Multi-objective stochastic programming for a multi-commodity multi-modal network flow model for flood disaster relief operations

by

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DECLARATION

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MULTI-OBJECTIVE STOCHASTIC PROGRAMMING FOR A MULTI-COMMODITY MULTI-MODAL NETWORK FLOW MODEL FOR FLOOD DISASTER RELIEF OPERATIONS

I declare the above thesis is my own work and that all the sources that I have used or quoted have been acknowledged by means of complete references.

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I further declare that I have not previously submitted this work, or part of it, for examination at UNISA for another qualification or at any other higher education institution.'

………………………… February 2023 ………………………………

Signature Date

DEDICATION

To my lovely wife, Grace.

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. Abstract

The increasing and alarming occurrence of disaster caused by flooding in Nigeria has necessitated this research work. There abound publications just describing the problem and calling for urgent help to reduce the effects on the citizenry but there appear no scientific/mathematical solutions offered to tackle the rescue operations. We therefore proposed a Mathematical Programming Model for disaster rescue operations. Our work is a Multi-Objective Stochastic Programming problem that seeks to minimize:

(i) proportion of unmet demand satisfaction,

(ii) total cost, and

(iii) total shipping time.

The study has root in practical problems facing the community. An empirical illustration of 2012 flood disaster was used as a case study. We considered four type of supply depots: National centre depot (NCD), Three Local Distribution Centres (LDC) and six points of Distribution (POD). The model comprised of vehicle types (a) air – helicopters and (b) land – trucks. Three basic types of emergency supply (item (l)): food, water and medical facilities were considered as relief materials. In the process, three basic scenarios: mild, medium, and severe situations were considered with associated probabilities: 0.25, 0.5 and 0.25 respectively. The work provided an adequate and efficient, mathematical model for quick response under emergency. This model proved effective and efficient in meeting the urgent needs of the devastated citizens who were involved in the disaster. It was efficient as there was a thin line between demand and demand met. The study equally proved that a minimized cost of about $1,016,673.37 could be used to carryout rescue operations. This figure becomes very necessary for the government, research agencies and other developmental agencies for the purpose of planning.

The model by using the air and road transport modes and allowing direct and indirect transporting to the PODs saved time, resulting to many lives being saved.

Keywords: Disaster, Emergency, Fairness, Flooding, Multi-objective, Multi-modal, Network-flow, Relief operation, Stochastic Programming, Uncertainty, Vulnerable people.

List of Abbreviations

NEMA	-	Nigeria Emergency Manager Agency
FEMA	-	Federal Emergency Management Agency
WHO	-	World Health Organization
CRED	-	Center of Research on Epidemiology
NCD/NDC	-	National Center Depot /National Depot center (They were used interchangeably in the work)
LDC	-	Local Distribution Centre
POD	-	Point of Distribution
RDCs	-	Relief of Distribution Centers

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Chapter One
Introduction

1.0 Introduction: This opening chapter discusses the general background of the thesis, providing working definitions and abbreviations. An overview of disaster occurrences in some parts of the world and its impact is discussed. Our motivation, the focus of the research, working objectives and the methodology to achieve the objectives are stated. Finally, we give the structure of the thesis.

1.1: Background: Numerous major catastrophes that have recently occurred around the world have had an impact on our society's safety. Large-scale catastrophes, the majority of which have been caused by natural causes, have been a source of increasing concern. Some examples of such catastrophic events include the earthquake and tsunami that struck Japan on March 11, 2011, the earthquakes that struck Chile on February 27, Haiti on January 12, 2010, Thailand between July and December 2011, and Nigeria (flooding, June-July 2012). The Thailand floods also affected over 12.8 million people, with the World Bank estimating economic damages of over $45 billion USD (Time, 2011); the Haiti earthquake killed between 217,000 and 230,000 people and affected over three million people (Time, 2011); Japan's experience recorded over 15,842 deaths (Japanese National Police Agency, 2011) with World Bank estimating over $235 billion as economic cost (Kim, 2011; Zhang, 2011). Nigeria's flooding according to the National Emergency Management Agency (NEMA) affected 30 of the 36 states of Nigeria, 7 million people were affected in these states, 597,476 houses were destroyed, 2.3 million displaced and 363 death were reported with large track of farmland and other means of livelihood destroyed, animals and other biodiversity were also gravely impacted upon. Nigeria lost about 500,000 barrels of crude oil output per day due to the severe flooding (Amangabara et al, 2015). It has become clear that a major disaster has an impact on business around the world, not only in the nation where it occurred. For instance, the floods in Thailand had an impact on the operations of the Intel businesses there, causing them to decrease their forecast for fourth-quarter 2011 sales from $14.7 billion USD to

$13.7 billion USD. Similar events occurred in Nigeria, which lost roughly 500,000 barrels of crude oil daily, affecting their supply on the global market.

Immediate action and comparable judgments are urgently required in the event of a large-scale catastrophic disaster in order to alleviate and control the effects. Governmental and non-governmental aid organizations must issue assistance requests. Numerous nations, humanitarian agencies, and NGOs have pledged and/or delivered aid in the form of cash, medical teams, supplies, food, water, sanitation equipment, engineers, shelter, and support staff. It is the responsibility of the supply chain/organizations for humanitarian/disaster relief to gather the necessary resources, transport them to the catastrophe locations, use them, and aid the affected areas in starting the recovery process. A FEMA-proposed framework states that an emergency management program evaluates potential emergencies and disasters based on the risks posed by hazards, then develops and implements programs intended to lessen the impact of these events on the community. It also prepares for risks that cannot be eliminated and specifies the steps to take to deal with the effects of actual events and to recover from them (FEMA 2012). These humanitarian disaster relief organizations are responsible for managing the four phases of emergency activity, which are mitigation, preparedness, response, and recovery. Disaster Management Operations is the name given to this exercise.

1.2: Definition of Disaster: The terms ‘disaster’ and ‘emergency’ have been defined in various ways by various persons. However, a lot of the definitions concur that emergencies and disasters are things that produce societal unrest and have a lot of unpredictability. Extreme environmental uncertainty, according to Dynes, necessitates efficient coordination among numerous parties (Dynes, 1970). From an operational standpoint, (Jamison et al., 2012; Roland et al., 2016) defined disaster as: Primarily a social phenomenon that arises when a risk interacts with a weak community in a way that exceeds or overwhelms the community's capacity to cope. This may result in serious harm to the safety, health, welfare, property, and environment of people. It can be set off by a geophysical or biological occurrence that occurs naturally, as well as by intentional or unintentional human behavior, such as technical malfunctions, accidents, and terrorist attacks. Disaster, in the words of Van Wassenhove (2006), is ‘a disruption that physically impacts a system as a whole and undermines its priorities and goals.’ At first, the damage could be swift or gradual. Furthermore, other scholars define disaster as ***‘activities such as planning, implementing and controlling the efficient, cost-effective flow of and storage of goods and materials as well as related information, from point of consumption for the purpose of alleviating the suffering of vulnerable people’ (Thomas and Kopezak, 2005).*** ‘Any incidence that causes damage, destruction, ecological disturbance, loss of human life, human suffering, or deterioration of health services on a scale sufficient to merit an extraordinary reaction from beyond the affected community or area’ (WHO, 1989). In contrast, according to the Center for Research on the Epidemiology of Disasters (CRED), a disaster is ‘a situation or event that overwhelms local capacity, necessitating a request to national or international level for external assistance, an unforeseen and often sudden event that causes great damages, destruction, and human suffering’ (CRED, 2007). When a disaster strikes, numerous agencies and humanitarian organizations swiftly organize their resources for emergency rescue operations to save lives and lessen the crisis's effects. The right rescue organizations and level of their involvement are required due to the nature of the incident. The immediate provision of food, housing, and healthcare services is mandated, and others are tasked with cleansing the area of trash and disposing of the bodies. These organizations place equal emphasis on providing manpower and funding to the event area. Sergio et al, (2004) identified three groups or stakeholders to include:

i. Donors
ii. Beneficiaries
iii. The international community.

Humanitarian logistics is a word frequently used to describe the process of supplying and dispersing help supplies in disaster relief situations. ‘The process of planning, implementing and controlling the efficient, cost-effective flow and storage of goods and materials, as well as related information, from the point of origin to the points of consumption for the purpose of alleviating the suffering of vulnerable people,’ has been defined by Thomas and Kopezak (2005:2). Various factors make it difficult to carry out effective humanitarian logistics. Due to the ambiguity and unpredictable nature of disaster situations, humanitarian specialists must devote a lot of attention to comprehending how these environments are developing. 'Logistics plays a critical part in disaster response operations; it serves as a link between headquarters and the field, and is crucial to the effectiveness and responsiveness to major humanitarian initiatives such as health, food, shelter, water, and sanitation,' (Thomas, 2003). In order to improve the safety and wellbeing of those in need of the rescue operations, a significant number of Local, State, and Federal disaster management specialists are brought together by the relief operations. The main objective is to save lives and property while properly utilizing the available resources. Similar to the above definition, Roland et al. (2016) describe an emergency as 'a present or imminent situation that demands immediate coordination of actions concerning individuals or property to safeguard health, safety, or welfare of people or to limit harm to property or environment.' We may infer from the aforementioned definitions that disasters are instances of events that result in an emergency scenario that will prompt swift action to prevent losses in human lives and infrastructure

1.2.1 Types of Disaster

Not every disaster is an earthquake, fire, flood, or tsunami. A disaster is any incident, whether natural or man-made, that affects a community or a nation and that they are unable to resolve with their own efforts or resources, leading them to ask for outside aid and support. To qualify as a disaster, an incident must possess one or more of the following characteristics: (Stromberg, 2007 and Wong 2013).

- 10 or more life loss.
- 100 or more injuries/displacements.
- The state of emergency declaration by affected country's Government.
- The call of international aid by affected country's Government

When categorizing different sorts of catastrophes in their article, Ahmet and Hatice (2015) stated that various disasters call for various tactics in humanitarian aid operations. They further classified disaster types as;

- Rapid onset natural disasters such as earthquakes, tornados, storms and floods.
- Rapid onset man-made disasters such as terror attacks, industrial accidents.
- Slow onset man-made disasters such as starvation, famine, epidemics.
- Slow onset man-made disasters such as economic crises, refugee crises.

The majorities of sudden natural disasters is perilous and frequently call for quick action. Within a short period of time, they invariably have a terrible and detrimental impact on the community. Long-term efforts for aid and development are needed because of the slow-onset calamities. For instance, most floods are unpredicted, as was the 2012 Nigerian flood tragedy, which resulted in numerous fatalities and extensive property damage. Famine and starvation have a sluggish beginning but have a large impact, can result in many fatalities over time, and cannot harm property or infrastructure. Every relief effort must therefore be organized and carried out in accordance with the type and severity of the crisis.

1.3.0 Occurrence of Natural Disasters

1.3.1 Occurrence by Disaster Type: 2018

CRED (2018) reported the following in her executive summary: ‘In 2018, there were 315 natural catastrophe occurrences registered with 11,804 fatalities, over 68 million people affected, and US $131.7 billion in economic losses around the world. The cost was not equitably distributed because Asia had the greatest impact, accounting for 80% of fatalities, 45% of disaster events, and 75% of those impacted. In terms of overall deaths worldwide, Indonesia accounted for nearly half (47%) of them, with India reporting the greatest number of affected individuals (35%). Flooding was the second deadliest type of disaster, accounting for 24% of fatalities, behind earthquakes, which claimed 45% of all fatalities. Flooding, which accounted for 50% of all impacted people, was followed by storms, which were responsible for 28% of the total. The results are not unexpected given Asia's substantial landmass, higher population density in comparison to other continents, and numerous risk factors for hazards.

More people have been impacted by floods than any other calamity in the twenty-first century, including 2018 (127 events). Over 504 people died in India's Kerala State's worst flood of the year, which also affected two-thirds of the state's population (over 23 million people). Nearly two million people were affected by flooding in Nigeria, which claimed 300 fatalities, and the deadliest floods in Japan since 1982, which claimed 230 lives. Take a look at figures (1), (2), (3), and (4): In contrast to the previous ten years (2008–2017), in 2018 there were fewer disasters than the average annual total of 348 events, fewer fatalities than the average annual total of 67572, fewer people affected than the average annual total of 198.8 million, and lower economic losses than the average annual total of $166.7 billion. The increase in humanitarian logistical efforts is partly to blame for this decline. However, natural disaster is still having large consequences on the global world.

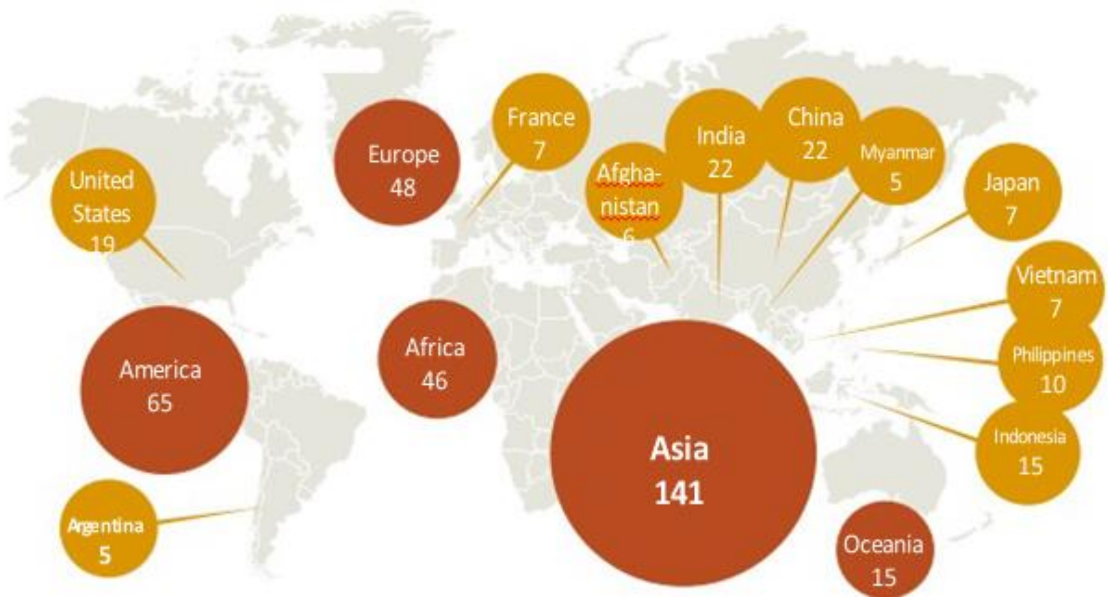

Figure 1: Occurrence by Disaster type: 2018 (Number of disasters by continent) compared to 2008 – 2017

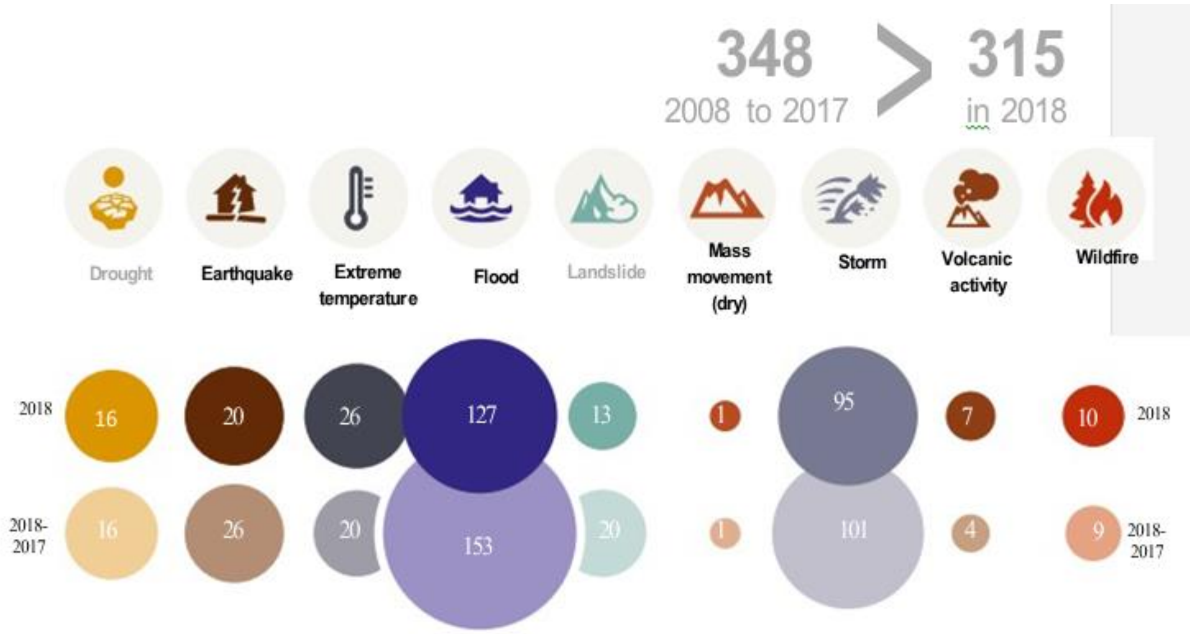

Figure 2: Number of deaths by disaster type: 2018 (deaths in %) compared to 2008 – 2017.

Figure 3: Number of affected (million) by disaster type: 2018 (in %) compared to 2008 – 2017.

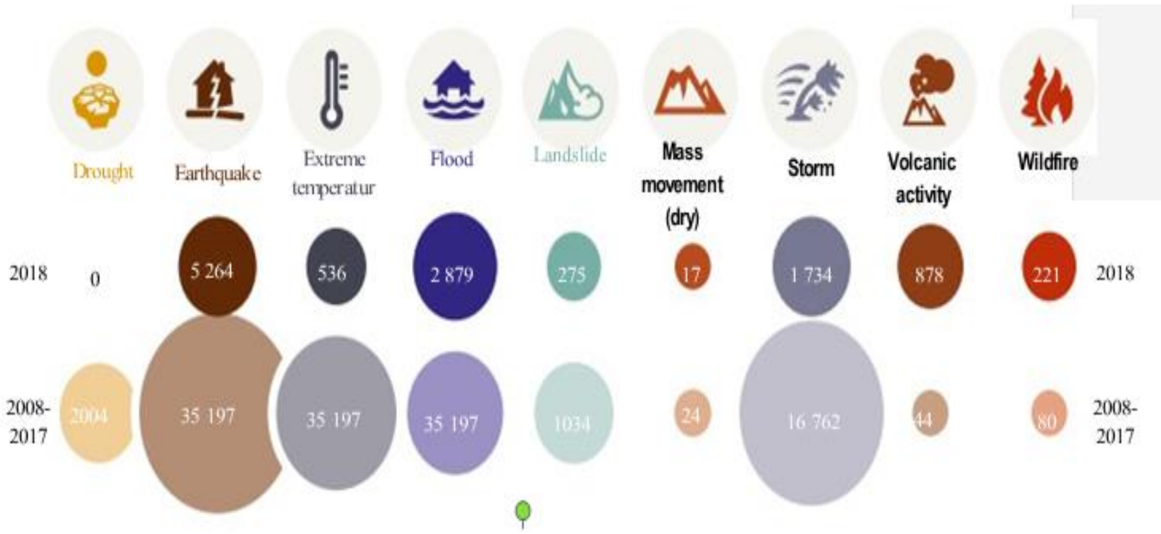

Figure 4: Economic losses (billion US$) by disaster type: 2018 compared to 2008 – 2017.

Table 1: Top 5 Mortality

Indonesia	Earthquake / Tsunami	4 340
Indonesia	Earthquake	564
India	Flood	504
Indonesia	Volcano / Tsunami	453
Guatemala	Volcano	425

Figure 6: Number of affected (million) by disaster type: 2018 compared to 2008-2017 annual average

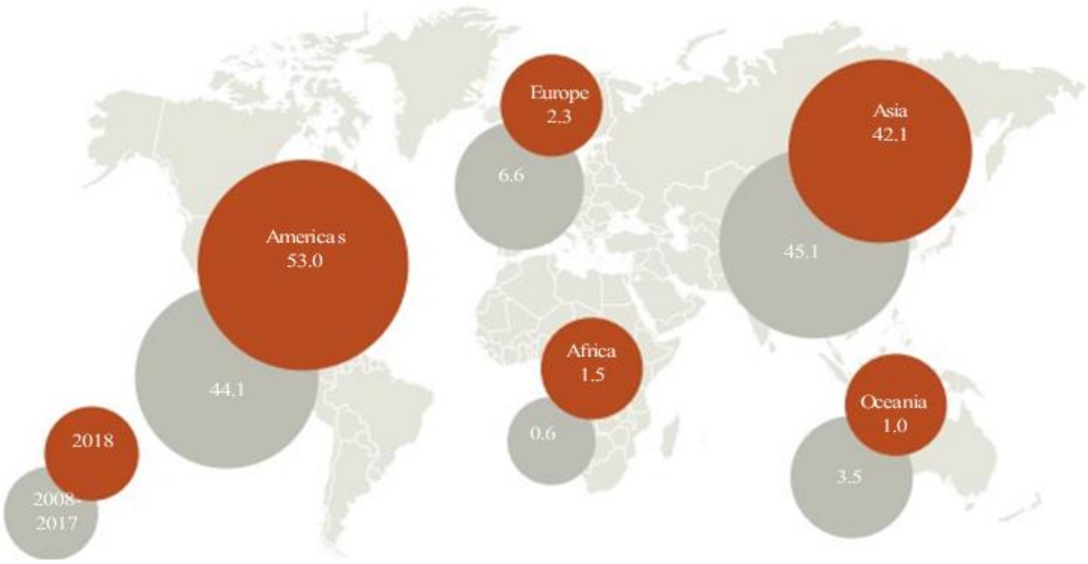

Figure 7: share of Economic losses (%) by continent

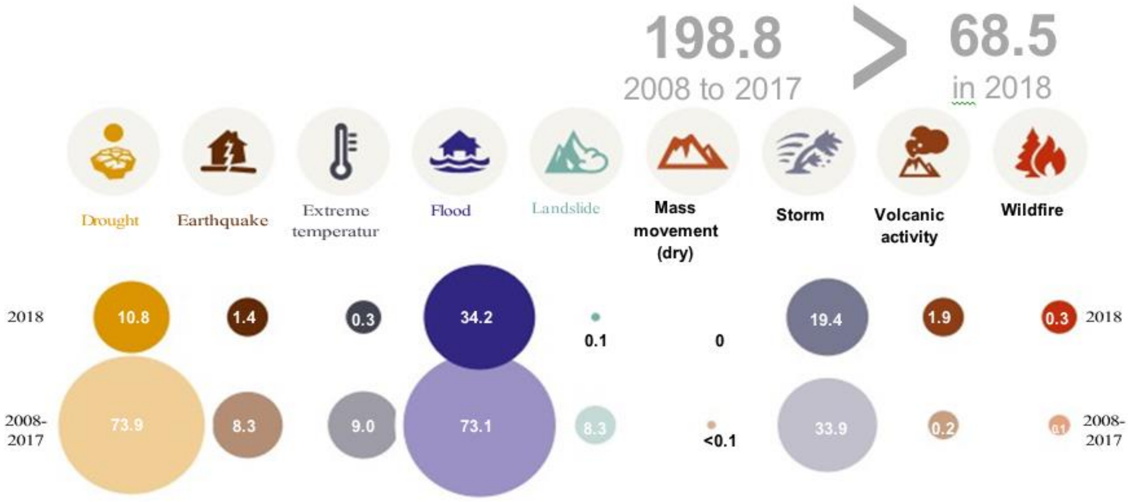

Figure 8: 2008 to 2017 losses compared with 2018

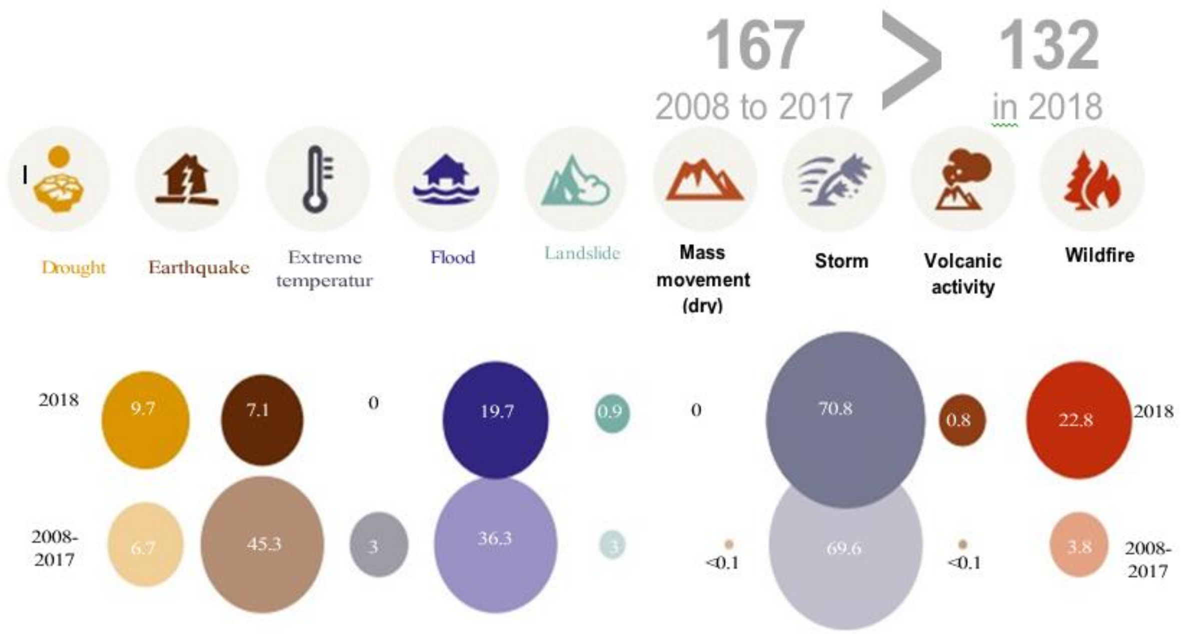

Figure 9: Economic losses (billion US$) by disaster type: 2018 compared to 2008-2017 annual average .

Table 3: Top economic losses

USA	Wildfire	**16.5 billion**
USA	Hurricane Michael	**16 billion**
USA	Hurricane Florence	**14 billion**
Japan	Typhoon Jebi	**12.5 billion**
Japan	Flood	**9.5 billion**

1.3.2 Global Deaths from Natural Disasters (1900 to 2019)

We may see that between 1920 and 1960 (Figure 9) there were between 500,000 and 35 million deaths attributed to natural disasters. We might observe a reduction to less than 100,000 in the second half of the 20th century and into the early 2000s (at least 5 times lower than the peaks). When we consider the rate of population growth over time, this drop is more striking (Figure 9).

