COORDINATED INVENTORY PLANNING FOR HUMANITARIAN RELIEF AGENCIES

A Thesis

by

Meserret Karaca

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Approved by:

Assoc. Prof. Okan Örsan Özener, Advisor Department of Industrial Engineering $\ddot{O}zye\ddot{g}in$ University

Assoc. Prof. Ali Ekici Department of Industrial Engineering $\ddot{O}zye\ddot{g}in$ University

Assoc. Prof. Burcu Balçık, Advisor Department of Industrial Engineering $Ozye\breve{q}in$ University

Assoc. Prof. Serhan Duran Department of Industrial Engineering Middle East Technical University

Date Approved: July, 2016

Assoc. Prof. Ulaş Özen Department of Management Information Systems $Ozye\check{g}in$ University

To unknowable "thing-in-itself",

ABSTRACT

Pre-positioning relief supplies in strategic locations around the world is essential for effective disaster response, especially during the critical 72 hours immediately following the disaster. Most of the existing studies that use quantitative models to determine pre-positioning decisions focus on a single relief agency and assume that the agency makes stock pre-positioning decisions independently of other agencies; that is, the possibility of sharing inventory among different agencies is not considered. In this study, we aim to investigate the potential benefits of making stock pre-positioning decisions collaboratively among multiple agencies. In particular, we consider two agencies that stock relief supplies in a joint depot owned and operated by a separate coordinator (such as the United Nations Humanitarian Response Depot). We assume that these agencies have several operating regions throughout the world. Each operating region may be served by a single agency or by several different agencies depending on its location. Once a disaster occurs in an agency's operating region, the agency aims to satisfy demand as much as possible. Also, other agencies may share their excess inventory with the responding agency. The amount of supplies that can be sent to the disaster region is affected by the uncertain post-disaster funding level of the responding agency. We consider a finite set of scenarios to characterize the uncertainties in disaster locations, impacts and post-disaster funding levels and develop a two-stage stochastic programming model to determine the amount of inventory to be pre-positioned at the joint depot by each agency. We perform a numerical analysis to establish when collaborative action would be beneficial for different types of agencies in different settings.

ÖZETCE

˙Insani yardım malzemelerinin afet ¨oncesinde ¨on konumlandırılması, etkin bir afet müdahelesi gerçekleştirmek için gereklidir. On konumlandırma kararlarını vermek için matematiksel modeller sunan mevcut çalışmaların çoğu tek bir insani yardım kuruluşuna odaklanmış ve kuruluşun ön konumlandırma kararlarını diğer kuruluşlardan bağımsız olarak aldığını kabul etmiştir; yani, farklı kuruluşlar arasında envanter paylaşma olanağı ele alınmamıştır. Bu çalışma, farklı kuruluşlar arasında iş birliği ile verilebilecek ön konumlandırma kararlarının potansiyel faydalarını incelemeyi amaçlamaktadır. Bir koordinatör tarafından yönetilen ortak bir depoda (Birleşmiş Milletler Insani Yardım Deposu gibi) yardım malzemesi stoklayan iki kuruluş düşünülmüştür. Bu kuruluşların dünya üzerinde faaliyetlerini yürüttükleri farklı bölgeler olduğu varsayılmıştır. Bir kuruluşun faaliyet yürüttüğü bölgede bir afet meydana gelirse, o kurulus karşılayabildiği kadar talebi kendi stoğundan karşılar. Ayrıca, kuruluşlar afet sonrasında envanter paylaşımı yapabilirler. Afet sonrası belirsiz olan fon miktarı afet bölgesine gönderilecek malzeme miktarını etkilemektedir. Bu çalışmada afet lokasyonları, afetin etkileri ve afet sonrası fon seviyesindeki belirsizlikler sonlu bir senaryolar kümesi kullanılarak tanımlanmıştır. Her kuruluş tarafından ortak depoda ön konumlandırılacak malzeme miktarını saptamak için iki aşamalı stokastik programlama modeli geliştirilmiştir. Farklı tipte kuruluşlar için iş birliği yapmanın faydalı olduğu durumları analiz eden sayısal çalışmalar sunulmuştur.

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Finally, I would like to thank my parents and my sister for their support.

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Chapter I

INTRODUCTION

Pre-positioning, which involves holding excess inventory to increase customer service level for a supplier, is one of the strategies used by humanitarian relief organizations. It has critical importance for them as they face demand and supply uncertainties in case of a disaster occurrence. Also, the result of unmet demand can cost lives which is incomparable with any other cost. Despite its importance, pre-positioning relief supplies in strategic areas around the world has not been given importance that it needs. While international non-govermental organizations invest 0.5 % of their total resources to pre-positioning activities for the disasters, this amount increases at most 2.2 % for governmental organizations [1].

The challenges, associated with pre-positioning in humanitarian systems, include uncertainties in disaster timing, size, impact, and location. Moreover, demand and amount of fundings after a disaster are unpredictable before the disaster occurrence. Hence managing the supply chain and making the right pre-positioning decisions are difficult for a relief organization. On the other hand, managing a warehouse for pre-positioning is costly on its own. Unfortunately, under these circumstances prepositioning is risky in terms of costs related with stocking and maintaining.

Pre-positioning for unexpected disasters is similar to the immune system of a human body which is ready to defend us in a case of a virus attack. While immune system is supported by the energy a human body produces, pre-positioning requires resources and funds. Donor funding, which is donated to relief agencies by people or organizations, are unpredictable especially in post-disaster stage. Making correct decisions on stocking, transportation, packaging, and delivering operations are directly constrained by the amount of funding gathered in pre-and post-disaster periods. Making effective pre-positioning decisions under uncertain funding levels can be challenging. On the other hand, in humanitarian relief context donors, which are like customers of humanitarian relief organizations [2], may want to fund for specific missions such as delivering specific items or religion similarity between victims and donors and this involves giving importance on operational activities rather than on building organizational infrastructure. Therefore, non-govermental organizations (NGO's) are encouraged to focus on operational disaster relief activities rather than disaster preparedness that will reduce expenses or make relief more effective over the long-term [3].

Although uncertainties of disaster timing, size, impact, and location presents challanges in pre-positioning operations, these are also the main reasons for requiring pre-positioning in the first place. Besides the uncertainties related to disaster occurrence, there are other factors that would encourage relief organizations to pre-position supplies. For instance, after the disaster occurs, prices for supplies in spot market might increase, and supply unavailability might occur due to fluctuations in demand or problems on the logistic side. All these factors justify the pre-positioning activities of the agencies from economic and operational perspectives. Despite the reasons which make pre-positioning preferrable, only a few relief organizations, such as World Food Program (WFP), use this strategy. For example, the WFP manages the United Nation Humanitarian Response Depots (UNHRD), which consist of five warehouses strategically located all around the world. These depots provide humanitarian relief organizations warehousing opportunity free of charge [4], [2].

Enhanced coordination among humanitarian relief organizations may be one of the methods, which can make pre-positioning less expensive. In the supply chain of the commercial sector, there are vertical and horizontal coordination mechanisms. Vertical coordination is defined as linking activities at higher levels and lower levels for the achievement of company objectives. In horizontal coordination, the companies in similar level harmonize their activities organizations. Similar to the coordination mechanisms in the supply chain of the commercial sector, humanitarian relief agencies can collaborate with the other organizations at different levels (e.g., other humanitarian organizations, suppliers, logistic providers, etc.). In [5], coordination mechanisms in humanitarian supply chains are explained. As an example, vertical coordination in humanitarian relief agencies is a coordination between an agency and a logistics company to deliver the items to the disaster area. Information sharing between agencies or sharing excess inventory among agencies can be given as an example to horizontal coordination. The organizations can decrease the cost of pre-positioning supplies with coordination as long as a fair allocation of the profit among the participants exists. Although enhanced coordination among agencies is beneficial to decrease the prepositioning costs, there still exist challenges for humanitarian relief agencies to make a coordinated system work. Due to the situations such as the differences in missions of agencies and donors, the competition between agencies, and the cost of coordination (cost of administration, staff, and packaging operations etc.), coordination may result costly and ineffective outcomes for the agencies. Also, unsuccessful coordinations can cause oversupply.

Despite the challenges, in 2000, WFP established UNHRD network which enables horizontal coordination among agencies. These depots are strategically located as succession of its idea in Brindisi, Panama City (Panama), Accra (Gana), Dubai City (UAE) and Subang (Malaysia). The network holds strategic stock reserves of emergency items. The WFP provides the administration and financial management of the UNHRD network. Humanitarian UN and non-UN Organizations, Humanitarian Agencies, Governmental and Non-Governmental Organizations can use the UNHRDs under a technical agreement (TA). Agencies can receive standard services (such as warehousing, routine maintaining free of charge) and specific services (such as major repairs, procurement and transportation of non-food items for a fee). Also, suppliers can stocks items in the UNHRD depots.

