the decision maker involves, in order to select among them, the most preferred one. In general, the most widely used, generation methods are the weighting method and the ε-constraint method. These methods can provide a representative subset of the Pareto set which in most cases is adequate.

### 3.1 The ε-constraint method

Assume the following MOMP problem:

max $\quad (f_1(x), f_2(x),..., f_p(x))$

st $\quad x \in S,$

Where $x$ is the vector of decision variables, $f_1(x),..., f_p(x)$ are the $p$ objective functions and S is the feasible region.

In the ε-constraint method we optimize one of the objective functions using the other objective functions as constraints, incorporating them in the constraint part of the model as shown below [78, 79].

max $\quad f_1(x)$

st

$$f_2(x) \geq e_2,$$

$$f_3(x) \geq e_3,$$

$$\cdots$$

$$f_p(x) \geq e_p,$$

$$x \in S.$$

By parametrical variation in the RHS of the constrained objective functions ($e_i$) the efficient solutions of the problem are obtained.

The ε-constraint method has several advantages over the weighting method.

1. For linear problems, the weighting method is applied to the original feasible region and results to a corner solution (extreme solution), thus generating only efficient extreme solutions. On the contrary, the ε-constraint method alters the original feasible region and is able to produce non-extreme efficient solutions. As a consequence, with the weighting method we may spend a lot of runs that are redundant in the sense that there can be a lot of combination of weights that result in the same efficient extreme solution. On the other hand, with the ε-constraint we can exploit almost every run to produce a different efficient solution, thus obtaining a more rich representation of the efficient set.
2. The weighting method cannot produce unsupported efficient solutions in multi-objective integer and mixed integer programming problems, while the ε-constraint method does not suffer from this pitfall [80, 81].
3. In the weighting method the scaling of the objective functions has strong influence in the obtained results. Therefore, we need to scale the objective functions to a common scale before forming the weighted sum. In the e-constrained method this is not necessary.
4. An additional advantage of the ε-constraint method is that we can control the number of the generated efficient solutions by properly adjusting the number of grid points in each one of the objective function ranges. This is not so easy with the weighting method.

However, despite its advantages over the weighting method, the ε-constraint method has three points that need attention in its implementation: (a) the calculation of the range of the objective functions over the efficient set, (b) the guarantee of efficiency of the obtained solution and (c) the increased solution time for problems with several (more than two) objective functions. Mavrotas G. [82] tried to address these three issues with a novel version of the ε-constraint method named augmented ε-constraint method (AUGMECON).

### 3.2 The augmented ε-constraint method (AUGMECON)

In order to properly apply the ε-constraint method we must have the range of every objective function, at least for the $p-1$ objective functions that will be used as constraints. The calculation of the range of the objective functions over the efficient set is not a trivial task. While the best value is easily attainable as the optimal of the individual optimization, the worst value over the efficient set (nadir value) is not. The most common approach is to calculate these ranges from the payoff table (the table with the results from the individual optimization of the p objective functions). The nadir value is usually approximated with the minimum of the corresponding column. However, even in this case, we must be sure that the obtained solutions from the individual optimization of the objective functions are indeed Pareto optimal solutions. In the presence of alternative optima that are obtained by a commercial software optimal solution is not a guaranteed Pareto optimal solution. In order to overcome this ambiguity, lexicographic optimization for every objective function is used in order to construct the payoff table with only Pareto optimal solutions. A simple remedy in order to bypass the difficulty of estimating the nadir values of the objective functions is to define reservation values for the objective functions. The reservation value acts like a lower (or upper for minimization objective functions) bound. Values worse than the reservation value are not allowed.

In general, the lexicographic optimization of a series of objective functions is to optimize the first objective function and then among the possible alternative optima optimize for the second objective function and so on. Practically, the lexicographic optimization is performed as follows: we optimize the first objective function (of higher priority), obtaining max $f_1 = z_1^*$. Then we optimize the second objective function by adding the constraint $f_1 = z_1^*$ in order to keep the optimal solution of the first optimization. Assume that we obtain max $f_2 = z_2^*$. Subsequently, we optimize the third objective function by adding the constraints $f_1 = z_1^*$ and $f_2 = z_2^*$ in order to keep the previous optimal solutions and so on, until we finish with the objective functions.

The second point of attention is that the optimal solution of is guaranteed to be an efficient solution only if all the ($p-1$) objective functions' constraints are binding [81, 83]. Otherwise, if there are alternative optima (that may improve one of the non-binding constraints that correspond to an objective function), the obtained optimal solution of is not in fact efficient, but it is a *weakly* efficient solution. In order to overcome this ambiguity, it is required to transform the objective function constraints to equalities by explicitly incorporating the appropriate slack or surplus variables. In the same time, these slack or surplus variables are used as a second term (with lower priority in a lexicographic manner) in the objective function, forcing the program to produce only efficient solutions. The new problem becomes:

max $(f_1(x) + eps \times (s_2 + s_3 + ... + s_p))$

st

$$f_2(x) - s_2 = e_2,$$
$$f_3(x) - s_3 = e_3,$$
$$...$$
$$f_p(x) - s_p = e_p,$$
$$x \in S \text{ and } s_i \in R^+,$$

Where eps is an adequately small number (usually between $10^{-3}$ and $10^{-6}$).

In order to avoid any scaling problems it is recommended to replace the $s_i$ in the second term of the objective function by $s_i / r_i$, where $r_i$ is the range of the *i*th objective function (as calculated from the payoff table). Thus, the objective function of the ε-constraint method becomes:

max $(f_1(x) + eps \times (s_2/r_2 + s_3/r_3 + ... + s_p/r_p))$.

Practically, the ε-constraint method is applied as follows: From the payoff table we obtain the range of each one of the $p-1$ objective functions that are going to be used as constraints. Then we divide the range of the *i*th objective function to $q_i$ equal intervals using ($q_i - 1$) intermediate equidistant grid points. Thus we have in total ($q_i + 1$) grid points that are used to vary parametrically the RHS ($e_i$) of the *i*th objective function. The total number of runs becomes $(q_2 + 1) \times (q_3 + 1) \times ... \times (q_p + 1)$ ).

A desirable characteristic of the ε-constraint method is that we can control the density of the efficient set representation by properly assigning the values to the $q_i$. The higher the number of grid points the more dense is the representation of the efficient set but with the cost of higher computation time. A tradeoff between the density of the efficient set and the computation time is always advisable. The flowchart of the algorithm is as follows:

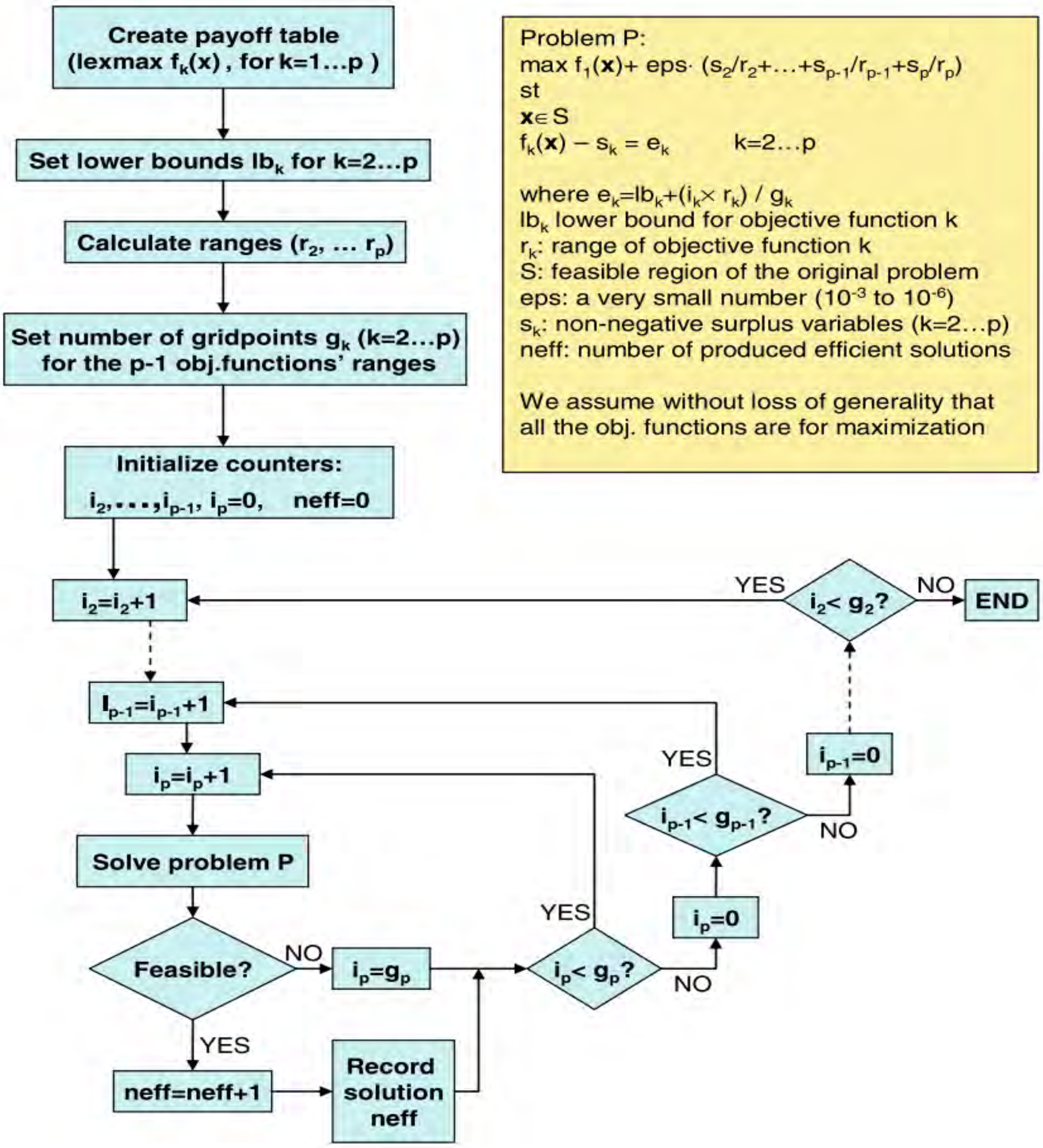


Figure 3.1: Flowchart of the AUGMECON method

# Chapter 4

# MODEL DEVELOPMENT

## 4.1 Problem Definition

In case of disaster response, efficient planning can reduce both the human suffering and economical expenses caused by the disastrous event. As a part of designing an efficient relief distribution network we must keep in mind that, there is a strong relation between the locations of facilities; the allocation of suppliers, vehicles, and customers to the facilities; and in the design of routes around the facilities. Thus, the need of an integrated logistic system has become a primary objective. In the current study, a constrained Mixed Integer Programming (MIP) model for relief chain logistics planning that integrates location, inventory, and routing decisions considering logistics flow of both commodities and injured people. In this model, the optimal number, the capacity, the location, and inventory levels of facilities are determined, and the optimal set of vehicle routes from each facility is sought as well.

The proposed research will develop a mathematical model to facilitate decision making process on facility location, resource allocation, and effective routing in disaster relief efforts. The proposed research methodology is outlined below:

- Appropriate locations for establishing Emergency Medical Centers (EMC) and Relief distribution centers (RDC) will be selected by using binary variables.
- Appropriate routes for dispatching injured person and relief commodities will be determined.
- Optimal number of injured person dispatched from affected areas (AA) will be determined based on the capacity of EMCs and optimal quantity of relief commodities dispatched from RDCs will be determined based on demand.
- To deal with the uncertainty on demand, supply and cost parameters; a scenario based approach will be used considering multiple disaster scenarios.

So, the model has five objectives-

- To minimize the weighted sum of unserved injured person waiting at affected area
- To minimize the travel time required to dispatch injured persons to medical facilities
- To minimize the weighted sum of unsatisfied demand over all commodities

- To minimize the travel time to ship items to demand points
- To minimize the total cost associated with commodity transportation to demand points

From the general supply chain concept we know that if the weighted sum of unserved injury and the weighted sum of unsatisfied demand decreases, the distribution cost will increase due to more frequent movement among EMCs, RDCs and demand nodes. Again while trying to minimize travel time of logistics flow, the inventories at distribution centers and shortage at affected areas might increase significantly. This is undesirable because increasing shortage or unmet demand means increase in human suffering. So we can see these objectives are conflicting in nature and must be minimized simultaneously. Hence the multi-objective problem will generate trade off solutions or Pareto optimal solutions, which will enable the decision makers to choose out of a set of diverse solutions according to their preferences. A number of constraint equations were also developed to ensure the model operates within acceptable boundaries.

## 4.2 Assumptions of the study

The following assumptions are made for the model:

- Demand nodes, supply nodes, emergency medical centers, hospitals and the distance among them are known during planning phase.
- There are several types of injured people with different priorities. These types of injured people and their priorities may be categorized dependent on factors such as the condition of the affected area or the strategies of the disaster coordination center.
- There are several types of commodities with different priorities. These types as well as their priorities can be defined dependent on several factors such as strategies of the disaster coordination center or the condition of the affected area.
- The level of demand for the AA, the cost, and travel time parameters are uncertain and depend on multiple factors including the disaster scenario and the impact of the disaster. To represent uncertain parameters, discrete scenarios are singled out from a set S of possible disaster situations. It is

assumed that the probability distribution of scenarios can be devised by subject matter experts or disaster planners.

- Demand and available supplier capacity will be obtained from historical data. In case of absence of historical data reasonable assumptions will be made to estimate those values.
- The logistics plan involves a planning time horizon consisting of a given number of time periods since it is concerned with time-variant demand, supply, and travel time.
- An RDC or EMC can be opened in only one of three possible configurations with distinct capacity (small, medium, or large), subject to the associated setup cost.
- A heterogeneous fleet that incorporates manifold transportation modes is utilized. Some vehicles are intended to carry injured people and some are intended to transport commodities.
- No vehicle can carry both commodities and injured people simultaneously.
- The transport capacity in both weight and volume of each vehicle carrying commodities as well as the transport capacity of a vehicle carrying injured people are known.
- Vehicles' routes begin and end at one of many designed centers. A route is defined as an ordered list of a subset of RDCs, EMCs or AAs with an initial center.
- Each vehicle can complete multiple deliveries in a single planning period, and each demand location can be visited multiple times with the same or different vehicles in the same planning period.
- An injured person is only considered served when he/she has been delivered to a hospital or an emergency medical center.

### 4.3 Model Development

In this study, a hypothetical relief logistics network has been considered which involves relief suppliers, relief distribution centers (RDCs), emergency medical centers (EMCs), hospitals and affected areas (AAs), forming a complete relief supply chain.

Each RDC has capacity for sending, receiving, and storing commodities. Similarly, each EMC and hospital has limited capacity for serving injured person. The demand is multi-commodity and usually overwhelms the capacity of the distribution network. Similar to the demand, the supply is multi-commodity and might be obtained from various sources. In order to model the complicated routing and delivery operations in disaster response, a method is proposed that utilizes a set of predetermined routes at the expense of a pre-processing effort.

**Set**

| | |
|---|---|
| $I$ | Set of suppliers indexed by $i \in I$ |
| $J$ | Set of candidate Relief Distribution Centers (RDCs) indexed by $j \in J$ |
| $H$ | Set of hospital indexed by $h \in H$ |
| $G$ | Set of candidate Emergency Medical Center (EMCs) indexed by $g \in G$ |
| $K$ | Set of Affected Areas (AAs) by disaster indexed by $k \in K$ |
| $M$ | Set of size of RDCs indexed by $m \in M$ |
| $N$ | Set of size of EMCs indexed by $n \in N$ |
| $S$ | Set of possible scenarios indexed by $s \in S$ |
| $C$ | Set of commodities indexed by $c \in C$ |
| $L$ | Set of injured people indexed by $l \in L$ |
| $V$ | Set of transportation modes indexed by $v \in V$ |
| $T$ | Set of periods indexed by $t \in T$ |
| $u, u'$ | Denotes a specific node containing either a supplier or a RDC, |
| $q, q'$ | Denotes a specific node containing either a RDC or an AA, |

**Deterministic Parameters**

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

| | |
|---|---|
| $f_{jm}$ | Fixed cost for opening a RDC of size m at location j |
| $f_{gn}$ | Fixed cost for opening a EMC of size n at location g |
| $\pi_{ct}$ | Inventory shortage cost for a unit commodity c in period t |
| $h_c$ | Inventory holding cost for a unit commodity c |
| $v_c$ | Unit volume of commodity c |

$CapV_v$ Volume capacity of vehicle type v

$CapP_v$ Person capacity of vehicle type v

$PR_c$ Priority of satisfying demand of commodity type c

$PR_l$ Priority of servicing injury of injured person type l

$FixedRDC$ Primary budget for RDC setup

$FixedEMC$ Primary budget for EMC setup

$M$ A very large number

$AC_{vc}$ 1 if vehicle type v is able to carry commodity type c, 0 otherwise

$AW_{vl}$ 1 if vehicle type v is able to carry injured person of type l, 0 otherwise

$VehicleLimit_v$ Maximum number of available vehicle of type *v*

$MinServiceLevel$ Minimum acceptable service level

**Stochastic Parameters**

$p_s$ Occurrence probability of scenario s

$\varphi_{cist}$ Procuring cost of a unit commodity c from supplier i under scenario s, in period t

$C_{cvst}$ Transportation cost of dispatching a unit commodity c using vehicle v under scenario s, in period t

$d_{ckst}$ Amount of demand for commodity c at AA k under scenario s, in period t

$d_{lkst}$ Number of injured people of type l at AA k under scenario s, in period t

$T_{uu'vst}$ Travel time of tour from node $u$ to node $u'$ by mode v under scenario s, in period t

$T_{qq'vst}$ Travel time of tour from node $j$ to node $j'$ by mode v under scenario s, in period t

$T_{kgvst}$ Travel time of tour from AA k by mode v under scenario s, in period t

$T_{ghvst}$ Travel time of tour from EMC g by mode v under scenario s, in period t

$CapSup_{cist}$ Capacity of supplier i for commodity type c under scenario s, in period t

$CapRDC_{cjst}$ Capacity of RDC j for commodity type c under scenario s, in period t

$CapEMC_{lgst}$ Capacity of EMC g for injury type l under scenario s, in period t

$CapHos_{lhst}$ Capacity of hospital h for injury type l under scenario s, in period t

**Deterministic Variables**

$Z_{jm}$ 1 if RDC with capacity category m is located at candidate RDC j; 0 if otherwise

$Z_{gn}$ 1 if EMC with capacity category n is located at candidate EMC g; 0 if otherwise

**Stochastic Variables**

$X_{cijvst}$ Amount of commodity c dispatched from tour r that is initiated from supplier i by mode v to RDC j in scenario s and period t

$X_{cjkvst}$ Amount of commodity c dispatched from tour r that is initiated from RDC j by mode v to AA k in scenario s and period t

$X_{lkgvst}$ Number of injured person type l dispatched from tour r that is initiated from AA k by mode v to EMC g in scenario s and period t

$X_{lghvst}$ Number of injured person type l dispatched from tour r that is initiated from EMC g by mode v to hospital h in scenario s and period t