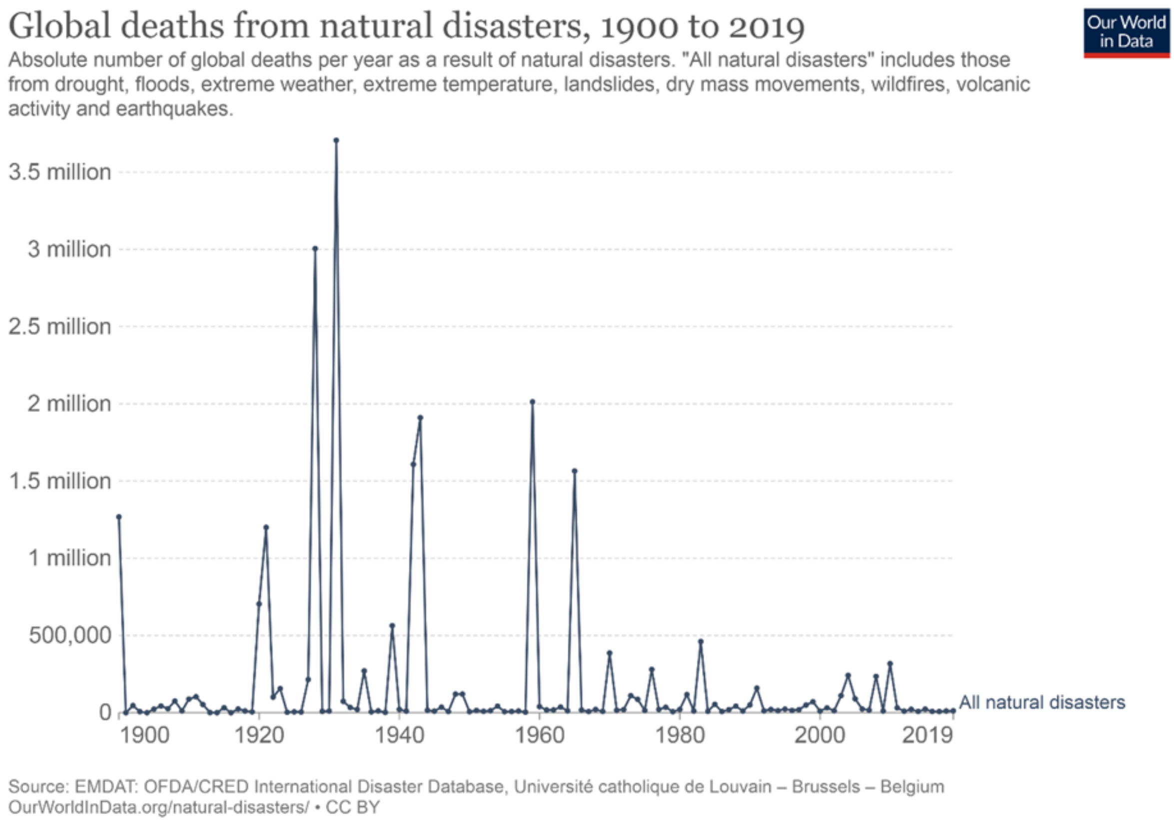

Fig. 10: Global Death from Disasters 1900 – 2019

1.3.3: Global Disaster Costs

Natural disasters create tremendous destruction with associated financial expenses in addition to their catastrophic effects on human life loss. Rising expenses are evident when the global economic cost is measured over time in absolute terms. Global gross domestic products have expanded more than fourfold since 1970, even as wealthier nations around the world. Therefore, we anticipate that the absolute economic consequences for any given calamity may be higher than in the past.

Disaster-hit nations reported direct economic losses totaling US $2,908 billion from 1998 to 2017, with climate-related disasters accounting for US $2,245 billion, or 77 percent, of the total. This is an increase from the $1,313 billion in losses, or 88 percent, that were reported between 1978 and 1997.

The USA experienced the most losses over the past 20 years in terms of absolute dollars ($945 billion), which is indicative of high asset prices. The World Bank estimates that disasters drive 26 million people into poverty each year, with the true cost to the world economy estimated to be a staggering $520 billion USD annually. The relative larger impact of calamity on the poor is also hidden by absolute losses. When economic expenses are stated as an average percentage of GDP, the amount increases significantly (GDP). Geo referencing has shown that for disasters since 2000, low - income countries saw an average of 130 fatalities per million residents in disaster-affected areas, compared to just 18 in high income countries. This implies that people exposed to natural hazards in the poorest nations were more than seven times, more likely to die than equivalent population in the richest nations.

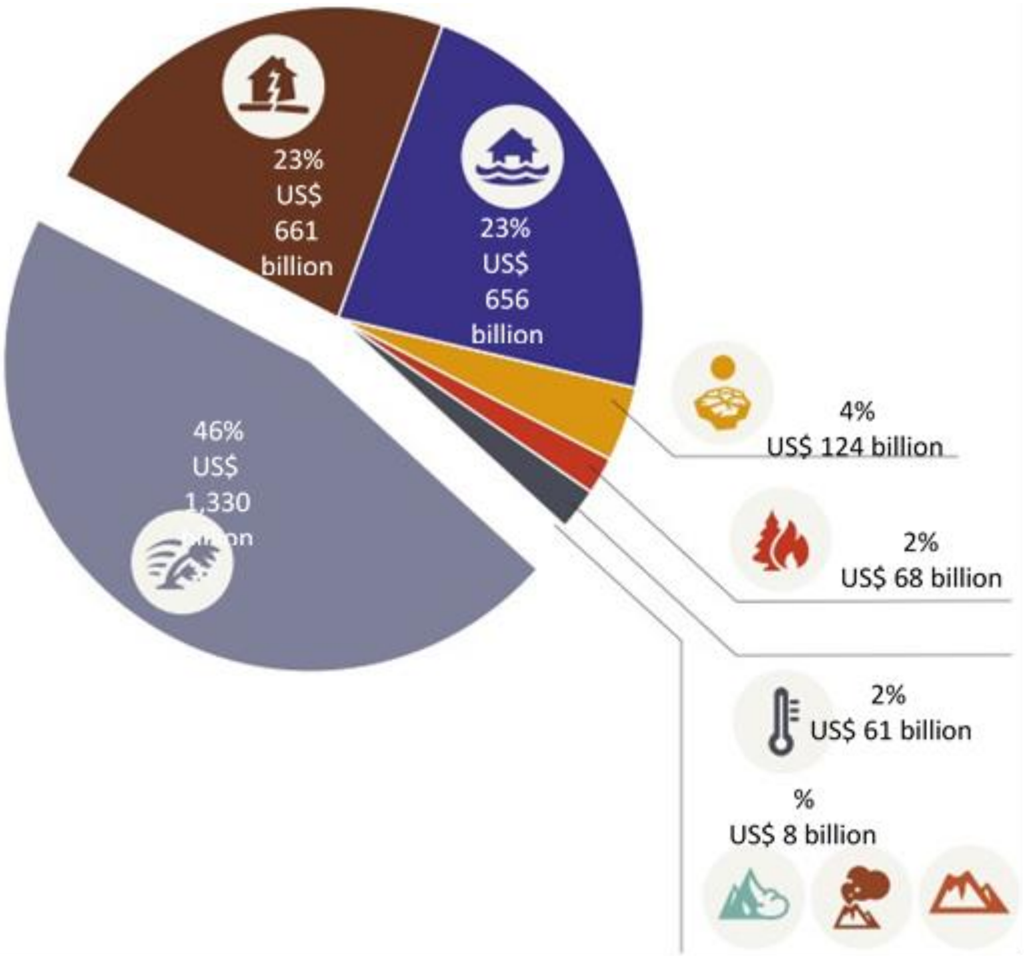

Fig. 11: Breakdown of Recorded Economic Losses Per Disaster Type 1998 – 20

This number demonstrated that over the course of 20 years, storm losses were US $1,300 billion (46%) and were by far the most expensive type of disaster. According to the graph, earthquakes and flooding each accounted for 23% of all natural disasters (6). All of them demonstrate the expanding demand for humanitarian logistics.

1.4. The Overview of Flood Response.

Flood disaster response plan is design to include maintaining and locating/allocating relief materials, budgets and human resources in a define place in advance. Tufekci and Wallace (1998) suggested that disaster response has this stages: the pre-disaster and post-disaster response period. They are predetermined location for preserving and allocating relief supplies, funds, and human resources is part of the flood disaster response strategy. Pre-disaster and post-disaster response periods were proposed by Tufekci and Wallace (1998) as stages in the disaster response process. They emphasized that establishing the necessary steps for mitigation during the pre-disaster stage entails anticipating and analyzing probable threats.

While the tragedy is still on-going, the post-disaster action begins. During this time, available resources will be located, allocated, coordinated, and managed. The activities taken prior to a disaster have a significant impact on how well the post-disaster response is carried out.

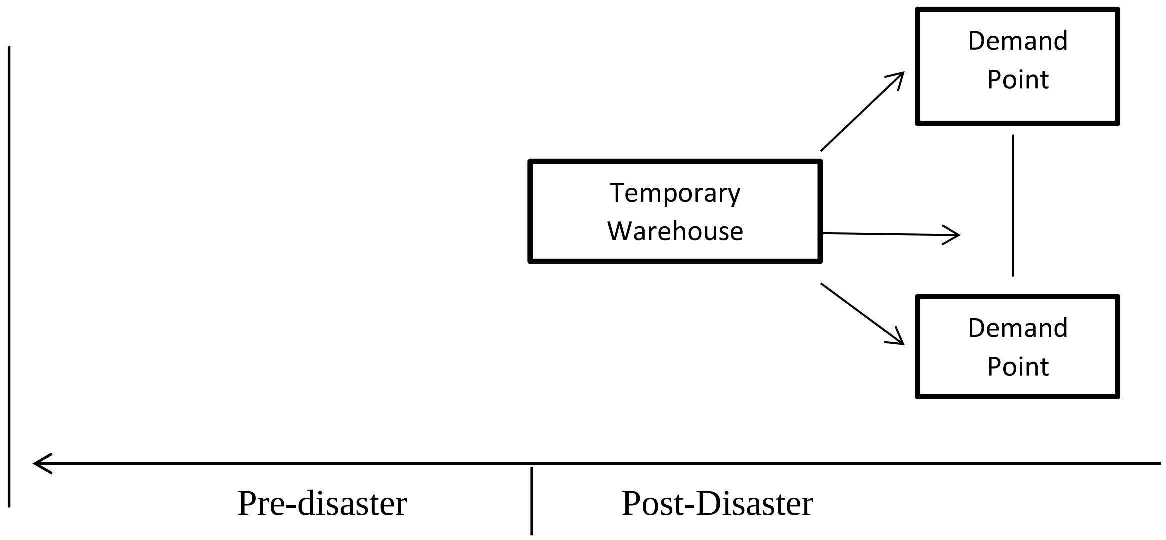

Figure 12: General approach of humanitarian logistics.

It is generally accepted that pre-disaster activities for distributing aid are neglected. According to Santosh (2020), the majority of rescue organizations conduct their disaster rescue operations using a reactive strategy rather than a proactive one. Rescue efforts become untimely as a result. Additionally, it has been noted that the phases of disaster rescue activities do not make sufficient use of the funds provided for disaster management. Most frequently, money is either misappropriated or embezzled during the preparation and mitigation phases.

The demand for flood-related emergency supplies explicitly includes a stochastic variable whose magnitude is proportional to the flood intensity.

The likelihood of a flood disaster is based on the fact that it could happen at any time. Both scholars and practitioners recommend this strategy. Many governmental organizations use this strategy (see Standards-Australia and Standards-New-Zealand, 2004; Marek, 2011; UK-Environment-Agency, 2009).

1.4.1: Some Characteristics of a flood

1.4.1.1 The size and cost of a flood

According to Feng and Luo (2010) 'the intensity of a flood can be defined as a quantitative index explaining the losses produced by the associated tragedy, while the magnitude of a flood may be defined as a quantitative index indicating the scale of a flood'. In order to calculate the social cost of a flood, which is compounded by two different types of impacts: direct and indirect, it should be emphasized that the two indices are essential. The immediate effects of flooding show the direct economic loss resulting from ruined infrastructure (such as bridge collapses and broken embankments, among other things), as well as human casualties from drowning. Several possible indirect impacts are utilities outages, cultivation postponement, productions shutdown, among others.

1.4.1.2 The emergency supplies after a flood

Fresh water, non-perishable food, flashlights, batteries, battery-operated radios, first aid kits, prescriptions, syringes, multipurpose tools, sanitation and personal hygiene products, among other things, are the main supplies after a flood, according to the American Red Cross (Red-Cross, 2014). The necessary demand must be met. Demand is high because floods are unpredictable and have a high level of stochasticity. The only option available to decision-makers after an incident is to solve an optimal assignment issue using the facilities and inventory levels that are now available. The attempts to arrange relief supplies before the occurrence of a flood disaster heavily influence the success of the movements.

1.4.2 System agents

Considering the characteristics of flood, the following agents would be helpful in emergency logistics system.

1.4.2.1: Product suppliers

The agents are willing to offer relief materials to potential demand points. If a flood occurs, some of the products will be moved from stocked zone or will be supplied for an amount to the demand point at a minimal cost flow program recommends.

1.4.2.2: Transportation providers

The transporters provide services to deliver the items through various modes to the demand points. They are placed in a zone and then transported, in accordance with the planned network, to the desired location. The transportation fees are calculated based on the amount of freight and the distance travelled, and they vary accordingly. It should be noted that following a flood, the road system is disrupted; a specific mode is required for a certain access road. The majority of the time, a compatibility matrix is established to limit the permitted vehicle-product pairings and to show the routes that are crossable. Each element of this matrix will be assigned value 1 if a given product can be transported by a certain type of vehicle or a particular road is transversible. If it is not, the value 0 will be assigned to it.

1.4.2.3: Demand points (or point of Distribution-POD)

This is a reference to the region of the world where the event occurred. Demands are required in this area of the afflicted people. It is the location where resources for rescue are uploaded. The amount of lives that are saved will depend on how well and quickly the rescue and relief goods are delivered to this location.

The rising frequency of natural disasters and their terrible impact on humanity have reached an alarming level, as can be seen from the previous sections. According to the IRFC (2006), 'When a disaster strikes, the correct commodities and people must be supplied to the right area, at the right time, and in the right number.' In order to accomplish the desired aims, Thomas (2003) and Van-Wassenhove (2006) noted that the effectiveness of the movement of people and products determines the success or failure of any humanitarian efforts. According to Mcguire (2003), the contribution of resources has consistently fallen short of the necessary level, forcing humanitarian groups to manage and make the most use of the resources at their disposal. The business sector has placed a strong emphasis on cost effectiveness, which is attained via making improvements to supply chains. It is odd, argues Thomas (2003), that a sector with such strict criteria for timeliness, affordability, and accountability be so underdeveloped. In fact, this contradiction has opened up a lot of possibilities for both this field's study and humanitarian efforts.

It is extremely difficult, if not impossible, to anticipate with any meaningful degree of precision the timing and location of occurrences (Christopher and Tathan, 2011). The scales of events shortly following a calamity also follow this pattern. The type of demand, the capacity of the facilities to be employed in the distribution process, and the transportation are all unclear. In order to avoid lives from being lost, decision-makers must also make these decisions as soon as feasible after a tragedy, according to Altay and Green III (2006) and Luis Torre et al (2012). They believe that one major risk of making decisions based on incomplete information is the risk of making crucial decisions that cannot be changed. The significant loss of infrastructure and the communication network, particularly the transportation system, is another difficult element in the event of a disaster. Distribution channels between supply centers and the impacted areas are greatly impacted by this. Accordingly, the goal of this research is to provide a decision-making tool for usage in catastrophic occurrences that takes stochastic factors into account. In order to make decisions when there is little information available and reduce the possibility of coming up with unworkable ideas, randomness is taken into consideration.

It is apparent that most nations throughout the world do not currently have flood preparation planning instruments in place. The goal of this effort is to create a decision-making model that might be applied to reduce the complexity of disasters. With the aim of obtaining optimum performance, which will maximize the number of lives saved by limiting the unfulfilled satisfaction and similarly minimizing cost, we want to put into play real issues of emergency logistics and existing methods or organizational structure.

The use of mathematical programming as a strategy to address the issue of uncertainty has become commonplace. One of such tool is the stochastic programming (SP) with recourse. The recent contribution of Adejuwon and Aina (2014), shows that flooding has largely affected most cities in Nigeria. It has got devastating effects on properties, built environments, near developed and under develop plans. Many people have lost their lives as a result of flooding. There is therefore urgent need to plan for a more scientific and mathematical techniques to handle this needful problems. To our knowledge such model is not on ground to address this urgent flood situation that has constantly affected the country in recent years.

1.5 P-Center Model

The P-center model defines a minimax solution comprising a set of P points with the objective of minimizing the maximum distance between a demand point and the closest point within the set (Springer.com, 2020). The challenge posed by the P-center problem involves determining the optimal placement of P facilities on a network to minimize the greatest distance between a demand point and its nearest facility.

1.6 P-Median Model

The P-median model is a specialized form of discrete location modeling. Within this model, the goal is to strategically position P facilities to minimize the average distance (weighed by demand) between a demand node and the location where a facility is situated. This approach approximates the total delivery cost.

1.7 NP-Hard Problems

A problem is categorized as NP-hard if its solving algorithm can be transformed into a solution algorithm for any NP-problem (nondeterministic polynomial time problem). If an algorithm can be adapted from an NP-hard problem to solve an NP problem, it is referred to as an NP-hard problem. This classification implies that NP-hard problems are more challenging than any problem within the class NP. Such problems often necessitate the application of advanced solvers to derive solutions. Frequently, challenges involving tasks like determining the minimum distance or finding the optimal route fall under the category of NP-hard problems

1.8 Backlogged Demand

Backlogged demand refers to the accumulation of unfulfilled or pending demands within a specific timeframe. This phenomenon significantly affects an organization's future planning and operations. It indicates an insufficiency in meeting demand requirements. The existence of backlogged demand can lead to adverse consequences for the given scenario.

1.9 Uncertainty

The exploration of uncertainty and randomness has garnered significant attention among researchers, particularly in the realm of natural disasters. Numerous factors influence the decision-making strategies of local agents, often narrowing down the viable alternatives. In the context of humanitarian logistics during disasters, uncertainty prevails with uncertain demand, unpredictable availability of medical personnel, and uncertain infrastructure conditions. Unforeseen demand patterns escalate the intricacy of distribution planning (Blacik et al., 2008). Beneficiaries may migrate across various regions in search of greater aid, and unforeseen challenges such as disease outbreaks can complicate relief efforts (de la Torre et al., 2012). Furthermore, newly acquired information about infrastructure damage necessitates the recalibration of vehicle schedules and movement plans.

1.10 Motivation and focus of research

The Figure 1-6, earlier discussed reveals the urgent needs for humanitarian logistics. Besides, other challenges that further highlight the importance of humanitarian logistics include:

i. Donors pressure: referring to the high expectation of philanthropic organizations who expert to see the use of the donated relief materials to saving the life of the affected persons. Their morals and affection is killed when such materials are not utilized for the purpose. Hence, decline future support.

ii. Social responsibility: here we mean the ethics of relief material distribution and the necessity of aid organizations to deliver quality relief to the victims.

iii. Inadequate relief resources at peak time: this speaks of the shortage of relief materials at the critical time when such materials are needed. Adequate and effective preparation strategy will avert such shortage at peak time.

Olunloyo (2020) stated: ‘Disasters in Nigeria are not very well managed. A methodology for lowering Disaster Response time, life causalities, and cost must be developed. If there was a system in place for handling calamities, many lives and properties would be saved. Disaster preparedness in the nation will be aided by a predesigned model that is adaptable enough to combine logistics and communications among all important stakeholders while lowering response time.

1.11 Objective of Study

The relief goods are among the most crucial and significant items used in disaster response operations. Humanitarian groups invest a considerable sum of money in the logistics of relief distribution, but sadly there is still a significant distance between the location of the tragedy and the victims who require the resources. In order to achieve optimum performance, which will ultimately increase the number of lives saved by reducing risk, the study's goal is to put existing techniques and realistic emergency logistics challenges into action.

i. The unmet satisfaction
ii. The cost of executing rescue operations, and
iii. Time spent for the operation

In our concept, the affected residents of the destroyed towns serve as the customers while the government, humanitarian organizations, and private sectors serve as the suppliers of the necessary goods. Materials are prepositioned at the warehouses designated as National Centre Depot (NCD) before being dispersed to the Point of Distribution (POD). The Local Distribution Centre (LDC) serves as the point in between.

According to Tufekci and Wallace (1998), if pre- and post-disaster stages are not included in an emergency response strategy's operational purpose, it could result in a less-than-ideal solution to the entire issue. With this in mind, we incorporate pre- and post-disaster steps to address uncertainty, particularly with inventory difficulties. As was previously indicated, organizations providing humanitarian relief are lacking in resources at a crucial time. Therefore, careful planning is necessary to reach the best outcome for the humanitarian organization.

We observe that different materials should be supplied to those living in disaster-affected areas after a calamity. Food, medical supplies, water, tents, blankets, and other supplies for relief are examples of these materials. In the case of a crisis, these supplies should be easily accessible. They should be pre-positioned in secure locations at the NCDs so that the procurement time is nil and distribution starts as soon as a disaster strikes. According to this concept, the prepositioned materials can either be slid directly to the PODs in the impacted area or indirectly through LDCs. Prior to the crisis, it is not entirely clear how long and how much it will cost to travel between NCDs, LDCs, and PODs, as well as how much demand there would be. The more prepositioning materials we have, the better able we are to meet the difficult demand requirements. The holding cost will, however, inevitably go up as a result. There's a chance that not all of the prepositional materials will work (or some will fail the expiring date policy). The LDCs' capacities are probabilistic and scenario-based.

1.12 Methodology

The study is based on actual issues that the community is currently facing. It develops a mathematical model that is intended to circumvent the bottlenecks present in real-world issues. While creating the essential empirical base through literature reviews and web reporting, it makes use of a mathematical programming tool (operation research).

As a case study, an empirical example of the 2012 Delta State flood tragedy in Nigeria was employed. The following towns and communities were taken into account in the case study as our NCDs, LDCs, and PODs.

Table 4: Case study Towns/communities

NCDs	**LDSs**	**PODs**
Asaba Warri Ughelli Agbor	Urhobo	Sapele Abraka
	Ukwauani	Kwale Aboh
	Isoko	Emevon Uzere

Because of the inherent randomness in the problems, they are not linear. It is significant that commercial software solutions exist for these non-linear issues. Therefore, LINGO Software has been used to overcome the optimization issues.

1.13 Thesis Structure

As can be seen in the graphic below, this thesis is broken up into six chapters. The opening chapter comes first. In the second chapter, a review of the literature is given. The theoretical underpinnings of the mathematical models are examined in this chapter along with the most recent response tactics. It highlights the work being done in this area and also highlights the tasks that must be completed to address the issues facing humanitarian organizations. The model formulation is covered in chapter three. By articulating the objectives and related restrictions, it provides the mathematical models. It also demonstrated the connection between the pre- and post-disaster responsibilities. After the massive flood disaster in 2012, the model is illustrated in Chapter 4 using data from Delta State. The results are presented in chapter five. The Conclusion and Recommendation are included in Chapter 6.

1.14 Chapter Summary

The general introduction of the thesis has shown that flood is a major disaster in Nigeria and in the world at large. It has resulted to many loss of lives and properties. In it, we have started our working objectives as minimizing: the unmet satisfaction, the cost of executing rescue operations and time spent for the operation. No doubt, some work have been done in this areas, we shall in the next chapter consider the previous work done by experts in this field.

Chapter Two
Review of Literature

2.0 Background introduction

Humanitarian help and disaster relief are now being studied by academics in an unusual way. With new researchers focusing on emergency logistics based on flood disasters and relief activities, emergency logistics is being studied more and more. We review articles that focus on disaster relief logistics and the uncertainty that can arise during rescue efforts. According to Ozdamar et al (2004), disaster logistics planning should include the efficient shipping of supplies (medical supplies, tents, clothing, rescue tools, specialized equipment, etc.) to the affected areas as soon as possible in order to speed up relief activities.

2.1 Disaster events

We understand that not all hazards are classified as disasters; some hazards are because of their effects. Risks are hypothetical physical events, natural phenomena, or human behaviors that have the potential to hurt a community or harm infrastructure. According to Cambridge Dictionary (2008), a hazard is any threat to health or safety (probabilities of event to produce harm or create damage).

When vulnerabilities and risks come together, an extreme event or disaster emerges, which, if it exceeds a community's capacity to respond, causes loss of life and property. Natural disasters are caused by changes in the biological or geographical environment; man-made disasters are caused by human error or action. According to CRED (2009), extreme events are unpredictable outcomes from natural or man-made risks that could cause harm and have a significant impact on populations.

Simply described, a disaster event is an impending catastrophe or an extraordinary occurrence that encourages coordinated action among individuals and groups to safeguard lives and/or property, hence minimizing casualties and/or damages. It entails action and potential collaboration or initiatives for risk mitigation (in the event of an impending disaster) or impact reduction (for present disasters).

2.2 Disaster Management

Disaster management is growing in importance due to degradation. This is because an increasing number of natural disasters are destroying lives and property every day. Two recent examples are the Durban (South Africa) flood disaster (Reliefweb: 2022) and the devastating earthquake in Turkiye/Syria (Reliefweb: February 2023). Disaster management attempts to lessen the damage caused by disasters, according to Isik et al. (2012). Stating that 'all procedures in damage reduction, readiness, reaction, and first aid, as well as the restoration and restructuring process, are planned and coordinated under the heading of disaster management.' According to Gogen (2004), Schulz (2008), and Koseoglu (2011), disaster planning, resource assessment, need analysis, and scenario building are all necessary components of disaster management. They also noted that disaster management must reduce financial, physical, and human losses while also lessening suffering in the immediate area and speeding up the rehabilitation process. They pointed out that the most significant and significant components of disaster management are logistics techniques. Security, communication, psychological support, sheltering, water-sanitation, transportation, food, and health modules are the cornerstones of emergency action plans, according to Isik et al. (2012). The interaction of these components must be communicated for disaster management to be effective. These modules' priorities alter in response to disasters. Each module has its own set of requirements.

2.2.1 Disaster Logistics/Humanitarian Aids

Humanitarian aid and catastrophe logistics are complementary ideas that are also somewhat intertwined. Logistics techniques are used in every aspect of humanitarian aid operations. Humanitarian aid is voluntary financial and human assistance, and the effectiveness of such assistance is dependent on the political and military environments of the donors and the receiving nations. The priorities of the donors and the ground-level coordination plans have an impact on the humanitarian relief operations, Oloruntoba and Gray (2006). The promptness with which relief supplies are delivered to the area where they are needed, as well as the provision of the appropriate individuals with the proper quantity and kind of supplies, determine the effectiveness and efficiency of humanitarian aid operations. Efficiency and cost are crucial factors in this process, along with preparation, procurement, transportation, tracing, storing, inventory management, and customs clearance, according to the United Nations Disaster Response and Coordination Team (2006). They also pointed out that government and non-government entities must work together to coordinate catastrophe logistics. Due to potential road and other infrastructure limitations, logistics delays, and political impediments, this operation requires many transportation options.

2.2.2 Stages of Disaster Logistics/Humanitarian Emergency Logistics

Humanitarian aid operations undertake their disaster logistics and emergency logistics tasks in four stages. Take a look at the image below (Figure 9).

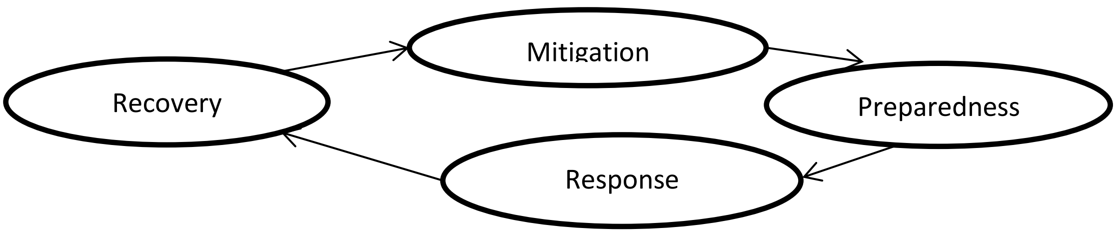

Figure 13: Stages of Disaster Logistics

2.2.2.1 Mitigation: This is defined as 'Taking consistent steps to minimize or eliminate dangers and their impacts' long-term risk to persons and property' (FEMA, 2012). The endeavor to limit the impact of disasters in order to reduce loss of life and property; taking action now (before the next disaster) in order to lessen the human and financial implications later (analyzing risk, reducing risk, insuring against risk). In order to reduce the rising costs of disaster in recent years, continuous action is now required. Worries are growing over the long-term risk that hazards and the aftermath of disaster provide to people and property. Mitigation is the term for this persistent action. It is regarded as the first stage of a catastrophe operation, which emergency management categorizes as an occurrence prior to a disaster or emergency. Additionally, it is thought that mitigation is a continual process that ought to be included in other emergency management stages. The major objectives of mitigation ought to be.

