PRE-POSITIONING RELIEF SUPPLIES AND SUPPLIER SELECTION STRATEGY IN DISASTER RELIEF

by

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DEDICATION

To my parent, siblings, and friends. I couldn't have done this without you. Thank you for your unfailing support and continuous encouragement throughout my years of study.

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ABSTRACT

Natural disasters have a life changing impact on individuals, the effect can be felt at various levels and can even affect an entire country. In the United States, major disasters have seriously affected the country's economy and the people. It has been also challenging the country's emergency response capacity. In order to reduce the damage caused by disasters, there is a need for the proper planning and efficient management of emergency supplies in place before the onset of a disaster.

This research focuses on the preparedness stage of disaster operations management, precisely on how the relief organization can best satisfy demand at minimum costs and risk. Currently in the United States, the system in place plans for the procurement of emergency supplies which are stored in a warehouse. However, the major challenge faced by relief organizations (e.g. Federal Emergency Management Agency) is the timely delivery of the relief items at a reasonable cost, while dealing with uncertainties of disasters.

This research addresses the problems encountered by the relief organization by concentrating on two aspects. Firstly, the commodity lifetime period is considered with the related costs associated with the storage and removal (when it is close to expiration) of relief items. This study provides relief agencies managerial insights about dynamic control of inventory over each scenario and dealing with relief supplies which will expire. Secondly, the decision on supplier selection is integrated into the pre-positioning stage for the efficient management of the relief supplies and timely distribution of the supplies to the disaster victims. Agreement terms such as the commitment quantity of the relief

organization, the reserve capacity of the suppliers, and the quantity discount rate are considered. This study gives the relief agencies insights on how the agreement terms affect the supplier selection decision, and how the total expected costs of having an agreement in place and procuring relief items from the suppliers can be minimized. Compared to the traditional two-stage stochastic programming approach, which is commonly used in the field of humanitarian relief, a multi-stage stochastic programming model is presented in each part because of the stochastic nature of the proposed problems, and the need to make sequential decisions over time.

In this research, a real-world setting which considers disasters such as earthquakes, floods and hurricanes in the mainland of the United States is used as a case study. The sensitivities of the models for variation of parameters are also studied. The first part of this research provides insight on how costs can be minimized when the relief organization finds a better way of disposing relief items close to expiration. The second part provides relief organization insights on how the costs involved in the supplier selection can be managed and the type of suppliers to be in agreement with.

1. INTRODUCTION

Disaster operations management is an important aspect of humanitarian relief which contributes to the improvement in readiness for disasters, reducing injuries, fatalities, and damages, and to ease recovery. It comprises four sequential stages during the occurrence of a disaster: mitigation, preparedness, response and recovery. This research focuses on the preparedness stage of disaster operations management. Precisely, on pre-positioning of relief supplies by the relief organizations, a strategic task in which the decision of supplier selection is integrated into the preparedness stage, before the occurrence of a disaster in the United States. Natural disasters, such as earthquakes, hurricanes or flood, have been a challenge all over the world due to their unpredictable nature because they give little or no notice about when and where they are going to occur, and the magnitude of impact. In the wake of natural disasters, there are always many people affected. For example, Hurricane Katrina ravaged New Orleans and the Mississippi gulf coast in 2005, wrecking in excess of more than 200,000 homes in New Orleans alone with over 70 percent of the inhabitant populace migrated outside the city. Assessments of over $105 billion in decreased duty income, infrastructure, and cost of recovery endeavors were lost to the city. Additionally, in 2017 the United States recorded its costliest natural disasters, with a price tag of $306 billion minimum (Sciencing, 2018). To reduce fatalities, the needed assistance must be rendered in a timely manner after the occurrence of the disaster. Therefore, there is always a tremendous amount of demand for various basic relief supplies such as water, food and medical kits. This brings about the need to have a good plan in place before a disaster occurs. The procurement of the relief supplies considered is done in the pre-disaster phase and post disaster phase. In the pre-disaster procurement of relief supplies, the relief agencies purchase relief items and store it in the warehouse in preparation for disaster occurrence. This process is known as the pre-positioning of relief supplies. The post disaster procurement is done in preparation for a disaster event after the occurrence of a disaster and the relief items have been used. The relief organization tend to source for suppliers to buy the needed relief items from. The process of finding the suitable suppliers to procure the relief items is known as the supplier selection strategy. These two phases of procurement are done at the preparedness stage of disaster operations management. Figure 1 shows the procurement phase and the stage the decision should be made. This research focuses on two major aspects. First, the pre-positioning of relief supplies while considering the expiration dates of relief items. In this section, the expiration date of relief item is considered to give the relief agency insights on how to manage the inventory in the pre-positioning stage. Secondly, the supplier selection which entails the integration of the decision of supplier selection in the pre-positioning of relief items. This aims to give efficient management of the relief supplies and timely distribution of the supplies to the disaster victims. Due to the dynamic nature of the problem statement in both sections, a multi-stage stochastic programming model which is a more powerful approach compared to other methods (e.g. two-stage stochastic approach) is proposed. This aid the optimization of the objectives when making sequential decision over certain time period.

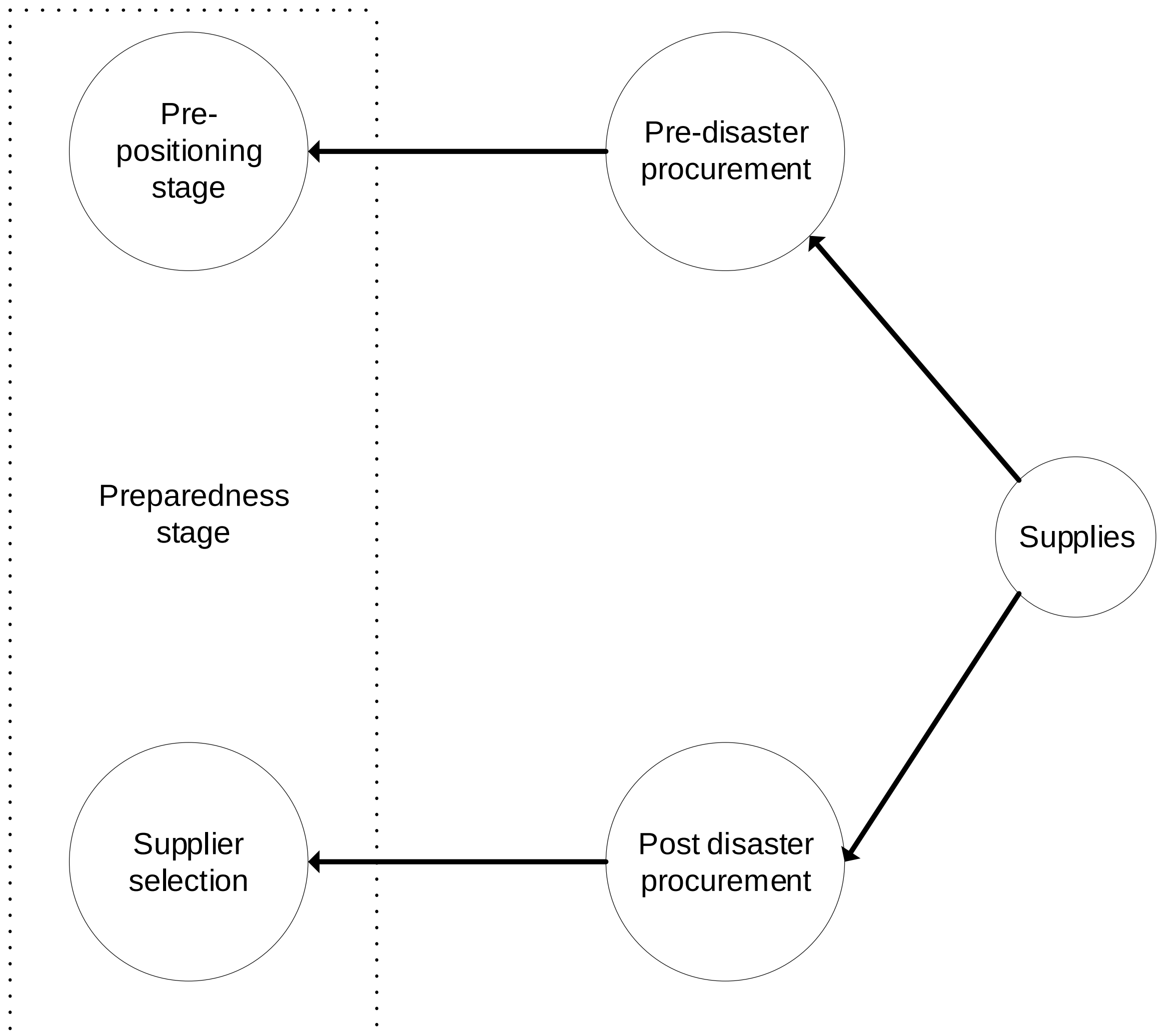

Figure 1: Procurement phase and the decision stage

Pre-positioning of relief supplies is a key activity in disaster operations management, which helps preparedness for natural disasters by advancing procurement of needed supplies and thereby decreasing the response time. However, this is challenging, because pre-positioning requires high investment (e.g., procurement and holding costs) at various locations, due to a high level of uncertainty in the timing and location of the next disaster. In addition, the expiration of relief items is another major problem (Kunz, Reiner, & Gold, 2014). For example, when the items in the warehouse have not been used due to the absence of a disaster, and it is close to its expiration date, the relief agency must donate or dispose these items. There have been several good previous works on the pre-positioning of relief supplies but none of them considers the expiration date of the relief items and also uses a multi-stage stochastic programming model to approach the problem. This first part of the research presents a multi-stage stochastic programming model that attends to the pre-positioning of relief supplies by considering uncertain demand for relief items while considering the lifetime of the relief items. This provides the relief organizations insights on how to control the inventory over scenarios as well as dealing with perishable relief supplies.

In the second model presented in this research (i.e., regarding supplier selection strategy), the provision of relief items when a disaster occur is contracted to the suppliers. The relief organization pledges to purchase certain amount of relief items (minimum commitment quantity) from the suppliers over a time period. The suppliers in return guarantee timely delivery of relief item and reserve relief supplies for the relief organization. This model is presented to minimize the costs associated with the decision of selecting suppliers to provide relief supplies upon the occurrence of disasters. In the pre-positioning of relief supplies the relief organization tends to manage all the activities involved in the preparedness stage while supplier selection is a strategic decision, which will help build a solid foundation for the continuous and stable relationships between the suppliers and relief organization. Creating a good relationship with suppliers will help the relief agencies to streamline costs, ensure timely delivery and availability of relief items upon the occurrence of a disaster events. There is always a contractual agreement between the relief agencies and suppliers selected in the preparedness stage to guarantee the availability, fast delivery, and cost-effective procurement of relief items when a disaster occurs. Factors such as the commitment requirement of the relief organization, reserve capacity of the supplier, the quantity discount rate given by the suppliers, and the distribution requirement are put into consideration when creating the agreement. The agreement entails the suppliers reserving inventories for the relief agencies and immediate delivery of supplies to the affected area when requested to (Mansini et al., 2012). Although, due to the uncertainties and complexities in humanitarian supply chains, building up agreements and selecting suppliers can be challenging for the relief agencies (Balcik et al., 2010). Specifically, in an uncertain environment, the relief organizations might be hesitant to make restricting pre-acquiring commitments. The unpredictable nature of disasters might give rise to an instance in which the agreement may not be initiated and the expenses for not utilizing the relief items connected to the agreement might be high. Hence, it is important for the relief organizations to cautiously examine the ramifications of the agreement terms provided by candidate suppliers.

The second part of this study addresses the integration of the decision of supplier selection into the pre-positioning stage considering uncertain demand, and the dynamic nature of disasters. A multi-stage stochastic model that captures the dynamic nature of the supplier selection decision at the preparedness stage in disaster operations management is developed. The goal of this research is to minimize the total expected costs associated with efficiently selecting the right suppliers that provides relief items during a disaster event such as earthquakes, floods, and hurricanes using real -world settings.

2. LITERATURE REVIEW

This chapter presents relevant work on pre-position of relief supplies and supplier selection. It shows the works of others in relation to this research, their limitations and the relevance to this research work. The chapter also includes a very brief review on multi-stage stochastic programming model which is the methodology used for this research.

2.1. Pre-positioning of relief supplies

Due to the frequent occurrence of natural disasters in the world, pre-positioning of relief supplies has been a major area that researchers have dived into. Sabbaghtorkan et al. (2019) did a comprehensive literature review on pre-positioning of assets and supplies in disaster operations management. They statistically analyzed the operation research journals based on their contributions in this area, the number of papers per year and types of disaster. The research gaps such as lack of papers to deal with uncertainty in funding, budget, asset and supply quantities, and infrastructure between the reviewed journals were also identified. Balcik et al. (2016) discussed extensively the literature on humanitarian inventory management, focusing on pre-disaster and post disaster inventory management. In the pre-disaster inventory management section, which is the focus of this research, Rabbani etal. (2015), observed that most papers focused on two stage stochastic programming and just one paper accounted for perishable relief supplies. Rawls & Turnquist (2010) developed an emergency response planning tool that determines the location and quantities of various types of emergency supplies to be pre-positioned. They presented a two-stage stochastic mixed integer program that helps in the pre-positioning strategy for hurricanes. Caunhye et al. (2016) proposed a two-stage location-routing model with recourse for integrated preparedness and response planning under uncertainty. The model is used for managing risk in disaster situations where there are uncertainties in demand and the state of the infrastructure. Javier & Aruna (2010) also developed a two-stage stochastic optimization model, but their focus was on allocation of budget to acquire and pre-positioning of relief assets with the aim of minimizing expected number of casualties. Manopiniwes & Irohara (2017) proposed a stochastic linear mixed-integer programming model for integrated decisions in the preparedness and response stages in pre- and post-disaster operation respectively while considering key areas such as facility and stock pre-positioning, evacuation planning and relief vehicle planning. Uncertainty of demand is a major problem in natural disaster that impacts the planning and coordination of inventory. Davis et al. (2013) proposed a stochastic model to determine how supplies should be positioned and distributed among a network of cooperatives warehouses. A model for pre-positioning of relief supplies that has as a distinguishing feature the possibility of the supply point being destroyed during a disaster event such as hurricane was proposed by Galindo & Batta (2013). Kunz et al. (2014) discussed how pre-positioning of relief inventory requires a high investment and proposed a dynamic model that entails the delivery process of ready-to-use therapeutic food items during the immediate response phase of a disaster. They also analyzed the performance of different preparedness scenarios.

Pacheco & Batta (2016) presented a forecast driven dynamic model for pre-positioning of relief items in preparation for a foreseen hurricane. The model uses forecast advisories which helps with updating the information to determine the amount and location of units to be pre-positioned and re-prepositioned. Tavana et al. (2018) proposed a multi-echelon humanitarian logistic network that examines the location of central warehouses, overseeing the inventory of perishable products in the pre-disaster phase, and routing the relief vehicles in the post-disaster phase. Baskaya et al. (2017) investigated the effect of including lateral transshipment opportunities into pre-positioning of relief items in humanitarian relief chain. Mansini et al. (2012) developed a new integrated model that determines the optimum location-allocation and distribution plan, coupled with the best ordering policy for renewing the stocked perishable commodities at the disaster phase. They were concerned with the periodic ordering policy of commodity while considering a fixed lifetime for the commodity. A model which assists decision makers in the logistics of flood emergency with the aim of optimizing inventory levels for emergency supplies as well as vehicles' availability, in order to deliver enough supplies to satisfy demands with a given probability is presented by Garrido et al. (2015). Julia (2014) discussed about how Federal Emergency Management Agency (FEMA) operates, the importance of distributions recovery centers and the role they play during disasters. Discussed above are good contributions to the literature on pre-positioning of relief supplies, however, the major limitation of their work is that they assumed that inventory is deterministic and that the relief items will not expire.