Emergency stocks in this network, as shown in Figure 1, can include physical and virtual stocks. According to [6], physical stocks are agencies' own stock, suppliers stock on-site and shared stocks. Agencies' own stocks are the emergency items being hold in shared warehouse; suppliers' stocks which are still owned by suppliers and shared stocks which agencies sell or loan to each others or exchange among themselves from their own stocks in the warehouse. Most common way to share is through a sale where one agency can buy some items from other agencies' stocks via bilateral agreements between agencies. This method requires standardization of items stocked by postponing packaging and labelling operations. Virtual stocks are the stocks not physically placed within UNHRD network. They are positioned within the suppliers' premises through long term agreements.

To the best of our knowledge, in the current UNHRD system (or alike), agencies make stocking decisions independently. That is, each agency determines the amount of stock to pre-position at the depot without considering the stock levels of other agencies for the same commodity. Agencies may borrow/lend stocks among each other; however, these bilateral relationships are managed usually in an ad-hoc manner, mostly appearing only after a disaster occurs. Given that the objective of the UNHRD or similar systems is to maximize the amount of emergency supplies that can be dispatched within the 72 hours after a disaster, coordination of pre-positioning decisions could highly help improve the performance of the depot in terms of response capacity and stock-related costs.

In this study, we present an example of pre-positioning mechanism used by humanitarian relief agencies which stock their emergency supplies in a shared depot. We also

Figure 1: Supply chain design of UNHRD.

show how coordination among agencies may affect their benefits from pre-positioning. Specifically, we consider a single joint depot in which multiple relief agencies stock emergency supplies, which are needed in the case of a sudden-onset natural disaster (such as tents or blankets). The depot is managed by a coordinator (similar to the WFP managing UNHRD). The agencies may have different operating regions throughout the world. Once a disaster occurs in any region, the agencies which operate in that specific region mobilize their supplies at the depot immediately to satisfy the demands of the region. The amount of supplies delivered to a region by an agency is primarily affected by the amount of pre-positioned supplies and the post-disaster funding available to deliver the supplies to the affected regions. We assume that a portion of post-disaster funding amount is dedicated to delivering pre-positioned items to the affected region as there may be other relief operations after a disaster occurrence. Therefore, we assume that total demand for relief supplies is so large

that an agency cannot satisfy all the demand by itself and the aim of the agencies is to satisfy demand as much as possible in any disaster scenario under post-disaster stochastic funding level. We also assume that this is a single period problem for the sake of simplicity.

We assume that agencies may coordinate; similar to the management of shared stocks in the UNHRD system. Firstly we consider that agencies can hold their own stocks in the warehouse. We also assume that the agencies can share their items by selling to each other, which is most preferable sharing method in UNHRD warehousing system. This study also aims to guide agencies to construct a decision mechanism to determine whether a centralized (i.e. the situation a coordination exist) or decentralized (i.e. the situation a coordination does not exist) mechanism is beneficial for given situations. Regarding this decision, agencies decide how much to stock before disaster, and how much to respond its affected operating region and how much to share with other agency after disaster. Our model is a two-stage stochastic model which covers pre-and post-disaster decisions for each agency in any scenario.

In this thesis, we present literature review in Chapter 2 to present how other studies are relevant to our problem. We continue with problem description and mathematical models in Chapter 3. In Chapter 4, we present our observations and a game theoretic approach. We present our conclusions in Chapter 5.

Chapter II

LITERATURE REVIEW

The majority of existing humanitarian logistics models focus on preparation or response to man-made or natural disasters. Humanitarian relief literature relevant to our study falls into three objectives: determining warehouse location, stocking decisions to respond effectively and how to deliver the stocks to the affected region. In this section, we discuss some of the studies about the pre-positioning of relief supplies and the coordination among agencies from the humanitarian relief literature.

Pre-positioning in humanitarian relief context requires preparedness activities such as opening a warehouse close to the critical areas around the world or stocking sufficient amount of necessity items to satisfy the demand incurred in first 72 hours after unexpected events. Optimal order inventory models are important topics in operations management and operations research since the satisfying the demand determine the quality of service. These models can determine the optimal quantity based on lowest holding and operational costs, and highest demand satisfaction. In humanitarian relief context, most of the studies concentrate demand to be met or a service level to be reached under uncertain parameters such as uncertain supply, demand, and network availability.

Past efforts in emergency response planning have solved inventory models as newsvendor inventory model. For example, [7] develops a stochastic inventory model in the form of (Q,r) that determines optimal order quantities and reorder points for a prepositioned warehouse responding to a complex humanitarian emergency. They allow for two types of lot sizes for ordering as regular and emergency order. Also, [8] proposes a stochastic inventory model with a newsvendor-type of analysis to determine optimal inventory levels. Besides, they consider multiple pre-hurricane seasons to characterize the stochastic inventory model and the demand predictions are revised at the beginning of each pre-hurricane season planning period. They assume a Markov chain associated with hurricane count rates to generate demand scenarios. Four variations of newsvendor model are introduced to assist a decision maker in determining appropriate inventory levels. The objective of this study is to determine an optimal ordering policy to satisfy the demand and reserve the supplies in a cost effective way. Similarly, [9] examine how much to stock at a location, and besides, the decision of where to preposition supplies before a disaster occurrence. They also consider the risk of a location that can be affected by the disaster and show how parameters impact the optimal stocking quantity. They derive the equations to determine the optimal stocking quantity and the total expected costs associated with delivering to a demand point from a supply point. In addition, [11] considers how to partition a fixed budget between stockpiling and shipping costs for a single item in order to satisfy the demand and how to ship relief items from the stockpile to a relief operation. They solve for the shipment policy using dynamic programming.

Also, in humanitarian relief literature there exists inventory models solved in the form of stochastic mixed integer programming formulation. For example, [15] proposes a mixed integer programming formulation to minimize the average response time required to deliver items from selected preposition warehouses or suppliers to the affected region in a disaster occurrence. Also, the study helps to give decisions on location of warehouses, quantities of supply from warehouses and from suppliers, and the quantity of supply held in a warehouse. The model finds optimal number and location of prepositioning warehouses such that the demand can be met. They allow multiple events to occur within a replenishment period and the probability of need for each item to depend on local conditions. Also to measure the demand, they use historical data. [16] also proposes mixed integer programming model to determine quantity of items to be stored in order to pre-position warehouses. They aim to minimize the time of arrival of relief items after disaster occurrence. They consider time windows with certain reliability by using probabilistic constraints to cover stochasticity of the situation. Moreover, a scenario-based formulation is also considered to enable comparisons.

Moreover, some of the studies proposes two-stage stochastic models: first stage is considered as the time period before an emergency event occurrence while the second stage is the time period after this event. One of the studies which proposes a two-stage stochastic model is [12]. They focus on determining the locations and the capacity of pre-positioning storage and quantity of items to be stored. They consider uncertainty of demand and transportation network availability by using scenarios and they also consider possibility of damaged supplies. Since solving deterministic equivalent of the two-stage stochastic programming model is problematic with large instances and they use a L-shaped method to solve it. [13] also proposes a two-stage stochastic programming model to determine locations of the facilities and inventory levels of medical supplies to be held. The model handles the uncertainty related with a disaster by using disaster scenarios. Similarly, [14] proposes a stochastic programming approach for pre-positioning relief items to determine location, number, and capacity of the facilities, and inventories to be held. They generate scenarios using the Monte Carlo procedure, solve a two-stage stochastic programming model.

In early 1990, numbers of multi-agency collaborations within NGOs increased. The reason was that each had common purpose of aiding the relief communities. As in every area which competition exists, the challenges of collaborations between humanitarian relief agencies were competition among them such as bidding for a good price from suppliers or having funding from donors. [17] defines successful collaborations efforts as the ones in which each agency performs similar procedures. Coordination can improve effectiveness of emergency response efforts (e.g. [4] ; [18]).

In our study, there are two humanitarian relief agencies which stock their emergency items in a warehouse to respond the regions affected by a disaster. They can collaborate by inventory sharing when one has excess fund and the other has excess inventory on hand. [19] remark that their paper is the first study in pre-positioning field considering inventory coordination in emergency planning. They present a stochastic programming model to determine how much supply from an outside agency, how much local supply to reposition, and where pre-positioning should be in the network which is such as Feeding America, a non-profit hunger relief organization, has warehouses across United States where they receive donated food. Agencies are referred as warehouses in affected or non-affected locations by an event. The paper also remarks that better planning and information regarding resources reduces redundancy, duplication of efforts and unused supply.

To the best of our knowledge, our study is the first study in preparedness domain to consider inventory levels and inventory sharing operations among two humanitarian relief agencies. There are studies close to our work in supply chain systems of commercial firms. [20] develop two stage model to analyze decentralized distribution systems which entails N retailers who face stochastic demands and hold stocks locally and/or at one or more central locations, and they build an allocation mechanism to satisfy retailers' excess demands with excess units from other locations. Excess profit generated by cooperation is shared by developing conditions for existence of a pure strategy Nash equilibrium. [21] adds an extra stage to [20] and in this stage the retailers are allowed to decide how much they want to share instead of one decision maker. [22] considers a threshold level in which each retailer decides on, and they characterize equilibrium solution in game theoretic approach for three special cases: full sharing game, fixed sharing level game, and inventory rationing game.