- To protect people and structures.
- The events that occur within the community.
- To reduce the cost of response and recovery.
- Mitigation activities when combined with hazard analysis helps identify.
- Possible occurrence of an event.
- Impact of causalities, destruction, disruption to vital services and possible cost of recovery.

Therefore, it is advised that local and state governments create various mitigation measures and put them into place to control potential calamities.

2.2.2.2 Preparedness: ‘Building the emergency to, and recovering from, any hazard’ is meant by this (FEMA, 2012). Sometimes it is impossible to eliminate every risk that could endanger life or property. As a result, preparedness strategies are developed to lessen the potential effects of any hazards by taking some action before an emergency arises. The term ‘preparedness’ can refer to a variety of plans or other activities taken to protect people and property while also facilitating response and recovery efforts. All parties involved in this phase are involved, including local, state, federal, and non-governmental organizations, and private donors. FEMA (2012), had summarized that activities in this phase may include:

- Developing an Emergency Operations Plan (EOP) that handles identified hazards, risks and response measures.
- Designating facilities for emergency use.
- Identifying resources and supplies that may be required in an emergency.

IFRCRCS (2002) on their part, had propose three objective programs at this stage to include:

- To increase efficiency, effectiveness and impact of disaster response by developing regular training, system's testing and establishing clear policies.
- To strength community preparedness by supporting local population through national programs.
- To develop activities addressing everyday risk faced by communities.

2.2.2.3 Response Phase: This is the procedure for setting up emergency operations to save lives and property by taking action to reduce the risk to bearable levels (or eliminate it completely), evacuating potential victims, giving aid to those in need, resuming essential public services, and providing food, water, shelter, and medical care. Response is the umbrella term for all actions made to preserve life, and it starts as soon as a disaster is obvious or occurs. This stage involves a variety of tasks.

- Providing emergency assistance to victims.
- Restoring critical infrastructure.
- Ensuring continuity of critical service.

Protecting its citizens comes priority to local government. When there is an emergency, the local government's authority should assess the situation and then take immediate action to protect lives and property. A timely and coordinated assessment helps the local government to:

- Prioritize activities.
- Allocate scarce resources appropriately.
- Request further assistance from other aid partners or from state.

It is obvious that accurate information from timely assessment reveals more information about:

- Lifesaving needs such as evacuation, search and rescue.
- States of the infrastructure, nature of road and required mode of communication, transportation and utilities.
- The needed medical facilities, fire services.
- Like hazards and imminent risk.
- Report of people who have been displaced.

2.2.2.4 Recovery: This is described as ‘rebuilding communities so that people can live as their own, return to regular lives, and protect against future threats’ (FEMA 2012). According to Sullivan (2003), recovery entails actions performed right after the initial response that enable affected communities to become self-sufficient and eliminate the need for outside support systems and resources.

The community's return to normal operations is the main goal of this phase. This process starts right away once the event occurs. It is necessary to reconstruct housing, community facilities, and the economy. Although it is true that the local government handles the initial emergency, the state and the federal governments should also be properly informed. They should also provide individuals and families with assistance that is efficient and readily available for temporary housing, repairs, replacement of possessions, and medical needs. The community and its leadership must rebuild as soon as the short-term recovery is finished, which includes getting the roads opened, debts paid off, supplies and shelters secured, communication channels opened, water and power restored, life safety, and other basic services restored. After that, the long-term recovery begins, which could take several months or years. This is due to the fact that it calls for a thorough rehabilitation of local companies, public facilities, and the economy. The federal government and other agencies should be contacted for financial and other support, and a presidential disaster declaration should be sought out due to the significant engagement in this phase. Additionally, it is crucial to consider ways to minimize future disaster damage.

The emergency disaster operations method teaches us how to effectively plan for, respond to, and mitigate any unforeseen circumstances in order to save lives and property. Performing the tasks repeatedly throughout a cycle creates improvement opportunities.

Table 2.1: Mitigation vs Preparedness

Mitigation	**Preparedness**
Zoning and land use controls to prevent occupation of high hazard areas	Recruiting personnel for the emergency services and for community volunteer groups
Barrier construction to deflect disaster forces	Emergency planning
Active preventive measures to control developing situations	Development of mutual aid agreements and memorandums of understanding
Development of codes to enhance resistance of structures during disaster.	Training for both response personnel and concerned citizens
Tax incentives or disincentives	Threat based public education
Controls on rebuilding after events	Making budget for vehicles and equipment and obtaining same
Risk analysis to measure the potential for extreme hazards	Maintaining emergency supplies
Insurance to reduce the financial impact of disaster	Building of an emergency center for operations.
	Establishment of communication systems.
	Carrying out disaster training exercises for their capabilities.

Table 2.2: Response vs Recovery

Response	**Recovery**
Activating the plan foe emergency operations	Disaster debris clean up
Activating the operation center for emergency take off,	Providing financial help to individuals and governments.
Evacuation of threatened populations	Reconstructing roads, bridges and important facilities.
Opening of shelters and provision of general care.	Sustained mass care for the animals and human beings that were displaced
Emergency rescue and medical care	Reburial of displaced human remains
Fire fighting	Full restoration of lifeline services
Urban search and rescue	Mental health and pastoral care
Emergency infrastructure protection and recovery of lifeline services	
Fatality management	

2.3 Importance of Humanitarian Logistics

As was indicated in earlier parts, humanitarian logistics is concerned with the procedures and systems used to mobilize personnel, materials, expertise, and knowledge to assist vulnerable individuals affected by natural disasters and other urgent situations (Meshach et al, 2018; Japheth, 2018; Omvir, 2017 and Yiping et al 2012). Transportation, procumbent monitoring and tracing, customs clearance, warehouse management, and last-mile delivery are some of the tasks it involves. The secret to successful catastrophe operations is humanitarian logistics.

- It serves as a bridge and uniting force between disaster preparedness and disaster response, between procurement and distribution, and between headquarters and the field.

- It is the pivot of disaster effectiveness and fastness of response in any large-scale humanitarian rescue activities.
- Because it makes it easier to collect and trace disaster-related actions in a systematic, directional manner, it gives data that can be examined to offer post-event learning. Analysis of the price, timeliness, or shortage of catastrophe operations is now possible.

2.4 Humanitarian Organizations and their Missions

Our nation and the rest of the globe are gravely concerned about the rising number of fatalities, injuries, and displaced people. Every year, almost five million people are temporarily displaced as a result of national disasters alone, which include things like earthquakes, famines, and floods. The terrorist organization Boko haram in Nigeria reports that over 20,000 individuals are displaced each year. As a result, the activity of disaster relief organizations has increased. These organizations occasionally collaborate with governments to establish refugee camps. Humanitarian organizations serve as the global community's first line of defense in providing aid to those impacted by both simple and complicated situations.

The main goal of humanitarian organizations (non-profit and non-governmental organizations) is to reduce fatalities and the government distributes relief supplies through routes that have those qualities and lessen the suffering of the populace. Several of these humanitarian groups include World Health Organizations (WHO).

- United Nations High Commissioner for Refugees (UNHCR).
- International Federation of Red Cross (IFRC).
- Red Cross Society of Nigeria (RCSN).
- Non-Governmental Organizations (NGO).
- Federal Emergency Management Agency (FEMA).
- National Emergency Management Agency (NEMA).

In the early aftermath of a natural disaster or man-made disaster, humanitarian groups are engaged in providing relief material to the point of demand, such as food, shelter, medication, clothing, and services. (Refer to figures 10 and 11)
a photo of the delivery of relief supplies

Figure 14: Food for the flood displace person

Figure 15: Camp for the flood displaced person

2.5 Flood Vulnerability of Niger-Delta States

About 12% of the entire surface area of Nigeria is made up by the Niger-Delta. It is in southern Nigeria, from the border between Nigeria and Cameroon in the east to Ondo state in the west. Enugu, Ebonyi, Anambra, Kogi, and Ekiti States comprise the region's northern border, and the Atlantic Ocean serves as its southern border. In 2015, there were about 48 million people living there (Amanagabara et al, 2015).

Over 90% of the water in the Niger-Benin River System and 100% of the water from streams rising in the Delta Region are received by the Niger-Delta. This geography makes the area extremely susceptible to flooding. In their research (Amanagabara et al., 2015), they demonstrated that 2,148 communities are at risk of flooding along 580 rivers in the area. They also noted that three of the nine Niger-Delta States will be particularly affected in the event of flooding. Together, they make up around 4,660,842 people, including both young and old. Therefore, the Niger-Delta Region's humanitarian disaster assistance agencies have a significant difficulty. (Figure 16, Map of the Niger Delta.)

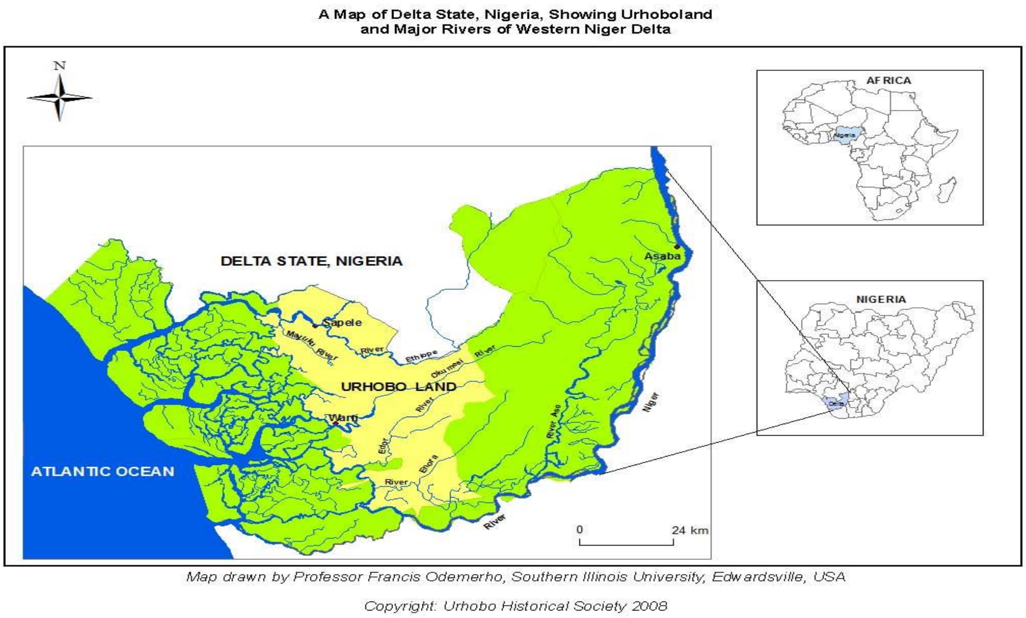

Figure 16: Niger Delta Map.

2.6 Challenges in Humanitarian Disaster Logistics

In this work, we want to draw attention to specific difficulties and issues that, in large part, affect humanitarian aid efforts and impede disaster relief efforts.

- Disaster management organizations are crippled by a lack of funding, resources, technology, and technical expertise.
- The efficiency of disaster management may suffer from a lack of political commitment to make it a top government priority.

- Insufficient security coverage is required to prevent theft and crowding.
- The type of magnitude of disaster determines the level of demand and relief materials needed to meet the needs of the people. This makes it difficult for responsible agencies to make adequate budget and manage resources efficiently.
- The inability of ports and airports to handle massive catastrophe activities.
- Storage facilities and loading equipment that is insufficient.
- Poorly maintained roads and railways, heavy traffic, and tunnel and bridge height restrictions.
- Due to poor communication networks and signals, it is challenging for humanitarian organizations to contact with one another during disaster operations and to obtain the necessary information and requests from the impacted people.
- Damages and movement distortions are brought on by the destruction and debris left behind by calamities like floods and landslides. It makes it impossible to send out the relief supplies on time. The distribution of the aid supplies is frequently inequitable. Because the emergency humanitarian organization did not reach all locations, certain distribution points suffered.
- Some humanitarian aid personnel loss their life during disaster rescue operations. World Health Organization used social media for announcing official information about any pandemic and the update about such pandemic. Where communication network is not effective, the people perish. It happened in China (WHO, 2013) during the outbreak of Avian Influenza, and currently in 2019 at the outbreak of COVID-19 pandemic (WHO, 2020).
- Inadequate personnel who are experienced to handle large-scale disaster rescue operations. Trained and qualified personnel are very necessary for disaster rescue operations.
- One major issue that the organizations that provide humanitarian help must deal with is corruption. Donations in kind and cash from local, state, and worldwide communities are accepted during large-scale catastrophe activities. Unfortunately, most of these funds are stolen before they reach the actual hands of the people

who are supposed to administer them—humanitarian organizations. Additionally, politicians divert monies intended for ecological expenditures and disaster preparations.

2.7 Fairness in Distribution of Relief Materials

It is crucial that the organizations participating distribute the supplies impartially and in accordance with the most urgent needs during the emergency distribution of relief supplies at the several PODs. Humanity, impartiality, and neutrality were the three principles Clark and Culkin (2007) offered to define a humanitarian. According to them, focusing on the most pressing demands should help to lessen suffering when it is discovered. The Sphere Handbook (The Sphere Project, 2011) makes the following claim regarding the provision of services by agencies: ‘Access to health care should be founded on the principles of equity and impartiality, ensuring equitable access according to need without any discrimination. In order to offer similar food rations to similarly impacted populations and population sub-groups, equity must be ensured.

The needs of the most vulnerable individuals or segments of the population, such as the injured, children, pregnant women, and women, should be given priority, according to Jaegar (2012a). As a result, the marginal usefulness of the provided goods will decline as they are distributed to the neediest people at each POD. Although there may still be a need for relief supplies in some areas, it will be more beneficial to assist those who are in greater need elsewhere before returning to the initial area. Most frequently, a lack of capacity or damage to the distribution network causes a need to prioritize.

2.8 Relief Supply Chain Management

The attempts of many authors to properly describe the meaning of relief supply chain management vary. Instead, everybody has clarified it in light of their particular area of expertise. Relief Supply Chain Management is defined by Scott and Westbrook (1991) and New and Payn (1995) as the network connecting each procurement and supply process from the source of the relief materials to the end user, spanning several organizational or agency borders. It starts with the procurement of relief supplies from the sources and proceeds through suppliers, distributors, and end users. When applicable, supply chain management also considers the materials' or products' ability to be recycled or reused.

Balcik et al. (2010) talked about many relief chains that need coordination, like transportation and purchasing. They describe the many techniques for coordination in their debate. They continued by identifying local governments, military personnel, and NGOs (non-governmental organizations) as the primary actors in the chain of relief.

In their contribution, Holguin-Veras et al. (2010) emphasized that ‘decision support tools’ is a significant area in the relief supply chain that needs immediate attention. They are referring to the preparedness and reaction stages of disaster relief logistics in emergency management. The period of preparation precedes a disaster (the phase before the occurrence of disaster). They talked about how several aspects affected the decision-making process. They also mention that the post-disaster response phase is (the phase after disaster had occurred). According to them, the parameters include the magnitude of the calamity or disaster, the characteristics of the demand, and the complexity of the necessary decision support system. NGOs, logistical companies, military organizations, the government, and nearby communities were all mentioned as stakeholders by Heaslip et al. (2012) in the case of a disaster. They noted that for any catastrophe rescue activities to be successful, these individuals must be completely prepared to provide their best. They urged the stakeholders to work together effectively and amicably. Mentzer et al. (2001) and La Londe and Masters (1994) view the relief supply chain in a similar way, viewing it as an integrated process where various parties like suppliers, manufacturers, distributors, and retailers collaborate to design, Coordinate and manage the movement of components, finished items, and materials from suppliers to customers (the parties involved) (Gatignon et al (2010).

2.9 Planning in Preparedness and Response

Between the moment of the tragedy and the delivery of rescue and relief supplies, there is a lag. According to Santosh (2020), many humanitarian groups use a reactive approach rather than a proactive one, acting only after a tragedy has occurred (i.e. take action before disaster happens). Prepositioning of inventories is typically recommended as a method to close this gap. Additionally, he recommended that proper response preparation be done to ensure the effectiveness of humanitarian logistical operations.

2.9.1 Characteristics of Facility Location Model in Preparedness

There are various types of location models created to improve effective logistics operations (Klose and Drexl, 2005). According to their goals, limitations, solutions, and other characteristics, each of them has unique characteristics.

Table 2.3: A list of location models' classifications according to various humanitarian logistics management

Author	Phase of disaster	Uncertain component	Model formation	Solution technique
Chang et al. (2007)	Preparation and response (location – allocation model)	Demand and location of demand	mix-integral programming	Spatial data analysis using ESRI Arc GIS 9x
Rawls and Turnquist (2010)	Preparation and response (location – allocation)	Route reliability and demand	Mix integer linear and mix-integer non-linear	Lagrangian L-shaped
Batzinpour and Esmaeili (2014)	Preparation and response (location – allocation)		Mixed – integer linear programming	Goal programming
Lin et al. (2011)	Response phase (resource allocation model)		Mixed-Integer programming	Two phase heuristic approach
Zhang et al. (2012)	Response phase (resource		Integer programming	Local search heuristic

	allocation model)			
Bozorgi – Amiri et al. (2012)	Preparation and response phase (location – allocation)	Demand and location, cost of procurement and transportation	Mixed-integer non-linear programming	Particle swarm optimization meta-heuristic
Tzeng et al. (1999)	Response phase (relief distribution model)	Demand	Fuzzy multi-objective programming	Fuzzy programming
Afshar and Haghani	Response phase (integrated supply chain)		Mixed integer programming	Cplex
Bozorgi-Amiri et al (2013)	Preparation and response phase (relief distribution model)	Demand and location of demand	Mixed integer non-linear programming	Robust stochastic optimization approach, compromise programming
Vitoriano et al. (2010)	Response phase (relief distribution model)	Route reliability	Mixed integer nonlinear programming	Goal programming
Sheu and Pan (2014)	Response phase (centralised emergency supply network model)		Mixed integer linear programming	Numerical case study on LINGO

Hsu and Peeta (2014)	Response phase (information based control evacuation model)	Demand	Mixed integer nonlinear programming	Fuzzy programming
Yi and Ozdamar (2007)	Response phase (location-distribution model for logistics support and evacuation operations)	Occurrence of disaster	Mixed integer linear programming	Routing algorithm
Najafi et al. (2013)	Response phase (integrated model)	Number of injured people demand	Mixed integer linear programming	Exact methodology

2.9.1.1 Topological Characteristics

The various location model types in a place are influenced by topological properties and demand sites. There are continuous location models (Plastria, 2004), discrete network models (Daskin, 2008), and hub connection models (Campbell, 1994). The site is given a specific location model that is suited to its topographic situation.

2.9.1.2 Features of facility:

The characteristics of the facilities are a further factor that categorizes locations. There are limitations to various location models; for instance, some may offer service facilities while others may not. We frequently have location facilities that are deterministic or stochastic, single stage or multi-stage, single product or multi-product, single period or multi-period, uncapacitated or capacitated, and single or multiple periods.

2.9.1.3 Input parameter

This categorizes location models according on the characteristics of their input parameter. Deterministic models anticipate the parameters with specific values in order to simplify the models for straightforward solutions. Real-world situations today are uncertain and probabilistic in nature. Therefore, stochastic models are appealing for capturing the uncertain real-world scenario. Researchers are now using stochastic models to address difficult issues.

2.9.1.4 Objectives

Most location models are categorized based on the research goal. Providing coverage to all demand nodes while minimizing the facility number is the goal of covering location models. All PODs, or demand points, must be ‘covered’ by coverageing models in order to achieve their main goal. If a facility is available to offer enough service to a demand location within a certain distance, we refer to that demand point as being ‘covered.’ The maximum distance (or transit time) between nodes and facilities, for instance, is intended to be as short as possible in P-center models.

2.9.2 Network Location Models

2.9.2.1 P-center model

Because the P-center model attempts to reduce the maximum distance between each demand location and its nearest facility, it is frequently referred to as the min-max model. The P-median model, on the other hand, seeks to minimize the average distance (sum of distances) between nodes and the facilities that follow them. In the p-center model, we need to meet every demand, but our main goal is to locate a specific number of facilities with the shortest possible coverage distance. Hakimi (1964) addressed this issue and pinpointed P facilities.

As an illustration, consider how the p-center problem is phrased: we set D (an additional choice variable) to equal the greatest distance between the node and the closest facility. The formulation for binary integer programming that follows comes next

Minimize D - - - - - - - - - 2.1

Subject to:

$$\sum_{j\in J} X_j \leq P \;\forall\; i\epsilon I \qquad - - - - - - - - \qquad 2.2$$

$$\sum_{j\in J} X_{ij} = 1 \;\forall\; i\epsilon I \qquad - - - - - - - - \qquad 2.3$$

$$Y_{ij} - X_j \leq 0 \;\forall\; i\epsilon I, j\epsilon J \qquad - - - - - - - \qquad 2.4$$

$$\sum_{j\in J} d_{ij}X_{ij} \leq D \;\forall\; i\epsilon \mathrm{I} \qquad - - - - - - - \qquad 2.5$$

$$X_{ij}X_{ij} \in \{0,1\} \;\forall\; i\epsilon I, j\epsilon J \qquad - - - - - - - \qquad 2.6$$

The objective function is given in Equation 2.1. This reduces the maximum distance between any demand node and its closest facility as much as possible. The maximum number of open facilities is capped at P by constraint equation 2.2. Every demand point must be connected to a facility, per constraint (2.3). The maximum distance between any demand node and the closest facility is specified by constraint (2.5). The decision variables are subject to integrality limitations in constraint (2.6). Binary variables are X and Y.

2.9.2.2 P-Median Model

It goes without saying that accessibility and facility efficiency rise as average distance decreases. Hakimi (1964) introduced the P-median model, which takes into account the metrics mentioned above. In order to reduce the average distance between demands and facilities, it chooses the location of P facilities. The average distance that people travel when they visit a facility is thought to be a good indicator of how effective the location is. Weighing the distance between demand nodes and facilities by the related demand quantity, then calculating the overall weighted travel distance between demands and facilities is an equivalent technique. This quantifies location effectiveness when we are not primarily concerned with the level of service. It is now our responsibility to choose the finest P sites from a variety of potential locations in order to reduce the overall demand-weighted travel distance between demand nodes and the facilities we have chosen. Where to locate p facilities and which facility will serve as each demand node are the two main decisions.

The following is the mathematical formulation.

Minimize $\sum_{j \in J} \sum_{j \in L} w_i d_{ij} y_{ij}$ - - - - - - - 2.7

Subject to:

$\sum_{j \in J} y_j = 1, \forall \ i \epsilon I$ - - - - - - - - 2.8

$y_{ij} - x_j \ \leq 0 \ \forall \ i \epsilon I \quad \forall \ j \epsilon J$ - - - - - - - 2.9

$\sum_{j \in J} x_{ij} \leq P, \qquad \forall \ j \epsilon J$ - - - - - - - - 2.10

$x_j X_{ij} \{0,1\}, \ \forall \ i \epsilon I, \qquad \forall \ j \epsilon J$ - - - - - - - 2.11

The inputs are the demands (or weights) w_i at each node iϵI, the distances d_{ij} between each demand node iϵI and each candidates facility site jϵJ and P, the maximum number of facilities to be located.

x_{ij} = 1 if a facility is located at candidate node jϵJ and O otherwise

y_{ij} = 1 if demand node iϵI is assigned to facility at candidate node jϵJ, and O otherwise.

Equation (2.7) is the objective function; it minimizes the demand-weighted total distance. Here, the demands are known, and the total demand is fixed, this is equivalent to minimizing the demand-weighted average distance. Constraint (2.8) enforces that each demand node is assigned. The restriction (2.9) states that only assignments to open facilities are permitted. The maximum number of P facilities that may be opened is specified in constraint (2.10). Standard integrality requirements can be found in constraint (2.11). Mladenovic et al. (2007) provided further solutions, but Berman et al. (2002) created a new P-median problem variation. They claimed that not all of the overall demand would be met, but at least % of it would. This strategy is known as dependable modeling.

2.9.2.3 Covering Problem

There are some facilities where it is inappropriate to choose sites that reduce the average distance travelled. For instance, the type of emergency service demand will determine the maximum allowed travel distance or duration when locating emergency services like fire stations or ambulances. Different measures of site efficiency will be needed for this kind of institution. If a demand can be met within a certain amount of time, it is considered to be covered. Set covering difficulties and the maximal covering problem were the subject of discussion by Schilling et al. in 1999.

In light of set-covering issues, the goal is to reduce facility site costs while still achieving a specific level of coverage. We formulate the set coverage problem mathematically.

C_j= Fixed cost of locating a facility at node j

S= Maximum acceptable distance or travel time

N_i= Set of facility sites j within acceptable distance of node ($N_i=\{j/d_{ij}\leq S\}$)

X_i = 1 if a facility is located at candidate node $j \epsilon J$ and O otherwise.

Minimize $\sum_{j\in J} C_j X_j$ - - - - - - - - 2.12

Subject to:

$$\sum_{j\in J} X_j \geq 1, \quad \forall \ i \epsilon I \qquad - - - - - \quad 2.13$$

$$X_j \in \{0,1\}, \quad \forall \ j \epsilon J \qquad - - - - - - \quad 2.14$$

The objective function that minimizes the cost of facility location is given by equation (2.12). The cost C_j is frequently believed to be the same for all feasible facility sites j.

Equation (2.13) makes sure that any demand has at least one facility that is close enough to be of service. Regardless of expense, every node must be covered. Equation (2.14) is the binary variable.

On the other hand, the Maximal coverage problem minimizes the amount of demand covered within the acceptable service distance S by locating a fixed number of facilities:

X_j = 1 if a facility is located at candidate node j϶J and o otherwise

T_i = 1 if a demand at node i϶i is covered and 0 otherwise.

$$\text{Minimize } \sum_{j \in I} r_j T_j \quad - \quad - \quad - \quad - \quad - \quad - \quad - \quad - \qquad 2.15$$

Subject to:

$$T_i \leq \sum_{j \in Ni} X_j \,, \quad \forall \; i \epsilon I \qquad - \quad - \quad - \quad - \quad - \qquad 2.16$$

$$\sum_{j \in I} X_j \; \leq P, \qquad \forall \; i \epsilon I \quad - \quad - \quad - \quad - \quad - \quad - \qquad 2.17$$

$$X_j, T_i \in \{0,1\}, \;\; \forall \; j \epsilon J \; - \quad - \quad - \qquad 2.18$$

The amount of demand met is maximized by the objective function (2.15). Which demand nodes are covered within the allowed service distance is determined by constraint (2.16). Only when T_i=1 and X_j=1 for some j=N_i are nodes covered. In the absence of such a facility, the right-hand side will be zero, making T_i zero. The number of facilities that can be fixed at P is constrained by constraint (2.17) It is important to remember that Farahani et al. (2012) conducted research on the coverage problem, and their literature is extensive.

2.9.3 Combinatorial Problem

The term ‘Combinatorial Problem’ refers to a class of situations where a fleet of vehicles situated at one or more depots must be assigned a set of routes for a number of geographically distant cities or clients some people can call it vehicle Routing problem

(VRP). The goal is to transport a group of clients with known needs along minimum-cost vehicle routes that start and conclude at a depot (Vigo, 2002).