2.1.1. Contribution

The contribution of this part of the research is three-fold. Compared to other literature in pre-positioning of relief supplies, the first part of this research has two distinctive features. Firstly, the lifetime of the commodity type and the cost associated with removing the item when it is close to expiration is considered, which makes the model closer to real situations. Each commodity type is assumed to have a remaining life-time period. Secondly, a multi-stage stochastic programming model which enables dynamic and stochastic control over the inventory is formulated. It considers the uncertainty of demand for relief supplies with the objective of minimizing total expected costs. Lastly, the research provides insight for relief agencies on how to have dynamic control of inventories over a time period and scenario and on the decisions to be made when the perishable item is close to expiration.

2.2. Supplier selection

Supplier selection is an important aspect considered by a relief agency when making procurement decisions. It is an extensive researched topic in the field of commercial supply chain. This supplier selection decision is influenced by key elements such as pricing, commitment and capacity of the suppliers, quantity discount, lead time, delivery time, and transport cost. Discussed below are important literature in the commercial supply chain field that considers different key elements in the decision of supplier selection. Mansini et al. (2012) considered both purchasing and transportation costs with the objective of minimizing the procurement expenditures. Hammami et al. (2014) formulated a two-stage mixed integer scenario-based stochastic model which addresses the supplier selection problem by considering uncertain fluctuations of currency exchange rates and price discounts. Soner Kara (2011) presents a two-stage stochastic programming model that considers qualitative data of supplier under fuzzy environment for supplier selection problem. Torabi et al. (2015) addresses supplier selection problem and order allocation problem by presenting a bi-objective mixed possibilistic, two-stage stochastic programming model, to build the resilient supply base under operational and disruption risks. Qian (2014) proposed a market-based strategy in supplier selection for the joint decision on price, delivery time, service level and investment. Jahre (2017) linked humanitarian logistics and supply chain risk management to provide an understanding of risk mitigation strategies that humanitarian organizations use, or could use, to improve their logistics preparedness. A non-deterministic polynomial-hard integer programming model was developed with the goal of selecting a set of suppliers that satisfies product demand at minimal total costs. A mixed non-linear integer programing model was developed by Ware et al. (2014) which addresses supplier selection as a dynamic problem. Luthra et al. (2017) proposed a framework to evaluate sustainable supplier selection using an integrated Analytical Hierarchy Process, a multi-criteria optimization and compromise solution approach. This is a systematic and sustainability-focused evaluation system for the selection of suppliers. Choi (2013) proposed a model for supplier selection problem in the fashion apparel supply chain in the presence of carbon emission tax. The scenario in which there are multiple suppliers in the market was considered. Hosseini & Barker (2016) proposed a Bayesian network, a paradigm that effectively models the causal relationships among variables to quantify the appropriateness of suppliers across primary, green, and resilience criteria. Li & Zabinsky (2011) incorporated the uncertainty of demand and capacity of suppliers in a two-stage stochastic programming model and a chance-constrained programming model. Ruan et al. (2016) considers the travel time, transfer time and vehicle delivery time of medical supplies to an emergency distribution centers can be optimized.

Literature on supplier selection in humanitarian relief is sparse compared to commercial supply chain. Hu et al. (2017) presents a two-stage stochastic programming model that considers the lead time discount, return price and equity, for supplier selection at the pre-disaster inventory level and post-disaster procurement quantity in humanitarian relief. Jahre et al. (2016) presented a warehouse location optimization model that considers accessibility, co-location, security and human resources for joint pre-positioning of relief supplies. Hu & Dong (2018) presented a two-stage stochastic programming model which considers factors such as facility location and inventory, supplier selection, and distribution of relief supplies in preparedness to the occurrence of natural disaster. Balcik & Ak (2014) is the most prominent paper for supplier selection in humanitarian relief field. They used a scenario-based approach to represent demand uncertainty and develop a stochastic programming model that selects framework suppliers to minimize the expected procurement and agreement costs while meeting service requirements. However, the major limitation of their work is that, they assumed 60% of the total demand will be met by the framework suppliers, thereby neglecting the remaining demand. Also, they consider only one type of disaster event (earthquake).

2.2.1. Contributions

For this part of the research work, the selected suppliers are assumed to have the capacity to meet all the disaster demand. A multi-stage stochastic programming model that considers the uncertainty of demand and effective selection of suppliers over the scenarios is presented. The model considers the agreement terms such as the reserve capacity of the suppliers, the minimum total commitment promised by the relief agency and the discount rate offered by the suppliers. The goal is to minimize total expected cost involved in the agreement and procurement of relief items from selected suppliers. Three type of disasters are considered for this model, which are earthquakes, hurricanes and floods disaster event are considered.

2.3. Multi-stage stochastic programming

In humanitarian relief research, the major modeling methodologies used are simulation, deterministic, and stochastic programming. Birge & Louveaux (2011) introduced stochastic programming and gave basic knowledge on multi-stage stochastic programming with recourse and different approaches which can be used to solve it. Two-stage stochastic programming is the most used stochastic programming model in disaster response field (Rawls & Turnquist., 2010; Caunhye et al., 2016; Hammami et al., 2014).

Multi-stage stochastic programming is an uncertainty programming method which deals with making decisions sequentially over a certain period of time based on values for some of the parameters being available or realized at each time period. It helps to consider the stochastic nature of disasters and demand when minimizing costs. Zahiri et al. (2017) discussed the importance of multi-stage stochastic programming compared to a two-stage stochastic programming when considering the problem in which the decision-making process is to be made sequentially over a time period. They also explain how the scenario tree works. Defourny et al. (2011) presented a multi-stage stochastic programming framework for sequential decision making under uncertainty. Zanjani et al. (2010) proposed a multi-stage stochastic programming model which is a full recourse for demand scenario and simple recourse for yield scenario. Nasution (2015) introduced a tutorial on some basic ideas on multi-stage stochastic programming and the setting in which it can be applied. They also provided a basic idea on how an inventory multi-stage stochastic model should be formulated. There are relatively few papers that used multi-stage stochastic programming model in humanitarian relief field but none of them considered the expiration of the relief item. Also, there is no multi-stage stochastic paper related to supplier selection in the humanitarian relief field.

Developing an efficient algorithm that solves the multi-stage stochastic programming is also important, but due to limited time this research only focusses on modeling and solving the problems with available optimization software.

3. MULTI-STAGE STOCHASTIC PROGRAMMING FOR PRE-POSITIONING OF RELIEF SUPPLIES CONSIDERING EXPIRATION DATES

3.1. Modeling

A multi-stage stochastic programming model is created such that the uncertainty of demand for relief supplies is presented through a scenario tree. The objective of this model is to determine sequential decisions on the amount of relief items to be procured and the balancing of the inventories. Figure 2 shows the scenario tree, which is planned over a time horizon, representing a discrete set of scenarios. The scenario tree consists of a number of nodes and arcs. The scenario tree node is represented as the scenario (Gul et al., 2015). In each stage, there could be several different scenarios, and only one scenario would be realized. The lifetime period corresponds to the time between each stage, which can be days, months, and years. The first stage consists of one node and it is denoted as the root node. Any scenario occurring after a specific scenario is named as the child scenario of this scenario, and this specific scenario is the parent scenario of the subsequent scenarios. For example, in Figure 2, scenario 1 is the parent scenario of scenario 2, scenario 2 is the parent scenario of scenario 5, and scenario 5 is the parent scenario of scenario 9. The sum of probabilities of each node at a given stage is equal to one (Kazemi Zanjani & Nourelfath, 2014), because the probability of occurrence of each child state of a given parent scenario has already happened in the previous stage.

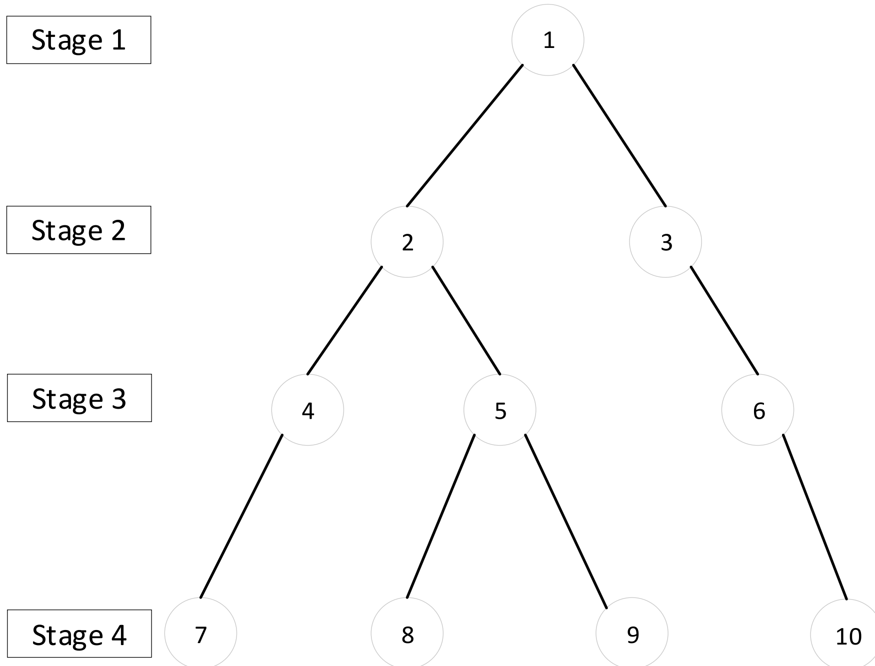

Figure 2. Example of a scenario tree

The following notations are used for the multi-stage stochastic programming model:

Table 1. Model Notation and Definition

Main sets	
C	set of commodities
S	set of discrete scenarios
K^s	set of parent scenarios
N	set of locations
T^c	set of remaining lifetime periods for type c items
Indices of sets	
c	type of commodity $c \in C$
s	scenario type $s \in S$
k	parent scenario $k \in K$
i,j	specific location $i,j \in N$

Table 1. Continued

t	remaining lifetime period for type c commodity $t \in T^c$
Deterministic parameters	
M_i	overall capacity of facility at location i
b^c	unit space required for commodity c
q^c	unit procurement cost of commodity c
r^c	unit removal cost of commodity c (The commodities have to be removed from warehouse when it is really close to expiration date.)
o_{ij}^c	unit cost of transporting commodity c across link *(i,j)*
u^c	holding cost of unused commodity c
v^c	penalty cost associated with shortage of commodity c
Stochastic parameters	
p^s	probability of occurrence of scenario s
d_j^{cs}	demand of commodity c at location j in scenario s
Decision variables	
x_i^{cs}	procurement quantity of commodity c at location *i in scenario s*
y_{ijt}^{cs}	amount of commodity c shipped across the link *(i,j)* within remaining lifetime period t in scenario s
g_j^{cs}	shortage of commodity c at location j in scenario s
h_{it}^{cs}	current inventory of commodity c at location i within remaining lifetime period t in scenario s

The lifetime of the commodity is discretized, and T^c is introduced to represent the set of remaining lifetime periods for commodity type c, where $t \epsilon T^c$. T^c represents a general setting because relief items usually have different lifetimes. For example, if four remaining lifetime periods for commodity type 1 is assumed, $T^1 = \{1,2,3,4\}$, it means that these are items with 12-months total lifetime and the lapse of time between remaining lifetime periods represents a 4-months life interval. Then t =1 represents 12 remaining months, t=2 represents 8 remaining months, t=3 represents remaining 4 months, and t=4 represents 0 month remaining (i.e., expired). Table 2 shows details about the variation of inventory over a lifetime for scenario tree 1-2-5-9, where $x(s)$ represents the procurement quantity at scenario s, , $y(s,t)$ represents the commodity used or demanded at lifetime period t at scenario s, and $h(s,t)$ represents the inventory at lifetime period t at scenario s, respectively. The assumption is that the relief supplies procured must have a maximum lifetime period (i.e., 12 months in the previous example). Therefore, inventory at remaining lifetime period 1 will be equal to procurement quantity. Inventories at other remaining lifetime periods depend on $x(s)$ and $y(s,t)$. The decisions made on $x(s)$ depend on the probabilities and demands of subsequent scenarios. For example, the inventory at scenario 2 when remaining lifetime period is 2 ($h(2,2)$) depends on the procurement quantity and the commodity used at the same scenario and lifetime (i.e., $h(2,2) = h(1,1) - y(2,2)$, $x(1) > 0$). It is worth mentioning that those relief supplies with total life time of 12 months which have been procured in scenario 1 will be disposed by the end of stage 4 and scenario 9 (i.e., when $h(9,4) > 0$) because they are expired. It is the same with scenarios 7, 8, and 10.

Table 2. Variation of inventory for perishable relief supplies with lifetime and scenario

Stage	Scenario	t=1 (12 months)	t=2 (8 months)	t=3 (4 months)	t=4 (0 month)
1	1	$x(1) \rightarrow h(1,1)$	0	0	0
2	2	$x(2) \rightarrow h(2,1)$	$h(2,2)$	0	0
3	5	$x(5) \rightarrow h(5,1)$	$h(5,2)$	$h(5,3)$	0
4	9	0	$h(9,2)$	$h(9,3)$	$h(9,4)$

The extensive formulation of the model is presented below:

$$\min \sum_{s} p^{s} \left[\sum_{c,i} q^{c} x_{i}^{cs} + \sum_{c,i,j,t} o_{ij}^{c} y_{ijt}^{cs} + \sum_{t<|\mathrm{T}^{c}|,c,i} u^{c} h_{it}^{cs} + \sum_{c,j} v^{c} g_{j}^{cs} + \sum_{c,i} r^{c} h_{i|\mathrm{T}^{c}|}^{cs} \right] \tag{1}$$

$$h_{it}^{c1} = 0, \quad t \geq 2, \forall i, c \tag{2}$$

$$h_{i1}^{cs} = x_{i}^{cs}, \quad \forall i, c, s \tag{3}$$

$$h_{it}^{cs} = h_{it-1}^{ck} - \sum_{j} y_{ijt}^{cs}, \quad s, t \geq 2, \forall i, k, c \tag{4}$$

$$y_{ij1}^{cs} = 0, \quad \forall c, i, j, s \tag{5}$$

$$\sum_{c,t} b^{c} h_{it}^{cs} \leq M_{i}, \quad \forall s, i \tag{6}$$

$$g_{j}^{cs} = d_{j}^{cs} - \sum_{i,t} y_{ijt}^{cs}, \quad \forall j, c, s \tag{7}$$

$$x_{i}^{cs}, y_{ijt}^{cs}, g_{j}^{cs}, h_{it}^{cs} \geq 0, \quad \forall i, j, c, t, s \tag{8}$$

The objective function (1) minimizes the total expected cost over all scenarios resulting from the selection of the pre-positioning locations and facility sizes, the commodity procurement and stocking decisions, the shipments of the supplies to the demand points, unmet demand penalties and holding costs for unused material. Constraint (2) limits the current inventory of the first scenario for all locations to be zero. Constraint (3) restricts the current inventory of scenario s at the first stage to be the same as the quantity of the procured commodity at location i. Constraint (4) states that the current inventory at a given stage is the difference between the inventory of the previous stage and amount of commodity shipped out. Constraint (5) limits the number of commodities shipped out at the first stage to zero. Constraint (6) restricts the space occupied by the stocked commodities not to exceed the facility capacity at location i. Constraint (7) shows how shortage of commodities is calculated. Constraint (8) defines the sign of the decision variables.

3.2. Numerical analysis

3.2.1. Data setting

The focus of this research is on pre-positioning of relief supplies in preparedness for hurricanes, floods and earthquakes threat in the United States. The states in mainland United States are considered as the demand locations. The distance between states are calculated using the most populous city in each state. Two commodities are considered: food and water. The unit of water and food is assumed to be 1000 gallons and 1000 meals ready to eat (MREs), respectively. For each commodity type a lapse of time between remaining life-time periods of four is considered. This corresponds to the time period between each stage. The facility locations considered are Texas (1.6 million sq. ft), California (110,000 sq. ft), Georgia (407,000 sq. ft) and Maryland (68,023 sq. ft). The facilities are already provided by FEMA (FEMA Fact Sheet, 2011). The values of procurement cost q^c, space estimate b^c, transport cost O_{IJ}^{C}, penalty cost v^c, removal cost r^c and holding cost u^c, are provided in Table 3. The cost of transporting a commodity between two locations is derived by multiplying the unit transport cost assigned to the commodity type and the distances between the locations. The holding cost is assumed to be 25% of the procurement cost of commodities. The penalty cost for unmet demand is assumed to be 10 times the procurement cost of commodities. The removal cost is assumed to be 40% of the procurement of commodities.