$I_{cjst}$ Amount of inventory of commodity c held at RDC j in scenario s and period t

$I_{ckst}$ Amount of inventory of commodity c held at AA k in scenario s and period t

$I_{lgst}$ Number of injured person of type l being served at EMC g in scenario s and period t

$I_{lhst}$ Total injured person of type l being served at hospital h in scenario s and period t

$dev_{ckst}$ Amount of unsatisfied demand of commodity c at AA k in scenario s and period t

$dev_{lkst}$ Number of unserved injured person of type l at AA k in scenario s and period t

$Prec_{uu'vst}$ Whether $u$ precedes $u'$ in a designated route or not

$Prec_{qq'vst}$ Whether $q$ precedes $q'$ in a designated route or not

$Y_{ijvst}$ 1 when tour r is initiated from supplier i and assigned to vehicle v in scenario s and period t; 0 if otherwise

$Y_{jkvst}$ 1 when tour r is initiated from RDC j and assigned to vehicle v in scenario s and period t; 0 if otherwise

$Y_{kgvst}$ 1 when tour r is initiated from AA k and assigned to vehicle v in scenario s and period t; 0 if otherwise

$Y_{ghvst}$ 1 when tour r is initiated from EMC g and assigned to vehicle v in scenario s and period t; 0 if otherwise

To minimize the weighted sum of unserved injured person waiting at affected area

$$Min Z_1 = \sum_s p_s . \sum_l \sum_k \sum_t PR_l . dev_{lkst}$$

To minimize the travel time required to dispatch injured persons to medical facilities

$$Min Z_2 = \sum_s p_s \cdot \left( \sum_k \sum_g \sum_v \sum_t T_{kgvst} . Y_{kgvst} + \sum_g \sum_h \sum_v \sum_t T_{ghvst} . Y_{ghvst} \right)$$

To minimize the weighted sum of unsatisfied demand over all commodities

$$Min Z_3 = \sum_s p_s . \sum_c \sum_k \sum_t PR_c . dev_{ckst}$$

To minimize the travel time to ship items to demand points

$$Min Z_4 = \sum_s p_s \cdot \left( \sum_u \sum_{u'} \sum_v \sum_t T_{uu'vst} \cdot Prec_{uu'vst} + \sum_q \sum_{q'} \sum_v \sum_t T_{qq'vst} \cdot Prec_{qq'vst} \right)$$

$$(\text{s.t. } u, u' \in I \cup J;\ q, q' \in J \cup K)$$

To minimize the total cost associated with commodity transportation to demand points

$$Min Z_5 = \sum_j \sum_m f_{jm} \cdot Z_{jm} + \sum_s p_s \cdot \begin{pmatrix} \sum_c \sum_i \sum_j \sum_v \sum_t \varphi_{cist} . X_{cijvst} + \\ \sum_c \sum_i \sum_j \sum_v \sum_t C_{cvst} . X_{cijvst} + \\ \sum_c \sum_j \sum_k \sum_v \sum_t C_{cvst} . X_{cjkvst} + \\ \sum_c \sum_j \sum_t h_c . I_{cjst} + \sum_c \sum_k \sum_t h_c . I_{ckst} + \\ \sum_c \sum_k \sum_t \pi_{ct} . dev_{ckst} \end{pmatrix}$$

Control Balance equation

Balance equation for logistics flow of injured person from affected areas (AAs)

$$d_{lkst} - \sum_{g} \sum_{v} X_{1kgvst} = dev_{lkst} \qquad \forall l \in L, k \in K, s \in S, t \in T$$

The number of injured person of type l dispatched from AA k cannot exceed the number of injured person at AA k in scenario s and period t

$$\sum_{g} \sum_{v} X_{1kgvst} \leq d_{lkst} \qquad \forall l \in L, k \in K, s \in S, t \in T$$

Balance equation of logistics flow of injured person from Emergency Medical Center (EMCs) at time period $t$ = 1

$$I_{\lg st} = \sum_{k} \sum_{v} X_{1kgvst} \qquad \forall l \in L, g \in G, s \in S, t = 1$$

Balance equation of logistics flow of injured person from Emergency Medical Center (EMCs) at time period t > 1

$$I_{\lg st} = \sum_{k} \sum_{v} X_{1kgvst} - \sum_{h} \sum_{v} X_{\lg hvst} \qquad \forall l \in L, g \in G, s \in S, t > 1$$

Balance equation of logistics flow of injured person at Hospitals

$$I_{1hst} = \sum_{g} \sum_{v} X_{\lg hvst} \qquad \forall l \in L, h \in H, s \in S, t \in T$$

Balance Equation for logistics flow of commodity to affected areas (AAs)

$$I_{cks(t-1)} + \sum_{j} \sum_{v} X_{cjkvst} - d_{ckst} = I_{ckst} - dev_{ckst} \qquad \forall c \in C, k \in K, s \in S, t \in T$$

The amount of commodity c dispatched to AA k cannot exceed the demand for commodity c at AA k in scenario s and period t

$$\sum_{k} \sum_{v} X_{cjkvst} \leq d_{ckst} \qquad \forall c \in C, j \in J, s \in S, t \in T$$

Balance equation of logistics flow of commodity c for Relief distribution center (RDCs) at time period $t = 1$

$$\sum_i \sum_v X_{cijvst} - \sum_k \sum_v X_{cjkvst} = I_{cjst} \qquad \forall c \in C, j \in J, s \in S, t = 1$$

Balance equation of logistics flow of commodity c for Relief distribution center (RDCs) at time period t > 1

$$\sum_i \sum_v X_{cijvst} + I_{cjs(t-1)} - \sum_k \sum_v X_{cjkvst} = I_{cjst} \quad \forall c \in C, j \in J, s \in S, t > 1$$

Capacity Constraints

Capacity of EMC g for injury type l in scenario s in period t = 1

$$\sum_k \sum_v X_{1kgvst} \leq CapEMC_{\lg st} \qquad \forall l \in L, g \in G, s \in S, t = 1$$

Capacity of EMC g for injury type l in scenario s in period t > 1

$$\sum_k \sum_v X_{1kgvst} - \sum_h \sum_v X_{\lg hvst} \leq CapEMC_{\lg st} \quad \forall l \in L, g \in G, s \in S, t > 1$$

Capacity of Hospital h for injury type l in scenario s in period t

$$\sum_g \sum_v X_{\lg hvst} \leq CapHos_{1hst} \qquad \forall l \in L, h \in H, s \in S, t \in T$$

Capacity of RDC j for commodity c in scenario s and period t = 1

$$\sum_i \sum_v X_{cijvst} \leq CapRDC_{cjst} \qquad \forall c \in C, j \in J, s \in S, t = 1$$

Capacity of RDC j for commodity c in scenario s and period t >1

$$\sum_i \sum_v X_{cijvst} + I_{cjs(t-1)} \leq CapRDC_{cjst} \qquad \forall c \in C, j \in J, s \in S, t > 1$$

Capacity of supplier i for commodity c in scenario s and period t

$$\sum_j \sum_v X_{cijvst} \leq CapSup_{cist} \qquad \forall c \in C, i \in I, s \in S, t \in T$$

Vehicles capacity is larger or equal to the total number of injured person transported from AAs to EMCs and EMCs to Hospitals respectively

$$\sum_{l} X_{lkgvst} \leq Y_{kgvst}.CapP_{v} \qquad \forall k \in K, g \in G, v \in V, s \in S, t \in T$$

$$\sum_{l} X_{lghvst} \leq Y_{ghvst}.CapP_{v} \qquad \forall g \in G, h \in H, v \in V, s \in S, t \in T$$

The amount of commodity dispatched from suppliers and RDCs must not exceed vehicle capacity

$$\sum_{j} \sum_{c} X_{cijvst} \cdot v_{c} \leq CapV_{v} \qquad \forall i \in I, v \in V, s \in S, t \in T$$

$$\sum_{k} \sum_{c} X_{cjkvst} \cdot v_{c} \leq CapV_{v} \qquad \forall j \in J, v \in V, s \in S, t \in T$$

Maximum total number of tour should not exceed total number of available vehicle

$$\sum_{k} \sum_{g} Y_{kgvst} + \sum_{g} \sum_{h} Y_{ghvst} \leq VehicleLimit_{v} \qquad \forall v \in V, s \in S, t \in T$$

Inventory Constraints

Upper bound of number of injured person of type l being served at EMC g in scenario s and period t

$$I_{lgst} \leq CapEMC_{lgst} \qquad \forall l \in L, g \in G, s \in S, t \in T$$

Lower bound of number of injured person of type l being served at EMC g in scenario s and period t

$$I_{lgst} \geq \sum_{k} \sum_{v} X_{lkgvst} - \sum_{h} \sum_{v} X_{lghvst} \qquad \forall l \in L, g \in G, s \in S, t \in T$$

Upper bound of number of injured person of type l being served at hospital h in scenario s and period t

$$I_{lhst} \leq CapHos_{lhst} \qquad \forall l \in L, h \in H, s \in S, t \in T$$

Upper bound of amount of commodity c being stored at RDC j in scenario s and period t

$$I_{cjst} \le CapRDC_{cjst} \qquad \forall c \in C, j \in J, s \in S, t \in T$$

Lower bound of amount of commodity c being stored at RDC j in scenario s and period t

$$I_{cjst} \ge \sum_i \sum_v X_{cijvst} - \sum_k \sum_v X_{cjkvst} \qquad \forall c \in C, j \in J, s \in S, t \in T$$

Facility location and budgetary constraints

Facility setup cost must stay within initial budgetary limit for EMCs and RDCs

$$\sum_g \sum_n f_{gn}.Z_{gn} \le FixedEMC$$

$$\sum_j \sum_m f_{jm} \cdot Z_{jm} \le FixedRDC$$

At most one facility of a certain capacity can be built in a certain location

$$\sum_n Z_{gn} \le 1 \qquad \forall g \in G$$

$$\sum_m Z_{jm} \le 1 \qquad \forall j \in J$$

Logistics Flow Constraints

Logistics flow of injured person of type l from AA k to EMC g is possible if an EMC is established at that location.

$$X_{lkgvst} \le M.\sum_n Z_{gn} \qquad \forall l \in L, g \in G, k \in K, v \in V, s \in S, t \in T$$

Logistics flow of injured person of type l from EMC g to Hospital h is possible if an EMC is established at that location.

$$X_{lghvst} \le M.\sum_n Z_{gn} \qquad \forall l \in L, g \in G, h \in H, v \in V, s \in S, t \in T$$

Logistics flow of commodity c from supplier i to RDC j is possible if an RDC is established at that location.

$$X_{cijvst} \leq M.\sum_{m} Z_{jm} \qquad \forall c \in C, i \in I, j \in J, v \in V, s \in S, t \in T$$

Logistics flow of commodity c from RDC j to AA k is possible if an RDC is established at that location.

$$X_{cjkvst} \leq M.\sum_{m} Z_{jm} \qquad \forall c \in C, j \in J, k \in K, v \in V, s \in S, t \in T$$

Enter and leave every RDC and AA only once in scenario s and period t

$$\sum_{u'} Prec_{u'uvst} = 1 \text{ (s.t. } u' \in I \cup J) \qquad \forall u \in J, v \in V, s \in S, t \in T$$

$$\sum_{u'} Prec_{uu'vst} = 1 \text{ (s.t. } u' \in I \cup J) \qquad \forall u \in J, v \in V, s \in S, t \in T$$

$$\sum_{q'} Prec_{q'qvst} = 1 \text{ (s.t. } q' \in J \cup K) \qquad \forall q \in K, v \in V, s \in S, t \in T$$

$$\sum_{q'} Prec_{qq'vst} = 1 \text{ (s.t. } q' \in J \cup K) \qquad \forall q \in K, v \in V, s \in S, t \in T$$

A particular tour must end at the node from where it started

$$\sum_{u'} Prec_{uu'vst} - \sum_{u'} Prec_{u'uvst} = 0 \text{ (s.t. } u' \in J) \qquad \forall u \in I, v \in V, s \in S, t \in T$$

$$\sum_{q'} Prec_{qq'vst} - \sum_{q'} Prec_{q'qvst} = 0 \text{ (s.t. } q' \in K) \qquad \forall q \in J, v \in V, s \in S, t \in T$$

Prevent dispatching injured person to EMCs or Hospitals where no tour is authorized

$$Y_{kgvst} \leq \sum_{l} X_{lkgvst} \qquad \forall k \in K, g \in G, v \in V, s \in S, t \in T$$

$$Y_{ghvst} \leq \sum_{l} X_{lghvst} \qquad \forall g \in G, h \in H, v \in V, s \in S, t \in T$$

Prevent dispatching commodities to RDCs or AAs where no tour is authorized

$$\sum_c X_{cijvst} \le M.Y_{ijvst} \qquad \forall i \in I, j \in J, v \in V, s \in S, t \in T$$

$$\sum_c X_{cjkvst} \le M.Y_{jkvst} \qquad \forall j \in J, k \in K, v \in V, s \in S, t \in T$$

All commodities and injured people must be transported by authorized vehicles

$$\sum_i \sum_j X_{cijvst} + \sum_j \sum_k X_{cjkvst} \le M.AC_{vc} \qquad \forall c \in C, v \in V, s \in S, t \in T$$

$$\sum_g \sum_k X_{\lg kvst} + \sum_g \sum_h X_{\lg hvst} \le M.AW_{vl} \qquad \forall l \in L, v \in V, s \in S, t \in T$$

Service Level Constraints

$$dev_{lkst} \le d_{lkst}.MinServiceLevel \qquad \forall l \in L, k \in K, s \in S, t \in T$$

$$\sum_h \sum_v X_{\lg hvst} \ge I_{\lg st}.MinServiceLevel \qquad \forall l \in L, g \in G, s \in S, t \in T$$

Feasible regions for variables

$$X_{cijvst}, X_{cjkvst}, I_{cjst}, I_{ckst}, dev_{ckst}, X_{1kgvst}, X_{\lg hvst}, I_{\lg st}, I_{1hst}, dev_{lkst}, Y_{kgvst}, Y_{ghvst} = \{0,1,2,\cdots,n\}$$

$$\forall i \in I, j \in J, k \in K, g \in G, h \in H, c \in C, l \in L, v \in V, t \in T, s \in S$$

$$Z_{jm}, Z_{gn}, Prec_{uu'vst}, Prec_{qq'vst}, Y_{ijvst}, Y_{jkvst} = \{0,1\}$$

$$\forall i \in I, j \in J, k \in K, g \in G, h \in H, m \in M, n \in N, v \in V, t \in T, s \in S, u \in I \cup J, u' \in I \cup J,$$
$$q \in J \cup K, q' \in J \cup K$$

# Chapter 5

# RESULTS AND DISCUSSIONS

The model proposed here aims to coordinate the transportation of commodities from major supply centers to distribution centers in affected areas and the transport of wounded people from affected areas to temporary and permanent emergency units. Both wounded people and commodities are categorized into a priority hierarchy, where different types of vehicles are utilized to serve priority transportation needs. The model involves a network flow formulation, where wounded people and vehicles are treated as integer valued commodities. This results in an efficient formulation where vehicles are not tracked individually. Once solved, routes and pick up/delivery instructions of vehicles are constructed from model solution. The proposed modeling framework is designed as a flexible dynamic (multi-period) coordination instrument that can adjust to frequent information updates, vehicle re-routing and re-allocation of service capacities. The planning horizon under consideration is short (in days or even hours) due to the fact that information flow is continuous after disasters and initial screening cannot capture the attrition numbers accurately, specially, in earthquakes where many people are under the debris. Continuity of commodity logistics is achieved by incorporating anticipated commodity demand for future periods.

## 5.1 Numerical Example

To illustrate the effectiveness of proposed mathematical model, a hypothetical case study is presented considering the scenario based on the perspective of Bangladesh where the Sylhet district of Bangladesh is selected as the subject area [84].

Some parameter values were estimated according to Tzeng et. al., Esmaeili and Barzinpour, Bozorgi-Amiri and Khorsi, and Najafi et al. [55, 67, 68, 85]. Tzeng et. al. performed their research for an incident in USA, while others performed their researches for different incidents occurred in Iran. So the parameters used in this numerical example have been modified according to the socio-economic situation in Bangladesh. Rest of the parameter values used in this study are based on rough estimation due to unavailability of actual data.

In this research multi-echelon logistics flow network of both relief commodities and injured person has been considered. Logistics flow of relief commodities involves transportation of commodities from supplier to relief distribution center (RDC) and from relief distribution center to affected area. Similarly, logistics flow of injured person involves transportation of injured person from affected area to emergency medical center (EMC) and from emergency medical center to hospitals. In this case study, the sets and parameter values of mathematical model are considered in following means:

Number of Suppliers: **2**

Number of Affected Area Location: **5**

Candidate RDC Location: **4**

Sizes of RDC: **(Small, Medium & Large)**

Candidate EMC Location: **4**

Sizes of EMC: **(Small, Medium & Large)**

Number of Hospitals: **3**

Disaster Scenarios: **3**

Time Periods: **3**

Types of Commodities: **2 (Food and Water)**

Types of Injury: **2 (Moderate and Severe injury)**

Types of Vehicle: **4 (2 for commodity, 2 for injured person)**

Locations of suppliers and hospitals are known in the preparedness phase. Tentative locations of affected areas, EMCs and RDCs are also known and provided in the following page.