The computational work needed to solve the VRP, an integer programming problem, grows exponentially in proportion to the size of the problem. In Toth and Vigo (2002), three fundamental methods for modelling VRP have been proposed. Vehicle flow formulation is the term for the first. This makes use of binary integer variables connected to each network arc, that displays whether a vehicle is traversing a particular arc or not. They are used in situations where the whole cost of the solution may be summed up with the costs of the arcs. When a solution's cost depends on the order of arcs traversed or the type of vehicle assigned to a route, for instance, vehicle flow models cannot be used to solve these problems. Commodity Flow Formulation is the name of the second method for VRP modelling. In this kind of model, arcs that depict the flow of the commodities along the paths taken by the vehicle are linked to extra integer variables.

The decision variables in the third method of VRP modelling are the cars' viable routes, which are all connected by a feasible route. The VRP is defined as a 'Set Partitioning Problem,' which chooses a set of routes with the lowest possible cost. The primary benefit is that it enables very general route cost. Cost may not be linear or may vary depending on the vehicle used or the order in which nodes are visited.

2.9.3.1 Mathematical formulation

We formulate vehicle flow based as a model, an incapacitated multi-vehicle single depot vehicle routing problem.

The decision variables X^{v}_{ij} which are, binary and it shows whether vehicle v travels from point i to point j, X^{y}_{ij} = 1 or X^{y}_{ij} = 0.

$$\text{Minimize} \sum_{i}\sum_{J}\sum_{V} C_{ij}\ X^{v}_{ij} \qquad - \quad - \quad - \quad - \quad - \quad - \qquad 2.19$$

Subject to:

$$\sum_{v\in V}\sum_{i\in I} X^{v}_{ij} = 1, \qquad \forall\ j\epsilon J \qquad - \quad - \quad - \quad - \quad - \qquad 2.20$$

$$\sum_{v\in V}\sum_{i\in J} X_{ij}^{v} = 1, \quad \forall\ j\epsilon J \quad - \quad - \quad - \quad - \quad - \qquad 2.21$$

$$\sum_{i\epsilon I} X_{ip}^{v} - \sum_{j\in J} X_{pj}^{v} = 0, \forall\ P\epsilon N, \forall\ v\epsilon V \quad - \quad - \quad - \quad - \qquad 2.22$$

$$\sum_{j\epsilon J} X_{oj}^{v} \leq 1, \quad \forall\ v\epsilon V \quad - \quad - \quad - \quad - \quad - \quad - \qquad 2.23$$

$$X_{ij}^{v} \in \{0,1\}, \ \forall\ i\epsilon I, \forall\ j\epsilon J\ given\ v \quad - \quad - \quad - \quad - \quad - \qquad 2.24$$

$$X \in S \quad - \quad - \quad - \quad - \quad - \quad - \quad - \quad - \qquad 2.25$$

The goal of function 2.19 is to reduce the overall cost or distance incurred by all vehicles. Only one vehicle may enter and leave each node in accordance with constraints (2.21) through (2.22). Each vehicle only ever departs the depot thanks to constraints (2.23). Binary variable (2.24) is a constraint. Matrix X is not allowed to have sub tours that do not contain the depot according to equation (2.25).

2.9.4 Mixed Integer Programming Models

A mixed integer programming issue (or model) is one in which some of the decision variables must have integer values at the best solution (i.e., full numbers like -1, 0, 1, 2, etc.). The fixed cost of opening facilities and the variable cost of transportation are traded off in mixed integer programming mode.

Klose and Drexl (2005), categorised models under this subhead as:

- Single stage (echelon) vs multi-stage
- Capacitated vs incapacitated
- Single products vs multi-product
- Single period multi-period (Dynamic models)
- Deterministic vs Stochastic

2.9.4.1 Single Stage (echelon) Vs Multi-Stage

A simple form of mixed integer facility location models is provided below:

$$\text{Minimize } \sum_{i \epsilon I} r_i y_i + \sum_{i \in J} \sum_{k \epsilon K} S_{ik} X_{ik} \quad - \quad - \quad - \quad - \quad - \quad - \qquad 2.26$$

Subject to

$$\sum_{i \in I} X_{ik} = 1, \qquad \forall \ k \epsilon K \qquad - \quad - \quad - \quad - \quad - \qquad 2.27$$

$$X_{ik} \leq y_i, \qquad \forall \ i \epsilon I, k \epsilon K \qquad - \quad - \quad - \quad - \quad - \qquad 2.28$$

y_i, μ_i, and $\epsilon\{0,1\}$

r_i is fixed cost of opening a facility at location i, s_{ik} is unit transportation cost between facility i and demand point k, y_i is 1 if a facility is opened at location i, and X_{ik} is 1 if demand of demand point K is satisfied by facility i. Equation (2.26) is the mixed-integer linear programming minimizing function assuming X_{ik} to be non-negative. Constraint (2.27) ensures that each demand point will be allocated to exactly one facility. Constraint (2.28) allows shipments from a facility only if it is opened.

The demand of each demand point is not shipped straight from facilities when multi-stage models are taken into account. It first receives one or two notes before being transferred to demand points. These nodes might be points of distribution, warehouses, or shops. The most popular two-stage model is one with just one set of intermediate nodes. (See below for a two-echelon company supply chain.)

Transhipment and complete allocation models are the two main approaches to modeling this type of problem, according to Syarif et al. (2002). We presume that a demand point can only be serviced by one facility through one intermediate node in a complete allocation model. Nevertheless, the transhipment model defies this supposition. The following is how we formulate complete allocation:

$$\text{Minimize} \sum_{i\epsilon I} r_i y_i + \sum_{j\in J} m_j z_j \sum_{i\epsilon I}\sum_{j\epsilon J}\sum_{k\epsilon K} S_{ijk} \,.\, x_{ijk} \quad - \quad - \quad - \quad - \quad - \qquad 2.29$$

Subject to:

$$\sum_{i\epsilon I}\sum_{j\epsilon J} x_{ijk} \geq 1, \qquad \forall\ k\epsilon K \quad - \quad - \quad - \quad - \quad - \quad - \quad - \qquad 2.30$$

$$X_{ijk} \leq y_i, \qquad \forall\ i\epsilon I, j\epsilon J, k\epsilon K - \quad - \quad - \quad - \quad - \quad - \quad - \qquad 2.31$$

$$X_{ijk} \leq Z_j, \qquad \forall\ i\epsilon I, j\epsilon J, k\epsilon K - \quad - \quad - \quad - \quad - \quad - \quad - \qquad 2.32$$

X_{ijk}, y_i and z_j are binary variable - - - - - 2.33

Where i is set of facilities, j is set of warehouses, k is set of demand points, r_i and m_j are fixed costs of opening a facility at location i and a warehouse at location j respectively.

2.10 Linear/Integer Programming Approach

In his 1987 study, Knott explored the application of the linear programming model to address the issue of minimizing transportation costs for bulk food. He continued his investigation in 1988 and used a linear programming approach to establish vehicle schedules for delivering bulk food to disaster areas. The multi-commodity, multi-modal network flow challenge for disaster relief operations was well done by Haghani and Oh (1996). Their goal was to reduce the total flow costs for commodities, vehicles, supply and demand, and transfers across all time periods. Their work served as a blueprint for initial disaster assistance planning. They did point out that it can be used in real-time if it is connected to a real-time updating data base. Similar to this, Ray (1987) investigated the flow of a single commodity over a multi-period planning horizon and created a model that took a capacitated network into account. In an emergency relief operation, he reduced storage and transportation costs. A detailed deterministic model for the determination of the distribution of commodities to demand places was established by the work of Tzeng et al. in 2007. It was a multi-objective that used fuzzy multi-objective programming to take into account demand satisfaction, response time, and cost. In order to establish the number, locations, and capabilities of the relief distribution centers

(RDCS) and the capacity of the warehouse and suppliers to meet the necessary demand, Balcik and Beamon (2008) explored a geographic model of pre-positioning relief goods. Their model had looked at budgets before and after disasters. They did not account for the expense of shortages. In their 2008 research, Yushimito and Ukkusuri tended to take into account the likelihood that, in the case of a transport network interruption, demand points may be met by a single supply facility. They adopted a strategy that selects the best area for pre-positioning goods in order to optimize the point at which demand is met.

Disaster planning, according to Whybark (2007), Ozbay and Ozguven (2007), and others, is mostly focused on disaster material inventories. They therefore focused on the method of delivery to the intended recipient. Based on a time-dependent inventory model for safety stock levels, Ozbay and Ozguven's approach improves pre- and post-disaster strategies. It is important to recognize that the earlier work of Guelat et al (1990) served as the basis for current effort. A multi-commodity, multi-modal network was shown. They sought to reduce the whole cost of routing and transfer as a whole. The algorithm for the solution took advantage of the natural decomposition of the commodity, which turned out to be a linear approximation in the Gauss-Seidel sense (GSLA). The Brazilian transportation system's 211 sources, destinations, 6 commodities, and 10 modes were used to test their concept. An investigation on the planning of restoration, construction, and salvage work for road networks was done by Tzeng and Chem (1999). Despite the fact that their approach provides guidance for numerous catastrophe recovery activities, they did not do much to distribute emergency assistance measures. However, Tzeng, el at. (2007) expanded on their approach by using fuzzy multiple goal models to guarantee the efficiency and fairness of the overall distribution system. Their concept outlined operational processes and, in large part, offered a strategy for the delivery of massive, coordinated relief.

It should also be emphasized that a number of other researchers have had some influence in this area. Balcik et al. (2008), Vehicle schedules were created by Barbarosoglu and Arda (2004), Nolz et al (2010), and Vitoriano et al (2009, 2010) to distribute supplies throughout the affected population from the accessible distribution hubs. They have demonstrated a propensity to favor particular stages of the recovery and response processes. For their part, Rawls and Turnquist (2010) worked on emergency response planning that aids in identifying the location and the quantity of emergency supplies that must be pre-positioned in the event of an emergency disaster. In 2012, Rawls and Turnquist expanded their work and created a model to improve pre-event planning for supplying short-term requests in the face of unknown demand location and volume. Raheem (2011) noted in his research that Nigeria is a country that is vulnerable to disasters, and that these disasters frequently cause environmental emergencies like flooding. He added that 'in Nigeria, emergency situations resulting from disasters, both natural and man-made, are common and vary in space, time, and size.' He further stated that all coastline states in the nation are affected by flooding, which is a major environmental emergency. He urged several organizations, including NEMA, to assume greater responsibility for life-saving emergency relief. But he made no blueprint for operations in the future.

2.11 Stochastic Optimization Approach

Today, many scientists studying natural disasters are interested in the topic of uncertainty and randomness. Using a rolling-horizon approach, Balcik et al. (2008) captured the demand and supply uncertainty in crisis situations. They linked the travel costs on arcs with different vehicle types to indicate vehicle-road compatibility, noting that if a road cannot be used by a certain vehicle, the cost of traveling along that arc is given a high value. This encouraged policymakers to take into account transportation infrastructure and omit unfavourable routes. One of the few scholars who have examined the issue of the placement and distribution of disaster rescue supplies in flood emergencies as diverse flood scenarios in an uncertain demand environment is Chang et al. (2007). The research neglected to adequately address the issue of vehicle scheduling, instead focusing primarily on a particular big metropolis flood disaster. A two-stage stochastic optimization model was developed by Salmeron and Apte (2010) as a tool for budget allocation planning for relief assets. Their model's first stage, 'help pre-positioning,' covered the expansion of resources including warehouses, hospitals, and shelters; the second stage covered logistics in the face of demand and cost uncertainty. Notably, their model overlooked the connection between relief locations and the potential for inventory destruction.

In their 2009 study, Stepanov and Smith examined the best routing procedures, while planning an evacuation study. They put forth an evacuation model that is built via simulation and integrated optimization. Multi-objective route optimization is the focus of their study, which aims to reduce travel times, traffic jams, and the need for simulation techniques to help decision-makers manage regional evacuation. Their work addresses the congested environment while reflecting the random character of the evacuation process.

By taking into account the shortest way, Lim et al. (2012) employed an optimization strategy to reduce the number of evacuees. The goal was to create a network with limited capacity that could locate evacuation routes, traffic patterns, and schedules to improve rescue efforts. In order to execute the flow for each time interval, they also utilized a greedy algorithm to assess the maximum flow of each path and timetable. A scheduling technique for evacuations was used to examine and measure their performance (ESA).

Na et al. (2012) additionally look at the journey time and evacuation process. Their study used a bio-objective model to optimize route assignment while taking secondary evacuation into account. They solved their model using an approximation approach, setting it to equally minimize trip time. Through numerical exercise, their model was tested. According to Bish and Sherali's (2013) research, a strategy of aggregate-level staging and routing is used. Their methodology gives users the freedom to apply lexicographic objectives to a hierarchy of evacuation-based objectives.

With an emphasis on demand and disruption uncertainty, Ali and Nakade (2014) suggested a stochastic programming approach to control supply chain disruptions of a company. The goal was to create a network with limited capacity that could locate evacuation routes, traffic patterns, and schedules to improve rescue efforts. In order to execute the flow for each time interval, they also utilized a greedy algorithm to assess the maximum flow of each path and timetable. Their approach took into account inventory costs, purchasing costs, and the cost of last-minute orders. For the purpose of sampling for a specific probability distribution of stochastic parameters, they employ the Monte Carlo sampling approach.

Wapee et al. (2014) conducted a time-constrained study on the logistics of humanitarian aid. Their plan was to help establish distribution hubs for housing emergency supplies in areas where floods and other disasters are expected to occur. In order to reduce the overall cost of relief operations, their approach integrates facility location and inventory decisions as a mixed integer programming problem with capacity limits and time restrictions.

An investigation into a two-stage procurement strategy for humanitarian aid was done by Falasca and Christopher in 2011. They recognized the element of uncertainty that surrounds catastrophe aid efforts and took a wait-and-see and stochastic solution approach to the issue. In order to reduce anticipated demand shortages as well as overall procurement costs, their model takes into account various logistics restrictions (such as the capacity of suppliers), various relief uncertainties (such as the level of donations), and other operational constraints.

A multi-objective relief chain site distribution model was employed by Barzinpour and Esrnaeili (2014) to present a disaster management issue in an urban setting. They create a reaction plan that takes into account the early stages of disaster management. Their model was a multi-objective mixed integer linear programming that addressed the crisis planning stage and used a goal programming method to take into account both humanitarian and cost-based objectives.

The issue of emergency location-allocation in a multi-supplier, multi-affected area, and multi-relief anti-multi-vehicle emergency logistics network was addressed by Sha-Lei and Nan (2011). Their focus was on reducing overall trip time and the percentage of unmet demand. They used goal programming to achieve their two objectives. We are considering three goals in our suggested model: the unmet demand, journey time, and overall cost. Additionally, we suggest that supply, which is stochastic in nature, could be made directly or indirectly to the afflicted areas.

An earthquake response plan can be developed using a multi-objective stochastic programming model that incorporates pre- and post-disaster decisions, according to Mohammadi, Ghomi, and Jolai (2016). They have three goals in mind:

(i) To maximize the total expected demand coverage,

(ii) To minimize the total expected cost, and

(iii) To minimize the difference in the satisfaction rate between the nodes'.

To resolve their model, a brand-new multi-objective particle swarm optimization (MOPSO) algorithm was created. The obtained results were contrasted with those of the non-dominated sorting generic algorithm and modified time-variant MOPSO. The analysis of uncertainty and their prior work on stochastic prepositioning of emergency supplies are interesting aspects of their work.

The authors Morteza, Abbas, and Behnam (2015) were also drawn to this area. They suggested a multi-depot location routing model that took network failure, numerous vehicle uses, and standard relief time into account. Their model examined the last mile distribution following an earthquake event. To determine the locations of distribution centers, they further extended their model into a two-stage stochastic program with random trip time. Their computational findings demonstrate that an unmet demand can be significantly decreased at the expense of adding more local depots and cars.

In their research on the logistics of humanitarian aid, Kristina and Sigrid (2012) made an important contribution. They created a methodology that aims to make decision-making more effective. The mathematical models aim to maximize the usefulness of help distribution while solving the challenge of catastrophe response.

Muer Yang, et al.(2021) develop scenario- robust optimization models for stocking multiple relief items at various facility. Using a hurricane preparedness in Southeastern of United State, as a case study and applying mixed-integer Quadratic programming, they were able to improve the robustness of solutions. Their work was advantageous by easing the difficulty and the task of obtaining the probability distribution for uncertain parameters in stochastic programming.

2.12 Assertion On Transportation Cost

In this work, we made the assumption that the cost of air travel is twice as high as the cost of land transit.

When we take into account the work of David (1996) and the contribution of Victoria Transport Policy Institute (2016), this assumption becomes significant and necessary. The predicted carrier costs for high-speed rail are slightly lower than the user financial costs of vehicles, according to David, who was comparing the three modes (planes, trains, and cars), while the air system has the highest carrier costs. Given the energy needed to maintain a plane in the air and the high expense of aviation in comparison to railroads and mass-produced cars, this is not surprising. The Victoria Transport Policy Institute added that while comparing transportation costs, other aspects should be taken into account. These variables could be geographical scope, time or period, weather conditions for drivers and pilots, variations in measurement units, and whether cost estimates are expressed as point values or ranges. Therefore, we have opted to assume that air travel costs twice as much as land travel in order to prevent ambiguity.

Additionally, the U.S. Chamber of Commerce and Ramboill (2006) study made an effort to compare the costs of the various means of transportation. They concurred with other commenters that shipping is significantly less expensive than land transportation, particularly when it comes to moving containers. In a similar vein, they found that ground transportation is the next least expensive option after air travel. However, they pointed out that because there are many factors involved and the computation of the actual cost of transportation is not simple. Therefore, it follows that the cost of air transportation is roughly twice as high as the cost of road transportation.

Table 2.4: Combined Transport (High value goods 120,000 USD)

Mode of Transport	Transport Cost	Time
Sea	3,000	28
Road	11,000	19
Air	25,000	5

Here, we make an effort to succinctly summarize the work of various writers, including their goals, restrictions, and issue categories.

Table 2.5: A summary of Relief Distribution Adopted by Some Humanitarian Supply Management

Authors	**Objective function**	**Constraints/decision**	**Model**
Vitoriano et al. (2010)	Minimize (time, cost) Maximize (equity, reliability)	Demand and supply balancing at each node, vehicle type, vehicle capacity	Relief distribution model
Tirado et al. (2014)	Minimize (deviation of relief materials according to planned amount)	Dynamic flow balance at each node, balance of flow vehicles, vehicle capacity, vehicle availability, amount of load.	Lexico-graphical dynamic flow model
Balcik et al. (2008)	Minimize (logistic costs, penalty cost, and storage cost)	Demand fulfilment, vehicle capacity	Last mile relief distribution model
Liberatore et al. (2014)	Maximize (demand satisfaction)	Total served demand, maximum ransack, property, arrival time.	Humanitarian aid distribution model
Bozorgi-Amiri et al (2013)	Minimize (total cost, sum of the maximum shortages, maximize satisfaction level)	Capacity limits of distribution numbers, commodity flow number of distribution centre.	Relief distribution model
Ozdamar and Demir (2012)	Minimize (estimate total travel time)	Commodity flow balance, unmet	Vehicle routing model

		demands, vehicle capacity, number of vehicles, routes.	
Afshar and Haghani (2012)	Minimize total amount of weighted unsatisfied demand)	Vehicle flow, facility location, commodity flow, capacity for facilities.	Relief distribution model
Ahmadi et al. (2015)	Minimize (fixed cost, unsatisfied demand, distribution time, penalty cost)	Number of vehicles, arrival and destination demand, working time	Multi depot location routing model
Chen et al. (2011)	Minimize (decision making and equipment transportation time)	Balance or inflow and outflow of various node, vehicle flow	Relief equipment distribution model
Lin et al. (2012)	Minimize (total travel time, unsatisfied demand, and penalty function)	Maximize service level, fairness, vehicle capacity and working hours	Relief distribution model
Shen et al. (2009)	Minimize (unsatisfied demand)	Time, service, demand flow, route feasibility	Vehicle routing model
Wohlgemuth et al. (2012)	Minimize (delay in delivery time) Maximize (equipment utilization)	Time consistency, time window, vehicle capacity	Last mile relief distribution mode

‘The number of natural and man-made disasters is noteworthy and threatened human life at the time of occurrence and even afterward,’ according to Omid et al. (2021). Therefore, an effective response after a tragedy can remove or reduce the negative effect. By adopting a disaster network design under uncertainty and the administration of emergency relief volunteers at the same time, they found a solution to the problems with humanitarian logistics. They looked at the emergency relief volunteers and suggested a robust fuzzy stochastic programming model to handle a supply chain for relief goods. 22 Tehrani neighbourhoods served as a case study for the model's testing. Their research shows that when a disaster strikes, numerous factors have an impact on the supply chain network. Controlling these variables is necessary to prevent or minimize.

The need for vendors to cut costs was stressed in a study on robust optimization using mixed-integer linear programming for the supply chain for LNG (liquefied natural gas) by Arun et al. (2020). They noticed that the manufacturer supply parameter is uncertain in practice, thus they classified the parameter as interval-based uncertain. To validate their model, they used a CPLEX solver of GAM. They also created a Cuckoo optimization algorithm (COA) and used it to solve their model. The vendor profit and the robust cost are compared and evaluated to find the ideal robustness level.

Doufour et al. (2018) suggested an optimal logistics service network architecture for humanitarian response. With the main goal of reducing overall expenses, they used modeling, statistical analysis, and optimization methods. They thought about the advantages of establishing a regional distribution hub in East Africa. They observed that it was affordable to add a regional distribution hub in Kampala. Their findings should indicate that the average cost decrease was around 21%.

A mathematical model to create a logistics network for humanitarian aid under ambiguous circumstances was put forth by Mohamadi et al. (2021). Three goals guided the way they structured their issue: reduce the maximum accident loss while distributing aid. They used a fuzzy solution strategy known as the T.H method, developed by Torabi and Hassini (2008), to solve their problem. They stated that a strong optimization technique was used to address these difficulties because the planning of humanitarian logistics problems is hampered by a variety of unpredictable elements, including demand, supply, costs, and facility capacity. A number of test problems were also offered to demonstrate the applicability of the suggested mathematical paradigm. The obtained findings show that the suggested model can be used to create a network of relief logistics in an uncertain environment, Mohamadi et al. (2021).

In his research on a multi-level facility location problem (FLP), Shavarani (2019) sorted to discover the optimal topology for both relief centers and recharge stations to cover a sizable area with the least amount of money spent and wait times necessary. He solved his model using a hybrid genetic algorithm. He got to the conclusion that the suggested paradigm increases the effectiveness and responsiveness of the humanitarian aid effort. In their study, drones are used to distribute aid, while refueling stations increase the drones' operational range. He achieves a lower expense and a shorter time necessary for survival.

The task at hand for Ali and Ahmadre (2022) was to locate a suitable location for makeshift shelters. Their study's objective was to take into account the important elements in selecting appropriate locations for shelters following a disaster. By assessing and computing the post-cross path and facilities using photogrammetric images captured by an unmanned aerial vehicle or satellite, they suggest an algorithm. The quickest escape route and least expensive construction should be used when establishing a shelter for catastrophe victims (Zhao et al; 2015). In order to help them reach their goal of integrating shelter medical and psychological care, Perez-Galarce et al. (2017) adopted optimization technique in shelter site and created an algorithm. The following criteria were agreed upon by Ali and Ahmandreza, (2022) and Saidpour and Kashefidust, (2018) when deciding where to locate a temporary shelter for an emergency relief operation.

- Establishing a temporary shelter should be feasible in desired location.
- The vastness of the selected area should allow the proper distribution of the facilities and equipment.
- Harmony of the shape, construction and installation of the equipment should comply with the environment to achieve balance and allow adjustment according to the environmental complication (rural, desert, mountain, forest and urban).

Multi-objective resilient mathematical modeling for disaster assistance under uncertainty was developed by Eshig et al. (2020). Their multi-objective, multi-commodity, multi-vehicle, and multi-level logistics optimization model was developed.

Their injury model took into account the range of injuries by prioritizing services for those who have sustained more injuries by searching for locations with unmet demand for a certain relief item. They welcomed donations of relief supplies, made use of equipped hospitals, and developed disaster management facilities.

They used a non-linear mixed integer programming model to simultaneously maximize three set goals: (i) maximizing service fairness to demand areas, (ii) optimizing fair commodity catastrophe management, and (iii) minimizing total logistics cost. To analyze their suggested model, the researchers used the non-dominated sorting genetic algorithm (NSGA-II) and the ε-constraint approach. Their outcome demonstrates the algorithm's efficiency in an acceptable amount of processing time.

2.13 Chapter Summary: In this chapter, we have successfully reviewed the work of some scholars covering the four stages of disaster logistics/humanitarian services: Mitigation, Preparedness, Response and Recovery. The work of authors on pre and post disaster operations was reviewed. Various optimization model used by the authors were considered. We will therefore in our next chapter, formulate our stochastic optimization method which is peculiar to our problem to achieve our desired objectives.

CHAPTER THREE

Mathematical Programming Models Formulation and Constraints

3.0 Introduction

We develop a stochastic programming model with some fundamental presumptions to accomplish the stated goals of this study. As was already mentioned, mathematical programming has evolved into a standard approach for dealing with uncertainty. Our model is pre-disaster and post-disaster in nature. It is a combination of linear and non-linear (mixed integer quadratic programming Problem). Stochastic programming, in our opinion, is a useful tool. We'll start by assuming the following fundamental truths.

3.1 Assumptions

(i) An inventory may be stored at the NCDs, but when that happened, it is penalized.

(ii) An LDC may be supplied by either NCD or other LDCs.

(iii) Given that no LDC is open within the area of a POD, such POD may be served by multiple LDCs.

(iv) When disaster occurs, roads or path and/or facility may be damaged or destroyed. This may likely affect the performance ability of suppliers and candidate NCDs.

(v) At the POD, the cost parameters and the demand levels are stochastic and are differ in: volume, procurement cost, storage and cost of transportation. The commodities for this model are: food, water and medical facilities.

(vi) The probability distribution of the scenarios shall be assumed to have been derived by experts in this field of study.

(vii) We shall assume that the Air transportation cost is twice that of the Land transportation cost.

(viii) In some cases, where the supplies and demands parameters of relief commodities differ from the real conditions, estimated information may become useful because of damages but it will be good estimation for planning.

(ix) The chosen PODs must be away from the disaster zone

3.2 Sets/Indices

I: Sets of candidates NCDs indexed by $i \in I$

J: Sets of candidate LDCs indexed by $j \in J$

K: Sets of demand points in the affected area: POD

L: Sets of relief material types indexed $l \in L$

N: Sets of scenarios indexed by $n \in N$

M: Sets of vehicles indexed by $m \in M$

3.3 Parameters

$P_{n:}$ Probability of scenario n.