Table 3. Unit procurement price, transport, holding, removal & penalty cost and storage volume occupied

	b^c(ft^3/unit)	q^c($/unit)	u^c($/unit)	v^c($/unit)	r^c($/unit)	O_{Ij}^{c} ($/unit-mile)
Water (1000 gals)	144.6	647.7	161.925	6477	259.08	0.3
Food(1000MREs)	83.33	5420	1355	54200	2168	0.04

Table 4. Top 10 locations with the highest occurrence of hurricanes, earthquakes and floods

Hurricane		Earthquake		Flood	
Rank	Location	Rank	Location	Rank	Location
1	Florida	1	Oklahoma	1	Texas
2	Texas	2	California	2	New York
3	Louisiana	3	Nevada	3	Florida
4	North Carolina	4	Wyoming	4	Pennsylvania
5	South Carolina	5	Kansas	5	Missouri
6	Alabama	6	Idaho	6	Louisiana
7	Georgia	7	Montana	7	Virginia
8	Mississippi	8	Texas	8	Illinois
9	New York	9	Utah	9	California
10	Virginia	10	Arkansas	10	Oklahoma

For the emergency demand data of each location, the top 10 ranked locations (USGS, 2017 & NOAA, 2017) with the highest occurrence of hurricanes, earthquakes and floods are selected as shown on Table 4. Note that the specific intensity for hurricanes, earthquakes and floods are not considered. To simplify data estimation, three impact levels for each disaster, (low, medium and high) are assumed. The demand for hurricane and flood is generated from a uniform distribution (U) by assigning U[100,200], U[200,400] and U[900,1000] for low, medium and high impact hurricanes and flood, respectively. The demand for earthquakes is generated by assigning U[1000,2000], U[2000,4000] and U[9000,10000] for low, medium and high impact respectively. The demands are computed based on the information on hurricanes, floods and earthquakes together. The same demand for both relief items is assumed. Appendix A presents the table that shows the stage, scenarios, parent scenario, and the corresponding probabilities used for the case study.

The model is solved using CPLEX Concert Technology (IBM ILOG CPLEX) in Microsoft Visual Studio as an integrated development environment (IDE) on a laptop with Intel Core i7-700 @3.60GHz and 8GB RAM. The optimal solution was obtained in 139.53 seconds.

3.2.2. Numerical results

In this section, sensitivity analysis is carried out in order to examine how different parameters in the proposed model will cause changes and affect decision making about pre-positioning relief supplies as well as all the costs. The unit transport cost o_{ij}^{c}, unit penalty cost v^c, unit removal cost r^c and unit holding cost u^c are the parameters to be varied. The focus is on the effects of varying parameters on the economic cost (the addition of procurement cost *pc*, transportation cost *tc*, holding cost *hc* and removal cost *rc*) and the penalty cost *pc'*.

3.2.2.1. Effects of transportation cost

The effects of transportation cost by modifying the original value from -50% to +50% are studied, and the effect in percentage is shown in Table 5. From Table 5, increase in unit transport cost has no effect on the total procurement cost. Changes in total penalty cost are negligible when unit transport cost changes. Figure 3 shows the behavior of total penalty cost and economic cost when the unit transport cost is being modified. When unit transport cost increases, the economic cost increases and there are no changes in the penalty cost. Increase in transport cost might result when disaster occur, there is a strong possibility that roads may be destroyed. The relief agency tends to reroute the vehicle to the next available route, which is always associated with a cost, that tends to increase the total budgeted cost.

Table 5. Sensitivity of costs to transportation cost (%)

	-50%	-25%	+25%	+50%
pc	+0.03	+0.03	0.00	0.00
tc	-49.88	-24.83	+25.00	+50.00
hc	+0.04	+0.04	0.00	0.00
pc'	-0.04	-0.04	0.00	0.00
rc	+0.05	+0.05	0.00	0.00
Total	-0.15	-0.07	+0.07	+0.15

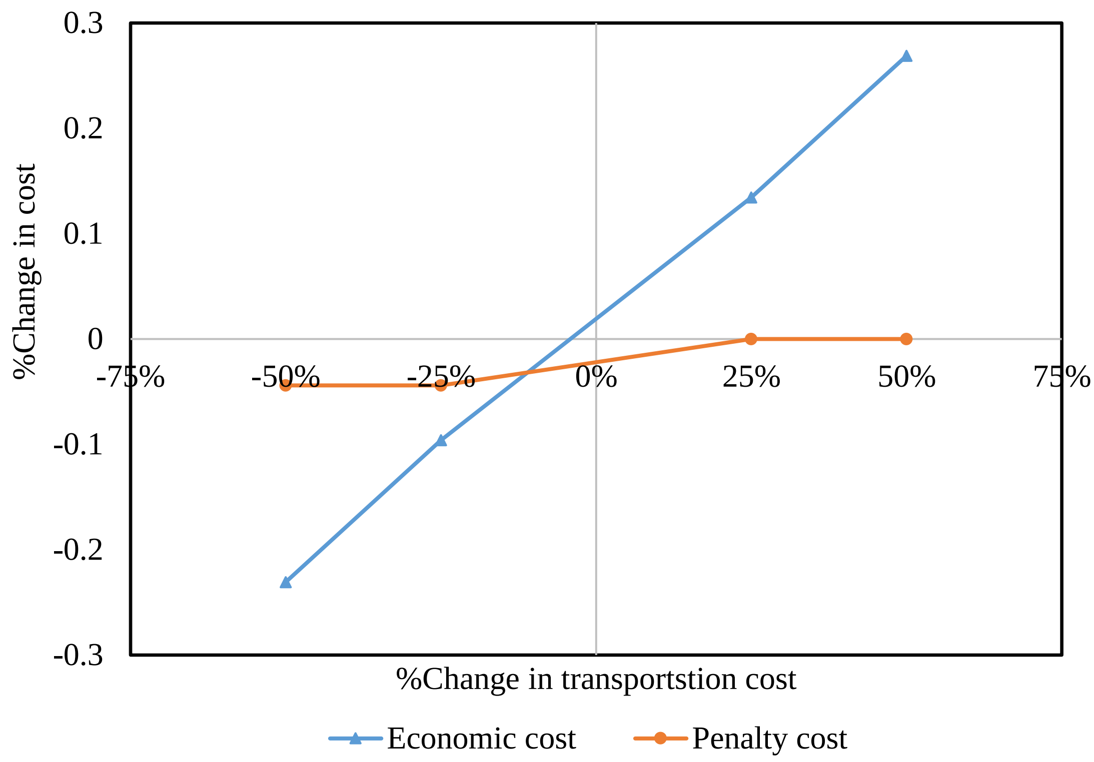

Figure 3. Observation on economic cost and penalty cost when varying the transportation cost.

3.2.2.2. Effects of holding cost

Because of uncertainty of disaster occurrence, the longer time the pre-positioned relief items spend in the warehouse, the larger the holding cost will be. When disasters occur earlier than expected or much later, the cost associated with keeping it safe in the store/warehouse, which is known as holding cost, will be affected. Thus, the unit holding cost is modified from -50% of the original inputs to +50% and the results obtained are summarized in Table 6. Holding cost is directly proportional to total penalty cost. But total procurement and removal cost decrease with increases in unit holding cost, because the procurement quantity decreases. Therefore, the relief agencies won't purchase new commodities due to increment in the holding cost. This in return leads to less relief items to dispose due to closeness to expiration. Figure 4 shows the behavior of total penalty cost and economic cost when the unit holding cost is being modified. The increase in unit holding cost directly affect the economic costs.

Table 6. Sensitivity of costs to holding cost (%)

	-50%	-25%	+25%	+50%
pc	+3.08	+2.17	-0.31	-2.48
tc	+2.36	+1.70	-0.30	-2.47
hc	-48.12	-23.20	+24.57	+46.41
pc'	-3.86	-2.62	+0.42	+3.16
rc	+5.12	+2.64	-0.51	-2.12
Total	-9.34	-4.64	+4.56	+9.07

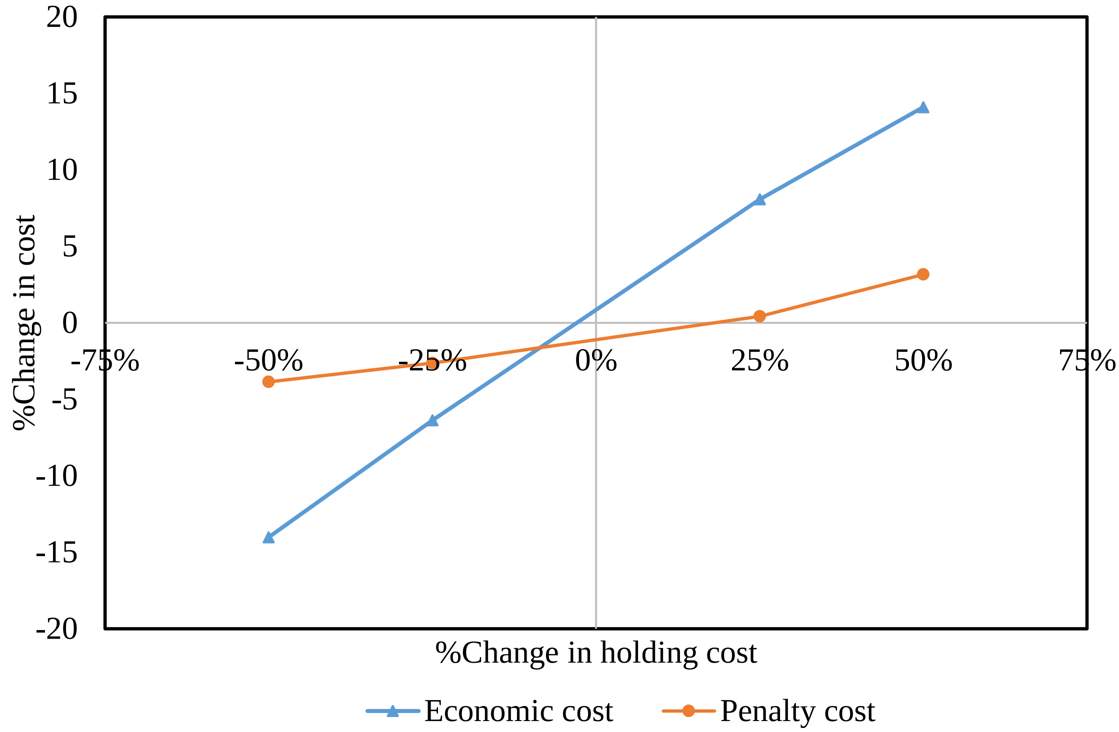

Figure 4. Observation on economic cost and penalty cost when varying the holding cost.

3.2.2.3. Effects of penalty cost

The unit penalty cost is varied from -50% of the original Input to +50% and the effects of this change on different costs terms are illustrated in Table 7. Increase in unit penalty cost leads to the increase of the procurement, removal and holding cost. The relief agencies tend to purchase more relief items when penalty associated with shortage of relief supplies is high. This then leads to the increase of relief items in store that if not used would lead to increase the number of relief items to dispose. At -50% there is a substantial decrease in the total cost. This can be as a result of when the penalty cost is very low, the relief agencies tend not to place emphasis on the shortage of commodities in the warehouse. Figure 5 shows how economic cost and total penalty cost changes when penalty cost changes. From the Figure 4 below, it can be observed that there is a sharp decrease in the economic cost when the unit penalty cost is decreased to -50%. When the unit penalty cost is at its lowest, the shortage of commodity at different locations increases. Relief agencies tend not to feel the urgency to ship commodity to a location if the consequence is negligible compared to when the penalty associated with not shipping the commodity is high.

Table 7. Sensitivity of costs to penalty cost (%)

	-50%	-25%	+25%	+50%
pc	-64.60	-6.20	+3.19	+3.67
tc	-53.77	-5.68	+2.54	+3.12
hc	-66.32	-5.55	+3.85	+5.51
pc'	+7.89	-18.99	+20.06	+42.35
rc	-77.85	-4.83	+5.17	+9.36
Total	-32.36	-11.88	+11.19	+22.15

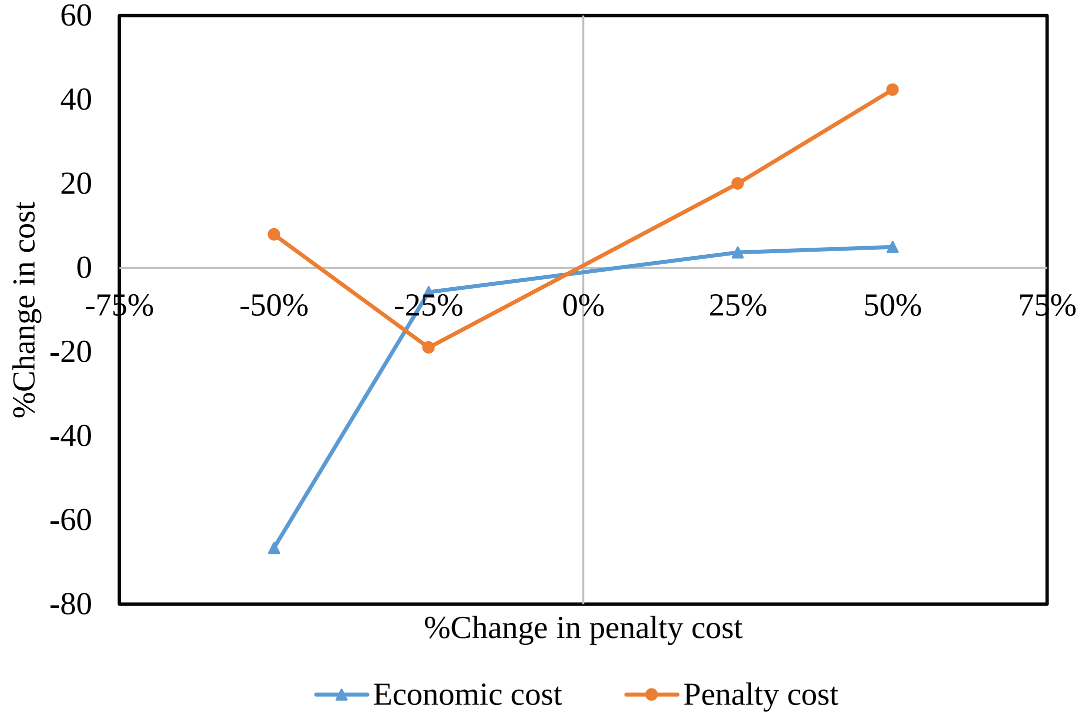

Figure 5. Observation on economic cost and penalty cost when varying the penalty cost.

3.2.2.4. Effects of removal cost

Removal cost is the cost associated with removing the relief item from the store or warehouse when its expiration date gets close. There is tendency for it to vary since it depends on whether disasters occur or not, and when it does, whether the items are put into use within their life-time period. To verify the effect, the unit removal cost is varied from -50% of the original inputs to +100% and the results obtained are summarized in Table 8. It is varied up to +100% in order to examine the behavior of the penalty cost. The total procurement cost and holding cost also decrease as the unit removal cost increases. This is due to the late procurement of relief items with the aim of reducing the amount of commodity close to expiration. Figure 6 shows the behavior of total penalty cost, economic cost when the unit removal cost is being modified. There is a steady increase in the penalty cost when the removal cost is increased compared to the economic costs. With the decrease in removal cost, the economic cost and the total penalty cost decreases. When disasters occur, the relief agent tends to use up commodities that have a shorter life-time period, which helps in prolonging the time the remaining commodities would be removed while waiting on disaster occurrence. When unit removal cost increases the total penalty cost tends to increase, because the procurement quantity reduces.