Four tentative locations has been selected for constructing Relief Distribution Centers (RDCs) which are

Table 5.1: Tentative RDC locations

| RDC Location no. | Tentative Location |
|---|---|
| 1 | Rajaganj, Kanaighat, Sylhet |
| 2 | Shaheber Bazar, Sylhet Sadar, Sylhet |
| 3 | Tultikar, Sylhet Sadar, Sylhet |
| 4 | Deokalas, Biswanath, Sylhet |

Four tentative locations has been selected for constructing Emergency Medical Centers (EMCs) which are

Table 5.2: Tentative EMC locations

| EMC Location no. | Tentative Location |
|---|---|
| 1 | Paschim Dighirpar, Kanaighat, Sylhet |
| 2 | Gowainghat Bazar, Gowainghat, Sylhet |
| 3 | Telikhal, Companyganj, Sylhet |
| 4 | Amura, Golapganj, Sylhet |

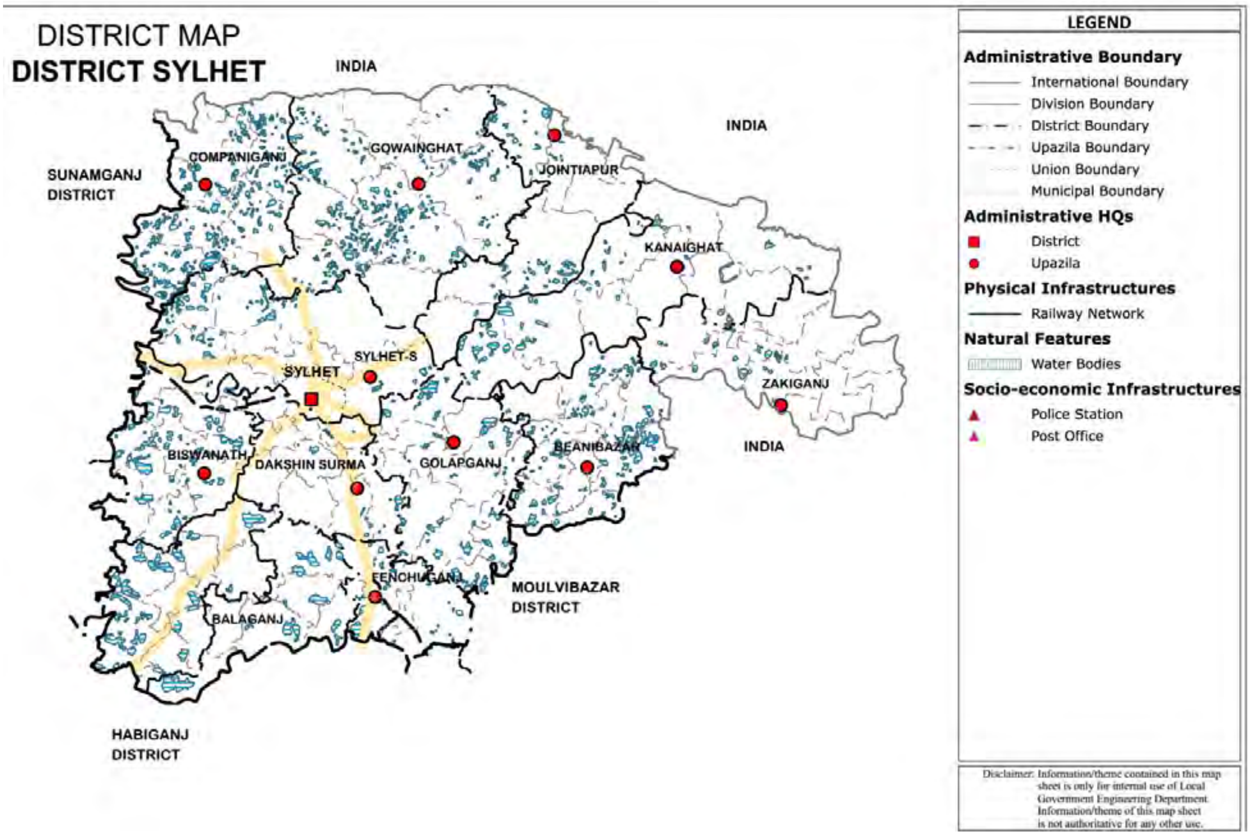


Figure 5.1: Sylhet District Map

Five tentative locations has been identified as Affected Areas (AAs) which are

Table 5.3: Tentative Affected Area (AA) locations

| Affected Area no. | Tentative Location |
|---|---|
| 1 | Purba Dighirpar, Kanaighat, Sylhet |
| 2 | Alirgaon, Gowainghat, Sylhet |
| 3 | Telikhal, Companyganj, Sylhet |
| 4 | Budbari Bazar, Golapganj, Sylhet |
| 5 | Daudpur, Dakshin Surma, Sylhet |

For the case study, the author assumes that the relative probabilities of scenario occurrence are 0.237, 0.352 and 0.411 respectively. Note that these scenarios and their associated probabilities are devised by the subject matter experts or disaster planners on the basis of historical data.

There are two types of injured person - moderately injured (Type L1) with service priority value of 0.4 and severely injured (Type L2) with service priority value of 0.6.

There are two types of relief commodities - food and water. The following table demonstrates the data for the volume occupied by each unit of commodity, the unit holding cost per unit time and priority of each type of relief commodity.

Table 5.4: Holding cost, unit volume and demand priority of commodities

| Commodity No. | Commodity Type | Holding Cost, $h_c$ (\$/unit/year) | Unit Volume, $v_c$ ($m^3$/unit) | Priority |
|---|---|---|---|---|
| C1 | Water | 0.2 | 0.02 | 0.35 |
| C2 | Food | 0.1 | 0.01 | 0.65 |

In this study, it is assumed that initial demand for relief commodities will be higher than the later time periods. So, the procurement cost of relief goods will also be higher in first period. Procurement costs of per unit relief commodities are given below:

Table 5.5: Procurement cost, $\varphi$ (\$/unit) of commodities

| Commodity Type \ Time period | T1 | T2 | T3 |
|---|---|---|---|
| C1 | 2 | 1.75 | 1.5 |
| C2 | 1 | 1 | 0.75 |

The penalty cost for unmet demand is estimated to be 50, 40 and 30 times, respectively, for the first, second, and third time period.

The transportation cost between nodes is assessed on the basis of distance. Under each scenario, per unit transportation cost for each type of relief goods are as follows:

Table 5.6: Transportation cost, $C_{cvst}$ ($/unit/unit distance) of commodities

| Commodity Type \ Scenario | S1 | S2 | S3 |
|---|---|---|---|
| C1 | 0.5 | 0.75 | 0.6 |
| C2 | 0.25 | 0.4 | 0.3 |

Two types of transportation modes are considered in this case study. Some vehicles are intended to carry injured people and some are intended to transport commodities. The following table demonstrates the data for the vehicle capacity for commodity and injured people. This table also shows maximum available number of vehicles.

Table 5.7: Volume capacity, person capacity and max. no. of available vehicles

| Vehicle | Volume Capacity (in m$^3$), $CapV_v$ | Person capacity, $CapP_v$ | Max. no. of vehicle, $VehicleLimit_v$ |
|---|---|---|---|
| V1 | 24 | N/A | N/A |
| V2 | 18 | N/A | N/A |
| V3 | N/A | 4 | 28 |
| V4 | N/A | 6 | 30 |

Estimates of injured people in each affected areas are as follows:

Table 5.8: Estimates of injured people in each affected areas

| Scenario → | | S1 | | | S2 | | | S3 | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Period → | | T1 | T2 | T3 | T1 | T2 | T3 | T1 | T2 | T3 |
| AA ↓ | Injury ↓ | | | | | | | | | |
| K1 | L1 | 25 | 30 | 23 | 23 | 28 | 21 | 20 | 24 | 18 |
| | L2 | 40 | 48 | 36 | 38 | 46 | 34 | 30 | 36 | 27 |
| K2 | L1 | 20 | 24 | 18 | 21 | 25 | 19 | 17 | 20 | 15 |
| | L2 | 30 | 36 | 27 | 32 | 38 | 29 | 20 | 24 | 18 |
| K3 | L1 | 18 | 22 | 16 | 17 | 20 | 15 | 22 | 26 | 20 |
| | L2 | 20 | 24 | 18 | 20 | 24 | 18 | 28 | 34 | 25 |
| K4 | L1 | 12 | 14 | 11 | 12 | 14 | 11 | 14 | 17 | 13 |
| | L2 | 25 | 30 | 23 | 22 | 26 | 20 | 16 | 19 | 14 |
| K5 | L1 | 14 | 17 | 13 | 14 | 17 | 13 | 10 | 12 | 9 |
| | L2 | 14 | 17 | 13 | 16 | 19 | 14 | 12 | 14 | 11 |

The demand data for each type of relief commodities in each affected areas are as follows:

Table 5.9: Demand data of relief commodities in each affected areas

| Scenario → | | S1 | | | S2 | | | S3 | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Period → | | T1 | T2 | T3 | T1 | T2 | T3 | T1 | T2 | T3 |
| AA ↓ | Commodity ↓ | | | | | | | | | |
| K1 | C1 | 50 | 40 | 60 | 46 | 50 | 40 | 30 | 36 | 40 |
| | C2 | 25 | 20 | 30 | 23 | 25 | 20 | 15 | 18 | 20 |
| K2 | C1 | 40 | 50 | 40 | 44 | 40 | 56 | 80 | 70 | 84 |
| | C2 | 20 | 25 | 20 | 22 | 20 | 28 | 40 | 35 | 42 |
| K3 | C1 | 80 | 70 | 76 | 70 | 50 | 60 | 30 | 36 | 40 |
| | C2 | 40 | 35 | 38 | 35 | 25 | 30 | 15 | 18 | 20 |
| K4 | C1 | 50 | 50 | 36 | 30 | 24 | 36 | 50 | 30 | 36 |
| | C2 | 25 | 25 | 18 | 15 | 12 | 18 | 25 | 15 | 18 |
| K5 | C1 | 30 | 36 | 36 | 46 | 50 | 56 | 50 | 60 | 36 |
| | C2 | 15 | 18 | 18 | 23 | 25 | 28 | 25 | 30 | 18 |

Capacity data for the Emergency Medical Center (EMC) for each type of injured people are as follows:

Table 5.10: Capacity data for Emergency Medical Centers (EMCs)

| Scenario → | | S1 | | | S2 | | | S3 | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Period → | | T1 | T2 | T3 | T1 | T2 | T3 | T1 | T2 | T3 |
| EMC ↓ | Injury ↓ | | | | | | | | | |
| G1 | L1 | 24 | 22 | 22 | 22 | 21 | 20 | 26 | 21 | 23 |
| | L2 | 30 | 35 | 28 | 24 | 32 | 31 | 22 | 20 | 21 |
| G2 | L1 | 20 | 25 | 18 | 18 | 24 | 26 | 24 | 19 | 22 |
| | L2 | 35 | 28 | 25 | 30 | 28 | 26 | 24 | 28 | 29 |
| G3 | L1 | 24 | 24 | 22 | 24 | 23 | 22 | 20 | 24 | 18 |
| | L2 | 28 | 37 | 32 | 25 | 32 | 32 | 32 | 27 | 27 |
| G4 | L1 | 12 | 20 | 11 | 16 | 18 | 13 | 15 | 18 | 15 |
| | L2 | 20 | 20 | 15 | 20 | 28 | 27 | 18 | 22 | 12 |

Capacity data for the hospitals for each type of injured people are as follows:

Table 5.11: Capacity data for the hospitals

| Scenario → | | S1 | | | S2 | | | S3 | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Period → | | T1 | T2 | T3 | T1 | T2 | T3 | T1 | T2 | T3 |
| Hospital ↓ | Injury ↓ | | | | | | | | | |
| H1 | L1 | 30 | 26 | 27 | 30 | 28 | 29 | 32 | 22 | 21 |
| | L2 | 35 | 38 | 35 | 30 | 44 | 33 | 26 | 28 | 20 |
| H2 | L1 | 35 | 35 | 25 | 22 | 27 | 21 | 30 | 28 | 29 |
| | L2 | 40 | 48 | 38 | 44 | 39 | 44 | 38 | 34 | 36 |
| H3 | L1 | 15 | 36 | 20 | 36 | 32 | 28 | 28 | 30 | 27 |
| | L2 | 38 | 38 | 28 | 20 | 36 | 38 | 34 | 36 | 33 |

Capacity data for the Relief Distribution Centers (RDCs) for each type of relief commodities are as follows:

Table 5.12: Capacity data for Relief Distribution Centers (RDCs)

| Scenario → | | S1 | | | S2 | | | S3 | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Period → | | T1 | T2 | T3 | T1 | T2 | T3 | T1 | T2 | T3 |
| RDC ↓ | Commodity ↓ | | | | | | | | | |
| J1 | C1 | 60 | 46 | 50 | 60 | 56 | 50 | 44 | 76 | 56 |
| | C2 | 30 | 23 | 25 | 30 | 28 | 25 | 22 | 38 | 28 |
| J2 | C1 | 30 | 48 | 60 | 50 | 36 | 48 | 40 | 30 | 36 |
| | C2 | 15 | 24 | 30 | 25 | 18 | 24 | 20 | 15 | 18 |
| J3 | C1 | 90 | 60 | 70 | 80 | 64 | 70 | 62 | 80 | 64 |
| | C2 | 45 | 30 | 35 | 40 | 32 | 35 | 31 | 40 | 32 |
| J4 | C1 | 50 | 36 | 40 | 20 | 40 | 36 | 60 | 56 | 56 |
| | C2 | 25 | 18 | 20 | 10 | 20 | 18 | 30 | 28 | 28 |

Capacity data for the suppliers for each type of relief commodities are as follows:

Table 5.13: Capacity data for suppliers

| Scenario → | | S1 | | | S2 | | | S3 | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Period → | | T1 | T2 | T3 | T1 | T2 | T3 | T1 | T2 | T3 |
| Supplier ↓ | Commodity ↓ | | | | | | | | | |
| I1 | C1 | 110 | 120 | 108 | 130 | 100 | 100 | 120 | 120 | 100 |
| | C2 | 55 | 60 | 54 | 65 | 50 | 50 | 60 | 60 | 50 |
| I2 | C1 | 120 | 136 | 120 | 120 | 110 | 100 | 100 | 120 | 120 |
| | C2 | 60 | 68 | 60 | 60 | 55 | 50 | 50 | 60 | 60 |

Travel times (in minute) of tours from affected areas to Emergency Medical Centers are as follows:

Table 5.14: Travel time of tours from affected areas to Emergency Medical Centers

| Vehicle → | V3 | | | |
|---|---|---|---|---|
| EMC / AA | G1 | G2 | G3 | G4 |
| K1 | 1 | 19 | 30 | 22 |
| K2 | 17 | 1 | 18 | 27 |
| K3 | 20 | 18 | 2 | 18 |
| K4 | 25 | 32 | 24 | 2 |
| K5 | 28 | 40 | 38 | 22 |

| Vehicle → | V4 | | | |
|---|---|---|---|---|
| EMC / AA | G1 | G1 | G1 | G1 |
| K1 | 1 | 21 | 33 | 24 |
| K2 | 19 | 1 | 20 | 30 |
| K3 | 22 | 20 | 2 | 20 |
| K4 | 28 | 35 | 26 | 2 |
| K5 | 31 | 44 | 42 | 42 |

Travel times (in minute) of tours from Emergency Medical Centers to hospitals are as follows:

Table 5.15: Travel time of tours from Emergency Medical Centers to hospitals

| Vehicle → | V3 | | |
|---|---|---|---|
| Hospital / EMC | H1 | H2 | H3 |
| G1 | 27 | 28 | 16 |
| G2 | 19 | 21 | 6 |
| G3 | 22 | 24 | 19 |
| G4 | 24 | 26 | 35 |

| Vehicle → | V4 | | |
|---|---|---|---|
| Hospital / EMC | H1 | H2 | H3 |
| G1 | 30 | 31 | 18 |
| G2 | 21 | 23 | 7 |
| G3 | 24 | 26 | 21 |
| G4 | 26 | 29 | 39 |

In this study, the initial budget for opening required number of EMCs has been assumed to be \$410,000. Facility setup costs at different tentative Emergency Medical Center locations for three different capacity types are as follows. All costs are given in terms of \$1000.

Table 5.16: Facility setup costs for Emergency Medical Centers

| Capacity type / EMC location | 1 | 2 | 3 |
|---|---|---|---|
| Paschim Dighirpar, Kanaighat | 92 | 113 | 128 |
| Gowainghat Bazar, Gowainghat | 89 | 109 | 123 |
| Telikhal, Companyganj | 84 | 101 | 116 |
| Amura, Golapganj | 87 | 104 | 121 |

The initial budget for opening required number of RDCs has been assumed to be \$570,000.Facility setup costs at different tentative Relief Distribution Center locations for three different capacity types are as follows. All costs are given in terms of \$1000.

Table 5.17: Facility setup costs for Relief Distribution Centers

| Capacity type / RDC location | 1 | 2 | 3 |
|---|---|---|---|
| Rajaganj, Kanaighat | 125 | 148 | 167 |
| Shaheber Bazar, Sylhet Sadar | 132 | 145 | 164 |
| Tultikar, Sylhet Sadar | 128 | 155 | 170 |
| Deokalas, Biswanath | 122 | 152 | 168 |

Travel times (in minute) of tours from suppliers to Relief Distribution Centers are as follows:

Table 5.18: Travel time of tours from suppliers to Relief Distribution Centers

| Vehicle | V1 | | | | | |
|---|---|---|---|---|---|---|
| Scenario | S1 | | | | | |
| | I1 | I2 | J1 | J2 | J3 | J4 |
| I1 | - | - | 25 | 50 | 35 | 45 |
| I2 | - | - | - | 30 | 70 | 80 |
| J1 | 25 | - | - | - | - | 60 |
| J2 | 50 | 30 | - | - | 60 | 75 |
| J3 | 35 | 70 | - | 60 | - | 10 |
| J4 | 45 | 80 | 60 | 75 | 10 | - |
| | | | | | | |
| Scenario | S2 | | | | | |
| | I1 | I2 | J1 | J2 | J3 | J4 |
| I1 | - | - | 25 | 50 | 35 | 45 |
| I2 | - | - | - | 30 | 70 | 80 |
| J1 | 25 | - | - | - | 60 | 60 |
| J2 | 50 | 30 | - | - | - | 75 |
| J3 | 35 | 70 | 60 | - | - | 10 |
| J4 | 45 | 80 | 60 | 75 | 10 | - |
| | | | | | | |
| Scenario | S3 | | | | | |
| | I1 | I2 | J1 | J2 | J3 | J4 |
| I1 | - | - | 25 | 50 | 35 | 45 |
| I2 | - | - | 40 | 30 | 70 | 80 |
| J1 | 25 | 40 | - | - | 60 | 60 |
| J2 | 50 | 30 | - | - | - | 70 |
| J3 | 35 | 70 | 60 | - | - | 10 |
| J4 | 45 | 80 | 60 | 70 | 10 | - |

| Vehicle | V2 | | | | | |
|---|---|---|---|---|---|---|
| Scenario | S1 | | | | | |
| | I1 | I2 | J1 | J2 | J3 | J4 |
| I1 | - | - | 20 | 40 | 28 | 36 |
| I2 | - | - | - | 24 | 56 | 64 |
| J1 | 20 | - | - | - | - | 48 |
| J2 | 40 | 24 | - | - | 48 | 60 |
| J3 | 28 | 56 | - | 48 | - | 8 |
| J4 | 36 | 64 | 48 | 60 | 8 | - |
| | | | | | | |
| Scenario | S2 | | | | | |
| | I1 | I2 | J1 | J2 | J3 | J4 |
| I1 | - | - | 20 | 40 | 28 | 36 |
| I2 | - | - | - | 24 | 56 | 64 |
| J1 | 20 | - | - | - | 48 | 48 |
| J2 | 40 | 24 | - | - | - | 60 |
| J3 | 28 | 56 | 48 | - | - | 8 |
| J4 | 36 | 64 | 48 | 60 | 8 | - |
| | | | | | | |
| Scenario | S3 | | | | | |
| | I1 | I2 | J1 | J2 | J3 | J4 |
| I1 | - | - | 20 | 40 | 28 | 36 |
| I2 | - | - | 32 | 24 | 56 | 64 |
| J1 | 20 | 32 | - | - | 48 | 48 |
| J2 | 40 | 24 | - | - | - | 56 |
| J3 | 28 | 56 | 48 | - | - | 8 |
| J4 | 36 | 64 | 48 | 56 | 8 | - |

Travel times (in minute) of tours from Relief Distribution Centers to affected areas are as follows:

Table 5.19: Travel time of tours from Relief Distribution Centers to affected areas

| Vehicle | V1 | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Scenario | S1 | | | | | | | | |
| | J1 | J2 | J3 | J4 | K1 | K2 | K3 | K4 | K5 |
| J1 | - | - | - | - | 30 | 45 | 95 | 35 | 60 |
| J2 | - | - | - | - | 60 | 30 | 25 | 90 | 70 |
| J3 | - | - | - | - | 60 | 70 | 30 | 25 | 45 |
| J4 | - | - | - | - | 45 | 80 | 40 | 65 | 20 |
| K1 | 30 | 60 | 60 | 45 | - | 20 | 45 | 30 | 35 |
| K2 | 45 | 30 | 70 | 80 | 20 | - | 40 | - | 25 |
| K3 | 95 | 25 | 30 | 40 | 45 | 40 | - | 20 | 50 |
| K4 | 35 | 90 | 25 | 65 | 30 | - | 20 | - | 30 |
| K5 | 60 | 70 | 45 | 20 | 25 | 25 | 50 | 30 | - |
| | | | | | | | | | |
| Scenario | S2 | | | | | | | | |
| | J1 | J2 | J3 | J4 | K1 | K2 | K3 | K4 | K5 |
| J1 | - | - | - | - | 30 | 45 | 95 | 35 | 60 |
| J2 | - | - | - | - | 60 | 30 | 25 | 90 | 70 |
| J3 | - | - | - | - | 60 | 70 | 30 | 25 | 45 |
| J4 | - | - | - | - | 45 | 80 | 40 | 65 | 20 |
| K1 | 30 | 60 | 60 | 45 | - | 20 | - | 30 | 35 |
| K2 | 45 | 30 | 70 | 80 | 20 | - | 40 | 45 | 25 |
| K3 | 95 | 25 | 30 | 40 | - | 40 | - | 20 | 50 |
| K4 | 35 | 90 | 25 | 65 | 30 | 45 | 20 | - | 30 |
| K5 | 60 | 70 | 45 | 20 | 25 | 25 | 50 | 30 | - |
| | | | | | | | | | |
| Scenario | S3 | | | | | | | | |
| | J1 | J2 | J3 | J4 | K1 | K2 | K3 | K4 | K5 |
| J1 | - | - | - | - | 30 | 45 | 95 | 35 | 60 |
| J2 | - | - | - | - | 60 | 30 | - | 90 | 70 |
| J3 | - | - | - | - | 60 | 70 | 30 | 25 | 45 |
| J4 | - | - | - | - | 45 | 80 | 40 | 65 | 20 |
| K1 | 30 | 60 | 60 | 45 | - | 20 | 45 | 30 | 35 |
| K2 | 45 | 30 | 70 | 80 | 20 | - | 40 | 25 | 25 |
| K3 | 95 | - | 30 | 40 | 45 | 40 | - | 20 | 50 |
| K4 | 35 | 90 | 25 | 65 | 30 | 25 | 20 | - | 30 |
| K5 | 60 | 70 | 45 | 20 | 25 | 25 | 50 | 30 | - |

| Vehicle | V2 | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Scenario | S1 | | | | | | | | |
| | J1 | J2 | J3 | J4 | K1 | K2 | K3 | K4 | K5 |
| J1 | - | - | - | - | 24 | 36 | 76 | 28 | 48 |
| J2 | - | - | - | - | 48 | 24 | 20 | 72 | 56 |
| J3 | - | - | - | - | 48 | 56 | 24 | 20 | 36 |
| J4 | - | - | - | - | 36 | 64 | 32 | 52 | 16 |
| K1 | 24 | 48 | 48 | 36 | - | 16 | 36 | 24 | 28 |
| K2 | 36 | 24 | 56 | 64 | 16 | - | 32 | - | 20 |
| K3 | 76 | 20 | 24 | 32 | 36 | 32 | - | 16 | 40 |
| K4 | 28 | 72 | 20 | 52 | 24 | - | 16 | - | 24 |
| K5 | 48 | 56 | 36 | 16 | 20 | 20 | 40 | 24 | - |
| | | | | | | | | | |
| Scenario | S2 | | | | | | | | |
| | J1 | J2 | J3 | J4 | K1 | K2 | K3 | K4 | K5 |
| J1 | - | - | - | - | 24 | 36 | 76 | 28 | 48 |
| J2 | - | - | - | - | 48 | 24 | 20 | 72 | 56 |
| J3 | - | - | - | - | 48 | 56 | 24 | 20 | 36 |
| J4 | - | - | - | - | 36 | 64 | 32 | 52 | 16 |
| K1 | 24 | 48 | 48 | 36 | - | 16 | - | 24 | 28 |
| K2 | 36 | 24 | 56 | 64 | 16 | - | 32 | 36 | 20 |
| K3 | 76 | 20 | 24 | 32 | - | 32 | - | 16 | 40 |
| K4 | 28 | 72 | 20 | 52 | 24 | 36 | 16 | - | 24 |
| K5 | 48 | 56 | 36 | 16 | 20 | 20 | 40 | 24 | - |
| | | | | | | | | | |
| Scenario | S3 | | | | | | | | |
| | J1 | J2 | J3 | J4 | K1 | K2 | K3 | K4 | K5 |
| J1 | - | - | - | - | 24 | 36 | 76 | 28 | 48 |
| J2 | - | - | - | - | 48 | 24 | - | 72 | 56 |
| J3 | - | - | - | - | 48 | 56 | 24 | 20 | 36 |
| J4 | - | - | - | - | 36 | 64 | 32 | 52 | 16 |
| K1 | 24 | 48 | 48 | 36 | - | 16 | 36 | 24 | 28 |
| K2 | 36 | 24 | 56 | 64 | 16 | - | 32 | 20 | 20 |
| K3 | 76 | - | 24 | 32 | 36 | 32 | - | 16 | 40 |
| K4 | 28 | 72 | 20 | 52 | 24 | 20 | 16 | - | 24 |
| K5 | 48 | 56 | 36 | 16 | 20 | 20 | 40 | 24 | - |

Routes initiating from suppliers, visited RDCs, and transportation times (in minute) are as follows:

Table 5.20: Routes initiating from suppliers, visited RDCs, and transportation time

| Supplier | Route | Transportation Time (Min) |
|---|---|---|
| I1 | I1-J1-I1 | 40 |
| I1 | I1-J1-J4-I1 | 104 |
| I1 | I1-J1-J4-J3-I1 | 104 |
| I1 | I1-J3-I1 | 56 |
| I1 | I1-J3-J4-I1 | 72 |
| I1 | I1-J4-I1 | 72 |
| I1 | I1-J4-J1-I1 | 104 |
| I1 | I1-J4-J3-I1 | 72 |
| I2 | I2-J2-I2 | 48 |

Routes initiating from RDCs, visited AAs, and transportation times (in minute) are as follows:

Table 5.21: Routes initiating from RDCs, visited AAs, and transportation time

| RDC | Route | Transportation Time (Min) |
|---|---|---|
| J1 | J1-K1-K2-J1 | 76 |
| J1 | J1-K1-K4-K3-J1 | 140 |
| J1 | J1-K2-K1-J1 | 76 |
| J1 | J1-K2-K3-K4-J1 | 112 |
| J1 | J1-K2-K5-J1 | 104 |
| J1 | J1-K4-K1-K2-J1 | 104 |
| J1 | J1-K4-K3-J1 | 120 |
| J2 | J2-K1-K2-J2 | 88 |
| J2 | J2-K2-J2 | 48 |
| J2 | J2-K2-K1-J2 | 88 |
| J2 | J2-K3-J2 | 40 |
| J2 | J2-K3-K4-J2 | 108 |
| J3 | J3-K3-K4-J3 | 60 |
| J3 | J3-K3-K4-K5-K1-J3 | 140 |
| J3 | J3-K4-J3 | 40 |
| J3 | J3-K4-K1-J3 | 92 |
| J3 | J3-K4-K3-J3 | 60 |
| J3 | J3-K5-K1-J3 | 112 |
| J3 | J3-K5-K1-K2-J3 | 136 |
| J3 | J3-K5-K2-K1-J3 | 120 |
| J4 | J4-K1-K2-K5-J4 | 88 |
| J4 | J4-K5-J4 | 32 |
| J4 | J4-K5-K1-K2-J4 | 124 |
| J4 | J4-K5-K2-J4 | 100 |
| J4 | J4-K5-K2-K1-J4 | 88 |

## 5.2 Result Analysis

In this section, the computational results are presented and the behavior of the proposed model is analyzed. The results reported below were obtained using GAMS/Cplex on a 3.1 GHz desktop computer with 4 GB of RAM under Windows 10 operating system [86, 87].

In a multi-objective optimization problem (MOOP), there can never exist a single absolute solution that can satisfy all the objectives to their best. For two or more objectives, each objective corresponds to a different optimal solution, but none of the tradeoff solutions is optimal with respect to all objectives. Though an optimal solution may have minimum total combined objective function value, it may not be the best solution with respect to all the objectives simultaneously. Because of the nature of MOOP, solution may be optimal with respect to one objective or the total fitness may be minimum by best satisfying all the objectives but may be a poor candidate for a particular objective. Hence, it is desirable to generate many optimal solutions considering all the objectives. Some of the unique solutions developed using augmented ε-constraint method are shown in the table below:

Table 5.22: Unique solutions

| Solution Number | Objective 1 Weighted Sum of Unserved Injury | Objective 2 Travel Time to Dispatch Injured Person | Objective 3 Weighted Sum of Unsatisfied Demand | Objective 4 Travel Time to Dispatch Relief Commodity | Objective 5 Total Cost of Commodity Transportation |
|---|---|---|---|---|---|
| 1 | 19.70 | 2796.30 | 16.00 | 2977.4 | 3399.7 |
| 2 | 20.03 | 2494.70 | 15.90 | 2495.6 | 3408.7 |
| 3 | 19.69 | 1990.90 | 15.96 | 2299.1 | 3408.7 |
| 4 | 20.10 | 1499.87 | 16.00 | 2242.6 | 3395.7 |
| 5 | 92.60 | 922.85 | 15.98 | 2248.8 | 3344.5 |
| 6 | 79.90 | 924.20 | 16.00 | 2245.5 | 3317.5 |
| 7 | 59.50 | 951.00 | 16.05 | 2249.7 | 3298.5 |
| 8 | 54.00 | 962.20 | 16.00 | 2214.6 | 3395.6 |
| 9 | 52.00 | 966.80 | 15.94 | 2210.8 | 3298.5 |
| 10 | 51.00 | 976.50 | 16.31 | 2218.9 | 3298.5 |

It can be noted that, augmented ε-constraint method failed to produce pareto optimal solution for this case study. To obtain non-optimal efficient solutions, the model has been divided into two segments and solved individually. The first segment consists of parameters, constraint equations and objective functions associated with dispatching injured person. Results obtained from this model has been utilized to solve the second segment which consists of parameters, constraint equations and objective functions associated with transportation of relief commodities. To prove the validity of the proposed entire model, two small scale example problems have been solved using augmented ε-constraint method which have been explained in the later portion of this chapter.

The relationship among the objective functions are depicted in Figure 5.2, 5.3, 5.4, 5.5, and 5.6, where objective 1 aims to minimize the weighted sum of unserved injury, objective 2 attempts to minimize the travel time required to dispatch injured persons to medical facilities, objective 3 aims to minimize the weighted sum of unsatisfied demand over all commodities, objective 4 attempts to minimize the travel time to ship relief goods to demand points, and objective 5 seeks to minimize the total cost associated with commodity transportation to demand points. They are obtained by using augmented ε-constraint method. In figure 5.2, the y-axis represents $Obj_1$, which is the weighted sum of unserved injury for all AAs, and the x-axis signifies the travel time required to dispatch injured person. In figures, the line represents the relationship between two objectives when all other objectives are fixed. As the weighted sum of unserved injury increases, the travel time required to dispatch injured person decreases.

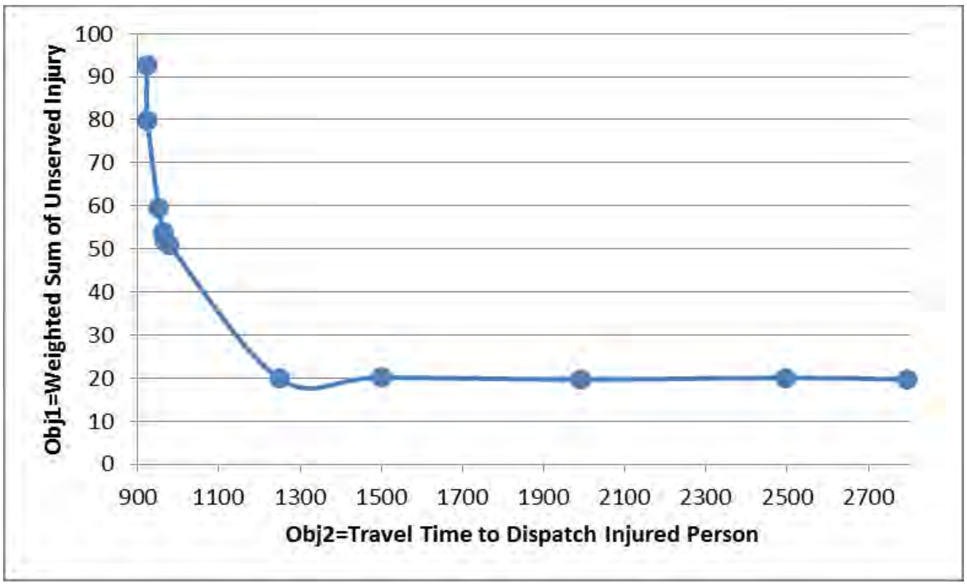


Figure 5.2: Relationship between Objective 1 and Objective 2

In figure 5.3, the y-axis represents $Obj_3$, which is the weighted sum of unsatisfied demand for all AAs, and the x-axis signifies the travel time required to dispatch relief commodity.

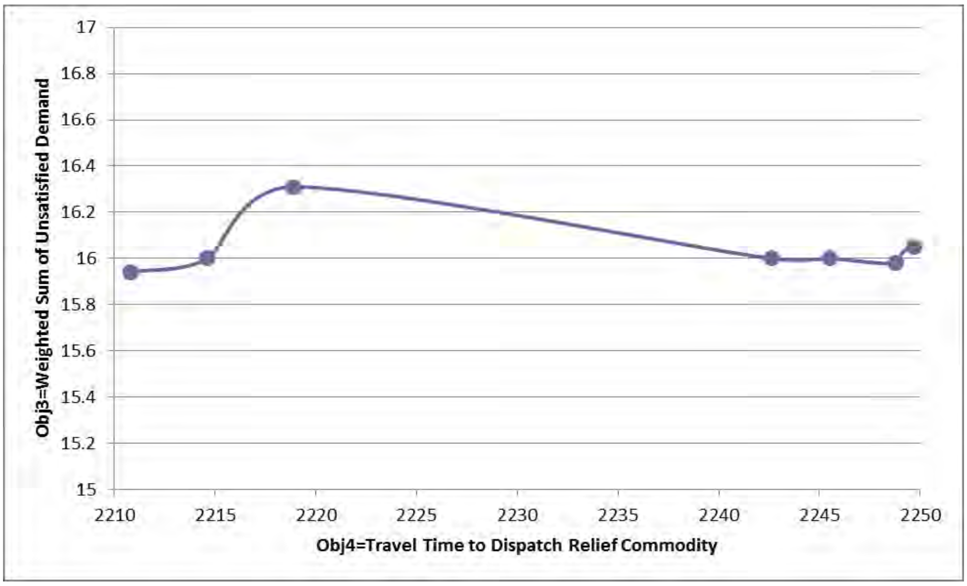


Figure 5.3: Relationship between Objective 3 and Objective 4

In figure 5.4, the y-axis represents $Obj_3$, which is the weighted sum of unsatisfied demand for all AAs, and the x-axis signifies $Obj_5$, which is the total cost associated with commodity transportation to demand points. As the unsatisfied demand increases, the total cost decreases.

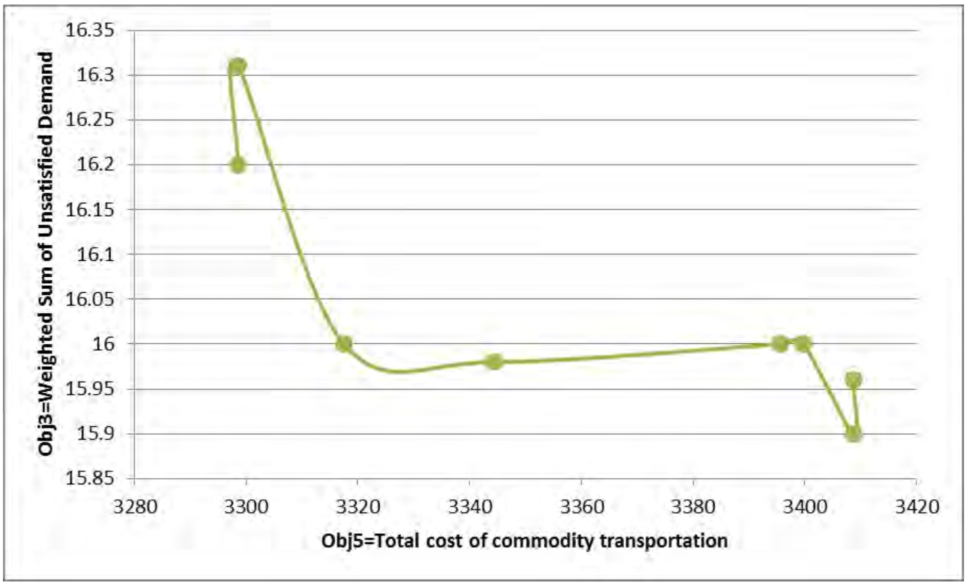


Figure 5.4: Relationship between Objective 3 and Objective 5

In figure 5.5, the y-axis represents $Obj_4$, which is the travel time required to dispatch relief commodity, and the x-axis signifies $Obj_5$, which is the total cost associated with commodity transportation to demand points. As the travel time increases, the total cost increases as well.