$V_{l:}$ volume of relief item 1 per unit

C^n_j: LDC, capacity under scenario n

Cl_J: Capacity of NCD, for item 1

d^n_{kl}: Amount of demand at the point k for relief type 1 under scenario n

Fl_J: Fixed cost of running NCD_i

$F2^n_j$: Fixed cost of running LDC_j

$\varphi_i l$: Cost of procuring and holding one unit of item 1 at NCD_i

$\varphi^n_i l$: Procuring and holding cost for one unit of item l at LDC_j under scenario n

s^n_{kl}: Unit shortage cost of item 1 under scenario n at demand point k

H_{il}: Maximum amount of supply of item 1 in NCD_i, with distribution function $\phi_i l$

U^n_l: Usable percentage of total amount of item 1 pre-positioned at NCD_i

α: Confidence level, $0 \leq \alpha \leq 1$

w: Service quality proportion

t_{max}: Maximum allowed delivery duration

tl^n_{ijk}: Transportation time from NCD_i to demand point k via LDC_j under scenario n

$t2^n_{ik}$: Direct transportation time from NCD_i to demand point k under scenario n

$a1^n_{ijklm}$: Transportation cost from NCD_i to demand point k via LDC_j under scenario n

$a2^n_{jklm}$: Cost of transportation one of unit of item l directly from NCD_i to demand point k: POD_k

T: Threshold of coverage

T_{ijk}: Distance from relief supplier i to k via j

T_{ik}: Distance from relief supplier i to k directly

$x2^n_{ijkm}$: Type m vehicle assigned from relief supplier *i* via point j to point k under scenario n (an integer)

$x3^n_{ikm}$: Type m vehicle assigned from relief supplier i directly to affected area k under scenario n (an integer)

$E1_{im}$: Type m vehicle capacity, in relief supplier i

$E2_{jm}$: Type m vehicle capacity, in relief supplier j

$E3_m$: load capacity of vehicle type m

W_l: Average weight of commodity 1

$AP1^n_{ijk}$: A path being available from supplier i to affected area k via point j

$AP2^n_{ik}$: A path being available from supplier i to affected area k directly

3.4 Decision variables

B_{ij}: Quantity of item 1 stored at NCD_i

$$yl_i = \begin{cases} 1\, if \quad NCDi \quad is\, opened \\ 0\, if\ otherwise \end{cases} \tag{3.1}$$

$$M1^n_j = \begin{cases} 1 \text{ if } \mathrm{LDC}_j \text{ is opened under scenario n} \\ 0 \qquad\qquad \text{if otherwise} \end{cases} \tag{3.2}$$

$$\beta^n_{ijk} = \begin{cases} 1 & \text{if any relief item is shipped from NCD}i\text{ to demand point k via LDCj under scenario n} \\ 0 & \text{otherwise} \end{cases} \tag{3.3}$$

$$\rho^{n}_{ik} = \begin{cases} 1 \text{ if any relief item is shipped directly from NCD}i \\ \quad \text{to demand point k under scenario n} \\ 0 \quad \text{otherwise} \end{cases} \tag{3.4}$$

$$\gamma^{n} = \begin{cases} 1 \text{ if scenario n is included in a reliabilit y set} \\ 0 \quad \text{otherwise} \end{cases} \tag{3.5}$$

$$\eta^{n}_{ik} = \begin{cases} 1 \text{ if path is available from relief supplier i to the} \\ \quad \text{affected area k directly under scenario n} \\ 0 \quad \text{otherwise} \end{cases} \tag{3.6}$$

X_{ijl}: Quantity of item 1 shipped from NCD_i to LDC_j

Y^n_{jkl}: Quantity of item 1 shipped from LDC_j to k under scenario n

Z^n_{ikl}: Quantity of item 1 shipped directly from NCD_i to point k under scenario n

SQ^n_{kl}: Shortage quantity of relief item 1 at point k under scenario n

X^n_{ijklm}: Quantity of commodity 1 assigned from relief supplier i to affected area k via point j by type m vehicle under scenario n

Y^n_{iklm}: Quantity of commodity 1 assigned from relief supplier i to affected area k directly by type m vehicle under scenario n

Furthermore, we will let:

AA^n_{ijk}: available distance from relief supply i to affected area k via point j under the scenario n.

BB^n_{ik}: available distance from relief supply i to affected area k directly under the scenario n.

Zd^n_{kl}: quantity of unmet demand for commodity 1 in affected area k under the scenario n

3. 5 Model Formulation

With the above definitions, we formulate the following objective function:

The Model

$$f_1 \quad = \quad \text{Min} \; \frac{\sum_k \sum_l \sum_n P_n \left| d_{kl}^n - \left(\sum_i \sum_j \sum_m X_{ijklm}^n + \sum_i \sum_m Y_{iklm}^n \right) \right|}{\sum_k \sum_i \sum_n P_n d_{kl}^n} \quad (3.7a)$$

$$f_2 = Min \sum_i F1iyi + P_n \left[\sum_j \sum_n F2_j^n M1_j^n + \sum_k \sum_l \sum_n SQ_{kl}^n s_{kl}^n + \sum_i \sum_j \sum_k \sum_l \sum_m \sum_n a1_{ijklm}^n X_{ijklm}^n \right.$$

$$\left. + \sum_i \sum_k \sum_l \sum_m \sum_n a2_{iklm}^n Y_{iklm}^n \right] + \sum_i \sum_l \varphi_{il} \beta_{il} \quad (3.7b)$$

$$f_3 = \overset{\min:}{\wedge} \sum_i \sum_k \sum_n p_n \left[t1_{ijk}^n \beta_{ijk}^n + t2_{ik}^n \rho_{ik}^n \right] \quad (3.7c)$$

Subject to:

$$d^n{}_{kl} - \sum_i \sum_j (X^n{}_{ijklm}) - \sum_i (Y^n{}_{iklm}) = S^n{}_{kl}, \forall i, l, m, n \quad (3.8)$$

$$U^n{}_{il} H_{il} \geq \sum_j \sum_k (X^n{}_{ijklm}) - \sum_k (Y^n{}_{iklm}), \forall k, l, m, n \quad (3.9)$$

$$H_{il} \leq C1_{il}\, y1, \forall i, l \quad (3.10)$$

$$\sum_i \sum_k \sum_l \sum_m X^n{}_{ijklm} V_1 \leq C^m{}_j M1_j^n, \forall j, n \quad (3.11)$$

$$\sum P_n \gamma^n \geq \alpha \quad (3.12)$$

$$S^n{}_{kl} \leq d^n{}_{kl} (1 - \gamma^n), \forall k, l, n \quad (3.13)$$

$$x1_{im} \leq \sum E1_{im} Yl, \forall i, m \quad (3.14)$$

$$\sum_k \sum_j x2^n{}_{ijkm} + \sum_k x3^n{}_{ikm} \leq x1_{im}, \forall i, \quad (3.15)$$

$$\sum_i w_l X^n{}_{ijklm} \leq E3x2^n{}_{kjim}, \forall i, j, k, m, n \quad (3.16)$$

$$\sum_i w_l Y^n{}_{iklm} \leq E3x3^n{}_{kjim}, \forall i, k, m, n \quad (3.17)$$

$$\sum_j \sum_k \sum_m X^n{}_{ijklm} + \sum_i \sum_m Y^n{}_{iklm} \leq d^n{}_{kl}, \forall i, l, n \quad (3.18)$$

$$Zd^n{}_{kl} = d^n{}_{kl} - \left(\sum_i \sum_j \sum_m X^n{}_{jklm} + \sum_l \sum_m Y^n{}_{iklm} \right), \forall k, l, n \quad (3.19)$$

$$t1^n{}_{ijk} \beta^n{}_{ijk} \leq t_{\max}, \forall i, j, k, n \quad (3.20)$$

$$t2^n{}_{ik} \rho^n{}_{ik} \leq t_{\max}, \forall i, j, k, n \quad (3.21)$$

$$\sum_{l}\sum_{m} X^{n}{}_{ijklm} \le MI\beta^{n}{}_{ijk}, \forall i, j, k, n \tag{3.22}$$

$$\sum_{i}\sum_{m} Y^{n}{}_{iklm} \le MI\rho^{n}{}_{lk}, \forall i, k, n \tag{3.23}$$

$$AA^{n}{}_{ijk} = \begin{cases} T_{i\,jk}, AP1^{n}{}_{ik} = 1 \\ +\infty, AP1^{n}{}_{ijk} = 0, \forall i, j, k, n \end{cases} \tag{3.24}$$

$$BB^{n}{}_{ik} = \begin{cases} T_{ik}, AP2^{n}{}_{ik} = 1 \\ +\infty, AP2^{n}{}_{ik} = 0, \forall i, k, n \end{cases} \tag{3.25}$$

$$x2^{n}{}_{ijkm} = \begin{cases} \ge 0 \qquad AA^{n}{}_{ijk} \le T \\ = 0\; AP1^{n}{}_{ijk} > T, \forall i, j, k, m, n \end{cases} \tag{3.26}$$

$$x3^{n}{}_{ikm} = \begin{cases} \ge 0 \qquad BB^{n}{}_{ik} \le T \\ = 0\; BB^{n}{}_{ik} > T, \forall i, k, m, n \end{cases} \tag{3.27}$$

$y1, \in (0, 1,)\forall i$ (3.28)

$x1_{im} \ge 0$, an integer, $\forall$i, m (3.29)(a)

$x2^{n}{}_{ijkm} \ge 0$, an integer, $\forall$i, j, k, m, n (3.29)(b)

$x3^{n}{}_{ikm} \ge 0$, an integer, $\forall$i, k, m, n (3.30)

3.6 Description of the Constraints

Here, we're thinking about designing an objective optimization model to address the issue of an emergency allocation network with:

(a) multi-supplier,

(b) multi-relief items,

(c) multi-vehicle,

(d) multi-affected areas.

The reduction of the anticipated percentage of unmet demands is the goal expressed in equation (3.7a). Fairness in the allocation of the relief materials goes beyond this.

The second goal is to solve Equation 3.7b. The goal of this equation is to reduce the overall cost of the relief allocation procedure. It clarifies the degree of economy at play. Equation 3.7c's third goal is to reduce the anticipated total journey time. It outlines the promptness of the distribution of aid to the impacted area.

According to the constraint equation (3.8), the shortage of item 1 at demand point k is equal to the difference between the quantity of item 1 demanded at point k and the quantity of item 1 transported both directly and indirectly to point k. Constraint (3:9) shows at scenario n, the total amount of relief material 1 which is ship directly and indirectly from NCD_i cannot exceed the total usable amount of relief material 1 which is stored in NCD_i. Constraint (3.10) is to ensure that the items of relief material 1 which is stored in NCD_i do not exceed its capacity. It further ensures that shipment from NCD_i can only happen if NCD_i is opened. Constraint (3.11) explains that not all the $LDCs_i$ need to be open before it can receive relief materials from $NCD_{i.}$ Further, that any relief material coming from NCD_i to LDC_j must not exceed its capacity. It cannot store relief material above its capacity. Constraint (3.12) establishes that the allocated relief materials do not exceed the amount supply. This constraint is defined as a chance constraint to be able to handle the uncertainty inherent in the supply of relief materials within a define confidence level, close to 1. Constraint (3.13) assures that if a shortage is associated with, it is zero. Constraint (3.14) defines the capacity limits of vehicles in the relief supplier center. Vehicles should only gather at the NCD_i where the relief supplier is available. The next constraint (3.15) demands that the number of vehicles at work should not exceed the supplier's actual capacity. Therefore, the number of vehicles both for direct and indirect shipment cannot exceed the capacity of the supplier. The load capacity restrictions of the vehicles are checked by Constraints (3.16) and (3.17), which also improve the free flow of the commodity at both indirect and direct shipping should not exceed the level of demand. The link between the allocation amount and demand is described by constraint (3.18). It demonstrates that allocation cannot be greater than the level of demand. The unfulfilled demand is defined by constraint (3.19). The maximum delivery time is an issue in Constraints 3.20 and 3.21. 3.20 and 3.21 are respectively complemented by constraints (3.22) and (3.23). (3.20) and (3.22) have the same relationship as (3.21) and (3.23). Constraint (3.21) is an indirect route employing binary variables to ship from NCD_i to POD_k under various scenarios ($\rho_{ijk}^{\;n}$). Constraint (3.23) is the direct shipment. Equation (3.24) guarantees the availability of path. When the path is destroyed, the distance available will be infinite for indirect shipment. In the event of direct shipment, constraint (3.25) holds true as well. The boundaries of coverage are outlined in constraints (3.26) and (3.27). The precise domains for the decision variables are defined by the constraints (3.28 to 3.30).

3.7 Chapter Summary

The assumptions were peculiar to the formulated stochastic programming. The working objectives were formulated with related restrictions and constraints as seen in the mathematical models. The model depicts the direct and indirect shipments. It is therefore important to see the workings of this formulated mathematical model with practical problem situation.

CHAPTER FOUR

Solution Approach

4.0 Software: LINDO

Due to the intrinsic randomness in our objective function, it is non-linear. The existence of commercial software solutions for such non-linear problems is notable. Gomez-Rocha and Hermandez-Gress (2022) successfully used Lingo 19.0 to solve a mixed integer, linear, multistage, stochastic programming model for multi-product aggregate production planning. Jin et al. (2020) successfully used Lingo, software in solving their practical multi-objectives decision-making programming problem. Hamiden et al. (2021) also used lingo Software in solving their stochastic multi-objective programming problem. In this case, we used the LINGO program from the LINDO system suite (2020), to solve a flood disaster problem. Data was collected and imputed into the Lingo software using the formulated mathematical equations. This software contains a unique syntax, language, and symbols.

4.1 Case Description

We consider four supply depots: the National Centre Deport (NCD), three local Distribution Centres (LDC), and six distribution points (POD). The model will include the following vehicle types: (a) helicopters for the air; and (b) trucks for the ground. The maximum supply of item l will be handled by NCD_i.

There shall be three categories of emergency supplies (item (l)): food, water, and medical services. Three scenarios—mild, medium, and severe—with corresponding probability of 0.25, 0.5, and 0.25 each will be taken into consideration. We assume that these probabilities were calculated by professionals. The cost of transportation is a linear function of distance, with the assumption that air transportation is twice as expensive as ground transportation. As a result, information on the distance to emergency facilities is presented in tables in light of the current situation and in light of the rescue effort during the Nigerian flood disaster of 2012. Experts may, however, assess that some are quite close to truth. We will let n = n_1, n_2, n_3 represent mild, medium and severe scenarios respectively. Let the weight function of the scenario n be *P(n)*, satisfying $0 \leq P(n) \leq 1$. Three element vectors in Table 4.14 depict the anticipated demand for each of the three emergency supply items at each demand point for each scenario. This is determined using the population density multiplied by the demand point's likelihood of vulnerability. However, it should be emphasized that this likelihood typically depends on the (a) type of disaster, (b) the disaster's intensity, and (c) environmental factors. The travel plans depend on how the disaster has affected the area. The type of the routes affects how quickly land-trucks may move around the area. According to specialists, the set of actable pathways is defined, according to Bozorgi-Amiri and Khorsi (2015), each starting at a supplier and traversing a sequence of Relief Distribution Center (RDC)'.

Our case study considered the following towns/communities as our NCDs, LDCs, and PODs.

Table 4.1: The NCDs, LDCs and PODs at glance

<table>
<tr><th>NCD</th><th>LDC</th><th>PODS</th></tr>
<tr><td rowspan="6">Asaba
Warri
Ughelli
Agbor</td><td rowspan="2">Urhobo</td><td>Sapele</td></tr>
<tr><td>Abraka</td></tr>
<tr><td rowspan="2">Ukwuani</td><td>Kwale</td></tr>
<tr><td>Aboh</td></tr>
<tr><td rowspan="2">Isoko</td><td>Emevo</td></tr>
<tr><td>Uzere</td></tr>
</table>

Table 4.2: Unit fixed cost of opening and operating NCDs (Fli)

i	FI
NCD1	20,000,000
NCD2	18,000,000
NCD3	15,000,000
NCD4	10,000,000

Table 4.3: Unit fixed cost of opening and operating LDC; (F2)

J	**(Small, Medium, Larger) {10^3}**
LDC_1	1,500
LDC_2	1,500
LDC_3	1,500

Table 4.4: El_{im}: Capacity of Vehicle type m in relief supplier i (NCDi)

	Vehicle Capacity (103) Type 1, Type 2	No. of (Type 1, Type 2) vehicles
NCD_1	(200,0)	(3,0)
NCD_2	(200,0)	(3,0)
NCD_3	(200,0)	(3,0)
NCD_4	(200,50)	(1,2)

Table 4.5: $E3_m$: Load Capacity of Vehicle type m {10^3}

Type 1	**150**
Type 2	**100**

Table 4.6: al_{ij}: **Unit travel cost of vehicle type m**

M	**TIME (hr)**
Air (1)	0.03
Truck (2)	0.9

Table 4.7: w_l: Average weight of commodity l

	w_l (Kilogram)
Food	4
Medical	2
Water	110

Table 4.8: Capacity of supplier for each commodity (10^3)

C1	WATER	FOOD	MEDICAL FACILITY
NCD1	350	450	300
NCD2	400	450	200
NCD3	550	550	250
NCD4	450	100	150

Table 4.9: Procurement price, transportation cost, volume occupied by commodity, and weight of commodity.

Commodity (10^3)	Procurement price for same commodity (10^3) naira per unit (φ**i**)	Vol. occupied each of the commodity initially (m^3 per unit)(v_l**)**	Transport (10^3) cost naira per unit per distance a1, a2	Weight in Kilogram of the items (w_l)
Water	10	15.5	1.5	100
Food	50	12.5	1.8	5
Medical	60	8.0	0.6	2

Table 4.10: Procurement price and shortage price.

Commodity (10^3)	Procurement price for same commodity (10^3) naira per unit	Shortage cost for same commodity (10^3) naira per unit (S^n_{kl}**)**
Water	10	100
Food	50	500
Medical	60	600

Table 4.11: El_{im}: Vehicle capacity and number of vehicles needed.

	Vehicle capacity (10^3) (Type1, Type 2)	No. of (Type1, Type 2)
NCD 1	(200,0)	(3,0)
NCD 2	(200,0)	(3,0)
NCD 3	(200,0)	(3,0)
NCD 4	(200,100)	(1,2)

Table 4.12: Expected number of vehicle, Unit capacity of vehicle type m, capacity of LDCs, and cost of opening LDCs.

	Expected No. of vehicles (Type1, Type 2)	Unit capacity of vehicle type m(10^3) naira per unit	Capacity of LDC (10^3) ($C^n j$)	Cost of opening LDC (10^3) (F2)
LDC1	(1,15)	(200,100)	400	1500
LDC2	(1,20)	(200,100)	400	1500
LDC3	(1,15)	(200,100)	400	1500

Table 4.13: E3m: Load capacity of vehicle type m and time in miles per hour t1, t2

M	E3m (10^3)	Time (mph)
Type 1	150	160
Type 2	100	40

Table 4.14: Expected demand d^n_{kl}, k= 1,2,…6, l = 1,2,3, n = 1,2,3

	WFM (10^3)	WFM (10^3)	WFM (10^3)
POD_1	10,20,18	11,24,20	12,28,25
POD_2	30,60,50	32,61,52	24,65,56
POD_3	30,20,40	32,25,42	33,25,45
POD_4	40,60,50	44,61,53	45,63,56
POD_5	50,70,45	52,71,46	55,72,49
POD_6	40,60,80	42,63,82	41,68,83

	NCD1	NCD2	NCD3	NCD4	LDC1	LDC2	LDC3	POD1	POD2	POD3	POD4	POD5	POD6
NCD1	0	336.3	341.8	207.3	310.3	331.1	414.0	313.3	316.3	334.1	337.1	415.0	418.0
NCD2	336.3	0	246.2	230.9	191.3	189.5	117.9	192.3	195.3	190.5	193.5	127.9	130.9
NCD3	311.8	246.2	0	134.5	103.0	84.9	283.9	104.0	106.0	85.9	87.9	284.9	286.9
NCD4	207.3	230.9	134.5	0	52.5	70.7	207.1	53.5	55.5	71.7	73.7	208.1	210.1
LDC1	310.3	191.3	103.0	52.5	0	21.1	224.6	1.0	4.0	26.1	25.1	225.6	227.6
LDC2	331.1	189.5	84.9	70.7	21.1	0	203.5	22.1	25.1	1.0	4.0	204.5	207.5
LDC3	414.0	117.9	283.9	207.1	224.6	203.5	0	225.6	227.6	204.5	207.5	1.0	1.0
POD1	313.3	192.3	104.0	53.5	1.0	22.1	225.6	0	3.0	22.1	25.1	204.6	207.5
POD2	316.3	195.33	106.0	55.5	4.0	25.1	227.6	33.0	0	25.9	28.1	225.6	227.5
POD3	334.1	190.5	85.9	71.7	26.1	1.0	204.5	22.1	25.1	0	3.0	204.5	207.5
POD4	337.1	19.5	87.9	73.7	25.1	4.0	207.5	25.1	28.1	3.0	0	207.5	210.5
POD5	415.0	127.9	284.9	208.1	225.6	204.5	1.0	204.6	225.6	204.5	207.5	0	4.0
POD6	418.0	130.9	286.9	210.1	227.6	207.5	4.0	207.5	227.6	207.5	210.5	4.0	0

Table 4.14(b): Distance between the areas (i,j) in miles

Table 4.15: Availability between the suppliers and affected areas.

i	1 2 3 4	1 2 3 4	1 2 3 4
1	1 1 1 1	0 1 1 0	0 1 1 0
2	1 1 1 1	1 1 1 0	0 0 1 0
3	1 1 1 1	1 0 1 1	1 0 0 0
4	1 1 1 1	1 1 0 1	1 0 0 1

Table 4.16: Probabilities for flood scenarios

(pr)	**a_1 a_2 a_3**
Probability	0.25 0.5 0.25

4.2 Description of the Model solver output

The solver produced the following:

Objective of met demand:

Mode Class: MIQP

State: Local Optimal Solution

Infeasibility: 4.77485e-012

Iterations: 607

Variables: Total 2297

Non-Linear: 339

Integers: 376

Constraints: Total: 3064

Nonlinear: 2160

Nonzero: 4320

General Memory Used: 746

Elapsed Runtime [hh:mm:ss]:

00:03:03

Extended Solver Status

Solver Type: B-and-B

Best Objective: 0.998902

Objective Bound: 0.998902

Update Interval √2

Objective on Cost:

Model Class: M1QP

State: Local Optimal Solution

Objective: 4.06145e+008

Infeasibility: 2.5556Be-009

Iterations: 3199

Variables: Total: 2297

Nonlinear: 2109

Integers: 376

Constraints: Total: 3064

Nonlinear: 2161

Generated Memory Used: (k) 740

Elapsed Runtime [hh:mm:ss]

= 00:00:32

Update Interval √2

Extended Solver Status

Solver Type: B – and – B

Best Objectives: 4.06145e+008

Objective Bound: 4.06145e+008

Step s:1

Active: 0

Objective on Time (Appendix II)

4.3 Chapter Summary

Different data was collected and inputted into the software in the language of the programme and output generated. We will therefore present the generated results in the next chapter.

CHAPTER FIVE
Presentation of Results

5.0 Presentation of results

The main objective of this research is to offer a plan for distributing essential emergency supplies to catastrophe victims. As a result, we take into account the following goals:

(a) Fairness of Distribution (Proportion of Unmet Demand)

(b) Cost Minimization

(c) Minimization of Time

Therefore, we present the results of the output in line with the objectives.

5.1 Fairness of Distribution

This goal aims to reduce the percentage of unfulfilled demand at PODs during emergency operations. It is well known that chaos reigns when a calamity strikes. This effort took into account the fact that during these periods, the majority of access routes are damaged, and people rely on aid from the government, social workers, and other humanitarian organizations for rescue and survival. This goal is taken into account when determining how well these relief organizations are able to address the needs of the impacted individuals. The Sphere Project (2011) asserts that ‘access to health care should be founded on the principles of equity and impartiality, ensuring equitable access according to need without any discrimination.’ Equity must be maintained to guarantee that similar food ratios are provided to similarly affected populations and populations sub-groups’. According to Kristina and Sigrid (2012), ‘the marginal utility of the given commodities reduces in accordance with help receipt by the most impoverished at each PODs.’ There may still be a need for relief supplies in a given region, but it is more profitable and satisfying to aid those in other PODs that are in greater need before going back to distribute to the initial PODs.

Fairness requires that the impacted individuals receive the aid at the point of distribution as soon as possible to lessen the effects of a scarcity. It also requires that the relief supplies are dispersed properly throughout the impacted areas, not only to one portion of the PODs. Having an uneven distribution leads to low satisfaction at the PODs.

The discrepancy between the demand and the met demand can be seen as a very thin line in table 5.0 and figure 5.0. It is evident from each POD that the relief supplies were sufficient with little variation. For instance, in POD1, the complete requirement was satisfied with only 3.637 units of water, 4.36 units of food, and 0.0 units of medical supplies, respectively. This explains whether the distribution strategy and mode of transportation used in the rescue effort are adequate. Figure 5.0 also demonstrated a very small discrepancy between the met demand and the demand. This demonstrates that the relief supplies were distributed equally.

Table 5.0: Demand and met Demand (Extract from Appendix 3)

	Demand	Met Demand	Unmet Demand
POD1WATER	6970	6966.363	3.637
POD1FOOD	8600	8595.637	4.363
POD1MED	4000	4000	0.0
POD2WATER	5650	5646	4.0
POD2FOOD	9130	9122	8.0
POD2MED	3200	3196	4.0
POD3WATER	4500	4496	4.0
POD3FOOD	5600	5596	4.0
POD3MED	1200	1192	8.0
POD4WATER	2340	2338	2.0
POD4FOOD	3240	3232	8.0
POD4MED	890	884	6.0
POD5WATER	3450	3448	2.0
POD5FOOD	5760	5752	8.0
POD5MED	2110	2104	6.0
POD6WATER	4560	4557.767	2.233
POD6FOOD	6765	6753	12.0
POD6MED	2150	2148.233	1.767

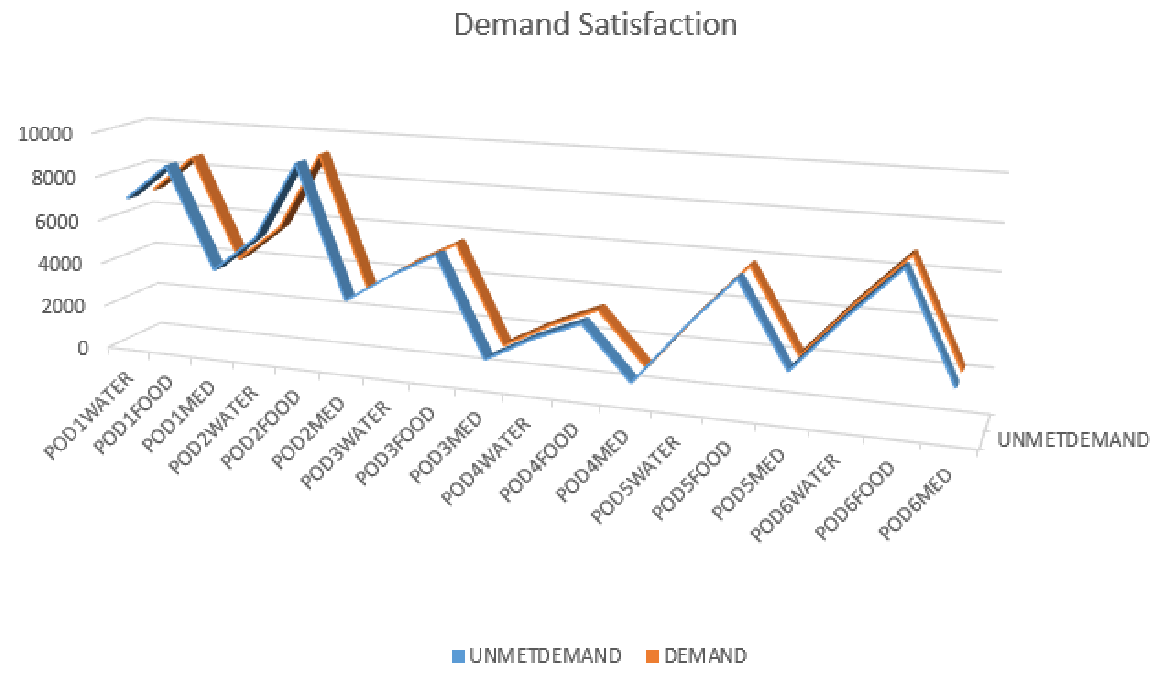

Figure 5.0

This has shown to be successful and efficient in addressing the urgent needs of the disaster's devastated residents. Because of this fine line between demand and met demand, the model is effective.