Table 8. Sensitivity of costs to removal cost (%)

	-50%	-25%	+25%	+50%	+75%	+100%
pc	+1.73	+1.51	-0.27	-0.31	-0.62	-1.11
tc	+1.55	+0.81	-0.03	-0.29	-0.82	-1.12
hc	+1.97	+1.66	-0.31	-0.34	-0.68	-1.23
pc'	-2.41	-1.91	+0.37	+0.42	+0.86	+1.60
rc	-47.38	-23.23	+24.42	+49.23	+73.27	+96.42
Total	-3.19	-1.58	+1.55	+3.10	+4.64	+6.18

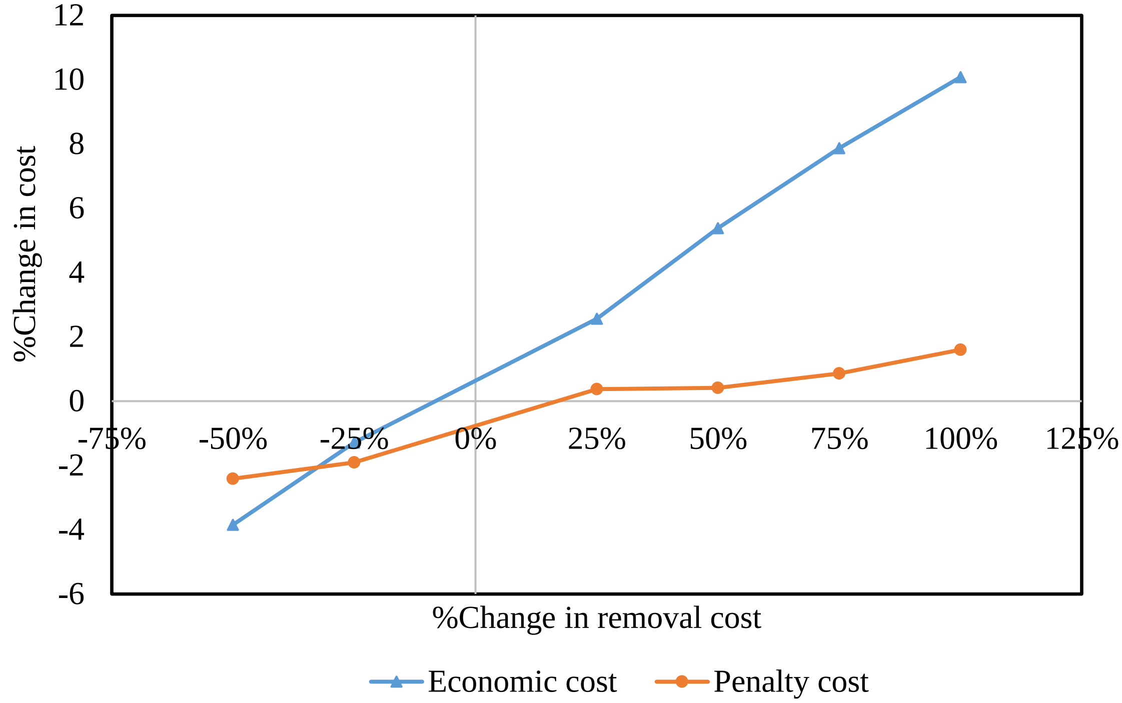

Figure 6. Observation on economic cost and penalty cost when varying the removal cost.

4. SUPPLIER SELECTION

4.1. Problem statement

In the preparedness stage of disaster operations management, the relief organization manages the procurement and storage of relief items. The uncertainty of disaster occurrence makes it uneconomical for the management of the inventory by the relief organization. In a case where disaster does not occur, there is a cost associated with storing the relief item for a longer period and there is tendency for the perishable relief item to expire. Therefore, there is a need to have an agreement with the right suppliers for the management of the inventory in the pre-disaster phase.

The aim of this research is to integrate the supplier selection strategy in the preparedness stage of disaster operations management using a multi-stage stochastic programming model that captures the agreement terms involved in supplier selection decisions in the real world in order to manage costs and decrease the risk of shortage of relief supplies. Precisely, a relief agency that is interested in suppliers for procurement of one relief item in anticipation to a disaster occurrence is considered. It may be hard to procure relief supplies efficiently after the occurrence of disaster; it is advisable for relief organizations to have a fixed agreement in place with suppliers in the pre-disaster phase. To ease the procurement of relief supplies from the suppliers, a fixed agreement terms between the suppliers and the relief agency is put into consideration. The relief agency pledges to purchase a minimum amount of supplies from each supplier over a fixed agreed horizon when a disaster occurs within this period. There is a penalty involved when the relief agencies purchase relief items below minimum commitment quantity of supplies in the agreement terms. The suppliers commit to reserve inventory for the relief organization and they cannot supply relief items above their reserved capacity upon the occurrence of a disaster. The suppliers offer a fixed pricing schedule and deliver supplies within the requested time. In this study, a set of candidate suppliers that are able to supply the desirable relief item and meet the necessary requirements is examined. Each candidate supplier has different characteristics and may specifically differ in the terms below. These terms are specified in the contractual agreement between the suppliers and the relief organization.

Fixed agreement cost

This is the costs paid by the relief organization upfront to the suppliers in order to show their commitment. The cost may vary according to the size of the candidate suppliers, their reserve capacity, and quantity size limit. In general, small suppliers have lower agreement cost while large suppliers have high agreement cost.

Reserve capacity

This is the maximum quantity of relief items the relief organization can purchase from candidate suppliers during a disaster event. This may be different for each supplier; the large suppliers have bigger reserve capacity compared to the small suppliers. In cases where there are high disaster demands, the relief agencies cannot request more than the suppliers reserve capacities. The relief organization can either source a single supplier or source multiple suppliers that can satisfy the demand when a disaster occurs in a particular location.

Commitment quantity

The suppliers set a minimum commitment quantity of relief items which the relief organization must purchase from them during a disaster event in the agreement term. This is known as the commitment quantity and it may vary according to the size of the suppliers, with the large suppliers having a higher commitment quantity compared to the smaller suppliers. Compared to the reserve capacity, there is a penalty if the relief organization buys relief items below the minimum commitment quantity.

Procurement cost and discount rate

The unit procurement cost can be the same for all the suppliers since the acquisition of only one type of relief item is put into consideration. The discount rate, however, might vary. The discount rate is set according to the quantity of relief items purchased by the relief organization. The quantity discount rate reflects on the procurement cost when the relief organization purchase relief items over a given quantity. The rate may differ with the suppliers, with the larger suppliers having higher discount rate compared to the small suppliers.

Transportation cost

This is the cost associated with transporting the relief item from the supplier to the disaster location. The unit transportation cost may also vary according to the supplier and the distance to the disaster location. The suppliers are charged with delivering the relief item to the people in need upon the occurrence of a disaster

4.2. Modeling

A multi-stage stochastic model is developed to determine the suppliers to be selected, the amount of supplies to be purchased from the selected suppliers, and whether the agreement with the suppliers in terms of the quantity size limit is executed. There are a few assumptions considered for this model. Firstly, each location is assumed to be a possible place for the suppliers. Secondly, no supplier selection is set to take place in the final stage of the scenario tree. The model notations and definition are shown below:

Table 9. Model Notation and Definition

Main sets	
J	set of candidate suppliers
S	set of discrete scenarios
K	set of parent scenarios
N	set of demand locations
L_j	set of quantity size limits provided by the suppliers *j*
Indices of sets	
J	type of supplier $j \in J$
S	scenario type $s \in S$
K	parent scenario $k \in K$
I	demand location $i \in N$
L	supplier quantity size limit $l \in L$
Parameters	
p^s	probability of occurrence of scenario *s*
d_j^s	demand for supplies at locations *i* in scenario *s*
h_{ji}	distance between supplier *j* and location *i*
$[\lambda_{jl}, \mu_{jl}]$	lower and upper quantity limit related to quantity size limit *l* for supplier *j*
$u_j^{\min}$	minimum total commitment quantity of supplier *j*
$u_j^{\max}$	reserved capacity of supplier *j*
v_j	unit penalty cost associated with shortage quantity for supplier *j*
b_{jl}	unit procurement cost of purchased supplies from supplier *j* with quantity size limit *l*
r_j	unit cost of transporting supplies from supplier *j* to demand location

Table 9. Continued

f_j	fixed agreement cost for supplier *j*
ω	the first scenario in the last stage.
Decision variables	
x_j^s	1, if supplier *j* is selected, 0 otherwise in scenario *s*
y_{jli}^s	1, if the agreement with supplier *j* is executed by purchasing supplies at quantity size limit *l* for location *i* in scenario *s*
z_{jli}^s	amount of supplies purchased from supplier *j* at quantity size limit *l* for location *i* in scenario *s*
g_j^s	auxiliary variable for defining shortage quantity for supplier *j* in scenario *s*

The mathematical model formulation is presented below:

$$\min \sum_s p^s \left[\sum_j f_j x_j^s + \sum_{j,l,i} b_{jl} z_{jli}^s + \sum_{j,l,i} r_j h_{ji} z_{jli}^s + \sum_j v_j g_j^s \right] \tag{9}$$

$$x_j^s = 0 \qquad s \geq \omega \tag{10}$$

$$\sum_l z_{jli}^s \leq u_j^{\max} x_j^k \qquad s \geq 2, \forall j, i, k \tag{11}$$

$$\sum_{j,l} z_{jli}^s \geq d_i^s \qquad \forall i, s \tag{12}$$

$$\sum_l y_{jli}^s \leq x_j^k \qquad s \geq 2, \forall j, i, k \tag{13}$$

$$z_{jli}^s \geq y_{jli}^s \lambda_{jl} \qquad \forall j, l, i, s \tag{14}$$

$$z_{jli}^s \leq y_{jli}^s \mu_{jl} \qquad \forall j, l, i, s \tag{15}$$

$$g_j^s \geq u_j^{\min} x_j^k - \sum_{l,i} z_{jli}^s \qquad s \geq 2, \forall j, k \tag{16}$$

$$g_j^s \geq 0 \quad \forall i, s \tag{17}$$

$$z_{jli}^s \geq 0 \quad \forall j, l, i, s \tag{18}$$

$$y_{jli}^s \in \{0,1\} \quad \forall j, l, i, s \tag{19}$$

$$x_j^s \in \{0,1\} \quad \forall j, s \tag{20}$$

The objective function (9) minimizes the sum of fixed agreement costs and total expected cost over all scenarios resulting from the selection of the suppliers, the commodity acquisition, the shipments of the supplies to the demand points, unmet demand penalties for the shortage of supplies. Constraint (10) restricts suppliers from being selected at the final stage. Constraint (11) states that the amount of supplies that can be purchased from each supplier should not exceed its reserve capacity. Constraint (12) ensures demand in each location is met from the framework suppliers. Constraint (13) restricts the purchasing of supplies to the selected supplies only. Constraints (14) and (15**)** ensures that each order corresponds to a quantity interval as defined. Constraint (16) shows how the shortage of supplies is derived. Constraints (17), (18), (19), and (20) define decision variables.

4.3. Numerical analysis

4.3.1. Test cases

In this section, a multi-stage stochastic programming model which consists of three stages with seven scenarios is examined. The scenario tree is shown in Figure 7, where each scenario represents a disaster occurrence. Five potential disaster locations are assumed. The assumption is that each location could be a possible candidate place for suppliers. Different disaster impacts were generated for various instances. Three case instances are considered with respect to the impact of disasters, which can either be high, medium or low. The cases considered are high- and low- impact disaster events, Medium-impact disaster events, and High-, low-, and medium- impact disaster events is considered (Balcik & Ak, 2014). The high-impact disaster has a low probability of occurrence, the low-impact disaster has a high probability of occurrence, and the medium-impact disaster has a medium probability of occurrence. The following case instances are considered.

Case A: High- and low-impact disasters (H/L).

Case B: Medium-impact disasters (M).

Case C: High-, low- and medium-impact disaster (H/L/M).

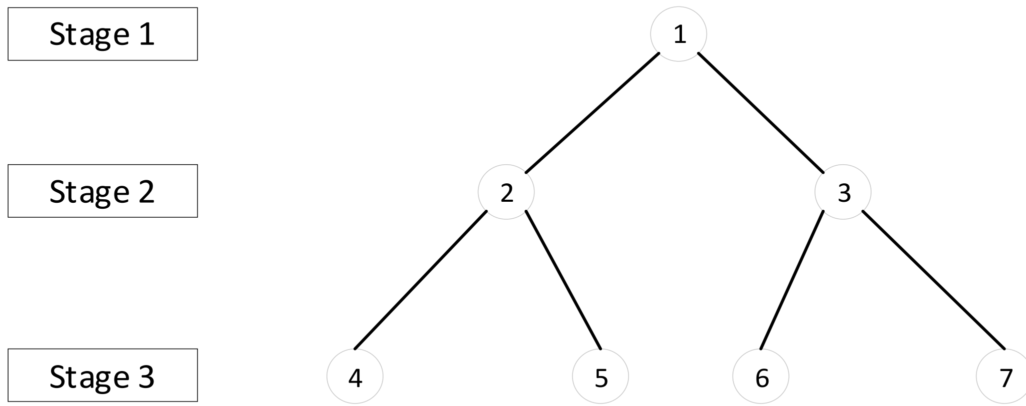

Figure 7. Scenario tree for the base cases

Detailed discussion about the scenario tree is provided in Section 3.1. In the last stage (scenarios 4 - 7), the assumption is that no supplier should be selected. Case A (H/L) contains two types of disasters, which are allocated equally for the scenarios (but may have different probabilities) in each stage. For example, in stage 3, high-impact disaster is assumed to occur in scenarios 5 & 6, and low-impact disaster for scenarios 4 & 7. For Case C (H/L/M), which contains three types of disasters, high- and low-impact disasters, is assumed to occur for scenarios in the second stage, and medium-impact disaster for scenarios in the third stage. Case B (M) contains only one type of disaster which is allocated to all the scenarios. The demands for the disasters were generated using uniform distribution for locations affected by disasters. The demand for the commodity is generated from uniform distribution (U) by assigning U[100,200] for low-impact disasters, U[200,400] for medium-impact disasters, and U[900,1000] high-impact disasters, respectively (Balcik & Ak, 2014). Each candidate supplier is assumed to have different reserve capacities and minimum total commitment quantities. The fixed agreement cost also varies for different candidate suppliers according to their capacities. Larger suppliers have higher agreement costs. The unit procurement costs charged by the candidate supplier is $12 per unit items. Furthermore, each supplier applies a discount for orders larger than 300 units. The large suppliers have a better discount rate when compared to the smaller suppliers. Appendix B presents the tables that contains the data used for the different test cases.

4.3.2. Test case results

The summary of the results of the case instances is shown in Table 10. The following is observed. The number of suppliers selected for Cases A & C (scenarios 1 and 3) with high-impact disaster is more when compared to Case B, because there is need for additional supply of relief items to satisfy demand in cases where there is a major disaster event. Although the same number of suppliers is selected in scenario 2 for all the cases, the suppliers selected are different in terms of capacity. For example, in Case B, suppliers selected have a large capacity that can satisfy the demand because the probability of occurrence of the disaster is high. The penalty costs for all the cases contribute the least to the total costs (1.2%, 1.7%, 2.2%). The transportation cost contributes the most for Cases A & C (74.9% & 62.2%), but procurement cost for Case B (48.7%). The total cost of the Cases A & C, which involves high-impact disaster is larger than that of the Case B which involves only medium-impact. The fixed agreement cost is more for cases involving high-impact disaster because of the larger number of suppliers selected to satisfy the resulting demand. The penalty cost is slightly high for Cases A and C because it contains high impact disaster resulting in more suppliers selected to satisfy the demand. The probability of the high-impact disasters is low, which causes procurement of relief items below the commitment quantity in order to satisfy disaster demand. The procurement cost is slightly low for Case C compared to Cases A & B. This occurs as a result of lower expected demand for Case C because of the presence of the three disaster types.