This study addresses a two-stage stochastic inventory problem faced by two humanitarian relief agencies which stock their emergency items in a shared depot. These agencies also can share their items if needed in a disaster scenario. The contribution of this study is inventory decisions of the agencies based on optimal stocking results that quantitative model proposed determines in a single-period under regional risk and probability settings. Another contribution is that unlike previous inventory models that consider single agency, this model allows inventory sharing among the agencies. Finally, our model contributes to research about the coordination of humanitarian relief agencies by analyzing optimal decisions of the agencies which are the preferences between centralized or decentralized system.

Chapter III

PROBLEM DESCRIPTION

This study considers two humanitarian relief agencies, which stock their emergency relief items in a joint depot and the owner of the depot who manages the consortium among agencies. We assume a single period inventory problem with two agencies responsible to help certain regions by satisfying the demand as much as they can. It is the fact that each agency is donated in pre-and post-disaster stage. We also assume that a certain proportion of these donations is devoted to pre-positioning activities. We refer to pre-and post-disaster funding for the amounts to be used in pre-positioning activities. Pre-disaster funding amount, which is known, can be used for buying items to store in the depot and delivering the items to the affected region. Post-disaster funding amount, which is uncertain, can be used for buying items from other agency's stock and delivering the items to the affected area. We consider a two-stage decision making framework which covers pre-and post-disaster stages. The first stage is the period until the disaster occurrence and the second stage is the first 48-72 hours after the disaster.

In this study, we assume that the location of the disaster and the post-disaster funding amounts of agencies are uncertain. A finite set of probabilistic scenarios is used to represent the uncertainties. We consider a two-stage decision making framework where the stock level of each agency is determined in the first stage with a known pre-disaster funding amount considering post-disaster funding uncertainty in second stage. In the second-stage, the amount to be shared by each agency with the other agency is determined. Also, the total amount of supplies delivered by each agency to meet demand as much as possible are determined depending on the first-stage decisions and the post-disaster funding. Both for first and second stages, we assume that holding inventories at the depot has no cost since stocking items in UNHRDs is free of charge.

We also model the disaster occurrence as low impact or high impact in critical regions around the shared depot. We assume that disaster affects only one region at the same specific time and the region is served either one agency or both. We differ the agencies as big or small agencies according to pre-disaster and post-disaster funding amounts. We assume that these funding amounts are correlated with the disaster impact in the region. We assume that each agency makes its own estimations as a mean of post-disaster funding level for disaster scenarios with low and high level impact.

In the first stage, each agency should decide whether it prefers to coordinate with the other agency. To be able to make a correct decision, the agency makes its own estimation about its own post-disaster funding level. Regarding this decision, they also should decide how much to store in the depot without exceeding pre-disaster funding amount. For the sake of simplicity, we assume that unit purchasing cost is same for both agencies.

In the second stage, a region is affected by a disaster. The agency who is responsible to serve the region decides how much to send to the region. The amount to be sent includes the amount stored in first stage and the amount purchased in the second stage if possible. If the agency sells its items to the other agency then the amount to be sent is equal to the amount stored in the first stage minus the amount sold in the second stage. Thus, before delivering the items to the affected area an agency should also decide on how much to sell to other agency or how much to buy from the excess inventory of the other agency if possible. Due to the uncertainty of the post-disaster funding level, an agency may have excess funds or excess inventories. Because of the

unavailability of the items or high prices in spot market and the benefits of dispatching more items from the warehouse due to the economies of scale, we assume that an agency prefer to buy extra amounts from the excess inventory of other agency if it has excess funds and the other has excess inventories. We accept that in the second stage agencies cannot purchase extra amount while they have inventory more than they can deliver and cannot keep extra inventory after purchasing. The unit purchasing cost in inventory sharing operations is same for both agencies. Also, for the sake of simplicity we assume that transportation cost is same for both agencies.

In this study, we aim to determine optimal inventory level of two humanitarian relief agencies to maximize the amount sent to the affected region. Thus, in Section 3.1, we develop newsboy model for single agency and two agencies and we solve for single agency. Also, in Section 3.2, we develop and solve two-stage stochastic model for single agency and two agencies.

Following notations are used to model the coordinated inventory problem:

Parameters:

 $N = \{1, 2\}$: Set of agencies.

 $K = \{1, 2, 3\}$: Set of scenarios.

 f_i^k : Random variable representing funding level of agency i over scenario k.

 $\phi(x)$: Cumulative distribution function of f_i^k .

 $\varphi(x)$: Probability density function of f_i^k .

 B_i : Pre-disaster funding level of agency *i*.

 F_i^k : Expected post-disaster funding level of agency *i* over scenario *k*; $F_i^k = E[f_i^k]$.

t: Unit transportation cost to the affected region.

 p^k : Probability of disaster scenario k.

c: Unit purchasing cost in the first stage (before the disaster).

 c' : Unit purchasing cost in second stage (after the disaster).

 z_i^k : 1, if agency *i* responds in scenario *k*; 0, otherwise.

Decision Variables in the First Stage:

 Q_i : The quantity of relief items owned by agency *i*.

Decision Variables in the Second Stage:

 \bar{Q}_i^k : The quantity of relief items sent to the region by agency i over scenario k.

 S_i^k : The quantity of relief items sold by agency i over scenario k.

 R_i^k : The quantity of relief items bought from the other agency by agency i over scenario k.

 I_i^k : The quantity of relief items remained in the warehouse by agency i after scenario k.

 v_i^k : 1, if $S_i^k \geq 0$; 0, otherwise.

 w_i^k : 1, if $R_i^k \geq 0$; 0, otherwise.

Recall that each agency's aim is to help the disaster victims as much as the possible. In the model, we represent this with \overline{Q}_i^k , which is the number of items delivered to the affected region by an agency under three different disaster scenarios. In the first stage, agency *i* stocks items represented by Q_i . In the second stage, agency *i* can sell items to the other agencies, which is represented by S_i^k , or buy items from the other agency, which is represented by R_i^k , and finally deliver some items to the affected region, which is the value of \overline{Q}_i^k , where $i \in N$ and $k \in K$.

3.1 Newsboy Model

Newsboy Model for Single Agency

We model the single agency problem and determine the optimal pre-disaster inventory level to be stocked in depot by deriving the newsboy solution of the single-agency system.

$$
G(Q_1) = E_{f_1^k}[min(Q_1, \frac{B_1 - cQ_1 + f_1^k}{t})]
$$
\n(1)

$$
G(Q_1) = \int_{Y_1^k}^{(t+c)Q_1 - B_1} \left(\frac{B_1 - cQ_1 + f_1^k}{t}\right) \varphi(f_1^k) df_1^k + \int_{(t+c)Q_1 - B_1}^{Y_2^k} (Q_1) \varphi(f_1^k) df_1^k \tag{2}
$$

where
$$
\phi(f_1^k) = \int_{Y_1^k}^{Y_2^k} \varphi(f_1^k) df_1^k
$$
 and $F_1^k = \frac{Y_1^k + Y_2^k}{2}$ (3)

Our objective is maximizing the profit function $G(Q_1)$. The profit function is equal to expected value of amount sent to the affected area. For the sake of simplicity, the profit function is assumed to be equal the number of items delivered to the affected region in disaster scenario k while funding amount f_1^k is uniformly distributed between lower bound, represented by Y_1^k , and upper bound, represented by Y_2^k i.e., $f_1^k \sim U[Y_1^k, Y_2^k]$. The amount sent by an agency in a single agency setting can be at most equal to the amount bought in the pre-disaster stage (Q_1) . If the agency receives sufficient funding after the disaster occurrence, then the amount sent is equal to Q_1 otherwise it can effort to send only $\left(\frac{B_1 - Q_1 c + f_1^k}{t}\right)$ which is less than Q_1 (2). By Leibniz Rule, we reach the optimal inventory level to stock in pre-disaster stage, which is equal to

$$
Q_1^* = \frac{1}{t+c} (\phi^{-1}(\frac{t}{t+c}) + B_1).
$$
 (4)

We refer appendix A.1 for the proof.

Newsboy Model for Two-Agency System

Next, we analyse two-agency centralized system by allowing inventory sharing among the agencies. Agencies share inventories by purchasing items from other agency at a $\cot c'.$

$$
G(Q_i) = E_{f_i^k}[min(Q_i + R_i^k, \frac{f_i^k + (B_i - cQ_i) + c'(S_i^k - R_i^k)}{t})],
$$
\n⁽⁵⁾

From inequality,

$$
\bar{Q}_i^k \le (B_i - cQ_i + f_i^k + c'S_i^k - c'R_i^k)/t,
$$
\n(6)

$$
R_i^k = \min(\max(0, \frac{f_i^k + B_i - cQ_i - tQ_i}{c' + t}), \max(0, Q_j - \frac{f_j^k + B_j - cQ_j}{t})), \quad (7)
$$

$$
S_i^k = \min(\max(0, \frac{f_j^k + B_j - cQ_j - tQ_j}{c' + t}), \max(0, Q_i - \frac{f_i^k + B_i - cQ_i}{t})), \quad (8)
$$

where $i, j \in N$ and $i \neq j$.