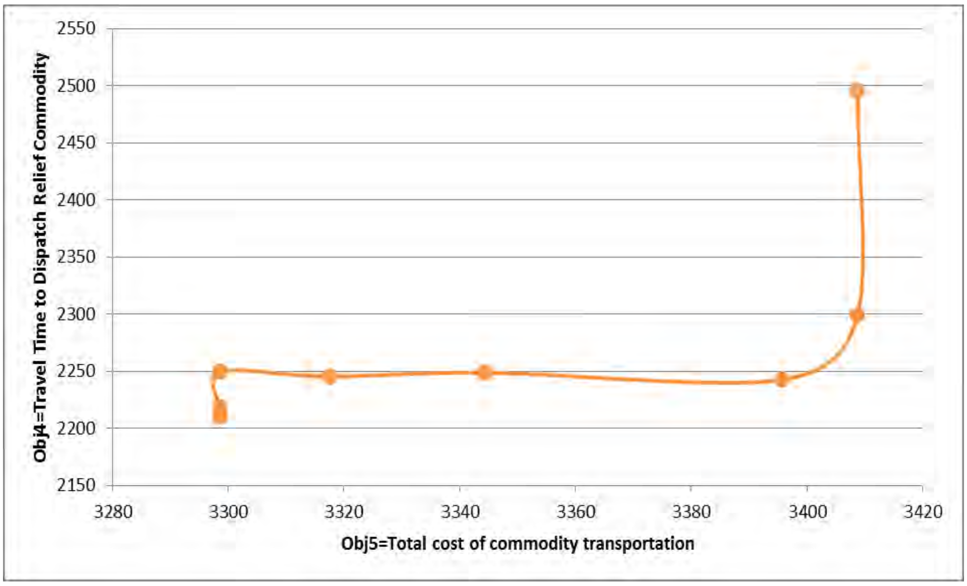


Figure 5.5: Relationship between Objective 4 and Objective 5

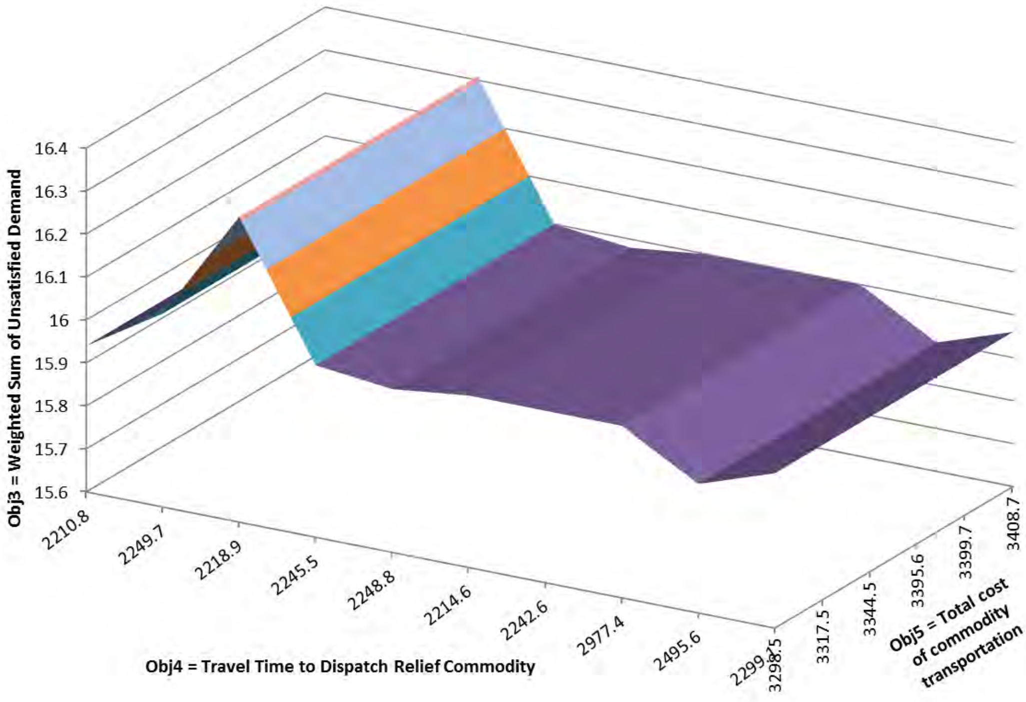


Figure 5.6: Pareto front surface

Moreover, if all three objectives associated with commodity transportation are considered concurrently, Figure 5.6 shows the approximate Pareto front surface by the augmented ε-constraint method. Based on the figure, the total cost does not affect too much unsatisfied demand under the same level of travel time, whereas the weighted sum of unsatisfied demand is significantly influenced by the travel time.

To solve our multi-objective model with the augmented ε-constraint method, Objective 1 is regarded as the foremost objective function that aims to minimize the weighted sum of unserved injury. Table 5.23 to Table 5.32 provide an insight into the output data characteristics.

The model opened three medium size EMC in first three locations and one small size EMC in fourth location. The result also suggests to open three small size RDCs in first three locations and one large size RDC in fourth location. Selected capacity types of EMCs and RDCs for constructing facilities at different locations are as follows:

Table 5.23: Selected locations for constructing EMCs and RDCs

| EMC Location | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| Capacity Type | 2 | 2 | 2 | 1 |
| | | | | |
| RDC Location | 1 | 2 | 3 | 4 |
| Capacity Type | 1 | 1 | 1 | 3 |

Table 5.24 displays number of unserved injured person at different affected areas under different scenario and time period. The result shows that, number of unserved injured person significantly decreases after each time period which confirms the validity of the model.

Table 5.24: Data of unserved injured person at different affected areas

| Scenario → | | S1 | | | S2 | | | S3 | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Period → | | T1 | T2 | T3 | T1 | T2 | T3 | T1 | T2 | T3 |
| AA ↓ | Injury ↓ | | | | | | | | | |
| K1 | L1 | 7 | 9 | 0 | 0 | 8 | 0 | 0 | 0 | 0 |
| | L2 | 10 | 1 | 0 | 11 | 0 | 0 | 1 | 0 | 0 |
| K2 | L1 | 0 | 6 | 0 | 0 | 7 | 0 | 0 | 2 | 0 |
| | L2 | 0 | 0 | 0 | 6 | 4 | 0 | 6 | 0 | 0 |
| K3 | L1 | 0 | 6 | 0 | 3 | 1 | 0 | 0 | 0 | 0 |
| | L2 | 6 | 0 | 0 | 6 | 0 | 0 | 0 | 0 | 0 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| K4 | L1 | 0 | 0 | 0 | 3 | 0 | 0 | 0 | 2 | 0 |
| | L2 | 0 | 2 | 0 | 2 | 0 | 0 | 0 | 0 | 0 |
| K5 | L1 | 2 | 5 | 0 | 1 | 2 | 0 | 0 | 0 | 0 |
| | L2 | 0 | 3 | 0 | 4 | 0 | 0 | 3 | 0 | 0 |

Table 5.25 shows the inventory data of injured person at different Emergency Medical Centers under different scenario and time period.

Table 5.25: Inventory data of injured person at different Emergency Medical Centers

| Scenario → | | S1 | | | S2 | | | S3 | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Period → | | T1 | T2 | T3 | T1 | T2 | T3 | T1 | T2 | T3 |
| EMC ↓ | Injury ↓ | | | | | | | | | |
| G1 | L1 | 24 | 14 | 12 | 22 | 16 | 18 | 26 | 20 | 0 |
| | L2 | 30 | 34 | 28 | 24 | 30 | 12 | 22 | 20 | 20 |
| G2 | L1 | 20 | 23 | 0 | 18 | 20 | 26 | 24 | 14 | 14 |
| | L2 | 35 | 26 | 25 | 30 | 26 | 17 | 24 | 28 | 14 |
| G3 | L1 | 24 | 8 | 22 | 24 | 16 | 9 | 20 | 16 | 16 |
| | L2 | 28 | 36 | 17 | 25 | 32 | 10 | 32 | 27 | 18 |
| G4 | L1 | 12 | 16 | 11 | 16 | 13 | 6 | 13 | 18 | 2 |
| | L2 | 20 | 16 | 15 | 20 | 26 | 21 | 18 | 20 | 0 |

Next table shows the inventory data of injured person at different hospitals. For example, under scenario two in the third day, hospital 1 has 10 patients with minor injury and 4 patients with severe injury.

Table 5.26: Inventory data of injured person at different hospitals

| Scenario → | | S1 | | | S2 | | | S3 | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Period → | | T1 | T2 | T3 | T1 | T2 | T3 | T1 | T2 | T3 |
| Hospital ↓ | Injury ↓ | | | | | | | | | |
| H1 | L1 | 8 | 3 | 23 | 13 | 4 | 10 | 6 | 7 | 11 |
| | L2 | 9 | 3 | 9 | 8 | 4 | 4 | 13 | 2 | 4 |
| H2 | L1 | 10 | 8 | 13 | 0 | 8 | 2 | 12 | 15 | 5 |
| | L2 | 6 | 16 | 7 | 8 | 16 | 33 | 0 | 12 | 12 |
| H3 | L1 | 8 | 9 | 0 | 13 | 9 | 8 | 8 | 5 | 27 |
| | L2 | 21 | 18 | 16 | 17 | 15 | 18 | 18 | 18 | 27 |

Next table shows data of unsatisfied needs of commodities at different affected areas under different scenario and time period. This model attempts to minimize unsatisfied needs of commodities at affected areas. Result demonstrates that the model has succeeded to eradicate shortage of commodities from affected area K1 and K2.

Table 5.27: Data of unsatisfied needs of commodities at different affected areas

| Scenario → | | S1 | | | S2 | | | S3 | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Period → | | T1 | T2 | T3 | T1 | T2 | T3 | T1 | T2 | T3 |
| AA ↓ | Commodity ↓ | | | | | | | | | |
| K1 | C1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | C2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| K2 | C1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | C2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| K3 | C1 | 5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | C2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| K4 | C1 | 5 | 0 | 0 | 11 | 0 | 0 | 10 | 0 | 0 |
| | C2 | 10 | 2 | 0 | 15 | 4 | 0 | 10 | 0 | 0 |
| K5 | C1 | 0 | 0 | 5 | 8 | 0 | 0 | 0 | 0 | 4 |
| | C2 | 0 | 0 | 3 | 0 | 0 | 0 | 0 | 0 | 4 |

Table 5.28 demonstrates inventory data of commodities at different Relief Distribution Centers under different scenario and time period.

Table 5.28: Inventory data of commodities at different Relief Distribution Centers

| Scenario → | | S1 | | | S2 | | | S3 | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Period → | | T1 | T2 | T3 | T1 | T2 | T3 | T1 | T2 | T3 |
| RDC ↓ | Commodity ↓ | | | | | | | | | |
| J1 | C1 | 0 | 5 | 0 | 26 | 0 | 0 | 0 | 4 | 0 |
| | C2 | 0 | 7 | 0 | 0 | 24 | 0 | 0 | 4 | 0 |
| J2 | C1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | C2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| J3 | C1 | 0 | 0 | 0 | 0 | 24 | 0 | 0 | 0 | 0 |
| | C2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| J4 | C1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | C2 | 0 | 0 | 0 | 22 | 0 | 0 | 0 | 0 | 0 |

Next table represents data of injured person dispatched from affected areas to EMCs by vehicle type V3 under different scenario and time period. For example, under scenario one in the second time period, 12 person with minor injury and 18 person with severe injury has been transferred from affected area K3 to EMC G1.

Table 5.29: Data of injured person dispatched from affected areas to EMCs by vehicle type V3

| Scenario → | S1 | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Period → | T1 | | | | T2 | | | | T3 | | | |
| EMC / AA | G1 | G2 | G3 | G4 | G1 | G2 | G3 | G4 | G1 | G2 | G3 | G4 |
| **K1** | | | | | | | | | | | | |
| L1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 4 | 0 | 0 | 0 | 0 |
| L2 | 23 | 7 | 0 | 0 | 0 | 0 | 0 | 4 | 0 | 0 | 0 | 20 |
| **K2** | | | | | | | | | | | | |
| L1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 0 | 0 | 0 | 0 |
| L2 | 7 | 0 | 23 | 0 | 0 | 16 | 0 | 1 | 0 | 0 | 0 | 0 |
| **K3** | | | | | | | | | | | | |
| L1 | 0 | 0 | 0 | 0 | 12 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| L2 | 0 | 14 | 0 | 0 | 18 | 4 | 0 | 0 | 12 | 0 | 0 | 0 |
| **K4** | | | | | | | | | | | | |
| L1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 11 |
| L2 | 0 | 0 | 0 | 0 | 11 | 0 | 0 | 0 | 0 | 0 | 23 | 0 |
| **K5** | | | | | | | | | | | | |
| L1 | 12 | 0 | 0 | 0 | 0 | 0 | 2 | 3 | 0 | 0 | 0 | 4 |
| L2 | 0 | 0 | 0 | 0 | 0 | 2 | 2 | 5 | 3 | 10 | 0 | 0 |
| | | | | | | | | | | | | |
| Scenario → | S2 | | | | | | | | | | | |
| Period → | T1 | | | | T2 | | | | T3 | | | |
| EMC / AA | G1 | G2 | G3 | G4 | G1 | G2 | G3 | G4 | G1 | G2 | G3 | G4 |
| **K1** | | | | | | | | | | | | |
| L1 | 0 | 0 | 12 | 0 | 0 | 12 | 0 | 6 | 0 | 19 | 0 | 0 |
| L2 | 0 | 0 | 11 | 0 | 0 | 0 | 4 | 2 | 0 | 5 | 14 | 0 |

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **K2** | | | | | | | | | | | | |
| L1 | 0 | 0 | 0 | 0 | 0 | 12 | 0 | 1 | 0 | 0 | 0 | 0 |
| L2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 0 | 0 | 0 | 0 |
| **K3** | | | | | | | | | | | | |
| L1 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 0 | 0 | 0 | 0 | 0 |
| L2 | 0 | 0 | 14 | 0 | 0 | 0 | 1 | 4 | 0 | 0 | 0 | 0 |
| **K4** | | | | | | | | | | | | |
| L1 | 0 | 0 | 0 | 0 | 0 | 0 | 4 | 0 | 0 | 0 | 0 | 0 |
| L2 | 0 | 0 | 0 | 20 | 0 | 0 | 0 | 0 | 20 | 0 | 0 | 0 |
| **K5** | | | | | | | | | | | | |
| L1 | 8 | 0 | 0 | 4 | 0 | 0 | 15 | 0 | 12 | 0 | 0 | 0 |
| L2 | 0 | 0 | 0 | 0 | 0 | 0 | 13 | 0 | 14 | 0 | 0 | 0 |
| | | | | | | | | | | | | |
| Scenario → | S3 | | | | | | | | | | | |
| Period → | T1 | | | | T2 | | | | T3 | | | |
| EMC / AA | G1 | G2 | G3 | G4 | G1 | G2 | G3 | G4 | G1 | G2 | G3 | G4 |
| **K1** | | | | | | | | | | | | |
| L1 | 0 | 20 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| L2 | 21 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **K2** | | | | | | | | | | | | |
| L1 | 0 | 0 | 0 | 0 | 0 | 8 | 0 | 0 | 0 | 0 | 15 | 0 |
| L2 | 0 | 0 | 0 | 14 | 8 | 0 | 8 | 0 | 0 | 0 | 5 | 0 |
| **K3** | | | | | | | | | | | | |
| L1 | 0 | 0 | 0 | 0 | 26 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| L2 | 0 | 0 | 0 | 0 | 18 | 0 | 0 | 0 | 25 | 0 | 0 | 0 |
| **K4** | | | | | | | | | | | | |
| L1 | 0 | 0 | 0 | 0 | 0 | 0 | 4 | 0 | 0 | 0 | 0 | 12 |
| L2 | 0 | 0 | 0 | 0 | 0 | 0 | 4 | 0 | 0 | 8 | 0 | 0 |
| **K5** | | | | | | | | | | | | |
| L1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 8 | 0 | 0 | 0 | 0 |
| L2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 11 | 0 | 0 |

Next table represents data of injured person dispatched from affected areas to EMCs by vehicle type V4 under different scenario and time period. For example, under scenario one in the second time period, 6 person with minor injury has been transferred from affected area K1 to EMC G2 and 18 person with severe injury has been transferred from affected area K2 to EMC G1 using vehicle type V4.

Table 5.30: Data of injured person dispatched from affected areas to EMCs by vehicle type V4

| Scenario → | S1 | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Period → | T1 | | | | T2 | | | | T3 | | | |
| AA \ EMC | G1 | G2 | G3 | G4 | G1 | G2 | G3 | G4 | G1 | G2 | G3 | G4 |
| **K1** | | | | | | | | | | | | |
| L1 | 12 | 2 | 4 | 0 | 6 | 6 | 5 | 0 | 0 | 0 | 23 | 0 |
| L2 | 0 | 0 | 0 | 0 | 0 | 0 | 43 | 0 | 16 | 0 | 0 | 0 |
| **K2** | | | | | | | | | | | | |
| L1 | 0 | 0 | 20 | 0 | 0 | 11 | 0 | 0 | 0 | 0 | 18 | 0 |
| L2 | 0 | 0 | 0 | 0 | 18 | 1 | 0 | 0 | 0 | 27 | 0 | 0 |
| **K3** | | | | | | | | | | | | |
| L1 | 0 | 18 | 0 | 0 | 0 | 0 | 4 | 0 | 16 | 0 | 0 | 0 |
| L2 | 0 | 0 | 0 | 0 | 0 | 0 | 2 | 0 | 6 | 0 | 0 | 0 |
| **K4** | | | | | | | | | | | | |
| L1 | 0 | 0 | 0 | 12 | 0 | 13 | 0 | 0 | 0 | 0 | 0 | 0 |
| L2 | 0 | 0 | 5 | 20 | 0 | 11 | 0 | 6 | 0 | 0 | 0 | 0 |
| **K5** | | | | | | | | | | | | |
| L1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 0 | 0 | 0 | 9 |
| L2 | 0 | 14 | 0 | 0 | 0 | 0 | 0 | 5 | 0 | 0 | 0 | 0 |
| | | | | | | | | | | | | |
| Scenario → | S2 | | | | | | | | | | | |
| Period → | T1 | | | | T2 | | | | T3 | | | |
| AA \ EMC | G1 | G2 | G3 | G4 | G1 | G2 | G3 | G4 | G1 | G2 | G3 | G4 |
| **K1** | | | | | | | | | | | | |
| L1 | 0 | 0 | 0 | 11 | 0 | 2 | 0 | 0 | 0 | 0 | 0 | 2 |
| L2 | 16 | 0 | 0 | 0 | 0 | 34 | 0 | 6 | 5 | 0 | 0 | 10 |
| **K2** | | | | | | | | | | | | |
| L1 | 0 | 9 | 12 | 0 | 5 | 0 | 0 | 0 | 0 | 0 | 12 | 7 |
| L2 | 0 | 26 | 0 | 0 | 31 | 0 | 0 | 0 | 0 | 0 | 0 | 29 |
| **K3** | | | | | | | | | | | | |
| L1 | 14 | 0 | 0 | 0 | 6 | 0 | 0 | 10 | 0 | 15 | 0 | 0 |
| L2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 19 | 0 | 18 | 0 | 0 |

| K4 | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| L1 | 0 | 9 | 0 | 0 | 10 | 0 | 0 | 0 | 11 | 0 | 0 | 0 |
| L2 | 0 | 0 | 0 | 0 | 8 | 0 | 18 | 0 | 0 | 0 | 0 | 0 |
| **K5** | | | | | | | | | | | | |
| L1 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 |
| L2 | 8 | 4 | 0 | 0 | 0 | 0 | 6 | 0 | 0 | 0 | 0 | 0 |
| | | | | | | | | | | | | |
| Scenario → | S3 | | | | | | | | | | | |
| Period → | T1 | | | | T2 | | | | T3 | | | |
| EMC / AA | G1 | G2 | G3 | G4 | G1 | G2 | G3 | G4 | G1 | G2 | G3 | G4 |
| **K1** | | | | | | | | | | | | |
| L1 | 0 | 0 | 0 | 0 | 0 | 1 | 6 | 17 | 0 | 0 | 18 | 0 |
| L2 | 0 | 0 | 8 | 0 | 0 | 23 | 0 | 13 | 0 | 0 | 27 | 0 |
| **K2** | | | | | | | | | | | | |
| L1 | 0 | 0 | 17 | 0 | 0 | 0 | 7 | 3 | 0 | 0 | 0 | 0 |
| L2 | 0 | 0 | 0 | 0 | 0 | 0 | 5 | 3 | 0 | 0 | 0 | 13 |
| **K3** | | | | | | | | | | | | |
| L1 | 6 | 0 | 3 | 13 | 0 | 0 | 0 | 0 | 0 | 20 | 0 | 0 |
| L2 | 0 | 0 | 24 | 4 | 0 | 5 | 0 | 11 | 0 | 0 | 0 | 0 |
| **K4** | | | | | | | | | | | | |
| L1 | 10 | 4 | 0 | 0 | 0 | 11 | 0 | 0 | 0 | 0 | 0 | 1 |
| L2 | 1 | 15 | 0 | 0 | 0 | 9 | 6 | 0 | 6 | 0 | 0 | 0 |
| **K5** | | | | | | | | | | | | |
| L1 | 10 | 0 | 0 | 0 | 0 | 0 | 4 | 0 | 0 | 0 | 9 | 0 |
| L2 | 0 | 9 | 0 | 0 | 0 | 0 | 14 | 0 | 0 | 0 | 0 | 0 |

Data of injured person dispatched from EMC to hospital by vehicle type V3 and V4 has been demonstrated in Table 5.31 and 5.32 respectively. Only those injured person have been transferred to hospitals who cannot be treated in EMCs. So, the number of dispatched injured person decreased significantly than the number of injured person dispatched from affected areas to EMCs.