Table 10. Test Case Results

	Case A (H/L)	Case B (M)	Case C (H/L/M)
Total cost ($)	46951	19739	28527
Fixed agreement cost ($)	899	621	867
Procurement cost ($)	10288	9621	9291
Transportation cost ($)	35184	9152	17737
Penalty cost ($)	579	345	633
Suppliers	Scenario 1 2 3 4 5 6 7	Scenario 1 2 3 4 5 6 7	Scenario 1 2 3 4 5 6 7
1	1 1 1 - - - -	1 0 1 - - - -	1 0 0 - - - -
2	0 1 0 - - - -	1 0 0 - - - -	1 1 1 - - - -
3	1 0 1 - - - -	0 0 1 - - - -	0 1 0 - - - -
4	1 0 1 - - - -	0 1 0 - - - -	1 0 1 - - - -
5	1 0 0 - - - -	1 1 0 - - - -	1 0 1 - - - -

In the case instances studied, the model allows the selection of suppliers for different scenarios over the stages in such a way that they can satisfy the demand for all locations. Figure 7 shows the disaster locations, since the assumption is that each location is a possible place for candidate suppliers. The diagram in Figure 8 represents the suppliers selected to cover the demand across all locations.

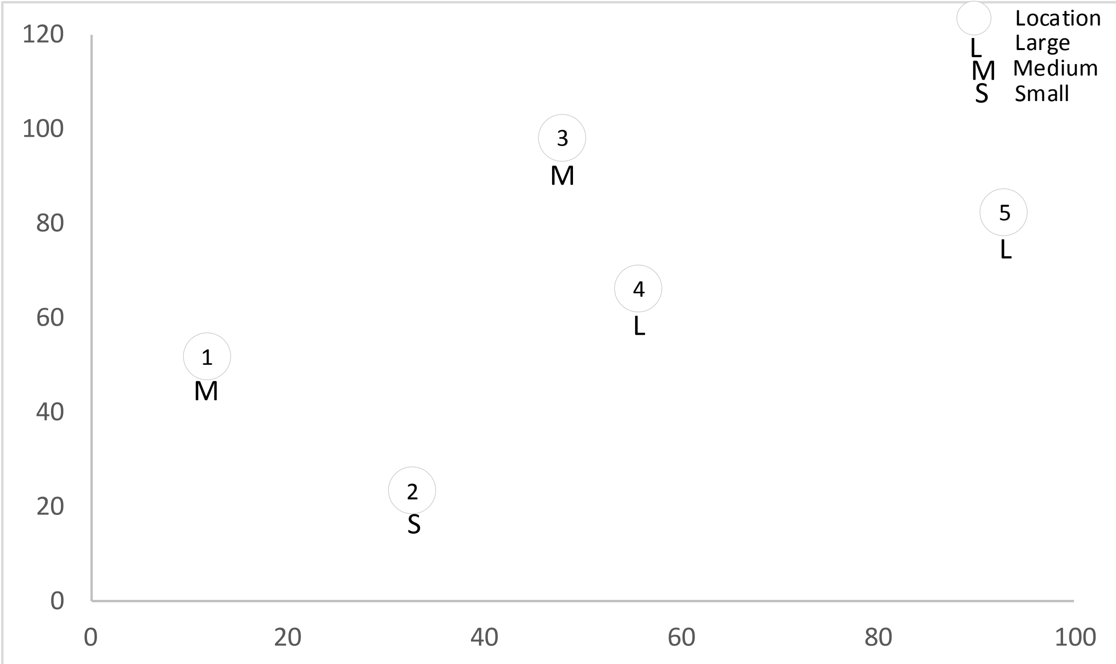

Figure 8. Disaster locations and size of suppliers

Case A (H/L) supplier selection: The suppliers selected for this case instance to meet the demand for relief items for the disaster locations vary as seen in Table 11. Suppliers 1,3,4 and 5 are selected for the first scenario to satisfy the demand in scenarios 2 & 3, suppliers 2 and 3 are selected in scenario 2 to satisfy the demand in scenarios 4 & 5, and suppliers 2,4 and 3 are selected for scenario 3 to satisfy the demand in scenarios 6 & 7. No supplier is selected for scenarios 4, 5 and 6 since they belong to the last stage. The occurrence of high-impact disasters results in increment of demands, which leads to the selection of more suppliers. The size of the suppliers which is determines the quantity discount rate of the suppliers is put into consideration when selecting the suppliers (i.e. the larger the size of the supplier the higher the discount rate offered and vice versa). The four suppliers are selected because high-impact disaster occurs. The decision on the number of suppliers selected depends on disaster demands, and it is directly proportional to the fixed agreement cost. This also applies for Cases B & C.

Table 11. Suppliers selected for Case A, B & C for all scenarios

Stage	Scenario	Parent Scenario	Suppliers Selected		
			Case A (H/L)	Case B (M)	Case C (H/L/M)
1	1	0	1,3,4,5	1,2,5	1,2,4,5
2	2	1	2,3	4,5	1,2
2	3	1	2,4,5	1,3	1,3,4
3	4	2	-	-	-
3	5	2	-	-	-
3	6	3	-	-	-
3	7	3	-	-	-

Case B (M) supplier selection: The suppliers selected for this case instance to meet the demand of commodities for the disaster locations vary as seen in Table 11. Suppliers 1,2,5 are selected for the first scenario to satisfy the demand in scenarios 2 & 3, suppliers 4 and 5 are selected in scenario 2 to satisfy the demand in scenarios 4 & 5, and suppliers 1 and 3 are selected for scenario 3 to satisfy the demand in scenarios 6 & 7. Compared to Case A, Case B selects a smaller number of suppliers for the scenarios 1 and 3. This is because of the absence of high-impact disaster that may cause the need to select more suppliers to satisfy disaster demand.

Case C (H/L/M) supplier selection: The suppliers selected for this case instance to meet the demand for relief items for the disaster locations vary as seen in Table 11. Suppliers 1,2,4, and 5 are selected for the first scenario, suppliers 1 and 2 are selected in scenario 2, and suppliers 1,3, and 4 are selected for scenario 3. Case C selects the same number of suppliers as Case A, but different suppliers are selected for the three scenarios. Due to the variability of costs associated with each supplier, the total fixed agreement costs are different for Cases A & C, even though they have the same number of selected suppliers.

4.3.3. Sensitivity analysis

In this section, the effect of the changes in different parameters in the proposed model on the agreement terms of selecting the suppliers such as fixed agreement cost (*fc*), procurement cost (*pc*), transportation cost (*tc*) and penalty cost (*p'c*), is examined. The parameters to be varied are minimum total commitment, reserved capacity and quantity discount rate. A sensitivity analysis is carried out in order to see how changes in the parameters affect the model.

4.3.3.1. Effects of minimum total commitment quantity

The effect of minimum total commitment quantity on the decisions on supplier selection is being analyzed by modifying the original inputs from -50% to 150% and the results is summarized in Table 12. Since the penalty cost of the cases is very small (between 1.2-2.2% of total costs), changes in the minimum total commitment quantity shows no effect on the fixed agreement costs, procurement costs and transportation costs for three different cases. However, it is directly proportional to the penalty costs for the three cases, with Case A having the highest percent change in penalty costs followed by Case C and Case B. This is as a result of difficulty in meeting the requirement for the minimum total commitment quantity for scenarios which involves low-disaster event due to extra capacity created in response to high-impact disaster. Figure 9 shows the relationship between the changes in minimum total commitment quantity and the total costs associated with the three cases. The total costs increase with the increase in minimum total commitment quantity due to the increase in the penalty costs. Compared to Cases A and Case B, Case C is more sensitive to the total cost when the minimum total commitment quantity changes. This occurs as a result of high variation in demand because Case C contains the three types of disasters. The same number of suppliers is selected over the scenarios for different stages when the minimum total commitment quantity changes for Case A, Case B and Case C.

Table 12. Sensitivity of costs to minimum total commitment quantity (%)

		-50%	-25%	25%	50%	75%	100%	125%	150%
Case A	*fc*	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(H/L)	*pc*	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	tc	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	p'c	-50.56	-25.78	+36.54	+73.02	+110.66	+147.72	+185.55	+222.62
	Total	-0.62	-0.32	+0.45	+0.90	+1.37	+1.82	+2.29	+2.75
Case B	*fc*	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(M)	*pc*	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	tc	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	p'c	-49.84	-24.87	+25.29	+50.16	+76.92	+105.27	+134.82	+169.43
	Total	-0.87	-0.44	+0.44	+0.88	+1.34	+1.84	+2.36	+2.96
Case C	*fc*	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(H/L/M)	*pc*	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	tc	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	p'c	-49.88	-24.79	+25.32	+50.60	+80.52	+111.65	+145.62	+178.96
	Total	-1.10	-0.55	+0.56	+1.12	+1.79	+2.47	+3.23	+3.97

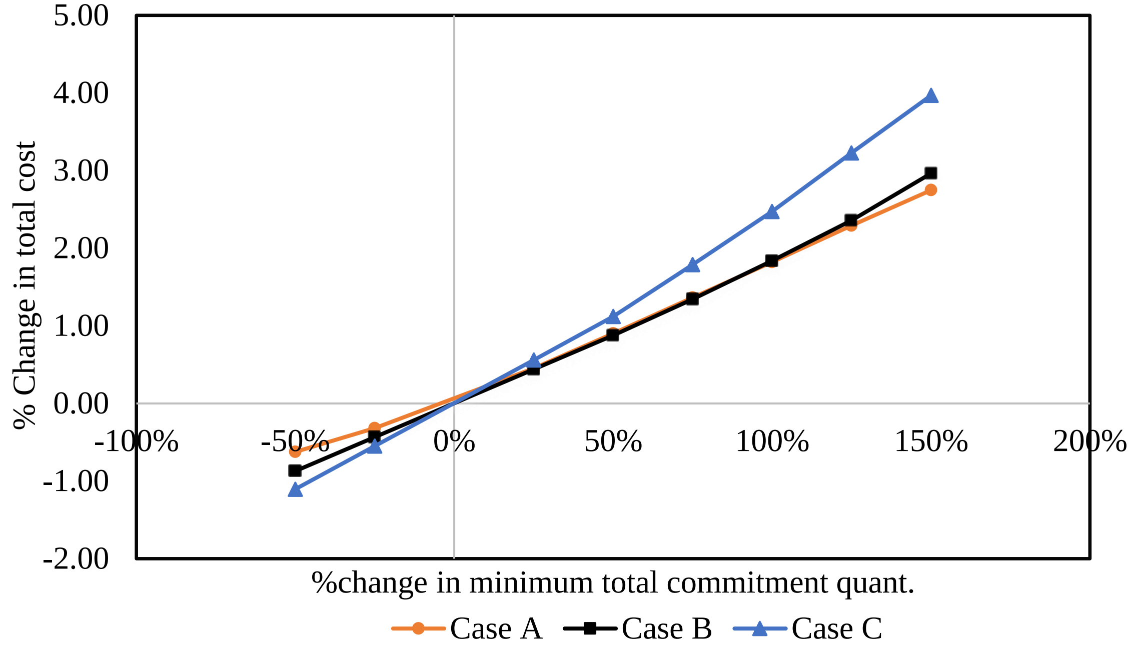

Figure 9. Observation on total costs when varying the minimum total commitment quantity.

4.3.3.2. Effect of reserve capacity

The effect of reserve capacity is being analyzed by modifying the original inputs from -50% to 150%, to check the impact on supplier selection decision. From Table 13 below, the procurement cost decreases with increase in reserve capacity for Cases A & C but shows no changes in Case B. This occurs because of the presence of high-impact disaster which results in high demand. The demand can be satisfied by contracting fewer suppliers with larger capacity. The quantity discount rate applies when a large number of relief supplies is purchased, thereby resulting in low procurement costs. The decrease in reserve capacity causes increase in the fixed agreement cost since large number of suppliers is selected to satisfy the demand for a disaster event due to low capacity. The increase in the reserve capacity has no effect on fixed agreement cost, procurement cost, transportation costs, and penalty costs for Case B because the suppliers selected are able to satisfy the disaster demand with no additional capacity. The effect on the total costs is shown in Figure 10 below. The decrease in reserve capacity results in the increase in total costs, with Case A showing the most change in total costs. While increase in reserve capacity causes the decrease in total cost for Case A and Case C but have no effect on Case B. This result shows that having an agreement with suppliers with vast reserve capacity in locations susceptible to high-impact disaster can be favorable to the relief organization.

Table 13. Sensitivity of costs to reserve capacity (%)

		-50%	-25%	25%	50%	75%	100%	125%	150%
Case A	*fc*	+38.26	+3.34	-11.57	-11.57	-28.25	-30.92	-30.92	-30.92
(H/L)	*pc*	+1.48	+0.02	+0.95	+0.23	+0.15	-0.02	-0.02	-0.02
	tc	+77.85	+31.50	-30.02	-55.41	-68.13	-72.65	-72.65	-72.65
	p'c	+60.74	+14.14	-10.10	-7.63	-35.23	-44.93	-44.93	-44.93
	Total	+60.15	+23.85	-22.63	-41.79	-52.00	-55.59	-55.59	-55.59
Case B	*fc*	+37.45	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(M)	*pc*	+2.56	+0.06	0.00	0.00	0.00	0.00	0.00	0.00
	tc	+114.99	+6.25	0.00	0.00	0.00	0.00	0.00	0.00
	p'c	+42.77	-2.19	0.00	0.00	0.00	0.00	0.00	0.00
	Total	+56.49	+2.89	0.00	0.00	0.00	0.00	0.00	0.00
Case C	*fc*	+28.85	0.00	0.00	-17.31	-17.31	-17.31	-17.31	-17.31
(H/L/M)	*pc*	+2.16	-0.51	+0.15	-0.24	-0.37	-0.37	-0.37	-0.37
	tc	+89.20	+25.99	-24.38	-43.52	-51.10	-51.10	-51.10	-51.10
	p'c	+35.13	-0.53	0.00	-26.73	-24.45	-24.45	-24.45	-24.45
	Total	+57.82	+15.98	-15.11	-28.25	-32.96	-32.96	-32.96	-32.96

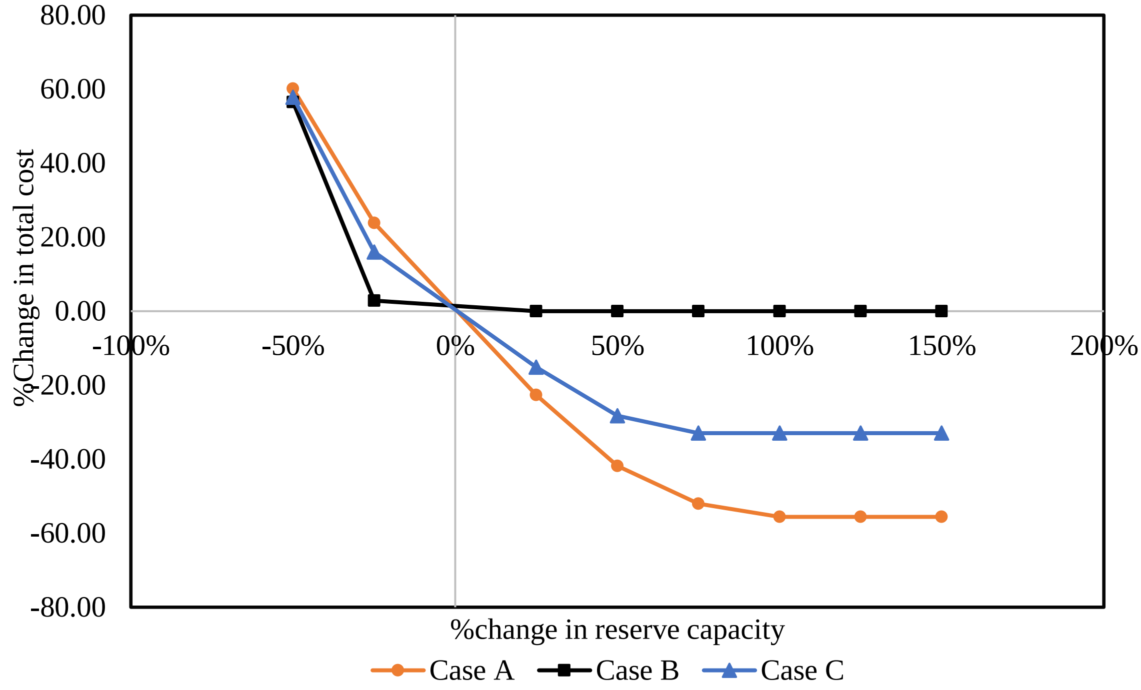

Figure 10. Observation on total costs when varying the reserve capacity.