We maximize the utility of each agency, which is the sum of the expected utility under three disaster scenarios. In two-agency system, the amount sent by an agency is also affected by the amount shared. If an agency receives sufficient funding after the disaster it can effort to send its own inventory and also can increase quantity sent by using the other agency's stock if the other agency has excess inventory; i.e., $(Q_i + R_i^k)$. If an agency does not receive sufficient funding after the disaster, the amount sent will be less than its stock level. The amount sent by the agency will be equal to the amount that the pre-disaster funding left on hand and the post-disaster funding can satisfy. If there exists excess inventory on hand and the other agency has excess funds the agency can sell its items charging c' per item. Then the agency has the opportunity to send more by using the money acquired via inventory sharing if there still exists inventory in its stock, $\left(\frac{f_i^k + (B_i - cQ_i) + c'(S_i^k)}{t}\right)$ $\frac{Q_i)+C(S_i^{\circ})}{t}.$

The optimal pre-disaster inventory level for each agency is hard to derive. Hence, we construct a two-stage stochastic model. To analyze the results clearly, we use expected funding level, F_i^k , instead of random variable, f_i^k . We also use newsboy model for two-agency system to validate the accuracy of two-stage stochastic model substituting the same data.

3.2 Two-Stage Stochastic Model

Single Agency System

$$
\text{Max} \qquad \qquad \sum_{k=1}^{3} p^{k} \bar{Q}_{1}^{k} \tag{9}
$$

$$
s.t. \t cQ_1 \leq B_1 \t (10)
$$

$$
\bar{Q}_1^k \le Q_1 \qquad \qquad \forall k \in K \tag{11}
$$

$$
t\overline{Q}_1^k \leq B_1 - cQ_1 + F_1^k \quad \forall k \in K \tag{12}
$$

$$
Q_1, \bar{Q}_1^k \ge 0 \text{ and integer } \forall k \in K \tag{13}
$$

The mathematical model above is for a single agency which wants to maximize its expected amount sent when a disaster hits one of three regions with a probability p^k . While constraint (10) prevents the amount of items to be purchased from exceeding pre-disaster funding amount, constraints (11) provide the number of items to be sent to the affected region not to exceed the number of items purchased and stocked in the pre-disaster stage. Constraints (12) prevent the cost of delivering the items to the affected area from exceeding the sum of funding amount on hand after purchasing in the first stage, post-disaster funding amount donated in the second stage.

Two-Agency System

We assume that there are two agencies to coordinate with each other and three regions which might be affected by a disaster and are to be served by at least one of these agencies. We define disaster scenarios as disaster occurrences in regions. As an example, a disaster occurrence in region 1 is a scenario. We also generate the probabilities of scenarios such that sum of the probabilities equals to 1.

The model is formulated using the deterministic equivalent of two-stage stochastic model, in which the objective is to maximize the total expected amount sent by two agencies over all scenarios.

Max P² i=1 P³ ^k=1 p ^kQ¯^k i (14) s.t. cQⁱ ≤ Bⁱ ∀i ∈ N (15) tQ¯^k ⁱ ≤ Bⁱ − cQⁱ + c 0S k ⁱ − c ⁰R^k ⁱ + F k ⁱ ∀i ∈ N, ∀k ∈ K (16) Q¯k ⁱ = Qⁱ − S k ⁱ + R^k ⁱ − I k ⁱ ∀i ∈ N, ∀k ∈ K (17) S k ⁱ ≤ Qⁱ ∀i ∈ N, ∀k ∈ K (18) S k ⁱ ≤ Mv^k ⁱ ∀i ∈ N, ∀k ∈ K (19) R^k ⁱ ≤ Mw^k ⁱ ∀i ∈ N, ∀k ∈ K (20) v k ⁱ + w k ⁱ ≤ 1 ∀i ∈ N, ∀k ∈ K (21) P² ⁱ=1 S k ⁱ = P² ⁱ=1 R^k ⁱ ∀k ∈ K (22) Qⁱ − Q¯^k ⁱ ≤ (1 − w k i)M ∀i ∈ N, ∀k ∈ K (23) I k ⁱ ≤ (1 − w k i)M ∀i ∈ N, ∀k ∈ K (24) Q¯k ⁱ ≤ Mz^k ⁱ ∀i ∈ N, ∀k ∈ K (25) P² ⁱ=1 v k ⁱ ≤ 1 ∀k ∈ K (26) P² ⁱ=1 w k ⁱ ≤ 1 ∀k ∈ K (27) v k i , w^k ⁱ ∈ {0, 1} ∀i ∈ N, ∀k ∈ K (28) Qi , Q¯^k i , S^k i , R^k i , I^k ⁱ ≥ 0 and integer ∀i ∈ N, ∀k ∈ K (29)

In the two-stage stochastic model, Q_i is the first stage decision while the rest of the variables constitute the second stage. Constraints (15) provide the amount of items to be purchased not to exceed pre-disaster funding amount. Constraints (16) prevent the amount of items to be sent to the affected area from exceeding the sum of funding amount on hand after purchasing in first stage, the post-disaster funding amount donated in second stage and the net value after inventory sharing. Constraints (17) are inventory balance equations. Constraints (18) keep the amount sold less than the amount stored for each agency. Constraints (19) and (20) provide binary variables to have a value of 1 with respect to existence of selling and purchasing operations. Constraints (21) prevent an agency from both selling and purchasing at the same time. Constraints (22) keep equal amount of items sold to amount purchased for both agencies. Constraints (23) and (24) prevent agencies from purchasing while they have inventory more than they can deliver and from keeping inventory after purchasing. Constraints (25) prevent the agency from delivering items if the agency does not respond to that region. Constraints (26) and (27) make sure that at most one agency purchases from other agency's excess stock while the other agency sells at the same time.

There are more efficient stochastic programming algorithms in the literature. However, deterministic equivalent model was sufficient for our study. We coded our models in C programming using the ILOG CPLEX callable library on a PC with 2.3 GHz processor. All the runs solved in less than 1 minute.

Chapter IV

ANALYSIS AND RESULTS

In this chapter, we perform a numerical analysis to discover the effect of disaster impact and disaster probabilities of regions on agencies' decisions. Given the complicating aspects of the humanitarian relief inventory problem (such as unpredictable post-disaster funding level), it may be difficult for agencies to evaluate the effects of different parameters without performing a systematic analysis. Our objective is assisting agencies by giving insights and making recommendations about the decision among coordinated (centralized) and uncoordinated (decentralized) system in different settings.

We demonstrate a numerical example in Section 4.1, describe test instances in Section 4.2, present disaster-impact based results in Section 4.3 and disaster-risk based results in Section 4.4. Moreover, we describe a benchmark solution in Section 4.5 and discuss a game theoretic approach in Section 4.6.

4.1 Numerical Example

We show an example to explain explicitly how the inventory sharing system works and how the inventory decisions of agencies change when they collaborate. For an easy understanding, in Table 1 and Table 2, we show the results of which is region 1, region 2 and region 3 can be affected by a disaster with low, high and low impact with probabilities $p^1, p^2, p^3 = 1/3, 1/3, 1/3$, respectively. Agency 1 and Agency 2 have pre-disaster funding level $B_1 = 750 and $B_2 = 750 , respectively. Also, Agency 1 and Agency 2 have post-disaster funding level $F_1^1 = F_1^3 = 375 and $F_2^2 = $750, F_2^3 = 750 , respectively.

		$Q_1 = 187$			$Q_2 = 250$			
Region	Impact			Сκ				
					250			

Table 1: Numerical Example 1, Decentralized System Solution

		$= 172$			$Q_2 = 203$		
Region	Impact			C∖k			
			-15				
				Чb		Ŧр	

Table 2: Numerical Example 1, Centralized System Solution

In Table 1 for Agency 1, post-disaster funding amounts for scenario 1 and 2 are same, thus $\bar{Q}_1^1 = \bar{Q}_1^2 = (B_1 - cQ_1 + F_1^1)/t = 187$. For Agency 2, post disaster funding amounts are different in scenario 2 and scenario 3. And expected amount sent of Agency 2 is $p^2Q_2 + p^3(3B_2/2 - cQ_2)/(t + c) = 1/3(3B_2 + Q_2t)/(t + c)$. While Q_2 increases expected utility of Agency 2 increases as much as the constraints (17) and (18) allow. Hence, Agency 2 buys 250 items in pre-disaster stage. While it sends whole inventory to the affected region in the occurrence of scenario 2, it sends only 175 items in scenario 3.