Table 5.31: Injured person dispatched from EMC to hospital by vehicle type V3

| Scenario → | S1 | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Period → | T1 | | | T2 | | | T3 | | |
| Hospital / EMC | H1 | H2 | H3 | H1 | H2 | H3 | H1 | H2 | H3 |
| **G1** | | | | | | | | | |
| L1 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 0 | 0 |
| L2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **G2** | | | | | | | | | |
| L1 | 0 | 6 | 0 | 0 | 0 | 4 | 0 | 0 | 0 |
| L2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 12 |
| **G3** | | | | | | | | | |
| L1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| L2 | 0 | 0 | 0 | 0 | 0 | 8 | 0 | 3 | 0 |
| **G4** | | | | | | | | | |
| L1 | 4 | 0 | 0 | 0 | 0 | 2 | 0 | 0 | 0 |
| L2 | 0 | 6 | 0 | 0 | 0 | 2 | 1 | 0 | 0 |
| | | | | | | | | | |
| Scenario → | S2 | | | | | | | | |
| Hospital / EMC | H1 | H2 | H3 | H1 | H2 | H3 | H1 | H2 | H3 |
| **G1** | | | | | | | | | |
| L1 | 7 | 0 | 0 | 0 | 0 | 5 | 4 | 0 | 0 |
| L2 | 0 | 0 | 0 | 0 | 0 | 3 | 0 | 0 | 0 |
| **G2** | | | | | | | | | |
| L1 | 6 | 0 | 0 | 0 | 6 | 0 | 0 | 0 | 8 |
| L2 | 0 | 0 | 0 | 0 | 2 | 0 | 0 | 0 | 0 |
| **G3** | | | | | | | | | |
| L1 | 0 | 0 | 0 | 0 | 0 | 4 | 3 | 0 | 0 |
| L2 | 0 | 8 | 0 | 0 | 0 | 0 | 4 | 0 | 0 |
| **G4** | | | | | | | | | |
| L1 | 0 | 0 | 0 | 4 | 0 | 0 | 3 | 0 | 0 |
| L2 | 0 | 0 | 8 | 4 | 4 | 0 | 0 | 0 | 0 |
| | | | | | | | | | |
| Scenario → | S3 | | | | | | | | |
| Hospital / EMC | H1 | H2 | H3 | H1 | H2 | H3 | H1 | H2 | H3 |
| **G1** | | | | | | | | | |
| L1 | 0 | 0 | 8 | 0 | 4 | 2 | 0 | 0 | 0 |
| L2 | 7 | 0 | 0 | 0 | 0 | 6 | 3 | 0 | 8 |
| **G2** | | | | | | | | | |
| L1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| L2 | 0 | 0 | 8 | 0 | 0 | 0 | 0 | 0 | 0 |
| **G3** | | | | | | | | | |
| L1 | 6 | 0 | 0 | 1 | 4 | 0 | 0 | 0 | 0 |
| L2 | 0 | 0 | 0 | 2 | 8 | 0 | 0 | 0 | 0 |
| **G4** | | | | | | | | | |
| L1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| L2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 12 | 0 |

Table 5.32: Injured person dispatched from EMC to hospital by vehicle type V4

| Scenario → | S1 | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Period → | T1 | | | T2 | | | T3 | | |
| EMC \ Hospital | H1 | H2 | H3 | H1 | H2 | H3 | H1 | H2 | H3 |
| **G1** | | | | | | | | | |
| L1 | 4 | 4 | 0 | 0 | 5 | 0 | 1 | 0 | 0 |
| L2 | 9 | 0 | 0 | 0 | 13 | 0 | 5 | 0 | 4 |
| **G2** | | | | | | | | | |
| L1 | 0 | 0 | 0 | 0 | 0 | 3 | 0 | 0 | 0 |
| L2 | 0 | 0 | 11 | 0 | 0 | 8 | 0 | 0 | 0 |
| **G3** | | | | | | | | | |
| L1 | 0 | 0 | 8 | 3 | 0 | 0 | 19 | 0 | 0 |
| L2 | 0 | 0 | 10 | 3 | 0 | 0 | 3 | 0 | 0 |
| **G4** | | | | | | | | | |
| L1 | 0 | 0 | 0 | 0 | 3 | 0 | 0 | 13 | 0 |
| L2 | 0 | 0 | 0 | 0 | 3 | 0 | 0 | 4 | 0 |
| | | | | | | | | | |
| Scenario → | S2 | | | | | | | | |
| EMC \ Hospital | H1 | H2 | H3 | H1 | H2 | H3 | H1 | H2 | H3 |
| **G1** | | | | | | | | | |
| L1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2 | 0 |
| L2 | 8 | 0 | 0 | 0 | 0 | 6 | 0 | 27 | 0 |
| **G2** | | | | | | | | | |
| L1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| L2 | 0 | 0 | 9 | 0 | 0 | 6 | 0 | 6 | 0 |
| **G3** | | | | | | | | | |
| L1 | 0 | 0 | 8 | 0 | 2 | 0 | 0 | 0 | 0 |
| L2 | 0 | 0 | 0 | 0 | 10 | 0 | 0 | 0 | 0 |
| **G4** | | | | | | | | | |
| L1 | 0 | 0 | 5 | 0 | 0 | 0 | 0 | 0 | 0 |
| L2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 18 |
| | | | | | | | | | |
| Scenario → | S3 | | | | | | | | |
| EMC \ Hospital | H1 | H2 | H3 | H1 | H2 | H3 | H1 | H2 | H3 |
| **G1** | | | | | | | | | |
| L1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| L2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **G2** | | | | | | | | | |
| L1 | 0 | 8 | 0 | 0 | 6 | 0 | 0 | 5 | 1 |
| L2 | 0 | 0 | 0 | 0 | 0 | 9 | 0 | 0 | 5 |
| **G3** | | | | | | | | | |
| L1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 26 |
| L2 | 0 | 0 | 10 | 0 | 0 | 0 | 0 | 0 | 14 |
| **G4** | | | | | | | | | |
| L1 | 0 | 4 | 0 | 6 | 1 | 3 | 11 | 0 | 0 |
| L2 | 6 | 0 | 0 | 0 | 4 | 3 | 1 | 0 | 0 |

Table 5.33 represents selected routes and amount of relief commodities transported from suppliers to RDCs. For example, under scenario two in first time period, a trip has been initiated from supplier 1 which transported 65 units of food to RDC 1, 37 units of food to RDC 4 and 37 units of water to RDC 3.

Table 5.33: Selected routes and amount of relief commodities transported from suppliers to RDCs

| | | | | Vehicle V1 | | Vehicle V2 | |
|---|---|---|---|---|---|---|---|
| Scenario | Supplier | Route | Period | Com1 | Com2 | Com1 | Com2 |
| S1 | I1 | I1-J1-I1 | T1 | | 30 | | |
| | | | T2 | | | 60 | 42 |
| | | I1-J1-J4-J3-I1 | T2 | | 0-18-0 | | |
| | | | T3 | 60-0 | 60-8 | | |
| | | I1-J3-I1 | T1 | | | | 60 |
| | | I1-J3-J4-I1 | T1 | 60-0 | 0-25 | | |
| | | | T3 | | | 0-54 | 46-0 |
| | I2 | I2-J2-I2 | T1 | 55 | | | |
| | | | T2 | | 68 | 68 | |
| | I1 | I1-J1-I1 | T1 | | | 65 | |
| S2 | | I1-J1-J4-J3-I1 | T1 | 0-0-37 | 65-37-0 | | |
| | | | T2 | 18-0-0 | 24-31-0 | | |
| | | | T3 | 0-0-50 | | | |
| | | I1-J4-J3-I1 | T1 | | | 23-0 | 0-23 |
| | | | T2 | | | 1-49 | |
| | | | T3 | | | | 0-50 |
| | I2 | I2-J2-I2 | T2 | 37 | 50 | | |
| | | | T3 | 50 | 50 | | |
| | I1 | I1-J1-I1 | T1 | 25 | 40 | | |
| | | | T2 | 60 | | | 60 |
| S3 | | | T3 | | | | 50 |
| | | I1-J4-J3-I1 | T1 | 0-60 | 40-20 | | |
| | | I1-J3-I1 | T1 | | | 10 | 10 |
| | | | T2 | | | 60 | 60 |
| | | I1-J4-J1-I1 | T1 | | | 15-0 | |
| | I2 | I2-J2-I2 | T3 | 50 | | 60 | 60 |

Next table shows the selected routes and amount of commodities transported from RDCs to AAs under different scenario and time period.

Table 5.34: Selected routes and amount of relief commodities transported from RDCs to AAs

| | | | | Vehicle V1 | | Vehicle V2 | |
|---|---|---|---|---|---|---|---|
| Scenario | RDC | Route | Period | Com1 | Com2 | Com1 | Com2 |
| S1 | J1 | J1-K2-K5-J1 | T2 | | | 25-0 | 0-18 |
| | | J1-K4-K3-J1 | T3 | | | 18-0 | |
| | J2 | J2-K2-K1-J2 | T3 | | | 20-9 | 20-0 |
| | | J2-K3-J2 | T2 | | | | 35 |
| | | J2-K3-K4-J2 | T2 | 35-0 | 0-23 | | |
| | J3 | J3-K4-J3 | T1 | | | 20 | |
| | | J3-K4-K1-J3 | T2 | | | 25-0 | 0-20 |
| | | J3-K4-K3-J3 | T1 | 0-35 | 15-40 | | |
| | | | T3 | 0-38 | 18-38 | | |
| | | J3-K5-K1-K2-J3 | T2 | 18-20-0 | 0-0-25 | | |
| | J4 | J4-K1-K2-K5-J4 | T1 | 0-0-15 | 25-0-15 | | |
| | | J4-K5-J4 | T3 | | | 13 | |
| | | J4-K5-K1-K2-J4 | T1 | | | 0-25-20 | 0-0-20 |
| | | J4-K5-K2-K1-J4 | T3 | 0-0-21 | 15-0-30 | | |
| S2 | J1 | J1-K4-K1-K2-J1 | T1 | | | 0-23-22 | 0-8-22 |
| | | | T2 | | | 12-0-20 | 8-0-20 |
| | | J1-K4-K3-J1 | T3 | | | 0-30 | |
| | J2 | J2-K1-K2-J2 | T3 | | | 0-28 | 0-24 |
| | | J2-K3-J2 | T1 | | | 35 | |
| | | | T2 | | | 25 | |
| | | J2-K3-K4-J2 | T3 | 0-18 | 30-18 | | |
| | J3 | J3-K3-K4-J3 | T1 | 0-4 | 35-0 | | |
| | | | T2 | | 25-0 | | |
| | | J3-K5-K2-K1-J3 | T3 | 28-0-20 | 0-4-20 | | |
| | J4 | J4-K1-K2-K5-J4 | T1 | 0-0-15 | 15-0-23 | | |
| | | | T2 | 25-0-25 | 25-0-25 | | |
| | | J4-K5-J4 | T3 | | | | 28 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| S3 | J1 | J1-K1-K2-J1 | T1 | | | 15-0 | 15-40 |
| | | J1-K1-K4-K3-J1 | T3 | | | 0-0-4 | |
| | | J1-K2-K1-J1 | T2 | | | 27-0 | 35-18 |
| | | J1-K2-K3-K4-J1 | T2 | 8-18-0 | 0-0-15 | | |
| | J2 | J2-K2-J2 | T1 | 40 | | | |
| | J3 | J3-K3-K4-J3 | T1 | | | 0-15 | 0-15 |
| | | J3-K3-K4-K5-K1-J3 | T1 | 15-0-0-0 | 15-0-0-0 | | |
| | | J3-K4-K3-J3 | T2 | | | 15-0 | 0-18 |
| | | | T3 | 18-16 | 18-20 | | |
| | | J3-K5-K1-J3 | T2 | 0-18 | 30-0 | | |
| | J4 | J4-K5-J4 | T1 | | | 25 | 25 |
| | | | T2 | | | 30 | |
| | | J4-K5-K2-J4 | T3 | | | 14-0 | 0-34 |
| | | J4-K5-K2-K1-J4 | T3 | 0-42-20 | 14-8-20 | | |

Two small scale version of the previous numerical example have been considered and solved to proof the validity of the proposed method. The parameters of these small version example problems are compared in the following table:

Table 5.35: Parameter values for small scale example problems

| **Parameters** | **Example 1** | **Example 2** |
|---|---|---|
| Number of Suppliers | 1 | 1 |
| Number of Affected Area Location | 3 | 3 |
| Candidate RDC Location | 2 | 2 |
| Sizes of RDC | Small, Medium & Large | |
| Candidate EMC Location | 2 | 2 |
| Sizes of EMC | Small, Medium & Large | |
| Number of Hospitals | 2 | 1 |
| Disaster Scenarios | 2 | 2 |
| Time Periods | 2 | 2 |
| Types of Commodities | 2 (Food and Water) | |
| Types of Injury | 2 (Moderate and Severe injury) | |
| Types of Vehicle | 4 (2 for commodity, 2 for injured person) | |

Pareto optimal solutions and pareto front between objective 1 and other objectives for the two example problems are showcased in the next page.

Table 5.36: Pareto optimal solutions for example 1

| Solution Number | Objective 1 Weighted Sum of Unserved Injury | Objective 2 Travel Time to Dispatch Injured Person | Objective 3 Weighted Sum of Unsatisfied Demand | Objective 4 Travel Time to Dispatch Relief Commodity | Objective 5 Total Cost of Commodity Transportation |
|---|---|---|---|---|---|
| 1 | 61.98 | 349.74 | 36.82 | 278.19 | 3855.11 |
| 2 | 173.58 | 0 | 36.82 | 278.19 | 3790.47 |
| 3 | 61.98 | 349.74 | 36.82 | 278.19 | 3790.47 |
| 4 | 61.98 | 804.35 | 43.81 | 265.86 | 4297.83 |
| 5 | 61.98 | 349.74 | 36.82 | 278.19 | 3790.47 |

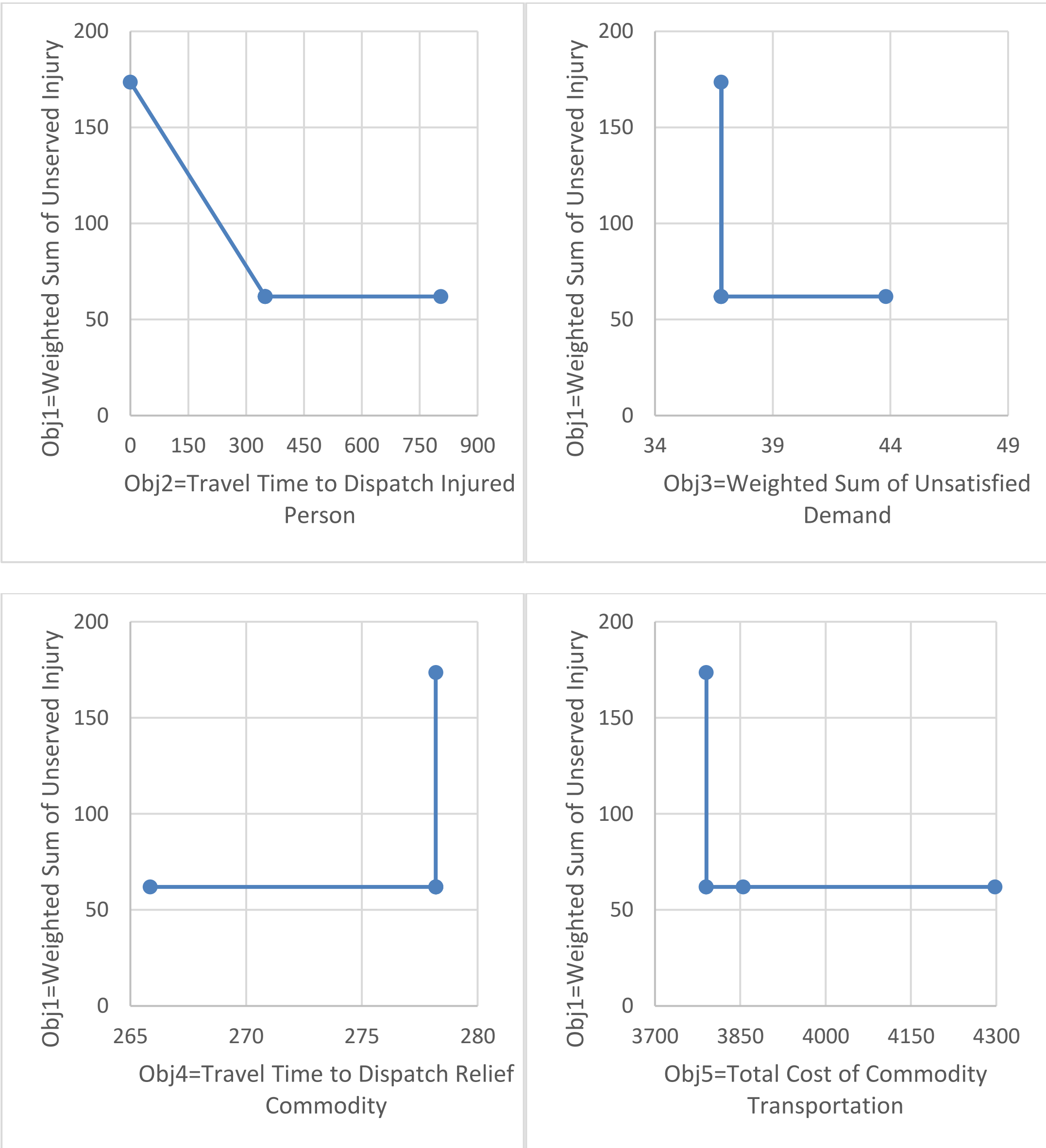


Figure 5.7: Pareto front between objective functions (Example 1)