5.2 Quantity of Items Assigned from NCDs to PODs via LDCs by VETP (Table 5.1 and Figure 5.1)

The distribution of aid from the NCDs to the PODs via the several LDCs utilizing a specific mode of transportation is shown in the table below. Depending on the availability of the road network and an appropriate method of transportation in a specific situation, any single NCD can serve any specific POD. Given the many alternatives accessible at each time, this option's availability has facilitated the distribution of relief supplies. It is apparent that each of the relief supplies might be found at the PODs in an amount sufficient to cover the typical requirements of the afflicted neighborhood. Figure 5.1's clumsiness reflects the fact that there are numerous options for supplying relief supplies.

5.3 Quantity of Items Assigned from NCDs to PODs by VETP (Table 5.2 and figure 5.2)

Additionally, the distribution of aid from NCDs to PODs directly is shown in this table along with the potential modes of conveyance for each feasible scenario. This technique makes it easier to distribute aid supplies in a way that is practical and meets needs at their core. It is observed that in one situation, air transport could cross a specific NCD to a POD, while in another, a vehicle might be used. This approach could significantly aid in the fair allocation of aid supplies.

5.4 Cost Minimization

It is common knowledge that the cost issue becomes less important when the question of life and death dominates the agenda of the mind. Budgetary restrictions must be taken into account, though. In this study, the costs of both direct and indirect rescue operations were taken into account. Direct operations cost more money, whereas indirect operations cost less. The numerous expenses taken into account include: the fixed costs at NCDs and LCDs; the direct and indirect costs of transportation; the scarcity and holding charges. The total cost derived from Table 5.1b was $1,016,673.37. For the purpose of planning, this sum becomes quite affordable for the government, research organizations, and other organizations engaged in development.

Table 5.1b: Summary of associated cost from model result (Extract from Appendix3)

Cost Parameter	Amount
Fixed cost for NCDs (f_1)	$630,000.00
Fixed cost for LDCs (f_2)	$330,820.00
Transport cost (A_1)	$17,256.42
Transport cost (A_2)	$17,283.95
Holding cost (Phil)	$14,842.00
Shortage cost	$6,471.00
Total	$1,016,673.37

Table 5.1: A display of quantity of Items assigned from NCDs to PODs via LDCs i.e. indirect