In Table 2, while each agency tries to maximize its own amount sent. Also an agency shares their excess inventory with the other agency in the situation of that the other agency is a responder agency in the scenario and has excess fund. In scenario 3 of decentralized system solution, Agency 2 sends 175 items although it can effort to send 188 items in centralized system solution. In centralized system solution, Agency 2 buys 203 items in pre-disaster stage, less than 250 compared to decentralized system solution, and can effort to send 188 items in scenario 3. In scenario 2, Agency 2 has excess fund and Agency 1, not responder agency in scenario 2, has excess inventory.

Hence, Agency 2 buys from Agency 1 with the cost $c' = 1.2$ as much as its funding amount left.

In this result, while decentralized system objection function value for the whole system is 266, centralized system objective function value is 270. We see that Agency 1 shares its items with Agency 2 if a disaster occurs in Region 2. Hence, in the situation of a disaster occurrence in Region 3, Agency 2 can send to the region more than it sent in decentralized system solution. It is seen that Agency 2 sends 2 units less in the situation of disaster occurrence in Region 2. Since we consider total expected units sent to the regions, the centralized system is more beneficial than the decentralized system.

4.2 Test Instances

We consider two humanitarian relief agencies that serve some of three regions. We generate instances with different disaster impact and different disaster probability of regions. We also check the reliability of results with three different pre-disaster funding levels as $B_1 = 750$ and $B_2 = 750$, $B_1 = 1000$ and $B_2 = 500$, and $B_1 = 1250$ and $B_2 = 250$. We assume that a disaster may happen in one of these regions with probabilities p^1, p^2, p^3 , where $\sum_{k=1}^3 p^k = 1$. These probabilities are forecasted by the agencies. We take the unit purchasing cost before disaster (c) as \$1; unit purchasing cost after disaster (c') as \$1.2; unit transportation cost (t) as \$5. We also assume that if the pre-disaster funding level of agency i is equal to B_i then after a disaster with low impact (L) , its funding level is equal to $B_i/2$ and after a disaster with high impact (H) , it is B_i . We solve our two-stage stochastic model for each regional risk and probability setting to be able to understand how the agencies should behave in different scenario realizations.

We generate 8 different disaster impact settings as in Table 3 including all possibilities depending on forecasted impacts of the disaster in each three region. While low impact is represented by L, high impact is represented by H.

Scenarios	Setting 1	Setting 21	Setting 3 Setting 4 Setting 5 Setting 6		Setting 7	Setting 8
Scenario						
Scenario 2						
Scenario 3						

Table 3: Scenarios and Disaster Impact Settings

We also generate different sets of probabilities and assign to the scenarios as the disaster occurrence probabilities in the regions. To figure out the effect of the size of probabilities, we create 13 different disaster risk settings. These consist of set of disaster probabilities such as the disaster probabilities in all regions are equal or different than each other; the disaster probabilities in any two regions are equal and greater or less than the other.

 $(p¹, p², p³) = (0.33, 0.33, 0.33), (0.4, 0.4, 0.2), (0.2, 0.4, 0.4), (0.4, 0.2, 0.4), (0.25, 0.25, 0.5),$ $(0.5, 0.25, 0.25), (0.25, 0.5, 0.25), (0.6, 0.3, 0.1), (0.6, 0.1, 0.3), (0.3, 0.6, 0.1),$ $(0.3, 0.1, 0.6), (0.1, 0.6, 0.3), (0.1, 0.3, 0.6).$

4.3 Effect of Disaster Impact

In this section, we analyse the results of the disaster impact settings while disaster probabilities in each region are equal to each other, i.e., $p^1, p^2, p^3 = 1/3, 1/3, 1/3$ to analyse effect of disaster impact independently. Also, values of the parameters are the same with the values in Section 4.2.

We refer type A agency as the agency whose both responding regions are affected by high impact or low impact disaster. Type B agency is referred as the agency whose one responding region is affected by high impact disaster while the other is affected by low impact disaster.

While one agency is type A and the other is type B, the region with low impact which type B agency is responsible for is the 'critical' region.

We make the following observations based on the results.

OBSERVATION 1: If both agencies are type A agencies then centralized and decentralized system solution are the same for the agencies.

This observation refers setting 1 (LLL) and 8 (HHH). Forecasted disaster impact level for an expected disaster in each region is same and both agencies' funding amounts stay stable in their operating regions. Therefore, agencies can overcome to manage their inventory easily.

OBSERVATION 2: If one agency is type A while the other is type B, centralized system solution always is worse than or equal to decentralized system solution for type A agency. For type B agency, centralized system is always profitable or equal to decentralized system solution.

Observation 2 refers setting 3 (HLL), setting 4 (HLH), setting 5 (LHL) and setting 6 (LHH). While one's funding amounts stay same, the other has difference between funding amounts in its responding regions. For system optimality, type A agency should share its own stocks when it has excess inventories and type B agency has excess fundings after a disaster occurrence.

OBSERVATION 3: If both agencies are type B agencies centralized system solution is beneficial for both when Region 3 is expected to be affected by low impact disaster. Otherwise, one loses while other earns depending on sizes of agencies and probabilities of disaster occurrence in the regions.

Observation 3 refers settings HHL and LLH. In the setting HHL, both agencies get benefit in their expected amount sent. Agency 1 and Agency 2 buy less considering the low funding level in the situation of disaster occurrence with low impact in Region 3. If they bought more to respond Region 1 and Region 2 then they would not have enough funding on hand to serve Region 3. However, with this solution in the scenario of disaster occurrence in Region 1, since Agency 1 is only agency responsible for the region it has the opportunity to buy some items from other agency and can send close enough to decentralized system solution for Region 1. Same conditions are also valid for Agency 2 in this setting. Both agencies win.

The improvement centralized system provides is at most 4.4% and it is seen in HHL setting.

OBSERVATION 4: In the settings which critical region is affected by a disaster with low impact, the improvement is higher than the improvement in the other settings.

4.4 Effect of Disaster Risk

In this section, we analyse the effect of different disaster risks of the regions over each disaster impact settings. Also, values of the parameters are the same with the values in Section 4.2.

We make the following observations based on the results.

OBSERVATION 5: Observation 1 is valid with all probability sets.

Whatever probabilities of disaster occurrence of regions are observation 1 is always true. Since both agencies are type A, then centralized and decentralized system solutions are the same.

OBSERVATION 6: As disaster occurrence probability of the critical region increases, the difference of type B agency's expected amount sent between centralized and decentralized system solution also increases in favor of the centralized system. Here, we present an algorithm to understand this observation clearly.

- First, define the critical region.
- Group the settings as $p^1 < p^2$, $p^1 = p^2$, and $p^2 < p^1$.
- Calculate total pre- and post-disaster funding amounts for each agency.
- Combine group $p^1 = p^2$ with the group $p^1 < p^2$ or $p^2 < p^1$ according to size of total expected funding and pre-disaster funding amounts of agencies. If total funding and pre-disaster funding amount of agencies are equal go on with 3 groups.
- Order the critical region's probability to see in which scenario an agency gets better than decentralized system solution in each group.

You can see an example of expected amount sent by the agencies whose pre-disaster funding levels $B_1 = 750$ and $B_2 = 750$ in setting 3 (HLL) over six different settings in Table 4 and Table 5. While C represents centralized system solutions, D represents decentralized system solution. In this situation, the critical region is Region

		0.6.0.3.0.1		0.6.0.1.0.3	0.3, 0.6, 0.1		0.3, 0.1, 0.6		0.1, 0.6, 0.3		0.1, 0.3, 0.6	
Agencies												
	168.9	167.5	206.7	202.5	92.8	92.5	188.4	180	80.8	\mathcal{C} .)	137.6	131.2
		′4.8	74	74.8	130.9	130.9	129.5	130.9	168.3	168.3	168.3	168.3

Table 4: Example to Observation 5

Agencies $\vert 0.6, 0.3, 0.1 \vert 0.6, 0.1, 0.3 \vert 0.3, 0.6, 0.1 \vert 0.3, 0.1, 0.6 \vert 0.1, 0.6, 0.3 \vert 0.1, 0.3, 0.6 \vert$			
-0.8	-0.8	-14	

Table 5: Observation 6, Difference between Amount Sent of Centralized and Decentralized System

3 because Agency 1' s responding region is expected to be affected by low impact disaster. Sum of Agency 1' pre-and post-disaster funding amount is larger than the total funding amount of Agency 2, i.e. Agency 1 is a big agency while Agency 2 is a small agency. Therefore, we check p^3 in the scenarios $p^1 \geq p^2$ and $p^1 < p^2$ separately. In the scenarios $p^1 \geq p^2$, $((0.6, 0.3, 0.1), (0.6, 0.1, 0.3), (0.3, 0.1, 0.6))$, as p^3 increases the difference between centralized and decentralized system increases for Agency 1. In these settings, Agency 2 sends less than or equal to decentralized system solution.

In the settings $p^1 < p^2$, $((0.3, 0.6, 0.1), (0.1, 0.6, 0.3), (0.1, 0.3, 0.6))$, as p^3 increases difference between centralized and decentralized system increases for Agency 1. In these settings, Agency 2 makes its best which is same as decentralized solution because its funding amounts are same and it cannot make more than decentralized system solution as mentioned in Observation 2.