Table 5.37: Pareto optimal solutions for example 2

| Solution Number | Objective 1 Weighted Sum of Unserved Injury | Objective 2 Travel Time to Dispatch Injured Person | Objective 3 Weighted Sum of Unsatisfied Demand | Objective 4 Travel Time to Dispatch Relief Commodity | Objective 5 Total Cost of Commodity Transportation |
|---|---|---|---|---|---|
| 1 | 66.25 | 315.41 | 36.82 | 278.19 | 3790.47 |
| 2 | 173.58 | 0 | 36.82 | 278.19 | 3790.47 |
| 3 | 66.25 | 315.41 | 36.82 | 278.19 | 3790.47 |
| 4 | 66.25 | 315.41 | 43.81 | 265.86 | 4297.83 |
| 5 | 66.25 | 315.41 | 36.82 | 278.19 | 3790.47 |

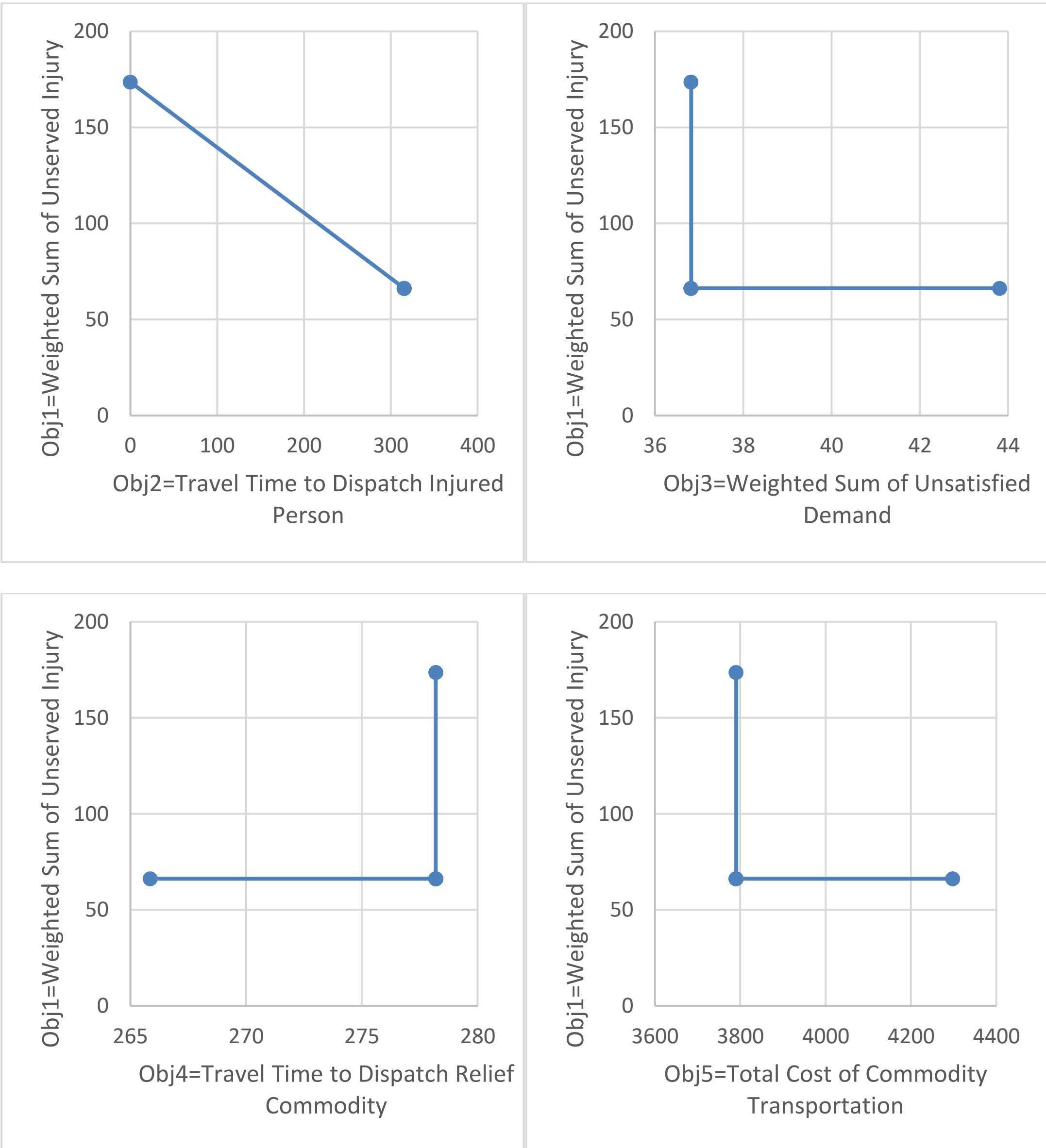


Figure 5.8: Pareto front between objective functions (Example 2)

# Chapter 6

# CONCLUSIONS AND RECOMMENDATIONS

## 6.1 Conclusions

This study aimed to present an integrated location-routing model for coordinating logistics support and evacuation operations in response to emergencies and natural disasters. To integrate strategic and operational decisions, a multi-objective dynamic stochastic programming model is proposed. The aim is maximizing response service level by enabling fast relief access to affected areas and locating temporary emergency units in appropriate sites. This model is composed of two stages; the first one determines the location of RDCs and EMCs as well as the required inventory quantities for each type of relief items under storage, and the second stage determines the routes and amount of transportation from suppliers to RDCs and RDCs to AAs as well as routes and number of transported injured person from AAs to EMCs and EMCs to Hospitals. This multi-objective model minimizes weighted sum of unserved demand and unserved injury, travel time for flow of commodities and injured people, and total costs associated with flow of commodities. In this model, the travel time parameters as well as the demand, supply, and cost are subject to uncertainty. To deal with these uncertain components of the humanitarian logistics network a scenario based approach was used to develop a stochastic model. Finally, this model is solved by applying the augmented ε-constraint method. To demonstrate the effectiveness of the proposed model, a case study has been presented. Computational analysis has been done to demonstrate the relationship among the objective functions.

## 6.2 Recommendations

There are some possible directions to which this research can be extended.

1. A set of solution techniques and heuristic algorithms can be introduced to solve the MIP problem for large cases in short times. For relatively small data instances, the problem can be solved using a commercial mixed-integer solver; however, this solution approach does not scale well to large problem instances.
2. Reliability concept can be incorporated in the model to minimize associated risk in the logistics network.

3. The robustness of this model can be investigated with respect to uncertainty in demand, supply, cost, and travel time values.
4. A new approach base can be developed, for example, on fuzzy logic, to determine the probability of occurrence behind real scenarios since the model results are highly dependent on them.

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# Appendix – GAMS Code

```
$eolcom //
$STitle HumanitarianLogistics model definitions
SETS
          node commodity node /I1,I2,J1*J4,K1*K5/
          nodeIJ(node) supplier+RDC /I1,I2,J1*J4/
          nodeJK(node) RDC+AA /J1*J4,K1*K5/
          I(node) suppliers /I1,I2/
          J(node) candidate RDC /J1*J4/
          K(node) affected area/K1*K5/
          H hospital /H1*H3/
          G candidate EMC /G1*G4/
          M size of RDC /M1*M3/
          N size of EMC /N1*N3/
          C type of commodity /C1, C2/
          L type of injured person /L1*L2/
          V type of vehicle /V1*V4/
          S possible scenario /S1*S3/
          T periods /T1*T3/
          O Objective functions /O1*O5/
;

PARAMETERS
          dir(O) direction of the objective functions 1 for max and -1»
 for min
          /o1  -1, o2  -1, o3  -1, o4  -1, o5  -1/
          HoldingCost(C) Holding cost of a unit commodity c
          /C1     0.2, C2     0.1/
          UnitVolume(C) unit volume of commodity c
          /C1     2, C2      1/
          CapV(V) volume capacity of vehicle type v
          /V1     240, V2      180/
          CapP(V) person capacity of vehicle type v
          /V3     4, V4      6/
          VehicleLimit(V) maximum available number of vehicles
          /V3     28, V4      30/
          PriorityCommodity(C) priority of satisfying demand of commod»
ity type c
          /C1     0.35, C2      0.65/
          PriorityInjury(L) priority of servicing for injured person t»
ype l
          /L1     0.4, L2      0.6/
          Probability(S) occurance probability of scenario s
          /S1     0.237
          S2      0.352
          S3      0.411/;
SCALAR FixedRDC primary budget for RDC setup in thousands of dollars »
/570/;
SCALAR FixedEMC primary budget for EMC setup in thousands of dollars »
/410/;
SCALAR MinServiceLevel Minimum service level for injured person /0.3/»
;
SCALAR BigM A very large number /999999/;

TABLE frdc(J,M) fixed cost for opening a RDC of size m at location j »
in thousands of dollars
$ondelim
$include frdc.csv
$offdelim ;
```

```
TABLE femc(G,N) fixed cost for opening a EMC of size n at location g in thousands of dollars
$ondelim
$include femc.csv
$offdelim ;
TABLE ShortageCost(C,T) Shortage Cost of a unit commodity c
$ondelim
$include ShortageCost.csv
$offdelim ;
TABLE ProcureCost(C,I,S,T) Procuring cost of a unit commodity c
$ondelim
$include ProcureCost.csv
$offdelim ;
TABLE TransportCost(C,V,T,S) Transportation cost of a unit commodity c
$ondelim
$include TransportCost.csv
$offdelim ;
TABLE demandC(C,S,T,K) demand for commodity c at AA k under scenario s in period t
$ondelim
$include demandC.csv
$offdelim ;
TABLE demandL(L,S,T,K) number of injured people of type l at AA k under scenario s in period t
$ondelim
$include demandL.csv
$offdelim ;
TABLE CapSup(C,S,T,I) Capacity of supplier i under scenario s in period t
$ondelim
$include CapSup.csv
$offdelim ;
TABLE CapRDC(C,S,T,J) demand for commodity c at RDC j under scenario s in period t
$ondelim
$include CapRDC.csv
$offdelim ;
TABLE CapEMC(L,S,T,G) capacity of EMC g for injury type l in scenario s in period t
$ondelim
$include CapEMC.csv
$offdelim ;
TABLE CapHos(L,S,T,H) capacity of hospital h for injury type l in scenario s in period t
$ondelim
$include CapHos.csv
$offdelim ;
TABLE TravelSuptoRDC(nodeIJ,V,S,T,nodeIJ1) Travel time of tour initiated from supplier to RDC by mode v in scenario s and period t
$ondelim
$include TravelSuptoRDC.csv
$offdelim ;
TABLE TravelRDCtoAA(nodeJK,V,S,T,nodeJK1) Travel time of tour initiated from RDC to AA by mode v in scenario s and period t
$ondelim
$include TravelRDCtoAA.csv
$offdelim ;
```

```
TABLE TravelAAtoEMC(K,V,S,T,G) Travel time of tour initiated from AA »
k to EMC g by mode v in scenario s and period t
$ondelim
$include TravelAAtoEMC.csv
$offdelim ;
TABLE TravelEMCtoHos(G,V,S,T,H) Travel time of tour initiated from EM»
C g to hospital h by mode v in scenario s and period t
$ondelim
$include TravelEMCtoHos.csv
$offdelim ;

VARIABLES
         Zrdc(J,M) whether RDC with capacity category m is located at»
 candidate RDC j or not
         Zemc(G,N) whether EMC with capacity category n is located at»
 candidate EMC g or not
         XSuptoRDC(C,I,J,V,S,T) amount of commodity c dispatched from»
 supplier i to RDC j by mode v in scenario s and period t
         XRDCtoAA(C,J,K,V,S,T) amount of commodity c dispatched from »
RDC j to AA k by mode v in scenario s and period t
         XAAtoEMC(L,K,G,V,S,T) number of injured person type l dispat»
ched from AA to EMC by mode v in scenario s and period t
         XEMCtoHos(L,G,H,V,S,T) number of injured person type l dispa»
tched from EMC to hospital by mode v in scenario s and period t
         IRDC(C,J,S,T) amount of commodity c held at RDC j in scenari»
o s and period t
         IAA(C,K,S,T) amount of commodity c held at AA k in scenario »
s and period t
         IEMC(L,G,S,T) number of injured person type l being served a»
t EMC g in scenario s and period t
         IHos(L,H,S,T) number of injured person type l being served a»
t hospital h in scenario s and period t
         DevC(C,K,S,T) amount of unserved commodity of type C at AA k»
 in scenario s and period t
         DevL(L,K,S,T) number of unserved injured person type l at AA»
 k in scenario s and period t
         precSuptoRDC(nodeIJ,nodeIJ1,V,S,T) whether i immediately pre»
cedes j or not
         precRDCtoAA(nodeJK,nodeJK1,V,S,T) whether j immediately prec»
edes k or not
         YSuptoRDC(I,J,V,S,T) whether tour is initiated from supplier»
 to RDC by mode v in scenario s and period t
         YRDCtoAA(J,K,V,S,T) whether tour is initiated from RDC to AA»
 by mode v in scenario s and period t
         YAAtoEMC(K,G,V,S,T) whether tour is initiated from AA to EMC»
 by mode v in scenario s and period t
         YEMCtoHos(G,H,V,S,T) whether tour is initiated from EMC to h»
ospital by mode v in scenario s and period t
         quantSuptoRDC(nodeIJ,C,V,S,T) quantity delivered upto i leng»
th
         quantRDCtoAA(nodeJK,C,V,S,T) quantity delivered upto j lengt»
h
         Z(O)      objective function variables;

INTEGER VARIABLES XSuptoRDC,XRDCtoAA,XAAtoEMC,XEMCtoHos,IRDC,IAA,IEMC»
,IHos,DevC,DevL,YAAtoEMC,YEMCtoHos;
BINARY VARIABLES Zrdc,Zemc,YSuptoRDC,YRDCtoAA,precSuptoRDC,precRDCtoA»
A;
```

```
EQUATIONS
        Objective1      weighted sum of unserved injured person wait»
ing at affected area
        Objective2      total travel time to dispatch injured person»
 from demand points
        Objective3      weighted sum of unsatisfied demand over all »
commodities
        Objective4      total travel time to ship items to demand po»
int
        Objective5      total cost associated with commodity transpo»
rtation to demand points
        BudgetEMC       budgetary constraints for EMCs
        BudgetRDC       budgetary constraints for RDCs
        EMClimit(G)     inhibits more than one EMC from being placed»
 at any nodes
        RDClimit(J)     inhibits more than one RDC from being placed»
 at any nodes

        BalanceEqAAInj(L,K,S,T)   balance equation for AAs
        DlimitAAInj(L,K,S,T)  number of injured person dispatched fr»
om AA cannot exceed the number of injured person at AA
        BalanceEqEMCfirst(L,G,S,T) balance equation for EMCs at time»
 period T=1
        BalanceEqEMC(L,G,S,T)  balance equation for EMCs at time per»
iod T>1
        BalanceEqHos(L,H,S,T)  balance equation for hospital
        BalanceEqAACom(C,K,S,T)   balance equation for AAs for commo»
dity
        DlimitAACom(C,J,S,T)  amount of commodity dispatched to AA c»
annot exceed demand for commodity at AA
        BalanceEqRDCfirst(C,J,S,T) balance equation for RDC at time »
period T=1
        BalanceEqRDC(C,J,S,T) balance equation for RDC at time perio»
d T>1
        BalanceEqSup(C,I,S,T) balance equation for supplier

        CapacityEMCfirst(L,G,S,T) capacity constraints for EMCs at t»
ime period T=1
        CapacityEMC(L,G,S,T)    capacity constraints for EMCs at tim»
e period T>1
        CapacityHospital(L,H,S,T)    capacity constraints for hospit»
al
        CapacityRDCfirst(C,J,S,T) Capacity of RDC at time period T=1
        CapacityRDC(C,J,S,T) Capacity of RDCs at time period T>1
        CapacityPAAtoEMC(K,G,V,S,T) person capacity of vehicles trav»
elling from AA to EMC
        CapacityPEMCtoHos(G,H,V,S,T)  person capacity of vehicles tr»
avelling from EMC to hospital
        MaxTripLimit(V,S,T) number of trip must be limited to maximu»
m available number of vehicles
        QuantFirstSuptoRDC(nodeIJ,nodeIJ1,V,S,T)
        QuantFirstRDCtoAA(nodeJK,nodeJK1,V,S,T)
        QuantSuccSuptoRDC(nodeIJ,nodeIJ1,V,S,T)
        QuantSuccRDCtoAA(nodeJK,nodeJK1,V,S,T)
        IemcLO(L,G,S,T) Iemc lower bound
        DispatchtoEMC(G,V,L,S,T,K)  prevent dispatching injured pers»
on from AA where no EMC has been opened
```

```
        DispatchtoHos(G,V,L,S,T,H) prevent dispatching injured perso»
n from EMC location where no EMC has been opened
        DispatchtoRDC(C,I,J,V,S,T) prevent dispatching commodity fro»
m supplier where no RDC has been opened
        DispatchtoAA(C,J,K,V,S,T)  prevent dispatching commodity fro»
m RDC location where no RDC has been opened
        EnterOnceSuptoRDC(nodeIJ,V,S,T) Enter every city only once
        EnterOnceRDCtoAA(nodeJK,V,S,T) Enter every city only once
        LeaveOnceSuptoRDC(nodeIJ,V,S,T) Leave every city only once
        LeaveOnceRDCtoAA(nodeJK,V,S,T) Leave every city only once
        FromtoSuptoRDC(nodeIJ,V,S,T) vehicle must return to the supp»
lier location from where it started
        FromtoRDCtoAA(nodeJK,V,S,T) vehicle must return to the RDC l»
ocation from where it started
        PreventTriptoEMC(K,G,V,S,T) prevent initiating trip when no »
injured person is dispatched from AA to emc
        PreventTriptoHos(G,H,V,S,T) prevent initiating trip when no »
injured person is dispatched from emc to hospital
        ServiceLevelEMC(L,K,S,T) maintain service level while dispat»
ching from AA to EMC
        ServiceLevelHos(L,G,S,T) maintain service level while dispat»
ching from EMC to hospital
        RouteCapacitySuptoRDC(nodeIJ,nodeIJ1,V,S,T)
        RouteCapacityRDCtoAA(nodeJK,nodeJK1,V,S,T);

Objective1..     SUM((L,K,S,T), Probability(S)*PriorityInjury(L)*DevL»
(L,K,S,T)) =E= Z('o1');
Objective2..     SUM((K,G,V,S,T), Probability(S)*TravelAAtoEMC(K,V,S,»
T,G)*YAAtoEMC(K,G,V,S,T)) +
                 SUM((G,H,V,S,T), Probability(S)*TravelEMCtoHos(G,V,S»
,T,H)*YEMCtoHos(G,H,V,S,T)) =E= Z('o2');
Objective3..     SUM((C,K,S,T), Probability(S)*PriorityCommodity(C)*D»
evC(C,K,S,T)) =E= Z('o3');
Objective4..     SUM((nodeIJ,nodeIJ1,V,S,T)$(ord(nodeIJ) ne ord(nodeI»
J1)), Probability(S)*TravelSuptoRDC(nodeIJ,V,S,T,nodeIJ1)*
                 precSuptoRDC(nodeIJ,nodeIJ1,V,S,T))+ SUM((nodeJK,nod»
eJK1,V,S,T)$(ord(nodeJK) ne ord(nodeJK1)),
                 Probability(S)*TravelRDCtoAA(nodeJK,V,S,T,nodeJK1)*p»
recRDCtoAA(nodeJK,nodeJK1,V,S,T)) =e= Z('o4');
Objective5..     SUM ((J,M), fcom(J,M)*Zrdc(J,M))
                 +SUM ((C,I,J,V,S,T), Probability(S)*ProcureCost(C,I,»
S,T)*XSuptoRDC(C,I,J,V,S,T))
                 +SUM ((C,I,J,V,S,T), Probability(S)*TransportCost(C,»
V,T,S)*XSuptoRDC(C,I,J,V,S,T))
                 +SUM ((C,J,K,V,S,T), Probability(S)*TransportCost(C,»
V,T,S)*XRDCtoAA(C,J,K,V,S,T))
                 +SUM ((C,J,S,T), Probability(S)*HoldingCost(C)*IRDC(»
C,J,S,T))
                 +SUM ((C,K,S,T), Probability(S)*HoldingCost(C)*IAA(C»
,K,S,T))
                 +SUM ((C,K,S,T), Probability(S)*ShortageCost(C,T)*De»
vC(C,K,S,T)) =E= Z('o5');

BudgetEMC..          SUM((G,N), femc(G,N)*Zemc(G,N)) =L= FixedEMC;
BudgetRDC..          SUM((J,M), frdc(J,M)*Zrdc(J,M)) =L= FixedRDC;
EMClimit(G)..        SUM((N), Zemc(G,N)) =L= 1;
RDClimit(J)..        SUM((M), Zrdc(J,M)) =L= 1;