4.3.3.3. Effect of quantity discount rate

The quantity discount rate on the decisions on supplier selection is examined by modifying the original inputs from -50% to 50%. The increase in the original value stopped at 50% because there is no notable effect above it. The effect on the costs is shown in Table 14. The procurement cost decrease with increase in the quantity discount rate for the three cases, with Case B showing the highest decrease. Changes in the quantity discount rate has no effect on the fixed agreement cost and penalty cost for the three case, as there are no changes to the number of suppliers selected. Figure 11 shows the effect of changes to the discount rate on the total costs for the three cases. The total costs decrease with increase in quantity discount rate in all cases. Case B shows the most change in total costs when the quantity discount rate increases compared to Cases A and C as seen in the Figure below.

Table 14. Sensitivity of costs to quantity discount rate (%)

		-50%	-25%	25%	50%
Case A	*fc*	0.00	0.00	0.00	0.00
(H/L)	*pc*	+3.53	+1.77	-1.76	-3.52
	tc	0.00	0.00	0.00	0.00
	p'c	0.00	0.00	0.00	0.00
	Total	+0.77	+0.39	-0.39	-0.77
Case B	*fc*	0.00	0.00	0.00	0.00
(M)	*pc*	+4.39	+2.42	-2.16	-4.31
	tc	-0.30	-0.30	0.00	0.00
	p'c	0.00	0.00	0.00	0.00
	Total	+2.00	+1.04	-1.05	-2.10
Case C	*fc*	0.00	0.00	0.00	0.00
(H/L/M)	*pc*	+3.18	+1.80	-1.57	-3.15
	tc	-0.16	-0.16	0.00	0.00
	p'c	0.00	0.00	0.00	0.00
	Total	+0.94	+0.49	-0.51	-1.02

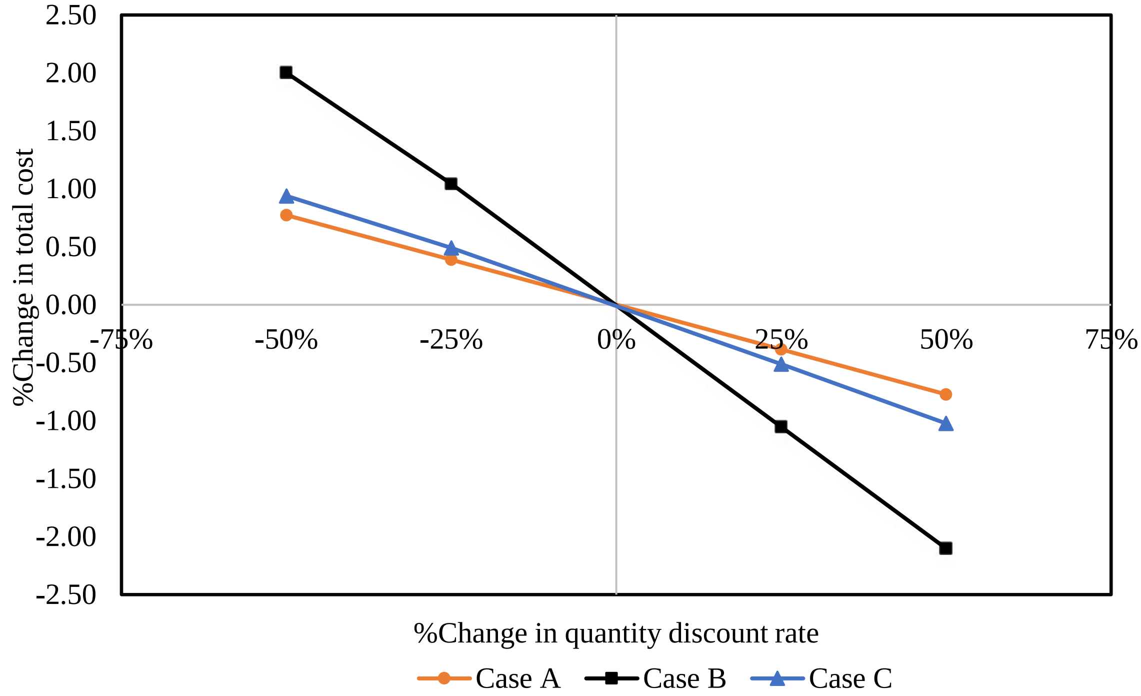

Figure 11. Observation on total costs when varying the quantity discount rate.

4.4. Case study

In this section, a case study based on real-world hurricanes, floods and earthquakes occurrence in the mainland United States is presented. This study is inspired based on the operation of FEMA. They are responsible for the management of relief network and the acquisitions of relief items in the United States. They also have a few logistic centers in which the relief items are being kept. The logistic centers are located in Texas, California, Georgia, and Maryland. The goal is to integrate supplier selection in the logistics area of disaster operations management with the aim of managing costs and reducing risk. For this research, the procurement of one type of relief item is considered, which is the bottled drinking water, through fixed agreements with suppliers. Having an agreement in place with bottle water suppliers can ensure immediate delivery of water to areas affected by disaster. This is can be a great help to the relief organization in terms or saving lives and costs.

The demand locations are the 48 states in the mainland United States. The distances between the states are derived using the distance between the most populous cities in each state. The unit of water is set to be 1,000 gallons. Each location has a supplier, that is, 48 commercial water suppliers is considered. The locations in which the supplier has a water bottling facility is said to have a large capacity (Food & Water watch report, 2009). The locations without any water bottling facility, assumes groceries stores such as H.E.B or Walmart to be the supplier, which has a lower capacity compared to locations that have suppliers with bottling water facilities. The discounts given by the suppliers vary according to the size of the suppliers. The suppliers apply their discounts for orders more than 100 units. Additional 10% discount is applied for orders above 1,000 units by the suppliers. The fixed agreement cost, and penalty cost vary according to the size of the suppliers. The minimum commitment capacity is assumed to be 20% of the reserve capacity.

The top 10 ranked locations used in setting the impact level for earthquakes, floods and hurricanes, are the same as the ones used in Section 3.2.1. The high-impact level is allocated to first 3 locations with the highest occurrence, medium-impact to the next 3 and low impact to the rest. The demand for flood and hurricane is generated using uniform distribution (U), with U[100,200], U[200,400] and U[900, 1000] for low, medium and high impact flood and hurricane, respectively. The demand for an earthquake is generated using U[1000,2000], U[2000,4000] and U[9000,10000] for low, medium and high impact respectively. Appendix C presents the table that shows the stage, scenarios, parent scenario, and the corresponding probabilities used in the multi-stage stochastic programming model for the case study.

4.4.1. Case results

The model was solved using CPLEX Concert Technology (IBM ILOG CPLEX) in a Microsoft Visual Studio IDE on a system with Intel Core i7-700 @3.60GHz and 8GB RAM. The optimal solution of the model was found within 114.59 seconds. The scenario tree is presented to in Appendix C. For example, the result of scenarios 1-2-5-17 is discussed below, with each scenario connected in the scenario tree and belonging to different stages. The three types of disasters considered occurs among the scenarios. Table 15 shows the stage each scenario belongs to, the probability of occurrence of disaster event in each scenario, the location of the selected suppliers, and the type of disaster responded to. The large suppliers are located in California and Texas, the small suppliers are located in Missouri, Wyoming, Nevada, Oklahoma, New York and South Carolina.

Table 15. Summary of scenarios 1-2-5-17 characteristic and results

Stage	Parent Scenario	Scenario	Probability of Disaster Occurrence	Location of Selected Suppliers	Type of Disaster Responded To
1	0	1	1	California, Missouri, Wyoming, Nevada, Oklahoma.	Earthquake
2	1	2	0.05	Texas, California, New York, Oklahoma.	Flood
3	2	5	0.0025	Texas, South Carolina, New York.	Hurricane
4	5	17	0.00025	---	---

In scenario 1 which belongs to the first stage, five suppliers (i.e., California, Missouri, Wyoming, Nevada, Oklahoma) are selected, to satisfy the demand of earthquake occurrence in scenarios 2 - 4, that is, the child scenarios of scenario 1. There are four disaster location, but five suppliers are selected to meet the demand because the probability of occurrence of a high-impact earthquake disaster is high. The number of suppliers selected in scenario 1 is larger compared to scenario 2, 5 and 17, but it only contains one large supplier. For scenario 2 in the second stage, Texas, California, New York, Oklahoma., are the locations in which suppliers are selected to satisfy the demand of flood occurrence in scenarios 5 - 8, that is, the child scenarios of scenario 2. The four suppliers are selected because they can satisfy the demand resulting from flood occurrence. In scenario 5 in the third stage, three suppliers (located in Texas, South Carolina, New York, respectively) are selected to meet the demand in scenarios 17 - 21, the child scenarios of scenario 5. The probability of occurrence of hurricanes at the location is high because of their closeness to the coastal lane. The suppliers selected can satisfy the demand resulting from hurricane event. The supplier selection decisions depend on the disaster-affected location. In scenario 17 the last stage, no suppliers are selected because there is no demand required to be satisfied from any child scenario. Figure 12 below shows the locations of the suppliers selected and the type of disaster that occurs in the location over scenarios 1-2-5-17.

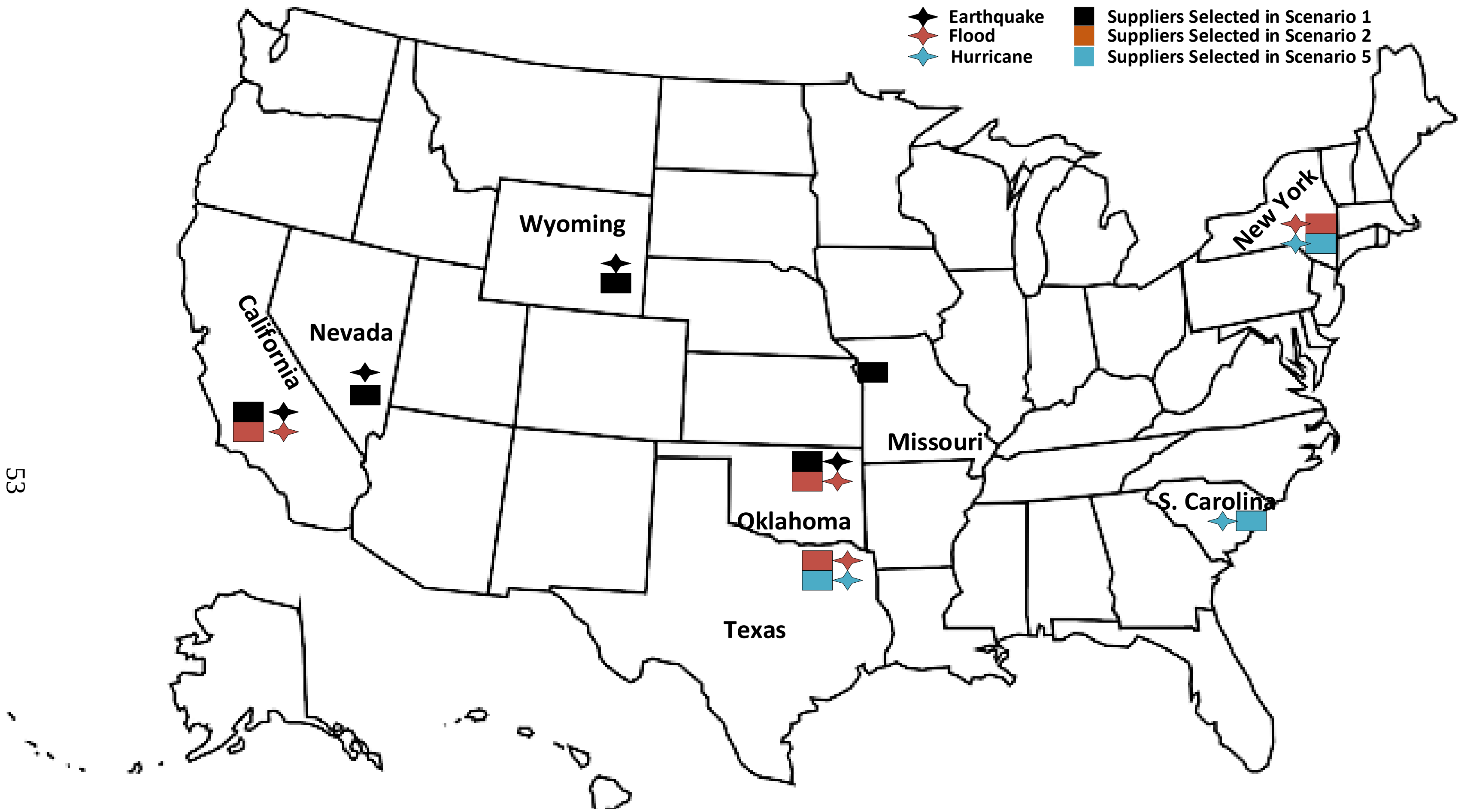

Figure 12. United States map showing location of selected suppliers and disaster type for scenarios 1,2,5,17

The result shows that multiple suppliers are selected for disasters with high demands, and a single supplier that can meet all the demands is selected for disasters with low demands. This case study consists of the combination of scenarios with disasters such as earthquakes, floods and hurricanes. Therefore, there is a large fluctuation of demand across the scenarios. Sensitivity analysis is carried out to test how changes in the parameters will affect the agreement terms of selecting the suppliers, the economic cost (i.e., the sum of fixed agreement cost (*fc*), procurement cost (*pc*), and transportation cost (*tc*)), penalty cost (*p'c*) and total costs. The parameters to be varied are minimum total commitment, reserved capacity and quantity discount rate.

4.4.2. Case sensitivity analysis

4.4.2.1. Effects of minimum total commitment quantity

The effect of the minimum total commitment quantity is studied by varying the original input from -50% to +100%, and the effect in percentage is shown in Table 16. It can be seen from the table that increase in minimum total commitment quantity causes increase in the procurement cost. This is as a result of the difference in procurement cost and discount rate for each supplier as the number of relief items purchased increases. Compared to the test case result in Section 4.3.3.1 where changes in minimum total commitment quantity does not affect the other costs because of the low value of the penalty cost in base result, the penalty cost for the case study is high (20% of the total cost). Therefore, changes in minimum total commitment quantity affect the other costs in other to attain a balance between the costs. The penalty cost increases with increase in minimum total commitment quantity because the relief items purchased by the relief agency below the commitment quantity increases. For example, if the demand for a disaster scenario is zero, the penalty costs increases because there is no need for the relief agency to purchase any relief items and the difference from the total commitment quantity goes up. The total costs also increase with increase in minimum total commitment quantity. This is consistent with our previous findings in the test cases. Figure 13 below shows the relationship between the economic cost, penalty cost, and the minimum total commitment quantity. The economic cost and penalty cost increases with increase in minimum total commitment quantity, with the penalty costs having the higher cost increment. This result implies that, having an agreement with suppliers with lower commitment quantity will be beneficial for the relief organization in response to a disaster event.