OBSERVATION 7: Observation 3 is valid for all scenarios.

If disaster impact is low in region 3 both send more than decentralized system. Otherwise, in the settings $p^2 < p^1$ while Agency 1 sends more than its decentralized solution Agency 2 sends less and in the settings $p¹ < p²$ while Agency 2 sends more than its decentralized solution Agency 1 sends less. Also, in the settings $p^1 = p^2$ centralized and decentralized system solution are the same. Table 6 and Table 7 show an example of this observation.

Agencies					$0.4, 0.4, 0.2 \mid 0.2, 0.4, 0.4 \mid 0.4, 0.2, 0.4 \mid 0.25, 0.25, 0.5 \mid 0.5, 0.25, 0.25$	$\vert 0.25, 0.5, 0.25 \vert$
	1.O		O.U		⊍.⊍	1.40
	. . <i>. .</i>	э.u		5 つ5 U.∠u		⊖.⊍

Table 6: Observation 7, Difference between Amount Sent of Centralized and Decentralized System, Case HHL

Agencies		$\mid 0.4, 0.4, 0.2 \mid 0.2, 0.4, 0.4 \mid 0.4, 0.2, 0.4 \mid 0.25, 0.25, 0.5 \mid 0.5, 0.25, 0.25 \mid 0.25, 0.5, 0.25$		
			5.25	
			-2.75	$5.25\,$

Table 7: Observation 7, Difference between Centralized and Decentralized System, Case LLH

The algorithm in Observation 6 is also valid here. In LLH case, critical regions for Agency 1 and Agency 2 are Region 1 and Reginon 2, respectively. Both agencies are type B agencies and operating regions, which they serve alone, are critical regions.

Table 8 shows each agency's decision under each disaster impact and risk settings.

While centralized system is represented by C, decentralized system is represented by

					$B_1 = 750, B_2 = 750$ $B_1 = 1000, B_2 = 500$ $B_1 = 1250, B_2 = 250$		
		A_1	A_2	A_1	A_2	A_1	A_2
LLL	$p^1 = p^2$	${\bf D}$	D	D	D	D	D
	$p^1 > p^2$	D	D	$\mathbf D$	D	D	D
	$p^1 < p^2$	$\mathbf D$	$\mathbf D$	$\mathbf D$	D	D	$\mathbf D$
LLH	$p^1=p^2$	${\rm D}$	D	D	D	D	D
	$p^1 > p^2$	$\mathbf C$	D	\mathcal{C}	D	$\rm C$	D
	$p^1 < p^2$	$\mathbf D$	\mathcal{C}	$\mathbf D$	$\rm C$	D	$\rm C$
HLL	$p^1 = p^2$	\overline{C}	D	\mathcal{C}	$\overline{D^*}$	\mathcal{C}	$\overline{\mathrm{D}^*}$
	$p^1 > p^2$	$\mathbf C$	D	\overline{C}	D	\mathcal{C}	D
	$p^1 < p^2$	\mathcal{C}	D^*	\mathcal{C}	D^*	\mathcal{C}	D^*
HLH	$p^1 = p^2$	${\rm D}$	$\mathbf D$	$\mathbf D$	\overline{C}	D	\mathcal{C}
	$p^1 > p^2$	\mathbb{D}	$\mathbf D$	D	D	D	D
	$p^1 < p^2$	D	\mathcal{C}	D	\mathcal{C}	D	$\mathbf C$
LHL	$p^1 = p^2$	$\mathbf D$	\overline{C}	D^*	\mathcal{C}	D^*	\overline{C}
	$p^1 > p^2$	D^*	\overline{C}	\mathbf{D}^*	\overline{C}	D^*	\overline{C}
	$p^1 < p^2$	\mathbf{D}	\overline{C}	D	\overline{C}	D^*	\overline{C}
LHH	$p^1 = p^2$	\mathbf{D}	D	\overline{C}	D	\mathcal{C}	$\mathbf D$
	$p^1 > p^2$	$\mathbf C$	${\rm D}$	\mathcal{C}	D	\mathcal{C}	${\rm D}$
	$p^1 < p^2$	$\mathbf D$	D	D	D	D	D
HHL	$p^1 = p^2$	\overline{C}	$\rm C$	\mathcal{C}	\mathcal{C}	\mathcal{C}	\mathcal{C}
	$p^1 > p^2$	\mathcal{C}	С	\overline{C}	С	\mathcal{C}	$\rm C$
	$p^1 < p^2$	\mathcal{C}	$\rm C$	\overline{C}	$\rm C$	\overline{C}	\overline{C}
HHH	$p^1=p^2$	\overline{D}	\overline{D}	\overline{D}	\overline{D}	\overline{D}	\overline{D}
	$p^1 > p^2$	\mathbf{D}	D	$\mathbf D$	D	D	$\mathbf D$
	$p^1 < p^2$	$\mathbf D$	D	D	D	D	D

OBSERVATION 8: While probability of disaster occurrence in common region, p^3 ,

Table 8: Decisions of Agencies

increases the improvement centralized system provides also increases for all disaster impact settings.

OBSERVATION 9: All observations are valid for all pre-disaster funding level settings which are $B_1 = 750$ and $B_2 = 750$, $B_1 = 1000$ and $B_2 = 500$, and $B_1 = 1250$ and $B_2 = 250.$

OBSERVATION 10: The improvement centralized system provides has the highest values in pre-disaster funding level setting $B_1 = 1000$ and $B_2 = 500$. Second highest values of improvement are seen in the setting $B_1 = 750$ and $B_2 = 750$ while the lowest values of the improvement are seen in the setting $B_1 = 1250$ and $B_2 = 250$. This observation is valid for all disaster impact and risk settings.

4.5 Benchmarking

In this study, we set a benchmark level as the value of amount sent when agencies consider each of their operating regions separately. Recall that if there is a difference between the forecasted impact levels of expected disasters in the operating regions of an agency then this agency's amount sent decreases in one of its responding regions. We show to which level they can increase their amount sent if they know where the disaster will occur.

To illustrate, we present an example in Table 9 and Table 10. The solution for setting HLH with the agencies whose pre-disaster funding levels are $B_1 = 1250, B_2 = 250$ is as following table.

		$P_1 = 429$			$\sqrt{2} = 70$		
Region	Impact						
				റ			

Table 9: Centralized System Solution, HLH

		$=416$			$= 83$ /ი		
Region	Impact			Cк			
					58		
						∣ີ	

Table 10: Decentralized System Solution, HLH

As we know from observation 2, the best solution for Agency 1 is the decentralized system solution. Agency 1 is type A and the maximum amount in both region is 416 from the equation

$$
\frac{B_1 + F_1^1}{t + c} \quad where \quad F_1^1 = F_1^3
$$

If Agency 2 considers its operating regions separately, the maximum amount is 62 in Region 2 and 83 in Region 3 from the equation

$$
\frac{B_2 + F_2^k}{t + c} \quad where \quad k = 2, 3
$$

Therefore, in this setting with these pre-disaster funding levels of agencies, the centralized system solution gives 99% of benchmark solution while decentralized gives 95%.

Under certain conditions, the centralized system solution exceeds the benchmark solution. In Table 11 and Table 12, we present another example with agencies whose pre-disaster funding levels are $B_1 = 1250, B_2 = 250$ in case LHL and in the scenario where probabilities are $p^1, p^2, p^3 = 0.4, 0.2, 0.4$.

		$= 297$			$= 78$		
Region	Impact			k.			
					83		
					63	Тb	

Table 11: Centralized System Solution, LHL

		$v_1 = 312$			$P_2 = 83$		
Region	Impact			сĸ			
		312					
		319					

Table 12: Decentralized System Solution, LHL

We know that from observation 2, the best solution for Agency 1 is the decentralized system solution. Agency 1 is type A agency and the largest amount it can send in both region is 312 from the equation

$$
\frac{B_1 + F_1^1}{t + c} \quad where \quad F_1^1 = F_1^3.
$$

However in this case, Agency 1 sends the same amount with decentralized system by sharing as well. The money on hand after a disaster occurrence is less than cost of buying and sending an extra unit. That is why, in optimal solution for the entire, it prefers to buy less and uses funding left to buy from Agency 2. Hence, it can help Agency 2 to send more by making Agency 2 earn from this buying operation. Although the result shows that amount sent in the decentralized and the centralized system are the same, the decentralized solution is more profitable by considering funding left on hand as well. The amount Agency 1 sends stays same, however, it loses money to help Agency 2. Hence, it chooses to be in decentralized system and acts on its own to save its funding. This case is exactly equal to the decision D* in the Table 8 .

If we look at the largest amount it can send in each region separately for Agency 2, it is 63 in Region 2 and 83 in Region 3 from the equation

$$
\frac{B_2 + F_2^k}{t + c} \quad where \quad k = 2, 3
$$

Therefore, in this case with these pre-disaster funding level of agencies, the centralized system solution gives more than 100% of benchmark solution.