```

```
BalanceEqAAInj(L,K,S,T)..  demandL(L,S,T,K) - SUM((G,V), XAAtoEMC(L,K»
,G,V,S,T))=E= DevL(L,K,S,T);
DlimitAAInj(L,K,S,T).. SUM((G,V), XAAtoEMC(L,K,G,V,S,T)) =L= demandL(»
L,S,T,K);
BalanceEqEMCfirst(L,G,S,'T1').. IEMC(L,G,S,'T1')=E= SUM((K,V), XAAtoE»
MC(L,K,G,V,S,'T1'));
BalanceEqEMC(L,G,S,T)$(ord(T) gt 1).. IEMC(L,G,S,T) =E= SUM((K,V), XA»
AtoEMC(L,K,G,V,S,T))-SUM((H,V), XEMCtoHos(L,G,H,V,S,T));
BalanceEqHos(L,H,S,T).. SUM((G,V), XEMCtoHos(L,G,H,V,S,T)) =E= IHos(L»
,H,S,T);
BalanceEqAACom(C,K,S,T)..  IAA(C,K,S,T-1)+SUM((J,V), XRDCtoAA(C,J,K,V»
,S,T))-demandC(C,S,T,K) =E= IAA(C,K,S,T)-DevC(C,K,S,T);
DlimitAACom(C,J,S,T).. SUM((K,V), XRDCtoAA(C,J,K,V,S,T)) =L= Capacity»
RDC(C,S,T,J);
BalanceEqRDCfirst(C,J,S,'T1').. SUM((I,V),XSuptoRDC(C,I,J,V,S,'T1'))-»
SUM((K,V), XRDCtoAA(C,J,K,V,S,'T1')) =E= IRDC(C,J,S,'T1');
BalanceEqRDC(C,J,S,T)$(ord(T) gt 1).. SUM((I,V),XSuptoRDC(C,I,J,V,S,T»
))+IRDC(C,J,S,T-1)
         -SUM((K,V), XRDCtoAA(C,J,K,V,S,T))=E= IRDC(C,J,S,T);
BalanceEqSup(C,I,S,T).. SUM((J,V),XSuptoRDC(C,I,J,V,S,T)) =E= CapSup(»
C,S,T,I);

CapacityEMCfirst(L,G,S,'T1')..   SUM((K,V), XAAtoEMC(L,K,G,V,S,'T1'))»
=L= CapEMC(L,S,'T1',G);
CapacityEMC(L,G,S,T)$(ord(T) gt 1)..   SUM((K,V), XAAtoEMC(L,K,G,V,S,»
T))-SUM((H,V), XEMCtoHos(L,G,H,V,S,T)) =L= CapEMC(L,S,T,G);
CapacityHospital(L,H,S,T)..   SUM((G,V), XEMCtoHos(L,G,H,V,S,T))=L= C»
apHos(L,S,T,H);
CapacityRDCfirst(C,J,S,'T1').. SUM((I,V),XSuptoRDC(C,I,J,V,S,'T1')) =»
E= CapRDC(C,S,'T1',J);
CapacityRDC(C,J,S,T)$(ord(T) gt 1).. SUM((I,V),XSuptoRDC(C,I,J,V,S,T)»
)+IRDC(C,J,S,T-1) =E= CapRDC(C,S,T,J);
CapacityPAAtoEMC(K,G,V,S,T)..  SUM((L), XAAtoEMC(L,K,G,V,S,T)) =L= YA»
AtoEMC(K,G,V,S,T)*CapP(V);
CapacityPEMCtoHos(G,H,V,S,T)..   SUM((L), XEMCtoHos(L,G,H,V,S,T)) =L=»
 YEMCtoHos(G,H,V,S,T)*CapP(V);
MaxTripLimit(V,S,T)..  SUM((K,G), YAAtoEMC(K,G,V,S,T))+SUM((G,H), YEM»
CtoHos(G,H,V,S,T))=L= VehicleLimit(V);
QuantFirstSuptoRDC(nodeIJ,nodeIJ1,V,S,T)$((I(nodeIJ)) and (J(nodeIJ1)»
) and (ord(nodeIJ) ne ord(nodeIJ1)))..
         SUM((C),quantSuptoRDC(nodeIJ1,C,V,S,T)) =l=
         CapV(V)+ {SUM((C),dRDC(C,S,T,nodeIJ1)*UnitVolume(C))-CapV(V)»
}*precSuptoRDC(nodeIJ,nodeIJ1,V,S,T);
QuantSuccSuptoRDC(nodeIJ,nodeIJ1,V,S,T)$((J(nodeIJ)) and (J(nodeIJ1))»
 and (ord(nodeIJ) ne ord(nodeIJ1)))..
         SUM((C),quantSuptoRDC(nodeIJ1,C,V,S,T)) =g=
         SUM((C),quantSuptoRDC(nodeIJ,C,V,S,T))+ SUM((C),dRDC(C,S,T,n»
odeIJ1)*UnitVolume(C))
         -CapV(V)+ CapV(V)*precSuptoRDC(nodeIJ,nodeIJ1,V,S,T)
         +(CapV(V)-SUM((C),dRDC(C,S,T,nodeIJ1)*UnitVolume(C))
         -SUM((C),dRDC(C,S,T,nodeIJ)*UnitVolume(C)))*precSuptoRDC(nod»
eIJ1,nodeIJ,V,S,T);
QuantFirstRDCtoAA(nodeJK,nodeJK1,V,S,T)$((J(nodeJK)) and (K(nodeJK1))»
 and (ord(nodeJK) ne ord(nodeJK1)))..
         SUM((C),quantRDCtoAA(nodeJK1,C,V,S,T)) =l=
         CapV(V)+ {SUM((C),dAA(C,S,T,nodeJK1)*UnitVolume(C))-CapV(V)}»
*precRDCtoAA(nodeJK,nodeJK1,V,S,T);
QuantSuccRDCtoAA(nodeJK,nodeJK1,V,S,T)$((K(nodeJK)) and (K(nodeJK1)) »
```

```
and (ord(nodeJK) ne ord(nodeJK1)))..
          SUM((C),quantRDCtoAA(nodeJK1,C,V,S,T)) =g=
          SUM((C),quantRDCtoAA(nodeJK,C,V,S,T))+ SUM((C),dAA(C,S,T,nod»
eJK1)*UnitVolume(C))
          -CapV(V)+ CapV(V)*precRDCtoAA(nodeJK,nodeJK1,V,S,T)
          +(CapV(V)-SUM((C),dAA(C,S,T,nodeJK1)*UnitVolume(C))
          -SUM((C),dAA(C,S,T,nodeJK)*UnitVolume(C)))*precRDCtoAA(nodeJ»
K1,nodeJK,V,S,T);

IemcLO(L,G,S,T).. IEMC(L,G,S,T) =G= SUM((K,V), XAAtoEMC(L,K,G,V,S,T))»
-SUM((H,V), XEMCtoHos(L,G,H,V,S,T));
IEMC.up(L,G,S,T) = CapEMC(L,S,T,G);
IHos.up(L,H,S,T) = CapHos(L,S,T,H);

DispatchtoEMC(G,V,L,S,T,K)..  XAAtoEMC(L,K,G,V,S,T) =L= BigM*SUM((N),»
 Zemc(G,N));
DispatchtoHos(G,V,L,S,T,H)..  XEMCtoHos(L,G,H,V,S,T) =L= BigM*SUM((N)»
, Zemc(G,N));
DispatchtoRDC(C,I,J,V,S,T)..  XSuptoRDC(C,I,J,V,S,T) =L= BigM*SUM((M)»
, Zrdc(J,M));
DispatchtoAA(C,J,K,V,S,T)..  XRDCtoAA(C,J,K,V,S,T) =L= BigM*SUM((M), »
Zrdc(J,M));

EnterOnceSuptoRDC(nodeIJ,V,S,T)$J(nodeIJ)..
          SUM{nodeIJ1$(ord(nodeIJ) ne ord(nodeIJ1)), precSuptoRDC(node»
IJ1,nodeIJ,V,S,T)} =e= 1;
EnterOnceRDCtoAA(nodeJK,V,S,T)$K(nodeJK)..
          SUM{nodeJK1$(ord(nodeJK) ne ord(nodeJK1)), precRDCtoAA(nodeJ»
K1,nodeJK,V,S,T)} =e= 1;
LeaveOnceSuptoRDC(nodeIJ,V,S,T)$J(nodeIJ)..
          SUM{nodeIJ1$(ord(nodeIJ) ne ord(nodeIJ1)), precSuptoRDC(node»
IJ,nodeIJ1,V,S,T)} =e= 1;
LeaveOnceRDCtoAA(nodeJK,V,S,T)$K(nodeJK)..
          SUM{nodeJK1$(ord(nodeJK) ne ord(nodeJK1)), precRDCtoAA(nodeJ»
K,nodeJK1,V,S,T)} =e= 1;
FromtoSuptoRDC(nodeIJ,V,S,T)$I(nodeIJ)..
          SUM{nodeIJ1$J(nodeIJ1), precSuptoRDC(nodeIJ,nodeIJ1,V,S,T)}
          -SUM{nodeIJ1$J(nodeIJ1), precSuptoRDC(nodeIJ1,nodeIJ,V,S,T)}»
 =e= 0;
FromtoRDCtoAA(nodeJK,V,S,T)$J(nodeJK)..
          SUM{nodeJK1$K(nodeJK1), precRDCtoAA(nodeJK,nodeJK1,V,S,T)}
          -SUM{nodeJK1$K(nodeJK1), precRDCtoAA(nodeJK1,nodeJK,V,S,T)} »
=e= 0;

PreventTriptoEMC(K,G,V,S,T)..   YAAtoEMC(K,G,V,S,T) =L= SUM((L), XAAt»
oEMC(L,K,G,V,S,T));
PreventTriptoHos(G,H,V,S,T)..   YEMCtoHos(G,H,V,S,T) =L= SUM((L), XEM»
CtoHos(L,G,H,V,S,T));
ServiceLevelEMC(L,K,S,T).. DevL(L,K,S,T) =L= demandL(L,S,T,K)*MinServ»
iceLevel;
ServiceLevelHos(L,G,S,T).. SUM((H,V), XEMCtoHos(L,G,H,V,S,T)) =G= IEM»
C(L,G,S,T)*MinServiceLevel;

RouteCapacitySuptoRDC(nodeIJ,nodeIJ1,V,S,T)$((J(nodeIJ)) and (J(nodeI»
J1)) and (ord(nodeIJ) ne ord(nodeIJ1)))..
          SUM((C), dRDC(C,S,T,nodeIJ)*precSuptoRDC(nodeIJ,nodeIJ1,V,S,»
T))
          +SUM((C),dRDC(C,S,T,nodeIJ1)*precSuptoRDC(nodeIJ,nodeIJ1,V,S»
```

```
,T)) =l=  CapV(V);
RouteCapacityRDCtoAA(nodeJK,nodeJK1,V,S,T)$((K(nodeJK)) and (K(nodeJK1)) and (ord(nodeJK) ne ord(nodeJK1)))..
         SUM((C), dAA(C,S,T,nodeJK)*precRDCtoAA(nodeJK,nodeJK1,V,S,T))
         +SUM((C),dAA(C,S,T,nodeJK1)*precRDCtoAA(nodeJK,nodeJK1,V,S,T)) =l=  CapV(V);

quantSuptoRDC.up(nodeIJ,C,V,S,T) = CapV(V);
quantSuptoRDC.lo(nodeIJ,C,V,S,T) = dRDC(C,S,T,nodeIJ)*UnitVolume(C);
quantRDCtoAA.up(nodeJK,C,V,S,T) = CapV(V);
quantRDCtoAA.lo(nodeJK,C,V,S,T) = dAA(C,S,T,nodeJK)*UnitVolume(C);

MODEL HumanitarianLogistics /ALL/;

$STitle eps-constraint method

Set o1(o)  the first element of o
    om1(o) all but the first elements of o
    oo(o)  active objective function in constraint allobj;
o1(o)$(ord(o)=1) = yes; om1(o)=yes; om1(o1) = no;

Parameter
    rhs(o)     right hand side of the constrained obj functions in eps-constraint
    maxobj(o)  maximum value from the payoff table
    minobj(o)  minimum value from the payoff table
    numo(o)    ordinal value of o starting with 1
Scalar
    iter         total number of iterations
    infeas       total number of infeasibilities
    elapsed_time elapsed time for payoff and e-sonstraint
    start        start time
    finish       finish time
Variables
   a_objval   auxiliary variable for the objective function
   obj        auxiliary variable during the construction of the payoff table
   sl(o)      slack or surplus variables for the eps-constraints
Positive Variables sl
Equations
   con_obj(o) constrained objective functions
   augm_obj   augmented objective function to avoid weakly efficient solutions
   allobj     all the objective functions in one expression;

con_obj(om1)..   z(om1) - dir(om1)*sl(om1) =e= rhs(om1);

augm_obj.. a_objval =e= sum(o1,dir(o1)*z(o1))
    + 1e-3*sum(om1,power(10,-(numo(om1)-1))*sl(om1)/(maxobj(om1)-minobj(om1)));

allobj..  sum(oo, dir(oo)*z(oo)) =e= obj;

Model mod_payoff    / HumanitarianLogistics, allobj / ;
Model mod_epsmethod / HumanitarianLogistics, con_obj, augm_obj / ;

Parameter
```

```
   payoff(o,o)  payoff tables entries;
Alias(o,op);

option optcr=0, limrow=0, limcol=0, solprint=off, solvelink=%Solvelink.LoadLibrary%;

* Generate payoff table applying lexicographic optimization
loop(op,
  oo(op)=yes;
  repeat
    solve mod_payoff using mip maximizing obj;
    payoff(op,oo) = z.l(oo);
    z.fx(oo) = z.l(oo); // freeze the value of the last objective optimized
    oo(o++1) = oo(o);   // cycle through the objective functions
  until oo(op); oo(op) = no;
* release the fixed values of the objective functions for the new iteration
  z.up(o) = inf; z.lo(o) =-inf;
);
if (mod_payoff.modelstat<>%ModelStat.Optimal% and
    mod_payoff.modelstat<>%ModelStat.Integer Solution%,
   abort 'no optimal solution for mod_payoff');

file fx  / 2op50_augmecon2_results.txt /;
put fx ' PAYOFF TABLE'/   ;
loop (op,
   loop(o, put payoff(op,o):12:2);
   put /);

minobj(o)=smin(op,payoff(op,o));
maxobj(o)=smax(op,payoff(op,o));

$if not set gridpoints $set gridpoints 473
Set q             grid points /q0*q%gridpoints%/
    grid(o,q)     grid
Parameter
    gridrhs(o,q) rhs of eps-constraint at grid point
    maxq(o)      maximum point in grid for objective
    posq(o)      grid position of objective
    firstOffMax, lastZero some counters
*    numo(o) ordinal value of o starting with 1
    numq(q)      ordinal value of q starting with 0
    step(o)      step of grid points in objective functions
    jump(o)      jumps in the grid points traversing;

lastZero=1; loop(om1, numo(om1)=lastZero; lastZero=lastZero+1); numq(q) = ord(q)-1;

grid(om1,q) = yes;
maxq(om1)   = smax(grid(om1,q), numq(q));
step(om1)   = (maxobj(om1)- minobj(om1))/maxq(om1);
gridrhs(grid(om1,q))$(dir(om1)=-1) = maxobj(om1) - numq(q)/maxq(om1)*(maxobj(om1)- minobj(om1));
gridrhs(grid(om1,q))$(dir(om1)= 1) = minobj(om1) + numq(q)/maxq(om1)*(maxobj(om1)- minobj(om1));

put / ' Grid points' /;
```

```
loop (q,
   loop(om1, put gridrhs(om1,q):12:2);
   put /);
put / 'Efficient solutions' /;

posq(om1) = 0; iter=0; infeas=0; start=jnow;

repeat
  rhs(om1) = sum(grid(om1,q)$(numq(q)=posq(om1)), gridrhs(om1,q));
  solve mod_epsmethod maximizing a_objval using mip;
  iter=iter+1;
  if (mod_epsmethod.modelstat<>%ModelStat.Optimal% and
      mod_epsmethod.modelstat<>%ModelStat.Integer Solution%,
    infeas=infeas+1;   // not optimal is in this case infeasible
    put iter:5:0, '  infeasible' /;
    lastZero = 0; loop(om1$(posq(om1)>0 and lastZero=0), lastZero=num»
o(om1));
    posq(om1)$(numo(om1)<=lastZero) = maxq(om1); // skip all solves f»
or more demanding values of rhs(om1)
  else
    put iter:5:0;
    loop(o, put z.l(o):12:2);
    jump(om1)=1;

    jump(om1)$(numo(om1)=1)=1+floor(sl.L(om1)/step(om1));
    loop(om1$(jump(om1)>1), put '   jump');
    put /;
    );

  firstOffMax = 0;
  loop(om1$(posq(om1)<maxq(om1) and firstOffMax=0),
     posq(om1)=min((posq(om1)+jump(om1)),maxq(om1)); firstOffMax=numo»
(om1));
  posq(om1)$(numo(om1)<firstOffMax) = 0;
  abort$(iter>1000) 'more than 1000 iterations, something seems to go»
 wrong'
until sum(om1$(posq(om1)=maxq(om1)),1)= card(om1) and firstOffMax=0;

finish=jnow; elapsed_time=(finish-start)*60*60*24;

put /;
put 'Infeasibilities = ', infeas:5:0 /;
put 'Elapsed time: ',elapsed_time:10:2, ' seconds' / ;
```