Variable	Value
X(NDC1, LDC1, POD1, WATER, AIR, MILD)	1.000000
X(NDC1, LDC1, POD1, WATER, AIR, MEDIUM	1.000000
X(NDC1, LDC1, POD1, WATER, TRUCK, MILD	1.000000
X(NDC1, LDC1, POD1, WATER, TRUCK, SEVE	0.7149212
X(NDC1, LDC1, POD1, FOOD, AIR, SEVERE)	1.000000
X(NDC1, LDC1, POD1, FOOD, TRUCK, MEDIU	1.000000
X(NDC1, LDC1, POD1, FOOD, TRUCK, SEVER	0.2850788
X(NDC1, LDC1, POD4, WATER, AIR, MEDIUM	0.7045989E-01
X(NDC1, LDC1, POD4, WATER, TRUCK, MEDI	0.7365728E-01
X(NDC1, LDC1, POD4, FOOD, AIR, MILD)	1.000000
X(NDC1, LDC1, POD4, FOOD, AIR, SEVERE)	1.000000
X(NDC1, LDC1, POD4, FOOD, TRUCK, MEDIU	0.9263427
X(NDC1, LDC1, POD4, FOOD, TRUCK, SEVER	1.000000
X(NDC1, LDC1, POD4, MEDI, AIR, MEDIUM)	0.9295401
X(NDC1, LDC1, POD4, MEDI, TRUCK, MILD)	1.000000
X(NDC1, LDC1, POD5, FOOD, AIR, MILD)	1.000000
X(NDC1, LDC1, POD5, FOOD, AIR, MEDIUM)	1.000000
X(NDC1, LDC1, POD5, FOOD, AIR, SEVERE)	1.000000
X(NDC1, LDC1, POD5, FOOD, TRUCK, MILD)	0.7372762
X(NDC1, LDC1, POD5, FOOD, TRUCK, MEDIU	1.000000
X(NDC1, LDC1, POD5, FOOD, TRUCK, SEVER	0.3934150
X(NDC1, LDC1, POD5, MEDI, TRUCK, MILD)	0.2627238
X(NDC1, LDC1, POD5, MEDI, TRUCK, SEVER	0.6065850
X(NDC1, LDC2, POD2, WATER, AIR, MILD)	1.000000
X(NDC1, LDC2, POD2, WATER, AIR, MEDIUM	0.1122918E-02
X(NDC1, LDC2, POD2, WATER, AIR, SEVERE	0.1078282E-02
X(NDC1, LDC2, POD2, WATER, TRUCK, MILD	0.4812487
X(NDC1, LDC2, POD2, WATER, TRUCK, SEVE	1.000000
X(NDC1, LDC2, POD2, FOOD, AIR, MEDIUM)	0.9988771
X(NDC1, LDC2, POD2, FOOD, AIR, SEVERE)	0.8626258E-02
X(NDC1, LDC2, POD2, MEDI, AIR, SEVERE)	0.9902955
X(NDC1, LDC2, POD2, MEDI, TRUCK, MILD)	0.5187513
X(NDC1, LDC2, POD2, MEDI, TRUCK, MEDIU	1.000000
X(NDC1, LDC2, POD3, WATER, AIR, MEDIUM	0.9972795
X(NDC1, LDC2, POD3, WATER, TRUCK, MILD	0.1267849
X(NDC1, LDC2, POD3, WATER, TRUCK, MEDI	1.000000
X(NDC1, LDC2, POD3, FOOD, AIR, MILD)	1.000000
X(NDC1, LDC2, POD3, FOOD, AIR, MEDIUM)	0.2720522E-02
X(NDC1, LDC2, POD3, FOOD, TRUCK, SEVER	1.000000
X(NDC1, LDC2, POD3, MEDI, AIR, SEVERE)	1.000000
X(NDC1, LDC2, POD3, MEDI, TRUCK, MILD)	0.8732151
X(NDC1, LDC2, POD4, FOOD, AIR, MILD)	1.000000
X(NDC1, LDC2, POD4, FOOD, AIR, MEDIUM)	1.000000
X(NDC1, LDC2, POD4, FOOD, AIR, SEVERE)	1.000000

```
X( NDC1, LDC2, POD6, FOOD, TRUCK, SEVER        1.000000
X( NDC1, LDC2, POD6, MEDI, AIR, SEVERE)       0.8371101E-02
X( NDC1, LDC2, POD6, MEDI, TRUCK, MILD)       0.1935264
X( NDC1, LDC3, POD2, WATER, AIR, SEVERE       0.1078282E-02
X( NDC1, LDC3, POD2, WATER, TRUCK, MILD        1.000000
X( NDC1, LDC3, POD2, WATER, TRUCK, MEDI        1.000000
X( NDC1, LDC3, POD2, FOOD, AIR, MILD)          1.000000
X( NDC1, LDC3, POD2, FOOD, AIR, SEVERE)       0.9978434
X( NDC1, LDC3, POD2, FOOD, TRUCK, SEVER        1.000000
X( NDC1, LDC3, POD2, MEDI, AIR, MEDIUM)        1.000000
X( NDC1, LDC3, POD2, MEDI, AIR, SEVERE)       0.1078282E-02
X( NDC1, LDC3, POD3, WATER, AIR, MILD)         1.000000
X( NDC1, LDC3, POD3, WATER, AIR, MEDIUM        1.000000
X( NDC1, LDC3, POD3, WATER, AIR, SEVERE        1.000000
X( NDC1, LDC3, POD3, WATER, TRUCK, MILD       0.4928603
X( NDC1, LDC3, POD3, WATER, TRUCK, MEDI        1.000000
X( NDC1, LDC3, POD3, MEDI, TRUCK, MILD)       0.5071397
X( NDC1, LDC3, POD3, MEDI, TRUCK, SEVER        1.000000
X( NDC1, LDC3, POD5, WATER, TRUCK, MEDI        1.000000
X( NDC1, LDC3, POD5, FOOD, AIR, MEDIUM)        1.000000
X( NDC1, LDC3, POD5, FOOD, AIR, SEVERE)        1.000000
X( NDC1, LDC3, POD5, FOOD, TRUCK, MILD)       0.7304341
X( NDC1, LDC3, POD5, MEDI, AIR, MILD)          1.000000
X( NDC1, LDC3, POD5, MEDI, TRUCK, MILD)       0.2695659
X( NDC1, LDC3, POD5, MEDI, TRUCK, SEVER        1.000000
X( NDC1, LDC3, POD6, WATER, AIR, MEDIUM       0.1163345
X( NDC1, LDC3, POD6, WATER, TRUCK, MILD       0.3174792
X( NDC1, LDC3, POD6, FOOD, AIR, MILD)          1.000000
X( NDC1, LDC3, POD6, FOOD, AIR, SEVERE)       0.9916289
X( NDC1, LDC3, POD6, FOOD, TRUCK, MILD)       0.5661863
X( NDC1, LDC3, POD6, FOOD, TRUCK, MEDIU        1.000000
X( NDC1, LDC3, POD6, FOOD, TRUCK, SEVER        1.000000
X( NDC1, LDC3, POD6, MEDI, AIR, MEDIUM)       0.8836655
X( NDC1, LDC3, POD6, MEDI, AIR, SEVERE)       0.8371101E-02
X( NDC1, LDC3, POD6, MEDI, TRUCK, MILD)       0.1163345
X( NDC2, LDC1, POD1, WATER, AIR, MILD)        0.6193681
X( NDC2, LDC1, POD1, WATER, TRUCK, MEDI        1.000000
X( NDC2, LDC1, POD1, WATER, TRUCK, SEVE       0.5180364E-01
X( NDC2, LDC1, POD1, FOOD, AIR, MILD)         0.3806319
X( NDC2, LDC1, POD1, FOOD, AIR, MEDIUM)        1.000000
X( NDC2, LDC1, POD1, FOOD, AIR, SEVERE)        1.000000
X( NDC2, LDC1, POD1, FOOD, TRUCK, MILD)        1.000000
X( NDC2, LDC1, POD1, FOOD, TRUCK, SEVER       0.9481964
X( NDC2, LDC1, POD4, WATER, AIR, MEDIUM       0.7045989E-01
X( NDC2, LDC1, POD4, WATER, AIR, SEVERE        1.000000
X( NDC2, LDC1, POD4, WATER, TRUCK, MEDI       0.7365728E-01
X( NDC2, LDC1, POD4, FOOD, AIR, MILD)         0.9820737
X( NDC2, LDC1, POD4, FOOD, TRUCK, MILD)        1.000000
X( NDC2, LDC1, POD4, FOOD, TRUCK, MEDIU       0.9263427
X( NDC2, LDC1, POD4, MEDI, AIR, MILD)         0.1792627E-01
X( NDC2, LDC1, POD4, MEDI, AIR, MEDIUM)       0.9295401
X( NDC2, LDC1, POD4, MEDI, TRUCK, SEVER        1.000000
X( NDC2, LDC1, POD5, FOOD, AIR, MILD)          1.000000
X( NDC2, LDC1, POD5, FOOD, AIR, MEDIUM)        1.000000
X( NDC2, LDC1, POD5, FOOD, TRUCK, MILD)       0.7304341
X( NDC2, LDC1, POD5, FOOD, TRUCK, MEDIU        1.000000
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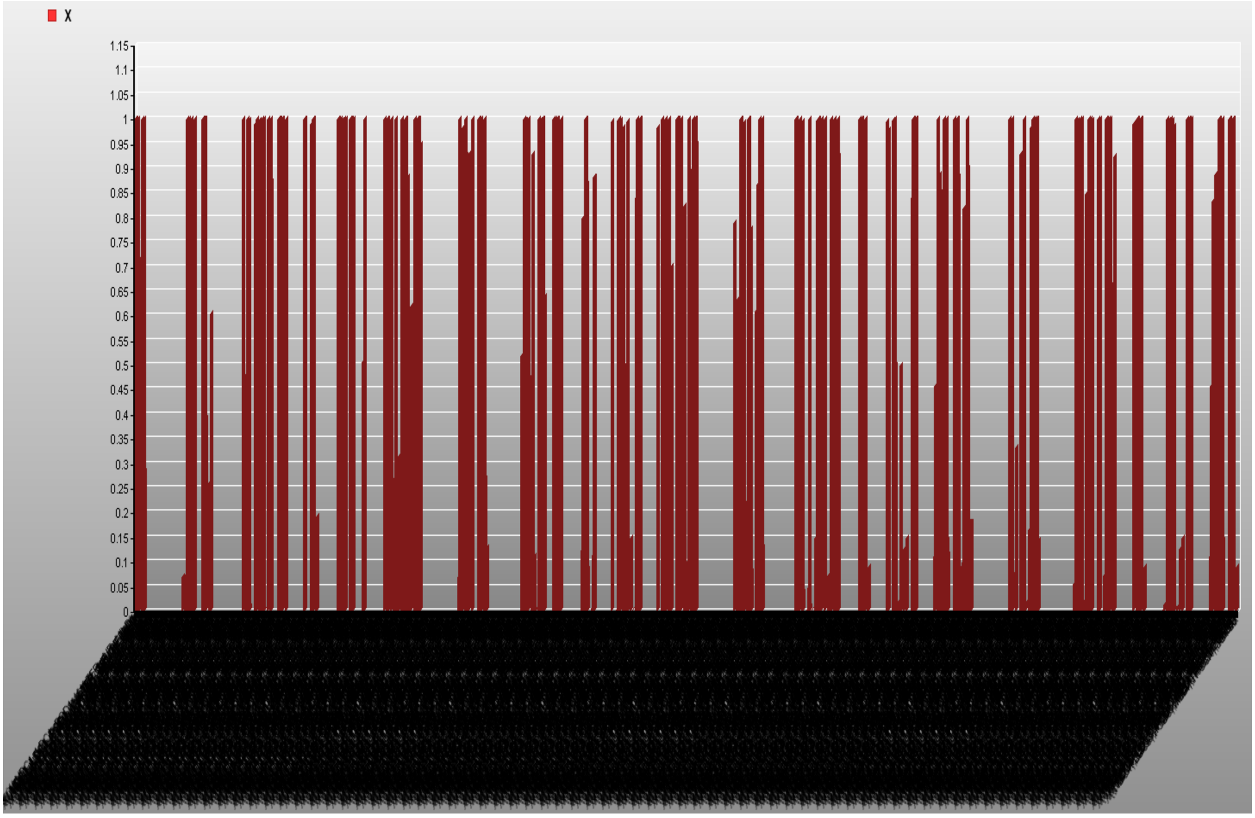

Figure. 5.1: A display of quantity of items assigned from NCDs to PODs via LDCs (Indirect)

Table 5.2: Quantity of Items assigned directly from NCDs to PODs

Variable	Value
Y(NDC1, POD2, MEDI, AIR, MILD)	3.763643
Y(NDC1, POD2, MEDI, AIR, MEDIUM)	3.763643
Y(NDC1, POD2, MEDI, AIR, SEVERE)	3.763643
Y(NDC1, POD2, MEDI, TRUCK, MILD)	3.763643
Y(NDC1, POD2, MEDI, TRUCK, MEDIUM)	3.763643
Y(NDC1, POD2, MEDI, TRUCK, SEVERE)	3.763643
Y(NDC1, POD3, MEDI, AIR, MILD)	3.763643
Y(NDC1, POD3, MEDI, AIR, MEDIUM)	3.763643
Y(NDC1, POD3, MEDI, AIR, SEVERE)	3.763643
Y(NDC1, POD3, MEDI, TRUCK, MILD)	3.763643
Y(NDC1, POD3, MEDI, TRUCK, MEDIUM)	3.763643
Y(NDC1, POD3, MEDI, TRUCK, SEVERE)	3.763643
Y(NDC1, POD6, MEDI, AIR, MILD)	3.763643
Y(NDC1, POD6, MEDI, AIR, MEDIUM)	3.763643
Y(NDC1, POD6, MEDI, AIR, SEVERE)	3.763643
Y(NDC1, POD6, MEDI, TRUCK, MILD)	3.763643
Y(NDC1, POD6, MEDI, TRUCK, MEDIUM)	3.763643
Y(NDC1, POD6, MEDI, TRUCK, SEVERE)	3.763643
Y(NDC2, POD1, MEDI, AIR, MILD)	7.527286
Y(NDC2, POD1, MEDI, AIR, MEDIUM)	7.527286
Y(NDC2, POD1, MEDI, AIR, SEVERE)	7.527286
Y(NDC2, POD1, MEDI, TRUCK, MILD)	3.763643
Y(NDC2, POD1, MEDI, TRUCK, MEDIUM)	3.763643
Y(NDC2, POD1, MEDI, TRUCK, SEVERE)	3.763643
Y(NDC2, POD5, MEDI, AIR, MILD)	7.527286
Y(NDC2, POD5, MEDI, TRUCK, MILD)	3.763643
Y(NDC2, POD5, MEDI, TRUCK, MEDIUM)	3.763643
Y(NDC2, POD5, MEDI, TRUCK, SEVERE)	3.763643
Y(NDC3, POD5, MEDI, AIR, MEDIUM)	7.527286
Y(NDC3, POD5, MEDI, AIR, SEVERE)	7.527286
Y(NDC3, POD5, MEDI, TRUCK, MILD)	3.763643
Y(NDC3, POD5, MEDI, TRUCK, MEDIUM)	3.763643
Y(NDC3, POD5, MEDI, TRUCK, SEVERE)	3.763643
Y(NDC4, POD1, MEDI, TRUCK, MILD)	3.763643
Y(NDC4, POD1, MEDI, TRUCK, MEDIUM)	3.763643

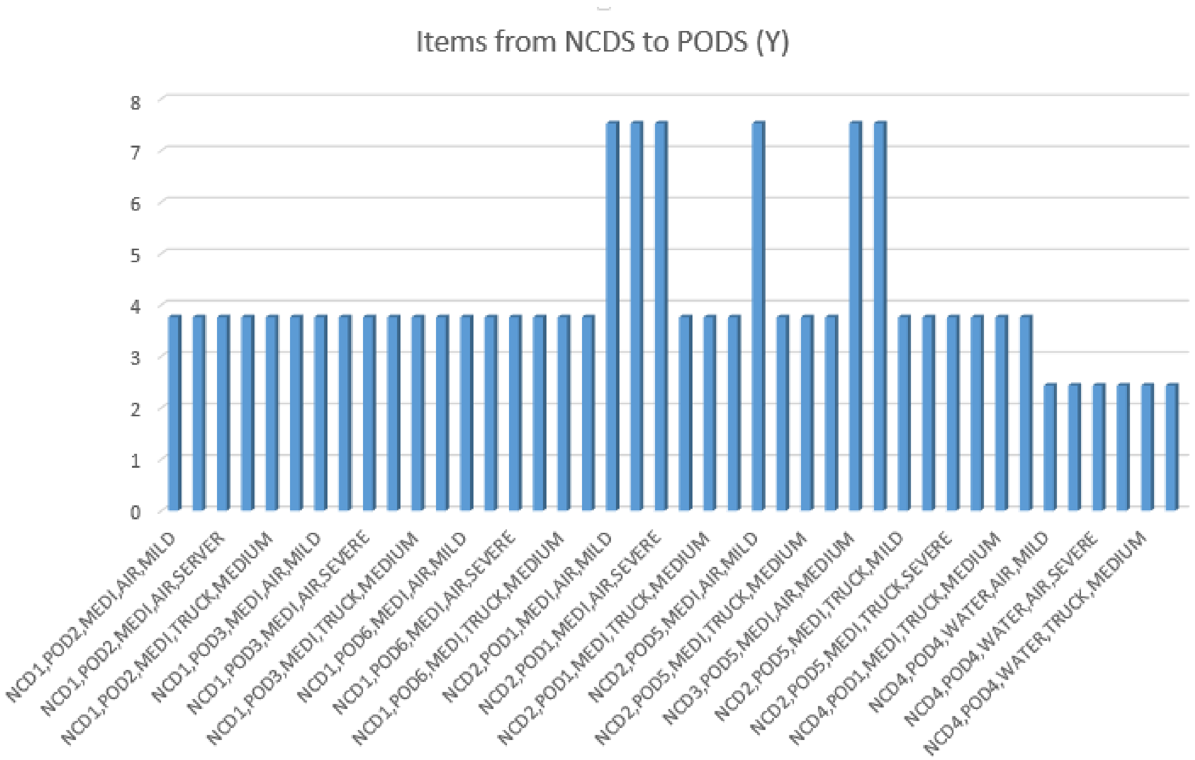

Figure 5.2: Items from NCDs to PODs

5.5 Minimization of coverage time

Table 5.3 Indirect (Extract from Appendix 3: T1)

			variable	Value
T1	(	LDC1,	POD1)	1.234568
T1	(	LDC1,	POD2)	1.234568
T1	(	LDC1,	POD3)	1.234568
T1	(	LDC1,	POD4)	1.234568
T1	(	LDC1,	POD5)	1.234568
T1	(	LDC1,	POD6)	1.234568
T1	(	LDC2,	POD1)	1.234568
T1	(	LDC2,	POD2)	1.234568
T1	(	LDC2,	POD3)	1.234568
T1	(	LDC2,	POD4)	1.234568
T1	(	LDC2,	POD5)	1.234568
T1	(	LDC2,	POD6)	1.234568
T1	(	LDC3,	POD1)	1.234568
T1	(	LDC3,	POD2)	1.234568
T1	(	LDC3,	POD3)	1.234568
T1	(	LDC3,	POD4)	1.234568
T1	(	LDC3,	POD5)	1.234568
T1	(	LDC3,	POD6)	1.234568

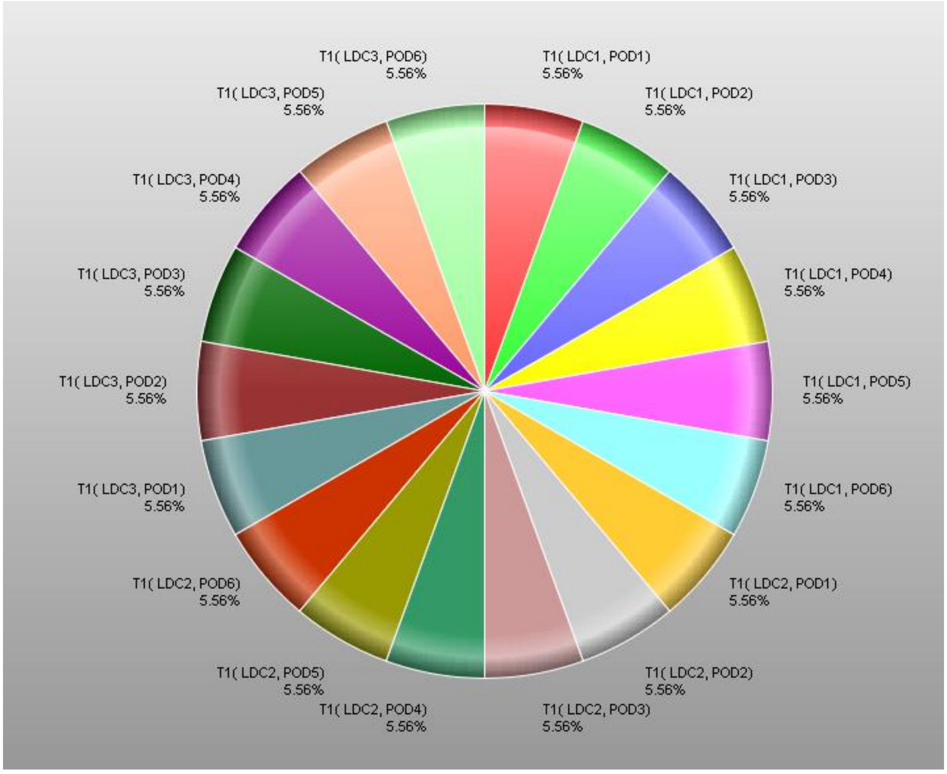

Figure 5.3: Indirect Time Coverage

Table 5.4: Direct Operation (Extract from Appendix 3: T2)

Variable	Value	Reduced Cost
A2 (NDC1, POD1)	1.234568	0.000000
A2 (NDC1, POD4)	1.234568	0.000000
A2 (NDC1, POD5)	1.234568	0.000000
A2 (NDC2, POD2)	1.234568	0.000000
A2 (NDC2, POD3)	1.234568	0.000000
A2 (NDC2, POD4)	1.234568	0.000000
A2 (NDC2, POD6)	1.234568	0.000000
A2 (NDC3, POD1)	1.234568	0.000000
A2 (NDC3, POD2)	1.234568	0.000000
A2 (NDC3, POD3)	1.234568	0.000000
A2 (NDC3, POD4)	1.234568	0.000000
A2 (NDC3, POD6)	1.234568	0.000000
A2 (NDC4, POD2)	1.234568	0.000000
A2 (NDC4, POD3)	1.234568	0.000000
A2 (NDC4, POD5)	1.234568	0.000000
A2 (NDC4, POD6)	1.234568	0.000000

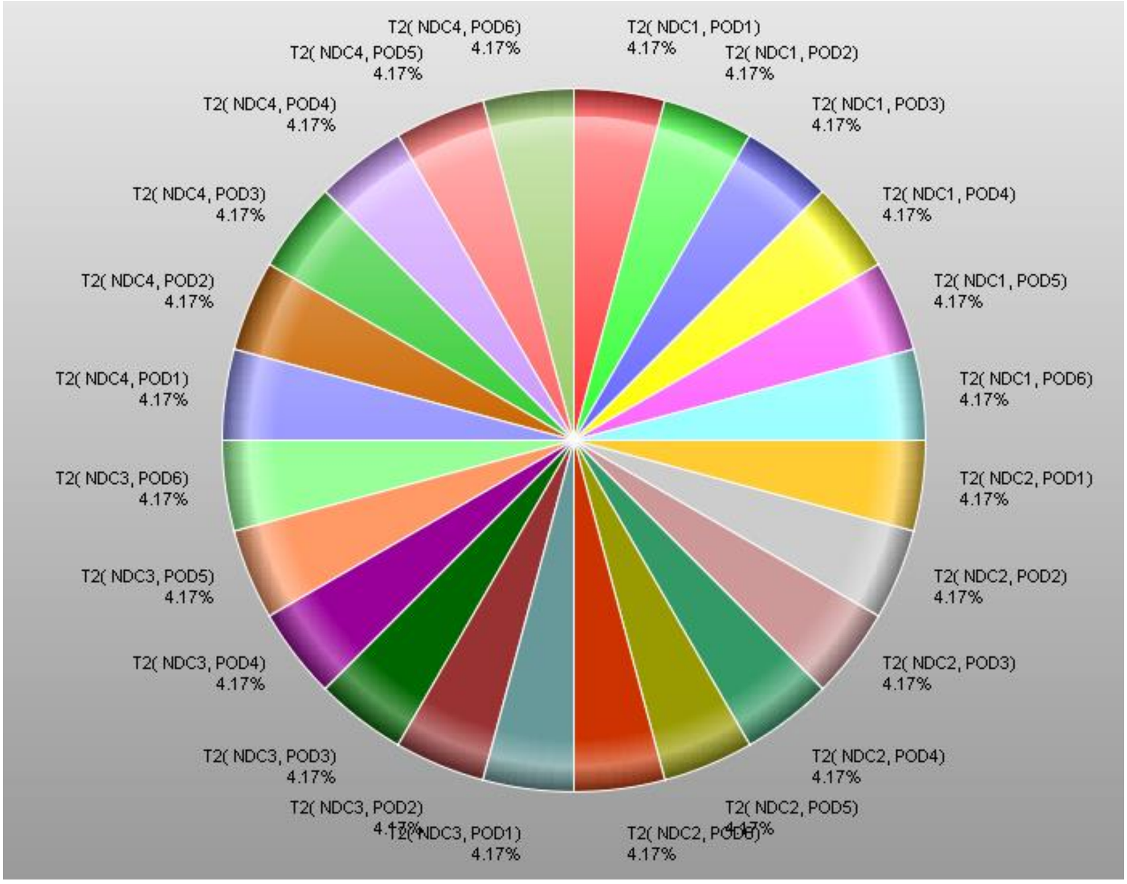

Figure 5.4: Direct Time Coverage

Minimization of Coverage Time

By minimizing delivery time, catastrophe operations can have less of a negative impact. The more lives that are saved, the faster the relief supplies can be distributed.

A minimal average speed of 1.234568 miles per hour seems quite fair for the rescue operations when taking into account the results in table 5.3 and figure 5.3 for the indirect distribution of aid via the LDCs. On the other hand, an average minimum time of 1.2346 with little variation in some routes for the direct delivery of relief items appears substantially better for emergency rescue operations.

4.17 percent of the time is shown for each basic connection route in table 5.4 and picture 5.4.

5.6 Variation in Threshold

Table 5.6a: Threshold > 6 ks' for Demands of Commodities

	Demand	Met Demand
POD1WATER	6970	6966
POD1FOOD	8600	8595
POD1MED	4000	4000
POD2WATER	5650	5646
POD2FOOD	9130	9122
POD2MED	3200	3196
POD3WATER	4500	4496
POD3FOOD	5600	5596
POD3MED	1200	1192
POD4WATER	2340	2338
POD4FOOD	3240	3232
POD4MED	890	884
POD5WATER	3450	3448
POD5FOOD	5760	5752
POD5MED	2110	2104
POD6WATER	4560	4557
POD6FOOD	6765	6753
POD6MED	2150	2148

Table 5.6b: Threshold ≤ 6 ks' for Demands of Commodities

	Demand	Met Demand
POD1WATER	6970	6964
POD1FOOD	8600	8598
POD1MED	4000	4000
POD2WATER	5650	5650
POD2FOOD	9130	9122
POD2MED	3200	3192
POD3WATER	4500	4498
POD3FOOD	5600	5600
POD3MED	1200	1186
POD4WATER	2340	2338
POD4FOOD	3240	3238
POD4MED	890	878
POD5WATER	3450	3442
POD5FOOD	5760	5754
POD5MED	2110	2108
POD6WATER	4560	4558
POD6FOOD	6765	6755
POD6MED	2150	2146

Met Demand Below Threshold 6	Met Demand Above Threshold 6	Demand
6964	6966	6970
8598	8595	8600
4000	4000	4000
5650	5646	5650
9122	9122	9130
3192	3196	3200
4498	4496	4500
5600	5596	5600
1186	1192	1200
2338	2338	2340
3238	3232	3240
878	884	890
3442	3448	3450
5754	5752	5760
2108	2104	2110
4558	4557	4560
6755	6753	6765
2146	2148	2150

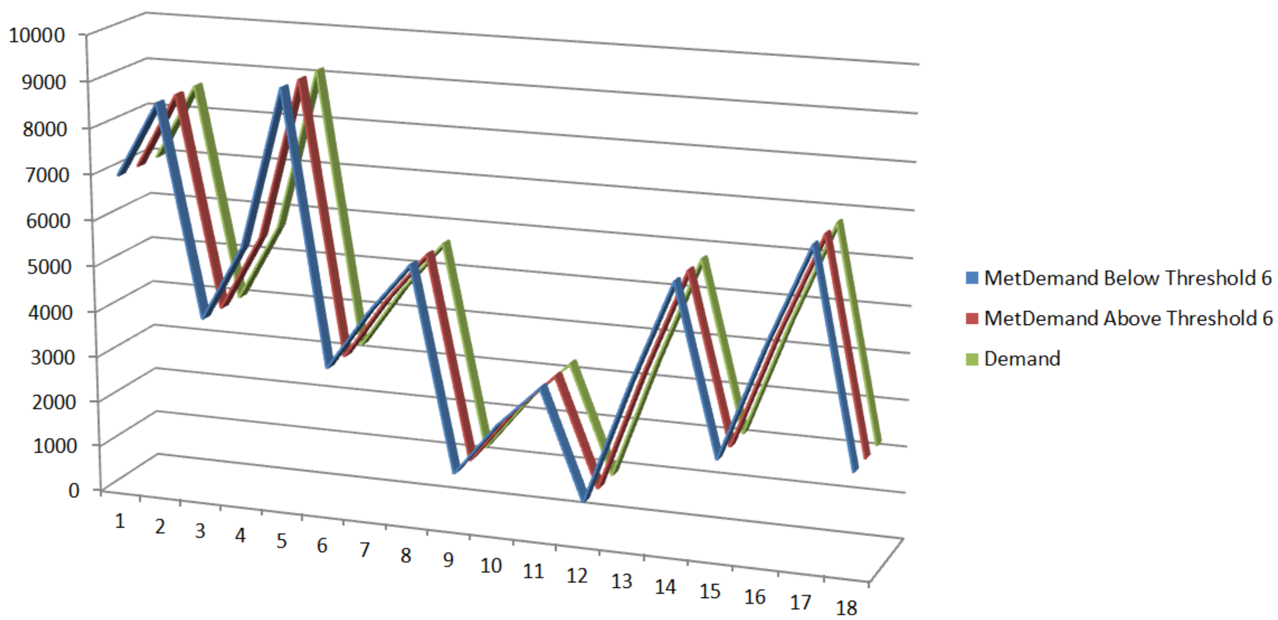

Figure 5.6: Variation in Threshold for Met Demands

Variation in threshold (K_s)

From table 5.6c and the associated figure above, using k = 6 as threshold of point of distribution, we observed that meeting the demand satisfaction becomes inconsistent at k < 6. Whereas at k < 6, the demand satisfaction would always be met. It shows that any point of distribution below this threshold will result to chaotic situation. POD will experience shortages of relief materials. This will result to more loss of lives. Adequate distribution of relief materials with adequate mode
assists the decision makes to save souls and crises situation.

5.7 Probabilities of the scenario

Since the scenario probabilities are the random influence taken into account in the stochastic model, we separately examined their impact here. In their analysis of the worst-case scenario and expected cost minimization for emergency supplies, Kelle et al. (2014) noted that 'for the P-reliable criteria solution, as P increases, extreme scenarios with small probabilities are dominating the allocation of resources, increasing the cost of transportation for scenarios with higher probability and thus increasing the expected total cost of transportation.' The tiny probability scenarios are more affected by changing individual scenario probabilities (and normalizing the rest so that they add up to 1).

However, because we modify the probability, our research is interconnected. We did not apply our analysis to a P-reliable criteria solution, it should be emphasized. We will make an effort to outline the impact on cost even if it may be challenging to capture all the changes for the various scenarios.

5.7.1: Discussion Two: Effect of Probability on the Cost of Indirect Distribution to the PODs

Table 5.7a: Probability of the Scenarios (0.25, 0.50, 0.25) on the Cost of Distribution to the PODs

Distribution from LDCs to PODs	Cost x 10^3
LDC1, POD1	1.234567
LDC1, POD2	1.234568
LDC1, POD3	1.234568
LDC1, POD4	1.234567
LDC1, POD5	1.234567
LDC1, POD6	1.234568
LDC2, POD1	1.234568
LDC2, POD2	1.234232
LDC2, POD3	1.234018
LDC2, POD4	1.234565
LDC2, POD5	1.234568
LDC2, POD6	1.234443
LDC3, POD1	1.234568
LDC3, POD2	1.233388
LDC3, POD3	1.233806
LDC3, POD4	1.234568
LDC3, POD5	1.234566
LDC3, POD6	1.234566

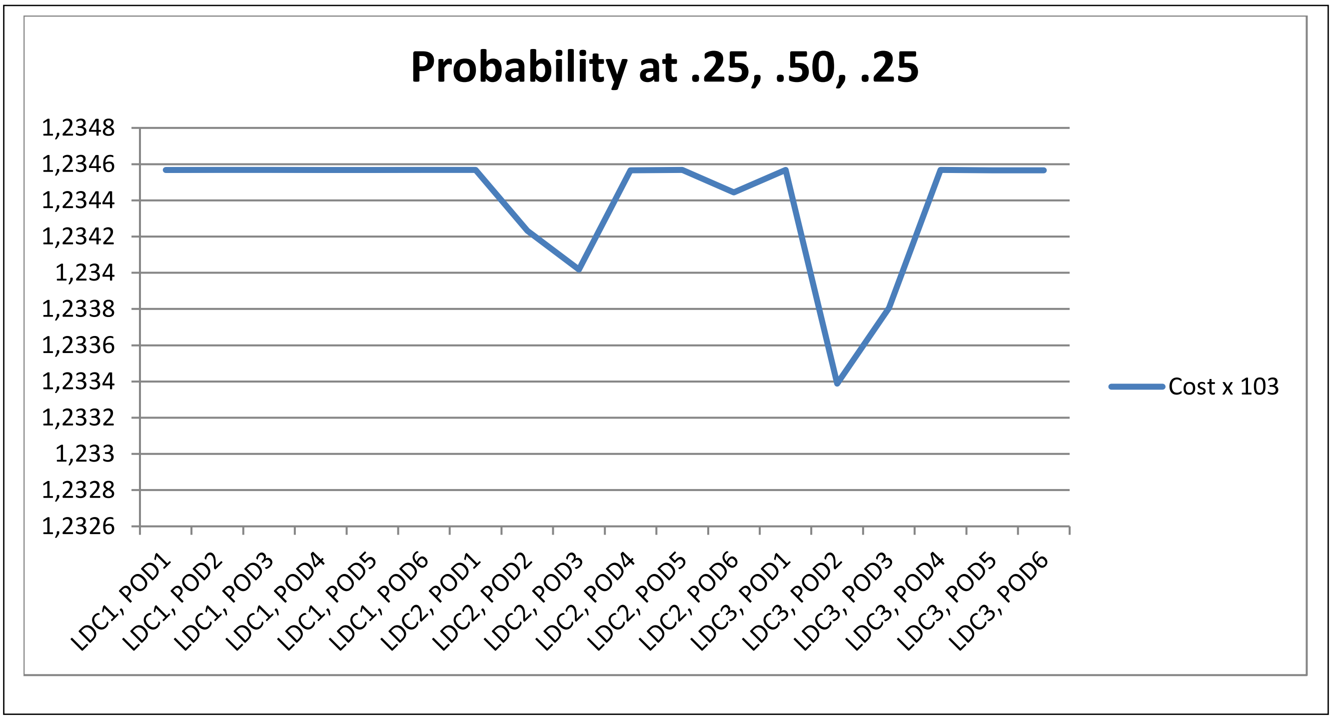

Figure 5.7a: (Probability at 0.25, 0.50, 0.25)

According to table 5.7a and figure 5.7a above, the intermediate scenario, which is the medium one, has a larger likelihood. Here, both the moderate and severe situations have a bigger cost impact. The cost experience in each of the situations is frequently impacted by transport logistics. The availability of pre-position materials is a significant barrier in a mild scenario. In a dire situation, a lacklustre network of access routes and insufficient communication and information are obstacles.

Table 5.7b: Probability of the Scenarios (0.25, 0.25, 0.50) on the Cost of Distribution to the PODs

Distribution from LDCs to PODs	**Cost x 10^3**
LDC1, POD1	1.234560
LDC1, POD2	1.234568
LDC1, POD3	1.234568
LDC1, POD4	1.234561
LDC1, POD5	1.234560
LDC1, POD6	1.234568
LDC2, POD1	1.234568
LDC2, POD2	1.234564
LDC2, POD3	1.234564
LDC2, POD4	1.234563
LDC2, POD5	1.234568
LDC2, POD6	1.234564
LDC3, POD1	1.234568
LDC3, POD2	0.000000
LDC3, POD3	0.000000
LDC3, POD4	1.234568
LDC3, POD5	0.000000
LDC3, POD6	0.000000

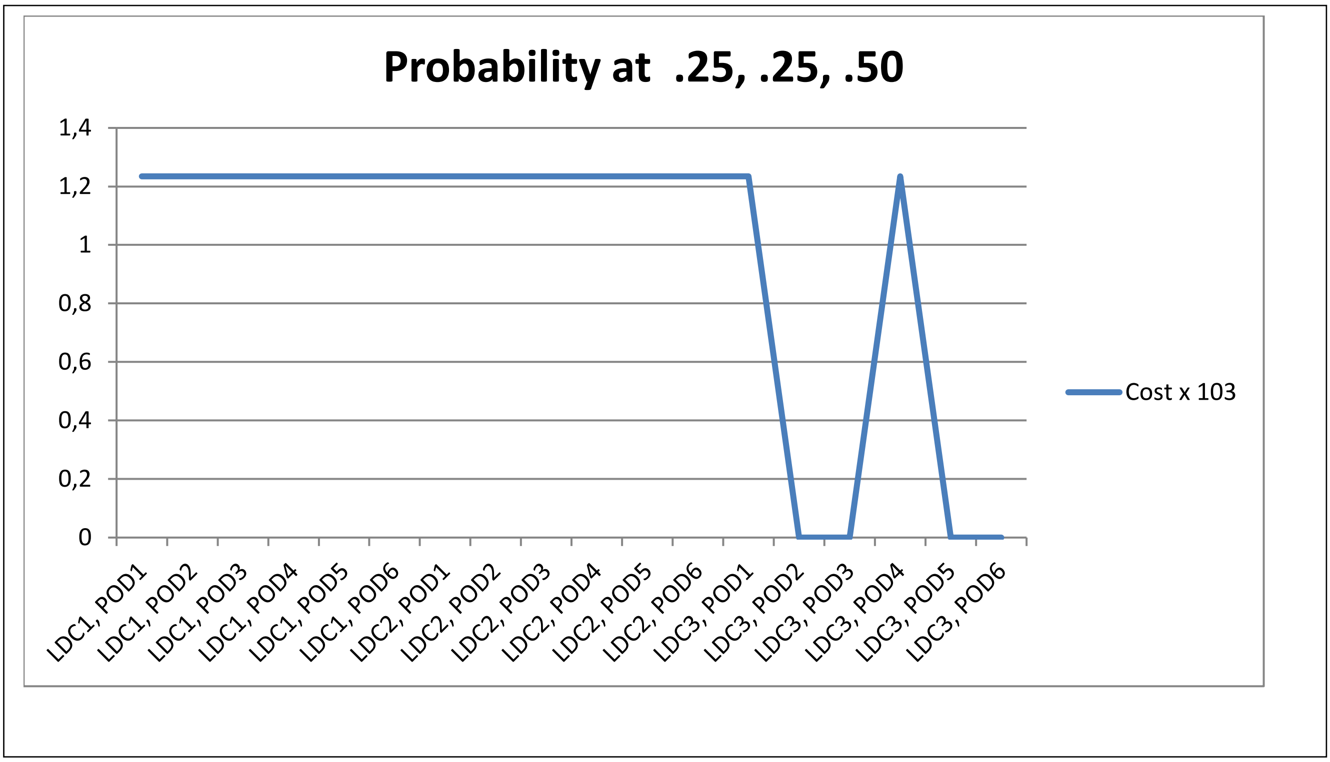

Figure 5.7b (Prob. At 0.25, 0.25, 0.50)

We found that the cost is higher in the scenario with lower probabilities when taking into account these probability fluctuations, with higher probability being the severe case. The distribution and transportation costs of relief supplies are higher in the moderate and medium situations.

Table 5.7c: Probability of the Scenarios (0.50, 0.25, 0.25) on the Cost of Distribution to the PODs

Distribution from LDCs to PODs	Cost x 10^3
LDC1, POD1	0.000000
LDC1, POD2	1.234568
LDC1, POD3	1.234568
LDC1, POD4	0.000000
LDC1, POD5	0.000000
LDC1, POD6	1.234568
LDC2, POD1	1.234568
LDC2, POD2	1.234567
LDC2, POD3	1.234566
LDC2, POD4	1.234566
LDC2, POD5	1.234568
LDC2, POD6	1.234566
LDC3, POD1	1.234568
LDC3, POD2	0.000000
LDC3, POD3	0.000000
LDC3, POD4	1.234568
LDC3, POD5	0.000000
LDC3, POD6	0.000000

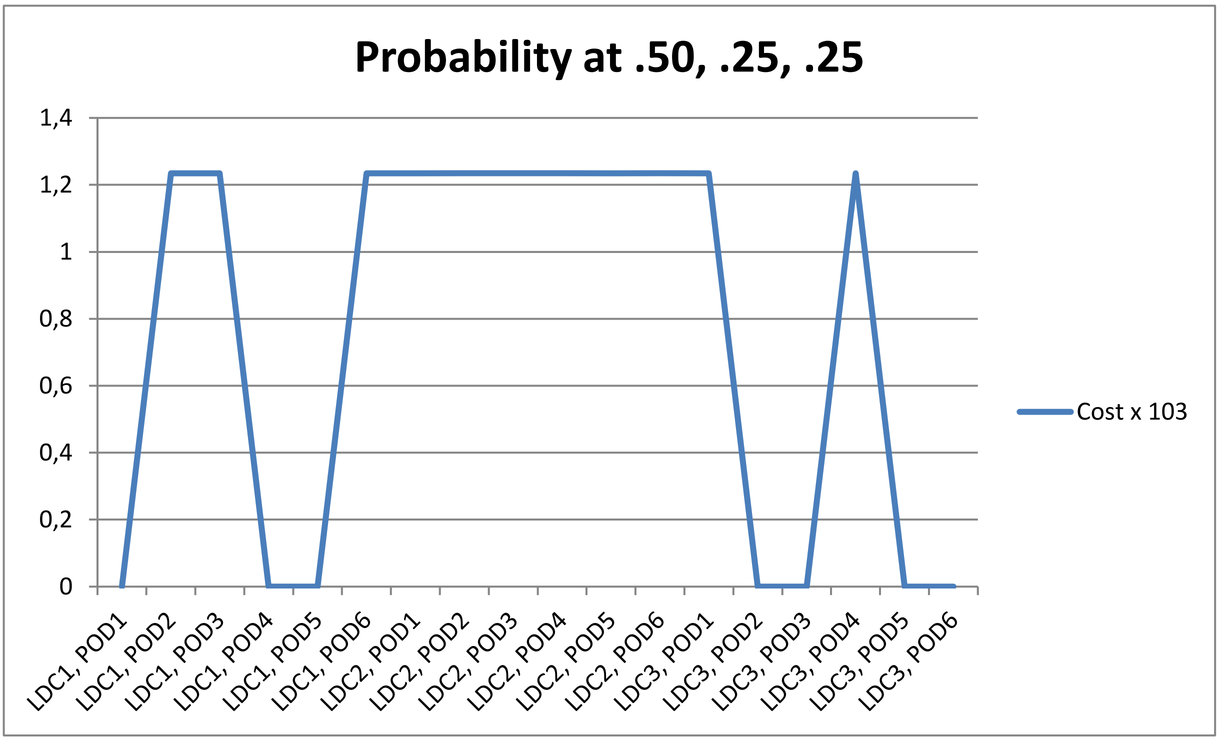

Figure 5.7c: (Prob. At 0.50, 0.25, 025)

Table 5.7c and figure 5.7c depict higher probability at the mild scenario and lower probability at the medium and severe scenarios. This case showed some zero cost as the LDC1 and LDC3, a case of 'reduce cost' situation. We shall discuss this better in the next section.

5.7.2: Effect of Probability on the Cost of Direct Distribution to the PODs

Table 5.7d: Probability of the Scenarios (0.50, 0.25, 0.25) on the Cost of Distribution to the PODs

Distribution from NCDs to PODs	**Cost x 10^3**	**Reduced Cost x 10^3**
NCD1, POD1	1.234568	0.000000
NCD1, POD2	0.000000	7.527286
NCD1, POD3	0.000000	7.527286
NCD1, POD4	1.234568	0.000000
NCD1, POD5	1.234568	0.000000
NCD1, POD6	0.000000	7.527286
NCD2, POD1	0.000000	3.763643
NCD2, POD2	1.234568	0.000000
NCD2, POD3	1.234568	0.000000
NCD2, POD4	1.234568	0.000000
NCD2, POD5	0.000000	7.527286
NCD2, POD6	1.234568	0.000000
NCD3, POD1	1.234568	0.000000
NCD3, POD2	1.234568	0.000000
NCD3, POD3	1.234568	0.000000
NCD3, POD4	1.234568	0.000000
NCD3, POD5	0.000000	7.527286
NCD3, POD6	1.234568	0.000000
NCD4, POD1	0.000000	11.29093
NCD4, POD2	1.234568	0.000000
NCD4, POD3	1.234568	0.000000
NCD4, POD4	0.000000	4.878049
NCD4, POD5	1.234568	0.000000
NCD4, POD6	1.234568	0.000000

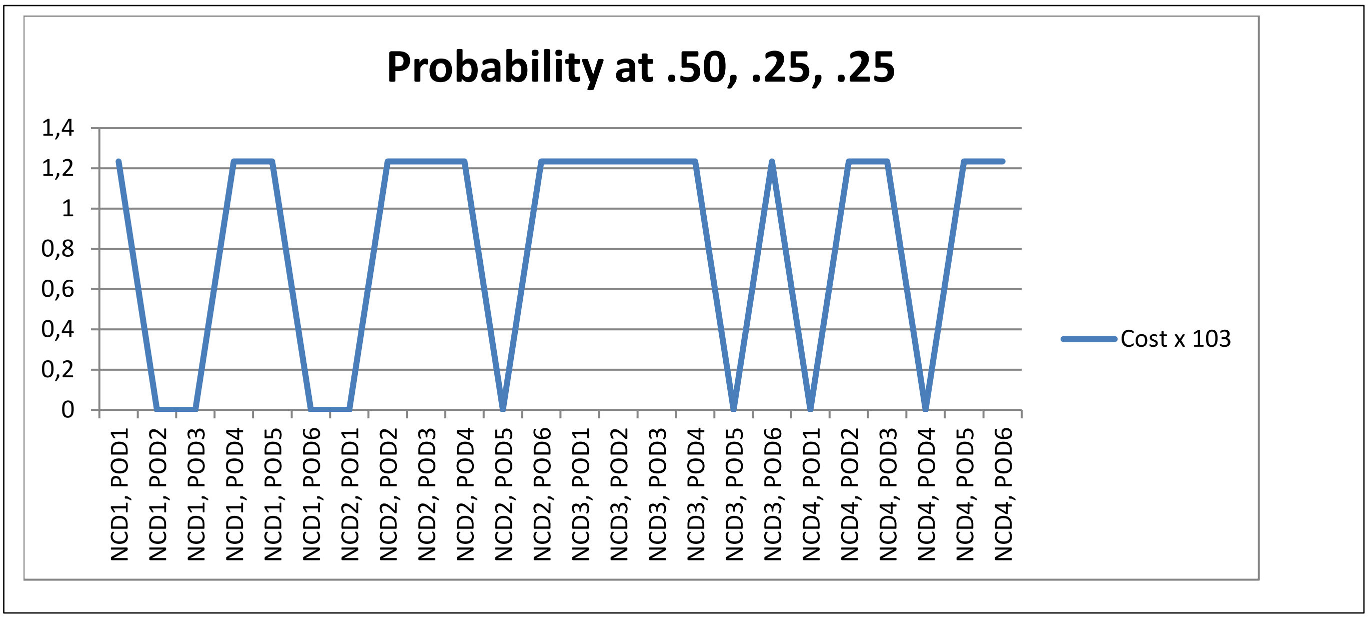

Figure 5.7d: (Prob. At 0.50, 0.25, 0.25 direct)

Here, we concentrate on how variations in probability affect the direct estimated cost. We want to introduce the idea of cost reduction. Our objective function value will vary by how much for every unit rise in the decision variable, as indicated by the reduce cost value for each choice variable. For each variable that is now zero, the reduction cost column provides an estimate of how much the objective function will change if we alter the variable to be non-zero. It is the row referred to as the variable's opportunity cost.

We know that, in order to reduce the impact of transportation costs as they affect direct movement from NCD_1 to the PODs, we must increase our investment in relief materials by at least 7527.286. This is because of the immediate table 5.7d and figure 5.7d above (.50,.25,.25). The direct cost effect of transportation is minimized at (NCD_4, POD_1) and (NCD4, POD4) by the opportunity cost of investing in improved relief materials by 112909.3 and 4878.049, respectively.

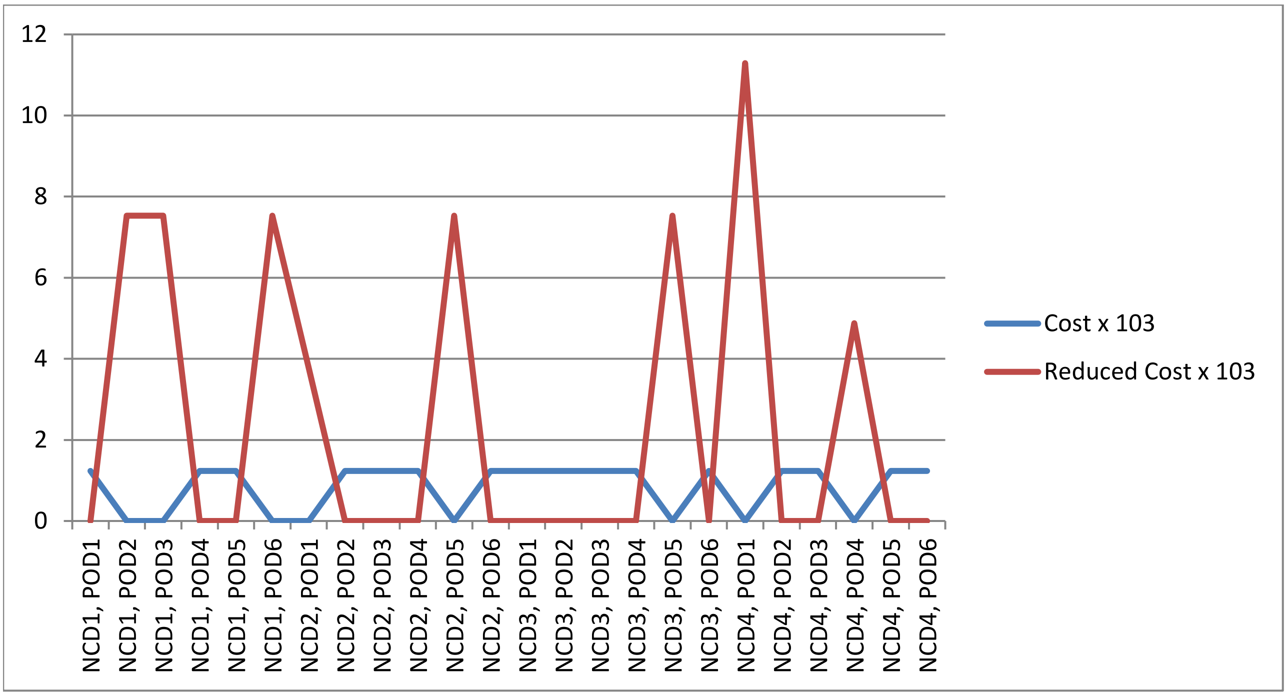

Figure 5.7d$_2$ (With Reduced Cost)

Table 5.7e: Probability of the Scenarios (0.25, 0.50, 0.25) on the Cost of Distribution to the PODs

Distribution from NCDs to PODs	**Cost x 10^3**	**Reduced Cost x 10^3**
NCD1, POD1	1.234568	0.000000
NCD1, POD2	0.000000	7.527286
NCD1, POD3	0.000000	7.527286
NCD1, POD4	1.234568	0.000000
NCD1, POD5	1.234568	0.000000
NCD1, POD6	0.000000	7.527286
NCD2, POD1	0.000000	3.763643
NCD2, POD2	1.234568	0.000000
NCD2, POD3	1.234568	0.000000
NCD2, POD4	1.234568	0.000000
NCD2, POD5	0.000000	11.29093
NCD2, POD6	1.234568	0.000000
NCD3, POD1	1.234568	0.000000
NCD3, POD2	1.234568	0.000000
NCD3, POD3	1.234568	0.000000
NCD3, POD4	1.234568	0.000000
NCD3, POD5	0.000000	3.763643
NCD3, POD6	1.234568	0.000000