Table 8 in the previous section is reached by results of the mathematical model. For an easy understanding about how these decisions are made, we present an algorithm.

• Define the agencies as type A and type B agencies and find the critical regions

if exists.

• If $p^1 = p^2$,

The system is in favor of the centralized system if critical region is where agencies serves together i.e. Region 3 in this study, where as (HLL, LHL, HHL). Type A agencies are always against to centralized system. Type B agencies choose the centralized system.

The system is in favor of decentralized system if critical regions are where an agency serves alone i.e. Region 1, Region 2, or both where as (HLH,LHH,LLH).

• If $p^1 > p^2$,

If critical regions are where agencies serve together, the system is in favor of the centralized system. Agency 1 approaches to its benchmark solution. If Agency 1 is type A agency then its benchmark solution is same as decentralized solution. If it is type B agency then it chooses to be in centralized system to achieve its benchmark solution.

If critical regions are where an agency serves alone and Agency 1 is a type A agency system is in favor of decentralized system and both chooses to be in decentralized system. If Agency 1 is a type B agency then system is in favor of centralized system. In this condition, type A agency chooses decentralized system while type B agency chooses centralized system.

Cases LLH and HHL are the cases which both agencies are type B agencies. In LLH, because of $p^1 > p^2$ Agency 1 chooses centralized system while Agency 2 chooses decentralized system. In HHL both choose centralized system.

• if $p^1 < p^2$;

This follows from the previous algorithm above.

We will explain the reason behind that the settings, where critical regions are different, cause different strategies for agencies. Suppose that Agency 1 is type A and Agency 2 is a type B agencies. In the case LHL or HLH, Agency 2's expected funding amount is equal to $p^2 F_2^2 + p^3 F_2^3$. From $p^1 + p^2 + p^3 = 1$ and since Agency 2 is not serving Region 1, while $p^2 + p^3 > 0$, to increase its utility it keeps amount sent in Region 2 or Region 3 high depending on how big these probabilities are. Thus, it buys at least $\frac{B_2+F_2^2}{c+t}$ and at most $\frac{B_2+F_2^3}{c+t}$. From the assumption, we know $F_i^k = B_i/2$ where region i is affected by a disaster with low impact and $F_i^k = B_i$ where region i is affected by a disaster with high impact.

If $p^2 > p^3$, in setting HLH it buys less to serve Region 2 efficiently and it needs to buy extra amount when a disaster hits to Region 3. The answer of the "what if it buys more in pre-disaster stage?" in this setting is that it cannot find candidate buyer to sell its excess amounts because Agency 1 does not serve Region 1 and Agency 2 loses in the region where its disaster probability is high. The optimal decision here is to buy less, to give the more effort to Region 2 and to buy from Agency 1 if a disaster hits the Region 3. But when $p^1 > p^2$ in setting HLH, the decentralized system solution is the optimal solution. If Agency 2 buys from Agency 1 in Region 3, the money Agency 1 earned will not help Agency 1 to send more and it is not economically efficient since both of their performances in Region 3 will affect objective function with same ratio. That is why being in the decentralized system is optimal for the entire.

However, in the case LHL while $p^2 > p^3$, it buys more in pre-disaster stage and sells its excess inventory to Agency 1 in region 3 to be able to send as much as it can. While $p^2 > p^3$, it buys less in pre-disaster stage and buys from Agency 1 with its excess fund if a disaster hits Region 2. Whatever the relation between p^2 and p^3 is, system optimality is in centralized system solution even if $p^1 > p^2$. However, Agency 1 chooses decentralized system while Agency 2 chooses centralized.

The setting HHL is the setting which centralized system is beneficial for both two

agencies. So far, we discussed the cases one agency loses and the other wins or the cases they should prefer decentralized system for system optimality. However, the setting HHL is most convenient case for this study. In pre-disaster stage, both agencies buy less than the amount they buy in decentralized system solution. When Region 1 or Region 2 is affected by a disaster they serve the affected region alone and they can use the money to buy extra amount from other agency's stock. If a disaster hits Region 3 they have enough pre-disaster funding to serve Region 3 because Region 3 is affected by a disaster with low impact and both agencies expect to be donated less as funding amount. Considering this situation they buy less in pre-disaster stage and they can effort to send all or a close amount to benchmark solution depending the relation between probabilities. As an example, if $p³$ is biggest, then agencies plan all process to serve Region 3 as much as possible. It also means they will lose small amount in Region 1 and 2 because there is a difference in prices of items in pre-and post-disaster stages. The truth is they cannot increase their amount sent in both two region which agencies responsible for. For example, if Agency 1's amount sent increases or stays same with decentralized solution in Region 1 then its amount sent in Region 3 decreases or stays same with decentralized solution. Depending the probabilities they can decide in which region they want to have a risk.

Table 13 shows how much centralized system solution close to benchmark solution as minimum and maximum percentages.

We see that in some cases centralized system solutions are quite different than benchmark solution. We imply on that these solutions are the ones which we suggest to replace with the decision of being in decentralized system for system optimality. These cases are LLH, HLH and LHH which critical regions are the ones agencies serves alone. In these setting we observe the minimum percentage level.

		$B_1 = 750, B_1 = 750$			$B_1 = 1000, B_1 = 500$	$B_1 = 1250, B_1 = 250$		
\rm{Cases}	Agency	min	max	min	max	min	max	
LLL	Agency 1	Ω		θ	0	θ	0	
	Agency 2	$\overline{0}$	$\left(\right)$	Ω	0	θ	0	
LLH	Agency 1	-9	-0.2	-6.8	-0.2	-5.3	0.1	
	Agency 2	-9	-0.2	-13.3	-0.1	-25.7	-0.2	
HLL	Agency 1	-1	0.6	-0.7	$0.5\,$	-1.8	-0.3	
	Agency 2	-1	θ	-2.4	$\overline{0}$	-3.2	$\overline{0}$	
HLH	Agency 1	-3.7	Ω	-1.7	$\overline{0}$	-0.7	0.1	
	Agency 2	-4.4	-0.2	-5	-0.1	-4.5	-0.2	
LHL	Agency 1	-1	Ω	-0.8	Ω	θ	Ω	
	Agency 2	-1	$0.6\,$	-0.5	0.5	θ	1.3	
LHH	Agency 1	-4.4	-0.2	-4.7	-0.2	-4.4	-0.1	
	Agency 2	-3.5	Ω	-6.8	$0.2\,$	-17.2	$0.2\,$	
HHL	Agency 1	-1.8	0.6	-1.1	0.5	-1.8	-0.3	
	Agency 2	-1.8	0.6	-2.4	0.5	-3	1	
HHH	Agency 1	Ω		Ω	$\overline{0}$	θ	$\overline{0}$	
	Agency 2	$\overline{0}$	θ	θ	θ	$\overline{0}$	0	

Table 13: Centralized System Solution vs Benchmark Solution

4.6 Game Theoretic Approach

In Table 8, there exist some rows that the agencies chooses to be in different systems, i.e., while one agency chooses centralized system the other prefers decentralized system. However, these are not applicable since a centralized system requires at least two agencies agreed on. If there exists a side payment allocation method, which makes all agencies profitable, for centralized system to be chosen by both agencies and thus to make the system effective in the settings centralized system is more profitable than decentralized system.

We see that centralized system is profitable or our model reaches decentralized system solution in the cases which the inventory sharing is efficient for the system. Mathematically, it means that difference of amount sent between centralized and decentralized system solution is either zero or positive. So, side payments to convince an agency to be in centralized system can be considered.

In this study, due to two stages side payments must be paid in one of two stages if required. Except the cases LLL, HHL and HHH, side payments are required where the decentralized system solution is worse than centralized system solution.

When we assume that side payments are made in pre-disaster stage we worked on examples to see whether there is an side payment allocation mechanism in core within game theoretic concept or not. In Table 14 and Table 15 we demonstrate an example of case LHH with the agencies which their pre-disaster funding levels $B_1 = 1000, B_2 = 500$ and the probabilities of disaster occurrence for the regions are $p^1, p^2, p^3 = 0.6, 0.3, 0.1.$

		$Q_1=250$			$Q_2 = 250$			
Region	Impact			CК				
					$150\,$			
		330			69ء			

Table 14: Centralized System Solution, LHH

		$= 250$			$Q_2 = 166$			
Region	Impact	þκ		сk				
		250						
					166			
		250			166			

Table 15: Decentralized System Solution, LHH

According to expected amount sent difference, while Agency 1 sends 8 units more than its decentralized system solution, Agency 2 sends 4.5 units less. To see with how much value of side payments Agency 2 wants to be in centralized system, we calculate numerically with the formulation of newsboy model for two agency system. Figure 2 shows differences between agencies' expected amount sent (y-axis) in centralized and decentralized system solutions while Agency 1 increases side payment value (x-axis) paid to Agency 2.