Table 16. Sensitivity of costs to minimum total commitment quantity (%)

	-50%	-25%	+25%	+50%	+75%	+100%
fc	+11.66	+3.78	-4.91	-4.62	+11.46	+8.67
pc	-0.07	-0.01	-0.11	-0.02	+0.51	+1.10
tc	-28.73	-6.04	+8.11	+16.30	+63.57	+73.81
p'c	-39.19	-24.00	+23.09	+45.35	+37.03	+49.33
Total	-11.54	-5.55	+5.55	+11.08	+15.93	+20.09

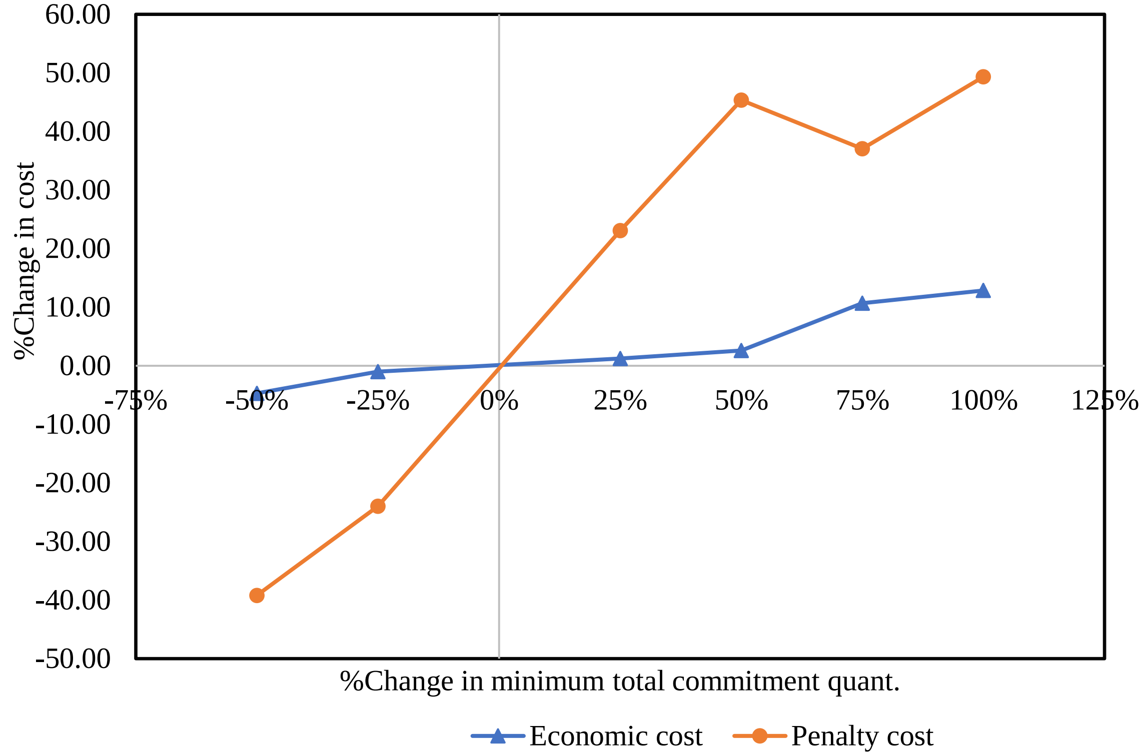

Figure 13. Observation on economic and penalty costs when varying minimum total commitment quantity.

4.4.2.2. Effect of reserve capacity

The reserve capacity, which is the maximum number of relief items that can be purchased from the supplier, is an important factor due to the uncertainty of demand when a disaster occurs. This plays a major role in the number of suppliers to be selected in response to disaster demands. The reserve capacities of the suppliers are modified from -50% to +200% and its effects are shown in Table 17 and Figure 14 below. The original value is increased to +200% in order to examine the behavior of the economic and penalty costs. The decrease in the reserve capacity shows a variation in costs as seen on Table 17. The fixed agreement cost, and the procurement cost increases with decrease in the reserve capacity of the suppliers. This is because the number of suppliers selected in order to meet the disaster demand for relief items increases. The penalty costs increase significantly with decrease in reserve capacities of the suppliers, because the number of suppliers contracted increases, thereby resulting in increased relief items purchased below commitment quantity. The penalty cost decreases significantly and follows a stepwise pattern (i.e. it follows a decreasing and stable pattern) as the reserve capacity increases. When the reserve capacity increase, more small suppliers with low commitment quantity are contracted to supply relief item, leading to a significant decrease in the penalty cost. The procurement costs slightly increase when the reserve capacity increases because the discount rate is lower for the smaller suppliers selected. The transportation cost also increases because the distance of the smaller suppliers contracted to the disaster location is relatively high. The increase in procurement and transportation costs affect the behavior of the economic cost. Figure 14 shows the pattern in which the economic and penalty costs follows when the reserve capacity increases. In addition, it is favorable for the relief organization to have an agreement with suppliers with larger reserve capacity in place in order to save costs.

Table 17. Sensitivity of costs to reserve capacity (%)

	-50%	-25%	25%	50%	75%	100%	125%	150%	175%	200%
fc	+81.53	+28.05	-13.97	-14.79	-19.01	-25.93	-25.81	-25.81	-30.93	-30.93
pc	+0.24	+0.19	-0.29	-0.16	-0.22	+0.20	+0.29	+0.35	+1.54	+1.59
tc	+53.65	+23.98	-8.80	+4.35	+3.02	+25.85	+22.07	+18.73	+34.10	+27.63
p'c	+67.52	+13.38	-6.69	-21.78	-24.90	-43.20	-43.11	-43.11	-59.80	-59.83
Total	+20.52	+5.90	-2.66	-3.86	-4.70	-5.09	-5.50	-5.90	-6.42	-7.22

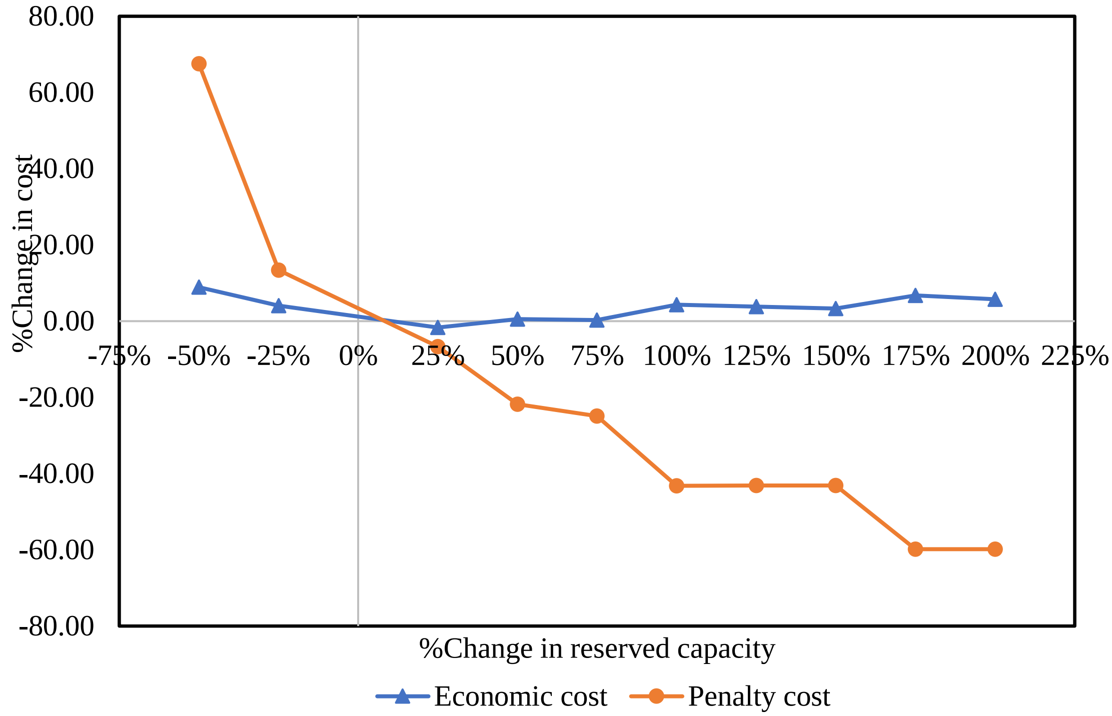

Figure 14. Observation on economic and penalty costs when varying reserve capacity.

4.4.2.3. Effect of quantity discount rate

The suppliers give discounts with respect to the amount of relief items purchased by the relief agency. The aim is to encourage the relief agency to have a fixed agreement with them and purchase more relief items. The effect of quantity discount rate on the decisions on supplier selection by modifying the original inputs from -50% to 200% is examined. The original value is increased to +200% in order to examine the pattern of the economic and penalty costs. The effect of the quantity discount rate on costs is shown in Table 18 and Figure 15 below. The fixed agreement costs and transportation cost decrease with increase in quantity discount rate because the relief organization tends to purchase more relief items from suppliers This can be attributed to the changes in the suppliers selected. There is a significant decrease in the penalty cost when the quantity discount rate increases from 25% to 50% as seen on Table 18. This occurs as a result of increase in discount rate which causes the unit procurement cost to be low, thereby enabling the relief organization to buy more relief items and reduce penalty cost associated with commitment quantity. The total costs also decrease with the increase in quantity discount rate. Figure 14 shows the effect of change in quantity discount rate on economic costs and penalty costs. There is a significant decrease in the penalty cost when the quantity discount rate increases above 25%. The economic cost increases with the decrease in the quantity discount rate because of the increase in the procurement cost. The increase in the quantity discount rate causes the decrease in the economic cost because it leads to a low procurement cost of the relief items. The increase in quantity discount rate leads to the reduction in procurement cost when procuring more relief item from a supplier. Fewer suppliers are selected to meet the disaster demand when the quantity discount rate is increased. The penalty costs also decrease because the relief agency can purchase more relief items with low procurement cost. The economic cost tends to decrease when the discount rate is above 50% because of the reduction in procurement cost. The result shows that having an agreement with suppliers with higher quantity discount rate may be of advantage to the relief organization.

Table 18. Sensitivity of costs to quantity discount rate (%)

	-50%	-25%	25%	50%	75%	100%	125%	150%	175%	200%
fc	+0.68	+0.52	+0.50	+0.42	+0.12	-2.37	-2.51	-2.85	+1.23	-3.46
pc	+11.71	+5.88	-5.92	+5.75	+4.87	-2.86	-10.75	-18.39	-15.79	-27.53
tc	-0.35	-0.20	+0.04	+0.17	+0.58	+3.27	+4.87	+5.51	-19.15	-20.95
p'c	+0.06	-0.01	+0.18	-63.07	-84.51	-85.91	-86.16	-86.82	-93.05	-96.04
Total	+7.84	+3.92	-3.93	-8.61	-13.41	-18.53	-23.68	-28.86	-31.53	-40.25

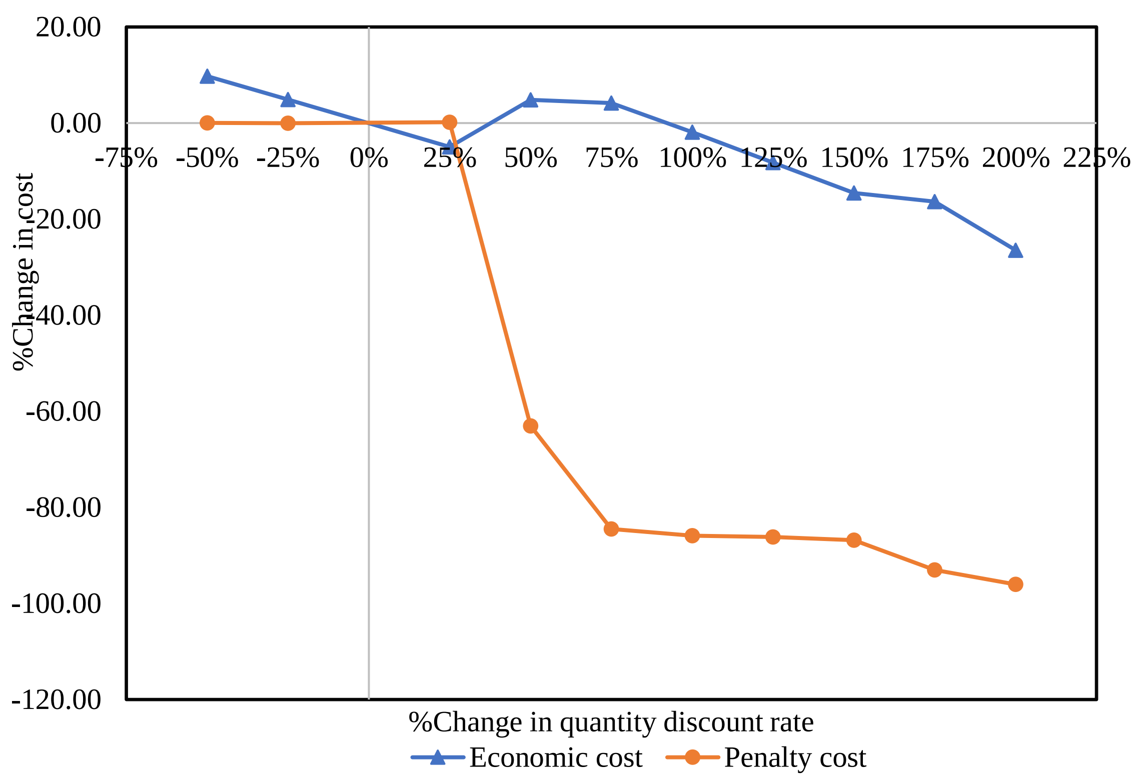

Figure 15. . Observation on economic and penalty costs when varying quantity discount rate.

5. CONCLUSION

This chapter presents the conclusion and the future research directions for both the pre-positioning of relief supplies and the supplier selection strategy.

5.1. Pre-positioning of relief supplies

This thesis addresses the pre-positioning of relief supplies during the preparedness stage of disaster management. A multi-stage stochastic programing model is formulated with the objective of minimizing the total cost, which consists of the procurement cost, space estimate, transport cost, penalty cost, removal cost, and holding cost. The major contribution of this part of the thesis is that it takes lifetime of relief products into consideration, thereby giving the relief agency insights on the control of inventory over each scenario if dealing with perishable relief items. The locations within the mainland of the United States with high occurrence of hurricanes, earthquakes and floods was considered as a case study.

The sensitivity analyses performed provide the relief agencies insights on how they can manage the cost associated with the pre-positioning of relief supplies while having dynamic control over the inventory. Firstly, avoiding the shortage of commodity is a good cost-effective process because of the penalty associated with not having the commodity. Secondly, having a better and more efficient way of disposing a commodity when it has a low lifetime period is also an aspect the relief agencies should consider. Thirdly, relief agencies should have a better plan in place for handling relief items, because the more time the commodity spends in the warehouse the larger the cost of holding it. Future research areas include bringing in suppliers as an alternative of removing relief items when its expiration is close instead of disposing items. To be more specific, commodities close to expiration are returned to suppliers to sell, and in the event that disasters occur, the commodities will be replaced by suppliers.

5.2. Supplier selection

This study addresses how the selection of suppliers can be integrated at the preparedness stage in disaster operations management. A multi-stage stochastic programming model that determines the number of suppliers to be selected, if the selected suppliers execute their agreement terms, and the amount of relief supplies purchased by the relief organization from the suppliers, is presented. This model is used to solve the problem for small test cases and also used to determine the solution to a real word problem. The study gives the relief agencies insight on how supplier selection problem may be made easier by establishing a flexible fixed agreement contract with the suppliers before a disaster event. Factors such as the commitment quantity, reserve capacity and the quantity discount rate given by the suppliers, are considered. The agreement terms involve the relief organization having to purchase a certain minimum number of relief items from the suppliers. The suppliers cannot supply relief items above their reserve capacity and must deliver relief items to affected locations when a disaster occurs. The mainland of the United States is used as a case study while considering earthquakes, hurricanes and floods disasters.

Sensitivity analysis is carried out by examining the effect of changes in few parameters on the costs. The analysis helps to provide relief organization insight on how the costs involved in the supplier selection can be managed and how suppliers can be selected efficiently. The relief organization should avoid procuring relief items below the commitment quantity they agreed with the suppliers, because of the penalty incurred when it happens. The relief agencies should try to avoid having an agreement with suppliers with lower reserve capacity in order to satisfy disaster demand. The future research direction involves considering lead time interval in the multi-stage stochastic programming model. This involves the relief organization setting a required time interval for the suppliers to satisfy the demand when disasters occur. Also, developing an efficient algorithm to solve the multi-stage stochastic programming model faster is another future direction for this research.