Figure 2: Side Payments vs Amounts Sent

Here, because Agency 2 is a type A agency its best solution is decentralized system solution. With the side payments, its amount sent increases but it never makes benefit. Hence, any side payment mechanism is not applicable for the cases LHL, LHH, HLL, HLH which are one agency is type A and the other is type B. For the cases LLL and HHH, decentralized system solution gives optimal solution for both agencies. In the cases LLH and HHL, they both are type B agencies but critical regions are different. Therefore, while centralized system makes only one agency profitable due to competition, HHL provides effectiveness for both two agencies. An allocation mechanism is convenient only for the case HHL.

When we assume that side payments are paid after demand realization, this is not applicable as well. If we consider that an event occurred in Region 2, according to the results in Table 14 and Table 15, Agency 1 should meet Agency 2's shortage which is 16 units. However, Agency 1 does not serve to Region 2, does not get any fund and it might spend its all pre-disaster funding in procurement in pre-disaster stage. That is why constructing a side payment mechanism is not possible in post-disaster stage.

$$
\sum_{i=1}^n \frac{1}{i} \int_{-\infty}^{\infty} \frac{dx_i^2}{(x-x_i)^2} \, dx_i
$$

Chapter V

CONCLUSIONS

In this study, we developed a two stage stochastic model which optimizes the system utility under some scenarios and cases. We showed that coordination is always beneficial or equals to the results without a coordination between agencies. We assumed that agencies are different organizations and are not branches of an organization. Hence, their individual decisions are another challenge in our work. Although coordination gives results close to the benchmark solutions or even better, due to the different characteristics of the agencies and importance of individual decisions we see the cases that one agency shows better performance than being single while the other makes worse. According to the scenarios, we categorized the cases to demonstrate agencies' optimal behaviours. When the differences of expected funding amounts in their responding regions exist the coordination is helpful.

As a managerial insight, with this study planners or agencies can decide when to coordinate with the other agency. The uncertainty of funding level is the most effective pattern in decision or pre-disaster planning stages.

In stock exchange coordination of commercial firms, after the demand realization they share items to meet unexpected demand and allocate the profit among them. In humanitarian relief area, agencies' profits are the items sent to the affected region. In the cases which single agency serves a region, sharing items to be sent to the affected region does not affect the agency which does not serve to the region because we consider a single time period in this work.

Appendix A

SOME ANCILLARY STUFF

A.1 Appendix

 $G(Q_1) = \int_{Y_1^k}^{(t+c)Q_1-B_1} \left(\frac{B_1-Q_1c+f_1^k}{t}\right) \varphi(f_1^k) df_1^k + \int_{(t+c)Q_1-B_1}^{Y_2^k} (Q_1) \varphi(f_1^k) dF_1^k$

$$
\frac{\partial G(Q_1)}{\partial Q_1} = \int_{Y_1^k}^{(t+c)Q_1 - B_1} \frac{-c}{t} \varphi(f_1^k) df_1^k
$$

+ $(t+c) \frac{(B_1 - Q_1 c + tQ_1 + Q_1 c - B_1)}{t} \varphi((t+c)Q_1 - B_1) + 0$
+ $\int_{(t+c)Q_1 - B_1}^{Y_2^k} \varphi(f_1^k) df_1^k + 0 - (t+c)Q_1 \varphi((t+c)Q_1 - B_1)$
= $\frac{-c}{t} \phi((t+c)Q_1 - B_1) + (1 - \phi((t+c)Q_1 - B_1))$

Equalizing it 0, we get $Q_1 = (\phi^{-1}(\frac{t}{t+1}))$ $\frac{t}{t+c}$ + B_1) $\frac{1}{t+}$ $_{t+c}$

Bibliography

- [1] M. Aslan, "Emergency aid after natural disaster," in International Humanitarian NGOs and Emergency Aid Workshop, Istanbul Policy Center, 2015.
- [2] B. M. Beamon and B. Balcik, "Performance measurement in humanitarian relief chains," International Journal of Public Sector Management, vol. 21, no. 1, pp. 4– 25, 2008.
- [3] A. Thomas, "Humanitarian logistics: Enabling disaster response," a, vol. b, no. c, p. d, 2007.
- [4] B. Balcik, B. M. Beamon, C. C. Krejci, K. M. Muramatsu, and M. Ramirez, "Coordination in humanitarian relief chains: Practices, challenges and opportunities," International Journal of Production Economics, vol. 126, no. 1, pp. 22– 34, 2010.
- [5] B. B. Michael Huang, Karen Smilowitz, "Models for relief routing: Equity, efficiency and efficacy," Transportation Research Part E: Logistics and Transportation Review, vol. 48, pp. 2–18, January 2012.
- [6] U. Network, "Standart operating procedures," wfp.org, 2011.
- [7] B. M. Beamon and S. A. Kotleba, "Inventory modelling for complex emergencies in humanitarian relief operations," International Journal of Logistics: Research and Applications, vol. 9, no. 1, pp. $1\n-18$, 2006.
- [8] S. Taskin and E. J. Lodree, "Inventory decisions for emergency supplies based on hurricane count predictions," International Journal of Production Economics, vol. 126, no. 1, pp. 66–75, 2010.
- [9] A. M. Campbell and P. C. Jones, "Prepositioning supplies in preparation for disasters," European Journal of Operational Research, vol. 209, no. 2, pp. 156– 165, 2011.
- [10] C. G. Rawls and M. A. Turnquist, "Pre-positioning and dynamic delivery planning for short-term response following a natural disaster," Socio-Economic Planning Sciences, vol. 46, no. 1, pp. 46–54, 2012.
- [11] J. H. McCoy and M. L. Brandeau, "Efficient stockpiling and shipping policies for humanitarian relief: Unhcr's inventory challenge," OR spectrum, vol. 33, no. 3, pp. 673–698, 2011.
- [12] C. G. Rawls and M. A. Turnquist, "Pre-positioning of emergency supplies for disaster response," Transportation research part B: Methodological, vol. 44, no. 4, pp. 521–534, 2010.
- [13] H. O. Mete and Z. B. Zabinsky, "Stochastic optimization of medical supply location and distribution in disaster management," International Journal of Production Economics, vol. 126, no. 1, pp. 76–84, 2010.
- [14] W. Klibi, S. Ichoua, and A. Martel, Prepositioning emergency supplies to support disaster relief: a stochastic programming approach. Faculté des sciences de l'administration, Université Laval, 2013.
- [15] S. Duran, M. A. Gutierrez, and P. Keskinocak, "Pre-positioning of emergency items for care international," Interfaces, vol. 41, no. 3, pp. 223–237, 2011.
- [16] C. Renkli and S. Duran, "Pre-positioning disaster response facilities and relief items," Human and Ecological Risk Assessment: An International Journal, vol. 21, no. 5, pp. 1169–1185, 2015.
- [17] B. M. Beamon and S. A. Kotleba, "Inventory management support systems for emergency humanitarian relief operations in south sudan," The International Journal of Logistics Management, vol. 17, no. 2, pp. 187–212, 2006.
- [18] L. N. Van Wassenhove, "Humanitarian aid logistics: supply chain management in high gear?," *Journal of the Operational Research Society*, vol. 57, no. 5, pp. 475– 489, 2006.
- [19] L. B. Davis, F. Samanlioglu, X. Qu, and S. Root, "Inventory planning and coordination in disaster relief efforts," International Journal of Production Economics, vol. 141, no. 2, pp. 561–573, 2013.
- [20] R. Anupindi, Y. Bassok, and E. Zemel, "A general framework for the study of decentralized distribution systems," Manufacturing & Service Operations Management, vol. 3, no. 4, pp. 349–368, 2001.
- [21] D. Granot and G. Sošic, "A three-stage model for a decentralized distribution system of retailers," Operations Research, vol. 51, no. 5, pp. 771–784, 2003.
- [22] H. Zhao, V. Deshpande, and J. K. Ryan, "Inventory sharing and rationing in decentralized dealer networks," Management Science, vol. 51, no. 4, pp. 531–547, 2005.
- [23] A. Apte, Humanitarian logistics: A new field of research and action, vol. 7. Now Publishers Inc, 2010.
- [24] E. J. L. Jr. and S. Taskin, "Supply chain planning for hurricane response with wind speed information updates," Computers $\mathcal C$ Operations Research, vol. 36, no. 1, pp. 2 – 15, 2009. Part Special Issue: Operations Research Approaches for Disaster Recovery Planning.
- [25] G. Barbarosoglu and Y. Arda, "A two-stage stochastic programming framework for transportation planning in disaster response," J Oper Res Soc, vol. 55, no. 1, pp. 43 – 53, 2004.

[26] J. McCoy and M. Brandeau, "Efficient stockpiling and shipping policies for humanitarian relief: Unhcr's inventory challenge," OR Spectrum, vol. 33, no. 3, pp. 673–698, 2011.

VITA

Meserret Karaca was born in Eskisehir, Turkey, on December 2nd, 1988. After finishing high school in 2006, she entered Fatih University in Istanbul. In June of 2011, she completed a Bachelor of Science in Mathematics. In February, 2012, she entered Graduate School of Engineering at Özyeğin University in Istanbul. During the following years she was employed as a teaching assistant at Oz yeğin University.