APPENDIX

APPENDIX A: Table 19: Stage, Scenario, Parent Scenario, and Probability Data for Pre-position of Relief Supplies

Stage	Scenario	Parent Scenario	Probability
1	1	0	1.00000
2	2	1	0.05000
2	3	1	0.10000
2	4	1	0.85000
3	5	2	0.00250
3	6	2	0.00500
3	7	2	0.01250
3	8	2	0.03000
3	9	3	0.00500
3	10	3	0.01000
3	11	3	0.02500
3	12	3	0.06000
3	13	4	0.04250
3	14	4	0.08500
3	15	4	0.21250
3	16	4	0.51000
4	17	5	0.00025
4	18	5	0.00063
4	19	5	0.00038
4	20	5	0.00075
4	21	5	0.00050
4	22	6	0.00050
4	23	6	0.00125
4	24	6	0.00075
4	25	6	0.00150
4	26	6	0.00100
4	27	7	0.00125
4	28	7	0.00313
4	29	7	0.00188
4	30	7	0.00375
4	31	7	0.00250
4	32	8	0.00300
4	33	8	0.00750
4	34	8	0.00450
4	35	8	0.00900
4	36	8	0.00600

Stage	Scenario	Parent Scenario	Probability
4	37	9	0.00050
4	38	9	0.00125
4	39	9	0.00075
4	40	9	0.00150
4	41	9	0.00100
4	42	10	0.00100
4	43	10	0.00250
4	44	10	0.00150
4	45	10	0.00300
4	46	10	0.00200
4	47	11	0.00250
4	48	11	0.00625
4	49	11	0.00375
4	50	11	0.00750
4	51	11	0.00500
4	52	12	0.00600
4	53	12	0.01500
4	54	12	0.00900
4	55	12	0.01800
4	56	12	0.01200
4	57	13	0.00425
4	58	13	0.01063
4	59	13	0.00638
4	60	13	0.01275
4	61	13	0.00850
4	62	14	0.00850
4	63	14	0.02125
4	64	14	0.01275
4	65	14	0.02550
4	66	14	0.01700
4	67	15	0.02125
4	68	15	0.05313
4	69	15	0.03188
4	70	15	0.06375
4	71	15	0.04250
4	72	16	0.05100
4	73	16	0.12750
4	74	16	0.07650
4	75	16	0.15300
4	76	16	0.10200
5	77	17	0.00001

Stage	Scenario	Parent Scenario	Probability
5	78	17	0.00004
5	79	17	0.00008
5	80	17	0.00013
5	81	18	0.00003
5	82	18	0.00009
5	83	18	0.00019
5	84	18	0.00031
5	85	19	0.00002
5	86	19	0.00006
5	87	19	0.00011
5	88	19	0.00019
5	89	20	0.00004
5	90	20	0.00011
5	91	20	0.00023
5	92	20	0.00038
5	93	21	0.00003
5	94	21	0.00008
5	95	21	0.00015
5	96	21	0.00025
5	97	22	0.00003
5	98	22	0.00008
5	99	22	0.00015
5	100	22	0.00025
5	101	23	0.00006
5	102	23	0.00019
5	103	23	0.00038
5	104	23	0.00063
5	105	24	0.00004
5	106	24	0.00011
5	107	24	0.00023
5	108	24	0.00038
5	109	25	0.00008
5	110	25	0.00023
5	111	25	0.00045
5	112	25	0.00075
5	113	26	0.00005
5	114	26	0.00015
5	115	26	0.00030
5	116	26	0.00050
5	117	27	0.00006
5	118	27	0.00019

Stage	Scenario	Parent Scenario	Probability
5	119	27	0.00038
5	120	27	0.00063
5	121	28	0.00016
5	122	28	0.00047
5	123	28	0.00094
5	124	28	0.00156
5	125	29	0.00009
5	126	29	0.00028
5	127	29	0.00056
5	128	29	0.00094
5	129	30	0.00019
5	130	30	0.00056
5	131	30	0.00113
5	132	30	0.00188
5	133	31	0.00013
5	134	31	0.00038
5	135	31	0.00075
5	136	31	0.00125
5	137	32	0.00015
5	138	32	0.00045
5	139	32	0.00090
5	140	32	0.00150
5	141	33	0.00038
5	142	33	0.00113
5	143	33	0.00225
5	144	33	0.00375
5	145	34	0.00023
5	146	34	0.00068
5	147	34	0.00135
5	148	34	0.00225
5	149	35	0.00045
5	150	35	0.00135
5	151	35	0.00270
5	152	35	0.00450
5	153	36	0.00030
5	154	36	0.00090
5	155	36	0.00180
5	156	36	0.00300
5	157	37	0.00003
5	158	37	0.00008
5	159	37	0.00015

Stage	Scenario	Parent Scenario	Probability
5	160	37	0.00025
5	161	38	0.00006
5	162	38	0.00019
5	163	38	0.00038
5	164	38	0.00063
5	165	39	0.00004
5	166	39	0.00011
5	167	39	0.00023
5	168	39	0.00038
5	169	40	0.00008
5	170	40	0.00023
5	171	40	0.00045
5	172	40	0.00075
5	173	41	0.00005
5	174	41	0.00015
5	175	41	0.00030
5	176	41	0.00050
5	177	42	0.00005
5	178	42	0.00015
5	179	42	0.00030
5	180	42	0.00050
5	181	43	0.00013
5	182	43	0.00038
5	183	43	0.00075
5	184	43	0.00125
5	185	44	0.00008
5	186	44	0.00023
5	187	44	0.00045
5	188	44	0.00075
5	189	45	0.00015
5	190	45	0.00045
5	191	45	0.00090
5	192	45	0.00150
5	193	46	0.00010
5	194	46	0.00030
5	195	46	0.00060
5	196	46	0.00100
5	197	47	0.00013
5	198	47	0.00038
5	199	47	0.00075
5	200	47	0.00125

Stage	Scenario	Parent Scenario	Probability
5	201	48	0.00031
5	202	48	0.00094
5	203	48	0.00188
5	204	48	0.00313
5	205	49	0.00019
5	206	49	0.00056
5	207	49	0.00113
5	208	49	0.00188
5	209	50	0.00038
5	210	50	0.00113
5	211	50	0.00225
5	212	50	0.00375
5	213	51	0.00025
5	214	51	0.00075
5	215	51	0.00150
5	216	51	0.00250
5	217	52	0.00030
5	218	52	0.00090
5	219	52	0.00180
5	220	52	0.00300
5	221	53	0.00075
5	222	53	0.00225
5	223	53	0.00450
5	224	53	0.00750
5	225	54	0.00045
5	226	54	0.00135
5	227	54	0.00270
5	228	54	0.00450
5	229	55	0.00090
5	230	55	0.00270
5	231	55	0.00540
5	232	55	0.00900
5	233	56	0.00060
5	234	56	0.00180
5	235	56	0.00360
5	236	56	0.00600
5	237	57	0.00021
5	238	57	0.00064
5	239	57	0.00128
5	240	57	0.00213
5	241	58	0.00053

Stage	Scenario	Parent Scenario	Probability
5	242	58	0.00159
5	243	58	0.00319
5	244	58	0.00531
5	245	59	0.00032
5	246	59	0.00096
5	247	59	0.00191
5	248	59	0.00319
5	249	60	0.00064
5	250	60	0.00191
5	251	60	0.00383
5	252	60	0.00638
5	253	61	0.00043
5	254	61	0.00128
5	255	61	0.00255
5	256	61	0.00425
5	257	62	0.00043
5	258	62	0.00128
5	259	62	0.00255
5	260	62	0.00425
5	261	63	0.00106
5	262	63	0.00319
5	263	63	0.00638
5	264	63	0.01063
5	265	64	0.00064
5	266	64	0.00191
5	267	64	0.00383
5	268	64	0.00638
5	269	65	0.00128
5	270	65	0.00383
5	271	65	0.00765
5	272	65	0.01275
5	273	66	0.00085
5	274	66	0.00255
5	275	66	0.00510
5	276	66	0.00850
5	277	67	0.00106
5	278	67	0.00319
5	279	67	0.00638
5	280	67	0.01063
5	281	68	0.00266
5	282	68	0.00797

Stage	Scenario	Parent Scenario	Probability
5	283	68	0.01594
5	284	68	0.02656
5	285	69	0.00159
5	286	69	0.00478
5	287	69	0.00956
5	288	69	0.01594
5	289	70	0.00319
5	290	70	0.00956
5	291	70	0.01913
5	292	70	0.03188
5	293	71	0.00213
5	294	71	0.00638
5	295	71	0.01275
5	296	71	0.02125
5	297	72	0.00255
5	298	72	0.00765
5	299	72	0.01530
5	300	72	0.02550
5	301	73	0.00638
5	302	73	0.01913
5	303	73	0.03825
5	304	73	0.06375
5	305	74	0.00383
5	306	74	0.01148
5	307	74	0.02295
5	308	74	0.03825
5	309	75	0.00765
5	310	75	0.02295
5	311	75	0.04590
5	312	75	0.07650
5	313	76	0.00510
5	314	76	0.01530
5	315	76	0.03060
5	316	76	0.05100

APPENDIX B: Table 20: Case A (H/L) Instance Data

Locations	5						
Suppliers	5						
Quantity size limit	5						
Scenarios	7						
Last Stage First Scenario	3						
Parent Scenario	0	0	0	1	1	2	2
Probability	1	0.2	0.8	0.15	0.45	0.3	0.1
Agreement cost	120	100	130	150	135		
Penalty cost	1.25	1.2	1.3	1.4	1.35		
Transport cost	0.3	0.35	0.3	0.25	0.3		
Minimum total commitment	100	120	150	130	125		
Reserved capacity	550	500	600	750	650		
Demand							
	0	904	0	0	0	0	932
	0	0	0	987	106	0	0
	0	0	152	0	0	0	0
	0	0	0	0	0	131	964
	0	954	0	0	0	0	0
Procurement cost							
	12	11.016	11.016	11.016	11.016		
	12	12.000	11.040	11.040	11.040		
	12	10.980	10.980	10.980	10.980		
	12	10.860	10.860	10.860	10.860		
	12	10.920	10.920	10.920	10.920		
Distance							
	35	350	590	450	860		
	350	30	760	470	830		
	590	760	34	340	480		
	450	470	340	41	410		
	860	830	480	410	36		
Lower limit							
	0	151	391	445	460		
	0	150	260	371	440		
	0	284	381	439	550		
	0	296	471	572	669		
	0	275	385	460	571		
Upper limit							
	150	390	444	459	1000		
	149	259	370	439	1000		
	283	380	438	549	1000		
	295	470	571	670	1000		
	274	384	459	570	1000		

Table 21: Case B (M) Instance Data

Locations	5						
Suppliers	5						
Quantity size limit	5						
Scenarios	7						
Last Stage First Scenario	3						
Parent Scenario	0	0	0	1	1	2	2
Probability	1	0.45	0.55	0.25	0.25	0.25	0.25
Agreement cost	120	100	130	150	135		
Penalty cost	1.25	1.2	1.3	1.4	1.35		
Transport cost	0.3	0.35	0.3	0.25	0.3		
Minimum total commitment	100	120	150	130	125		
Reserved capacity	550	500	600	750	650		
Demand							
	0	271	0	0	0	0	273
	0	0	386	0	0	0	0
	0	0	0	0	0	359	244
	0	0	0	308	0	0	0
	0	382	0	0	265	0	0
Procurement cost							
	12	11.016	11.016	11.016	11.016		
	12	12.000	11.040	11.040	11.040		
	12	10.980	10.980	10.980	10.980		
	12	10.860	10.860	10.860	10.860		
	12	10.920	10.920	10.920	10.920		
Distance							
	35	350	590	450	860		
	350	30	760	470	830		
	590	760	34	340	480		
	450	470	340	41	410		
	860	830	480	410	36		
Lower limit							
	0	151	391	445	460		
	0	150	260	371	440		
	0	284	381	439	550		
	0	296	471	572	669		
	0	275	385	460	571		
Upper limit							
	150	390	444	459	1000		
	149	259	370	439	1000		
	283	380	438	549	1000		
	295	470	571	670	1000		
	274	384	459	570	1000		

Table 22: Case C (H/L/M) Instance Data

Locations	5						
Suppliers	5						
Quantity size limit	5						
Scenarios	7						
Last Stage First Scenario	3						
Parent Scenario	0	0	0	1	1	2	2
Probability	1	0.15	0.85	0.245	0.255	0.24	0.26
Agreement cost	120	100	130	150	135		
Penalty cost	1.25	1.2	1.3	1.4	1.35		
Transport cost	0.3	0.35	0.3	0.25	0.3		
Minimum total commitment	100	120	150	130	125		
Reserved capacity	550	500	600	750	650		
Demand							
	0	905	0	0	0	0	0
	0	0	177	0	303	385	0
	0	0	0	273	0	0	0
	0	0	0	0	0	0	248
	0	914	0	0	0	0	369
Procurement cost							
	12	11.016	11.016	11.016	11.016		
	12	12.000	11.040	11.040	11.040		
	12	10.980	10.980	10.980	10.980		
	12	10.860	10.860	10.860	10.860		
	12	10.920	10.920	10.920	10.920		
Distance							
	35	350	590	450	860		
	350	30	760	470	830		
	590	760	34	340	480		
	450	470	340	41	410		
	860	830	480	410	36		
Lower limit							
	0	151	391	445	460		
	0	150	260	371	440		
	0	284	381	439	550		
	0	296	471	572	669		
	0	275	385	460	571		
Upper limit							
	150	390	444	459	1000		
	149	259	370	439	1000		
	283	380	438	549	1000		
	295	470	571	670	1000		
	274	384	459	570	1000		

APPENDIX C: Table 23: Stage, Scenario, Parent Scenario, and Probability

Data for Supply Selection Strategy Case Study

Stage	Scenario	Parent Scenario	Probability
1	1	0	1.00000
2	2	1	0.05000
2	3	1	0.10000
2	4	1	0.85000
3	5	2	0.00250
3	6	2	0.00500
3	7	2	0.01250
3	8	2	0.03000
3	9	3	0.00500
3	10	3	0.01000
3	11	3	0.02500
3	12	3	0.06000
3	13	4	0.04250
3	14	4	0.08500
3	15	4	0.21250
3	16	4	0.51000
4	17	5	0.00025
4	18	5	0.00063
4	19	5	0.00038
4	20	5	0.00075
4	21	5	0.00050
4	22	6	0.00050
4	23	6	0.00125
4	24	6	0.00075
4	25	6	0.00150
4	26	6	0.00100
4	27	7	0.00125
4	28	7	0.00313
4	29	7	0.00188
4	30	7	0.00375
4	31	7	0.00250
4	32	8	0.00300
4	33	8	0.00750
4	34	8	0.00450
4	35	8	0.00900
4	36	8	0.00600
4	37	9	0.00050

Stage	Scenario	Parent Scenario	Probability
4	38	9	0.00125
4	39	9	0.00075
4	40	9	0.00150
4	41	9	0.00100
4	42	10	0.00100
4	43	10	0.00250
4	44	10	0.00150
4	45	10	0.00300
4	46	10	0.00200
4	47	11	0.00250
4	48	11	0.00625
4	49	11	0.00375
4	50	11	0.00750
4	51	11	0.00500
4	52	12	0.00600
4	53	12	0.01500
4	54	12	0.00900
4	55	12	0.01800
4	56	12	0.01200
4	57	13	0.00425
4	58	13	0.01063
4	59	13	0.00638
4	60	13	0.01275
4	61	13	0.00850
4	62	14	0.00850
4	63	14	0.02125
4	64	14	0.01275
4	65	14	0.02550
4	66	14	0.01700
4	67	15	0.02125
4	68	15	0.05313
4	69	15	0.03188
4	70	15	0.06375
4	71	15	0.04250
4	72	16	0.05100
4	73	16	0.12750
4	74	16	0.07650
4	75	16	0.15300
4	76	16	0.10200

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