NCD4, POD1	0.000000	11.29093
NCD4, POD2	1.234568	0.000000
NCD4, POD3	1.234568	0.000000
NCD4, POD4	0.000000	4.878049
NCD4, POD5	1.234568	0.000000
NCD4, POD6	1.234568	0.000000

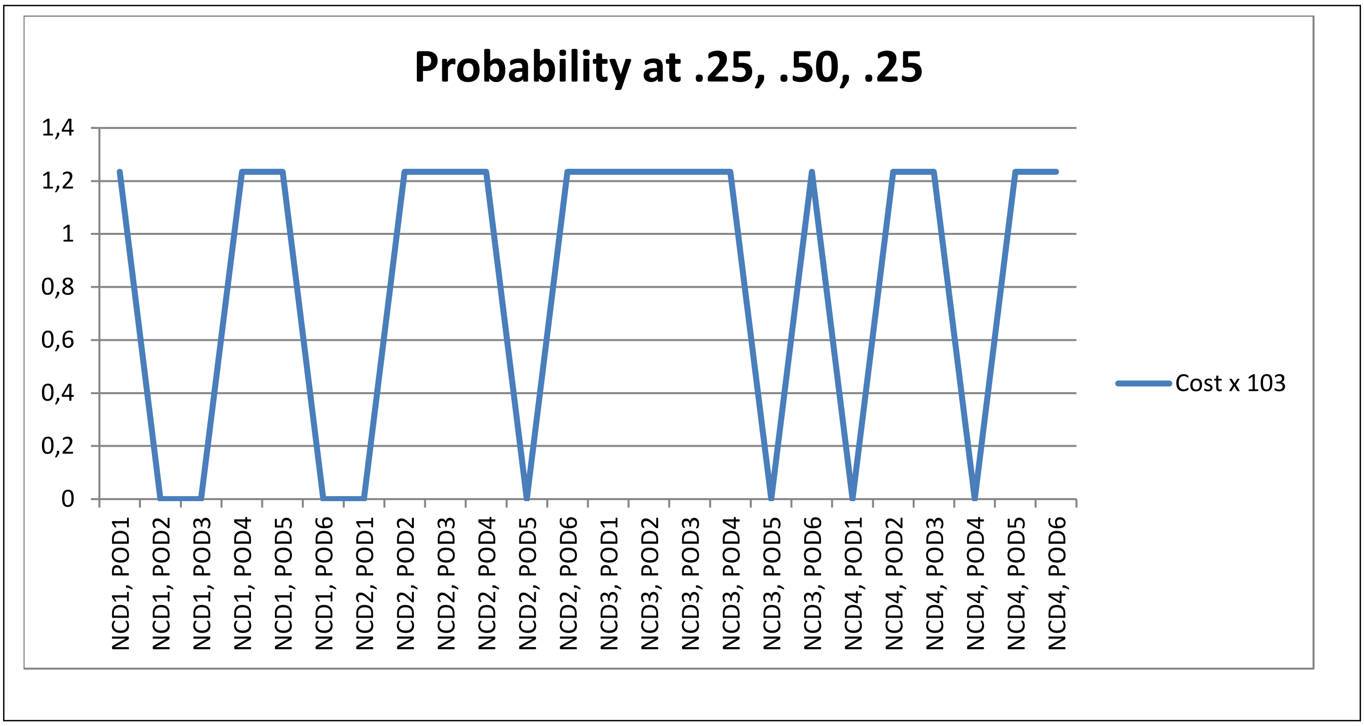

Figure 5.7e: Cost (This section has relatively the same effect as the previous section).

Table 5.7f: Probability of the Scenarios (0.25, 0.25, 0.50) on the Cost of Distribution to the PODs

Distribution from NCDs to PODs	**Cost x 10^3**	**Reduced Cost x 10^3**
NCD1, POD1	1.234568	0.000000
NCD1, POD2	0.000000	7.520877
NCD1, POD3	0.000000	7.527704
NCD1, POD4	1.234568	0.000000
NCD1, POD5	1.234568	0.000000
NCD1, POD6	0.000000	7.521605
NCD2, POD1	0.000000	3.763643
NCD2, POD2	1.234568	0.000000
NCD2, POD3	1.234568	0.000000
NCD2, POD4	1.234568	0.000000
NCD2, POD5	0.000000	5.645465
NCD2, POD6	1.234568	0.000000
NCD3, POD1	1.234568	0.000000
NCD3, POD2	1.234568	0.000000
NCD3, POD3	1.234568	0.000000
NCD3, POD4	1.234568	0.000000
NCD3, POD5	0.000000	9.409108
NCD3, POD6	1.234568	0.000000
NCD4, POD1	0.000000	11.29093
NCD4, POD2	1.234568	0.000000
NCD4, POD3	1.234568	0.000000
NCD4, POD4	0.000000	4.878049
NCD4, POD5	1.234568	0.000000
NCD4, POD6	1.234568	0.000000

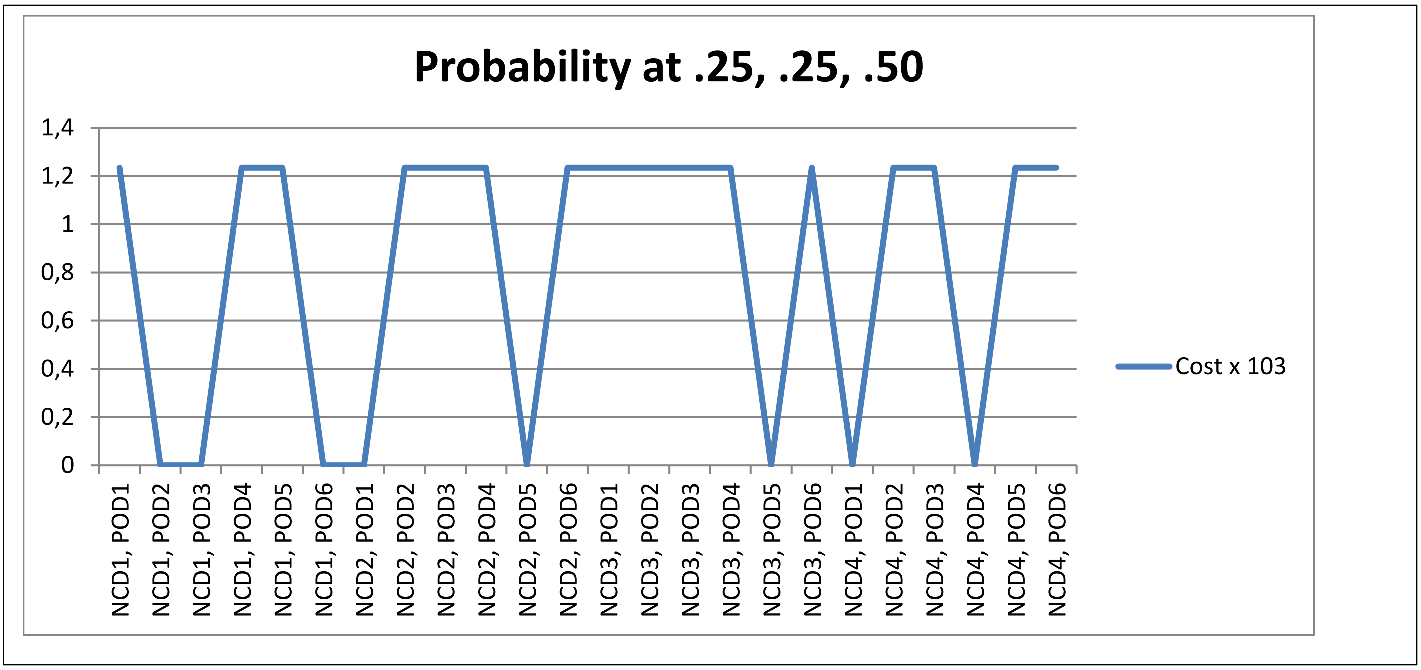

Figure 5.7f (Direct)

At this variation of probability, at (NCD_1, POD5), we need to improve our relief materials by 7520.877, at (NCD_1, POD_3), we need to increase the resources relief materials by 7527.704, at (NCD_1, POD_6), we increase by 7521.605, at (NCD_2, POD_1), we increase by 3763.643; at (NCD_2, POD_5), we increase by 5645.465; at (NCD_4, POD_1), we increase by 112909.3; and at (NCD_4, POD_4), we increase by 4878.049. These will have a corresponding reduction of cost of transportation at direct shipment.

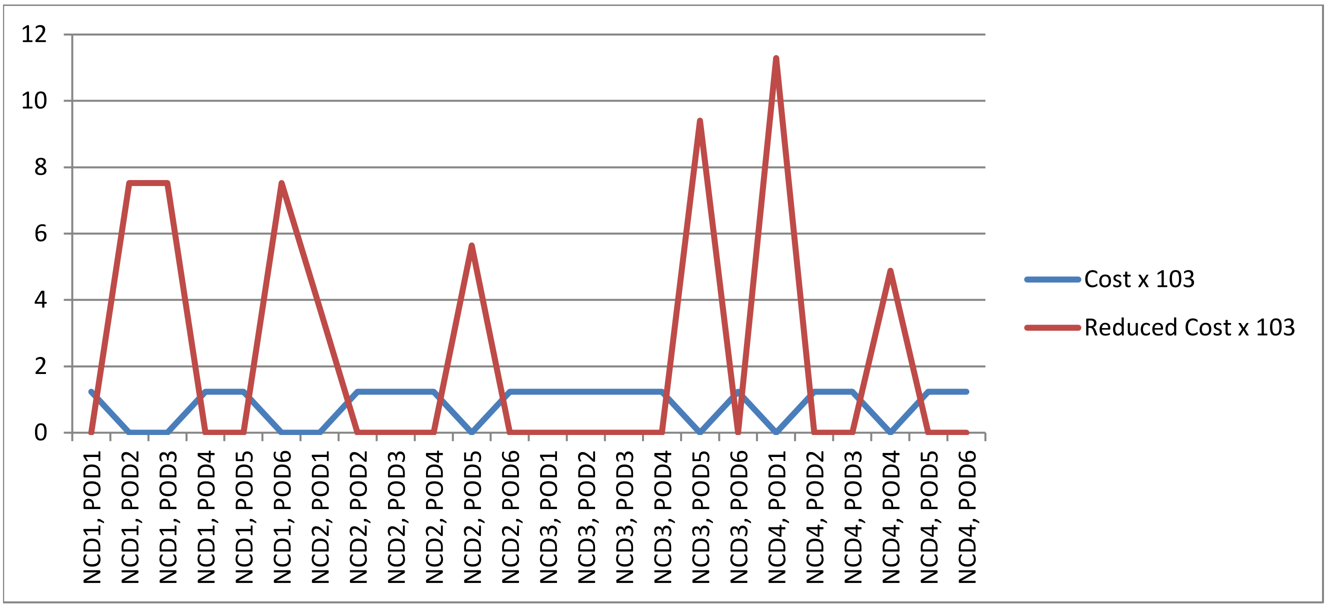

Figure 5.7f: (Direct with reduced cost)

Table 5.8: Shortage Quantity of Item Shipped

	Demand	Met Demand	Shortage
POD1WATER	6970	6966	4
POD1FOOD	8600	8595	5
POD1MED	4000	4000	0
POD2WATER	5650	5646	4
POD2FOOD	9130	9122	8
POD2MED	3200	3196	4
POD3WATER	4500	4496	4
POD3FOOD	5600	5596	4
POD3MED	1200	1192	8
POD4WATER	2340	2338	2
POD4FOOD	3240	3232	8
POD4MED	890	884	6
POD5WATER	3450	3448	2
POD5FOOD	5760	5752	8
POD5MED	2110	2104	6
POD6WATER	4560	4557	3
POD6FOOD	6765	6753	12
POD6MED	2150	2148	4

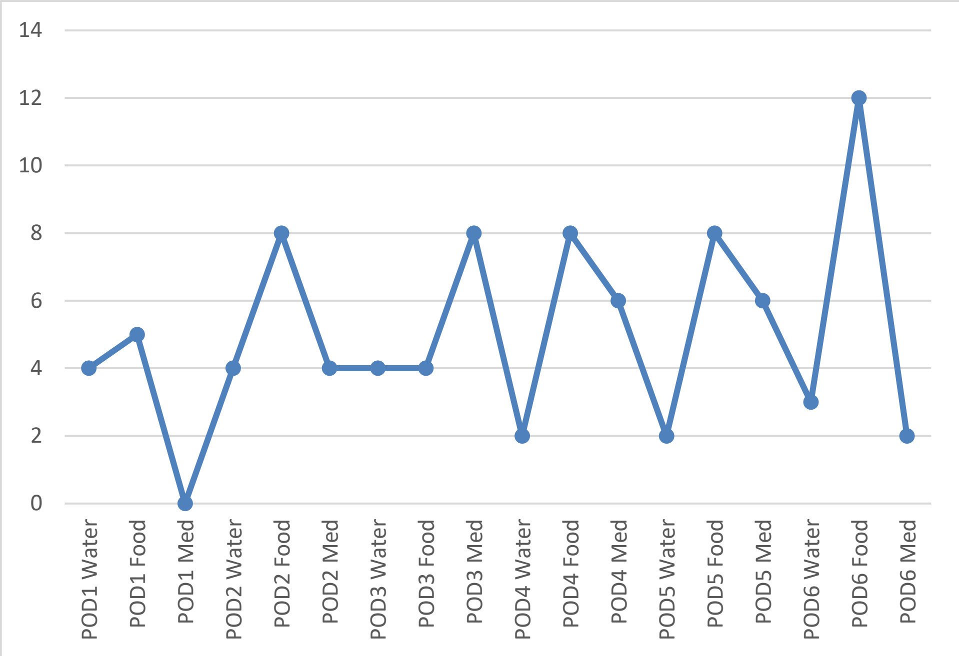

Figure 5.8: Shortage cost

As previously indicated, a number of costs are taken into account, including fixed costs in NCDs and LDCs, indirect and direct transport costs, shortage costs, and holding costs. In general, the better for the decision-makers is a higher pre-position of materials, especially at the NCDs. By itself, this has a growing impact on storage costs and the risk of spoilage for perishable goods. This frequently makes the point of dispersion more constrained.

When looking at figure 5.8, even if it seems like the distribution of aid materials is fair, there are still some regions where a lack is apparent. The shortage amount of item l at demand point K is shown in table 5.8 as being the difference between the demand of the demand point k and the met demands. In this paradigm, there are substantial repercussions if there is a shortage at the demand point. These include rescued individuals starving to death and injured people dying. Therefore, it is crucial that sufficient arrangements be made to guarantee that the overall served demand is met.

The supply should be balanced such that it does not fall below the overall demand. It is important to have supply and demand equality. The ratio of the difference should be very small in areas where it seems difficult to attain this equality.

5.8 Possible presence of Backlogged in the distribution process

It goes without saying that the cost of a shortage will rise if there are not enough pre-positioned supplies in the NCDs. However, prepositioning such relief supplies will increase the holding costs and add to the fixed costs of establishing NCDs.

There may be at least one demand point that is entirely or partially backlogged when a scenario is not included in a reliable set. One of the potential causes could be a lack of prepared relief supplies at the NCDs that could be transported to the PODs. Another possibility is that the opened LDCs do not have adequate space to send prepositioned supplies indirectly (via LDCs) to the PODs. Given the NCDs and LDCs that are open, a time constraint is another possible explanation.

We must identify the most likely reason for the backlog in order to attain reliability. The body of the solution will be severely impacted if the NCD's capacity is the cause, making it impossible to attain feasibility. The straightforward explanation is that choosing an NCD occurs at the beginning of the solution-building process, and the fixed cost of opening and maintaining an NCD contributes significantly more.

Therefore, as a fundamental step in identifying the problem, we must first assess each NCD's potential. If the backlog of demand exceeds the total of all opened NCDs' remaining capacity (taking into account the percentage of useable relief materials), it indicates that the scenario cannot become reliable without creating a new NCD. It is crucial to take into account the possibility of sending direct shipments to PODs with backlogged demands. This is due to the fact that, given the expense of founding and operating LDCs, it is sometimes preferable to ship directly. However, it is advisable to determine whether the entire backlogged demand is similar with the total remained capacity by looking at the available LDCs' remaining capacity. There may not be a need to open a new facility where capacity exceeds or is equivalent to the backlogged demand. Using the remaining NCD capacity and delivery times, direct shipments then become the preferred option. One or more additional LDCs should be formed to meet the immediate need of meeting all the backlogged demands whenever this option is once more rendered unfeasible. It is implied that the problem cannot be solved with all the available sets of LDCs when new LDCs cannot be formed or when time constraints prevent shipping through the newly opened LDCs.

5.9 Chapter Summary

We have presented the results in tables and in figures. Some figures are large in volume, we have included such in appendix. Interpretations and discussions followed the tables and the figures. The work highlighted possible presence of backlogged in distributions, and the possible reasons were presented. In the light of this, conclusion and recommendation forms the concluding chapter.

CHAPTER 6

Conclution And Recommendation

6.0 Introduction

Having gone through the various steps set to make this work successful, we wish to draw a general conclusion on the work and to make some recommendation that we help the Government, educationist, learners and future researchers.

6.1 Conclusion

Natural or man-made disasters can occur at any time and are unavoidable. The typical response to a disaster is to begin the process of rescue and relief in the afflicted area. However, if the right precautions were taken, the severity of the calamity would undoubtedly be lessened.

This thesis offers a thorough solution to the problem of disaster response, including facility location and last mile distribution of relief in the event of flooding. We have examined the distribution of supplies following a catastrophe as well as the number of supplies pre-positioned at each NCD. We considered the flow of relief materials from NCDs $\rightarrow$ PODs or from NCDs $\rightarrow$ LDCs $\rightarrow$ PODs. The first is the direct shipment while the latter is the indirect shipment.

The model's fundamental presumptions and constraints attest to its usefulness in terms of producing trustworthy solutions. The model takes into account a variety of relief supplies, including food, water, and medical services. The work took into account some ambiguity in a few crucial elements. Due to the unpredictable nature of occurrences, many distinct aspects were subject to uncertainty, and this previously unrealized knowledge became apparent at various times during the distribution process.

Due to its stochastic nature, this model clearly took distribution fairness into account as a crucial component of humanitarian logistics. To reduce the number of fatalities, it is essential to be able to organize a quick response in accordance with the most pressing needs as indicated by the utility that aid will produce.

When it came to addressing the immediate needs of the disaster's displaced inhabitants, the methodology proved successful and efficient. Due to the tiny margin between the demand and the met demand, it was effective.

The costs of both direct and indirect rescue operations were taken into account in this study along with other costs related to emergency rescue efforts. The numerous costs taken into account include the fixed costs of NCDs and LDCs, the direct and indirect costs of transportation, the costs associated with shortages, and the costs associated with holding. The sum calculated was $1,016,673.37. For the purpose of planning, this figure becomes extremely important to the government, research organizations, and other developmental organizations.

It is clear from the studies that floods have had a profound and alarmingly large impact on Nigeria, particularly in Delta state. It is of a dangerous magnitude, causing the loss of several lives and properties.

The study showed that the 2012 flood tragedy cost billions of Naira, and we also realized that the politicians do not account for the billions of Naira they annually allot during budget presentation for the ecological fund. Planning carefully to avoid these hazards to the entire nation becomes a top priority.

By minimizing delivery time, catastrophe operations can have less of a negative impact. The less time it takes to deploy the aid supplies, the fewer lives will be lost. This concept, which combines direct and indirect transportation to the PODs using the modes of air and ground transportation, saves time and helps save a lot of lives.

The government must implement a sustainable flood control mechanism that incorporates current best practices and keeps up with environmental changes as well as historical flood control system shortcomings. Additionally, establishing connections among local, state, federal, and international professionals will open up room for managing regional problems.

6.2 Implications

This model has demonstrated that merging the direct and indirect models would allow for speedy action in the event of a crisis. It has demonstrated that it is possible to distribute aid in a fair and equal manner. It has also demonstrated that, if properly carried out, the amount of deaths during relief operations might be considerably reduced.

The model demonstrated that the cost of disaster operations may be reduced and that sufficient budgeting could be done in advance of any event.

It is possible to curb significant corruption and waste in the public sector. Time is saved during rescue operations by combining air and ground transportation in the model and permitting both direct and indirect modes.

6.3 Recommendation/Policy Guidelines

- Need for wholesome water sources for inhabitants of the area
- Key stakeholders including local and regional government should urgently revamp and equip emergency response services.
- Prosper town planning and removal of illegal structures from water ways.
- Constant dredging of rivers should be carried out.
- Government agencies like NEMA should be empowered for effective performance.
- Rescue facilities operational tool, should be made available for quick response.
- Those who embezzle ecological fund should be punished.

  These current recommendations do not directly emanate from the thesis, they are just to prevent the reoccurrence of the disaster.

6.4 Future Studies

- One important area for future work is to relax some assumptions. For example, allowing a network that permits the vendors to introduce relief materials within the network operations.
- An opportunity of network development of a location-routing model which permits two-stage network. First, an echelon that allows hypothetical locating-routing problems that enhances result in the determinant of locations NCDs, LDCs and preliminary distribution scheme. Then the second echelon, will be a realization of the corrections of the deterministic process.
- As the disaster strength increases, the initial safety stock appears in- sequential and insufficient, thereby calling for additional safety stock because of the limited deliveries because of damage roads. The system will be observed to be highly stochastic. The probabilistic constraints are satisfied if additional safety stock is high, thereby increasing costs.
- Multi-suppliers or cross shipping and transportation of very important and perishable commodities require extra attention while deciding on safety stock levels. Decision makers could consider vital or perishable commodities adopting a single-commodity analysis.
- Although this thesis proposed a scenario of high flood situation, a robust emergency of hurricane, earthquake and Covid -19 related incidents situation could be considered for this model. Some of these extreme events, the best immediate course of action may be to create shelter immediately. Shelter could be in the victims' house or any other place close to the points where the event occurs.
- A more realistic and robust calculation of functional time of delivery will be highly advisable. Studying different approaches for state-space system formulation and comparing these different models on system performance requires extra attention.
- A well-articulated budgetary constraint into the model is a promising solution to adequate planning and protection of government revenues.

- Future work should include more objective functions and/or constraints in the formation of the model to enable us to obtain more efficient results.
- More National Centres Depot (NCD), Local Distribution Centres (LDC), and Points of Distribution (POD) may be considered in the model formulation.
- More than three emergency relief items may be considered.

6.5 Chapter Summary

The conclusions, the various recommendations, and the suggestions stated if adhered and implemented will be a great blessing, rich for advancement of knowledge and safety of lives.

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APPENDIX I

Handling Expectation Objective Functions

We consider the analytical expression of the fairness objective function, that is

$$f1 = Min \frac{\sum_k \sum_l \sum_n P_n \left[d_{Kl}^n - \left(\sum_i \sum_j \sum_m X_{ijklm}^n + \sum_i \sum_m Y_{iklm}\right)\right]}{\sum_k \sum_l \sum_n P_n d_{Kl}^n}$$

Theorem 1: Consider the fairness objective function of equation (1) in emergency supplies allocation (problem 1 – 15). Suppose that the disaster scenario is discrete random variable. For any Ws, the corresponding scenario is a normalized discrete variable with the following possibility distribution.

$$\mu_{(\gamma)} = \begin{cases} \mu_1 & if \quad \gamma = \gamma_1 \\ \mu_2 & if \quad \gamma = \gamma_2 \\ \vdots & \vdots \quad \vdots \quad \vdots \\ \mu_N & if \quad \gamma = \gamma_N \end{cases}$$

Where μ_n = Pos {γ = Y_n} > 0 and $Max_{n=1}^{\mu}$ μ_n = 1

Let the probability of w_s be P_s, and $\sum_{s=1}^{S} P_s = 1$

The fairness objective function is equivalent to

$$f1 = \frac{\sum_{s\in S} \sum_{n\in N} \sum_{k\in K} \sum_{l\in L} P_S q_n \left[d_{kl}^{sn} - \left(\sum_i \sum_j \sum_m X_{ijklm}^n + \sum_i \sum_m Y_{iklm}\right)\right]}{\sum_{s\in S} \sum_{n\in N} \sum_{k\in K} \sum_{l\in L} P_S q_n d_{kl}^n}$$

where $q_n = \frac{1}{2}\left(Max_{h=1}^{n} \mu_h - Max_{h=0}^{n-1} \mu_h\right) + \frac{1}{2}\left(Max_{h=n}^{N} \mu_h - Max_{h=n+1}^{N+1} \mu_h\right)$

and $\mu_0 = \mu_{N+1} = 0$

Proof:

Given that the disaster scenario is a discrete random variable, for any w_s, the corresponding scenario is a normalized discrete variable with the following possibility distribution:

$$\mu_{(\gamma)} = \begin{cases} \mu_1 & if \quad \gamma \quad = \gamma_1 \\ \mu_2 & if \quad \gamma \quad = \gamma_2 \\ \vdots & \vdots \quad \vdots \quad\quad \vdots \\ \mu_N & if \quad \gamma \quad = \mu_N \end{cases}$$

Where μ_n = Pos $\{\gamma = Y_n\} > 0$ and $Max_{n=1}^{N}$ $\mu_n = 1$

Without loss of generality, suppose that $d_{jk,ws}(\gamma_n)$, n = 1, 2, …, N, satisfy $d_{jk,ws}(\gamma_1) \leq d_{jk,ws,}(\gamma_2) \leq \dots \leq d_{jk,ws,}(\gamma_N)$. Then the expected value of variable $d_{jk,ws}$ is

$$E_\gamma \lfloor d_{jk,ws} \rfloor = \sum_{n \in N} q_n \, d_{jk,ws}(\gamma_n)$$

Where

$$q_n = \frac{1}{2}\left(Max_{h=1}^{n}\mu_h - Max_{h=0}^{n-1}\mu_h\right) + \frac{1}{2}\left(Max_{h=n}^{N}\mu_h - Max_{h=n+1}^{N+1}\mu_h\right)$$

and $\mu_0 = \mu_{N+1} = 0$

It is know that $q_n \geq 0$ and $\sum_{n=1}^{N} q_n = Max_{n-1}^{N}\mu_n = 1$

With the fact that the probability of w_s is P_s and $\sum_{s=1}^{S} P_S = 1$, we therefore have:

$$E\lfloor d_{jk} \rfloor = E_w E_y \lfloor d_{jk,ws} \rfloor = \sum_{s \in S} \sum_{n = N} P_s q_n d_{jk,ws}(\gamma_n)$$

$$= \sum_{s \in S} \sum_{n \in N} P_s q_n d_{jk}^{sn}$$

Therefore, this implies our formulation

$$f_1 = \frac{\sum_k \sum_l \sum_n P_S \left[d_{kll}^{n} - \left(\sum_i \sum_j \sum_m X_{ijklm}^{n} + \sum_i Y_{iklm} \right) \right]}{\sum_k \sum_i \sum_n P_n d_{kl}^{n}}$$

APPENDIX 2: Quantity of Items assigned from NCDs to PODs via LDCs via LDCs by VETP

Variable	Value
X(NDC1, LDC1, POD1, WATER, AIR, MILD)	1.000000
X(NDC1, LDC1, POD1, WATER, AIR, MEDIUM	1.000000
X(NDC1, LDC1, POD1, WATER, TRUCK, MILD	1.000000
X(NDC1, LDC1, POD1, WATER, TRUCK, SEVE	0.7149212
X(NDC1, LDC1, POD1, FOOD, AIR, SEVERE)	1.000000
X(NDC1, LDC1, POD1, FOOD, TRUCK, MEDIU	1.000000
X(NDC1, LDC1, POD1, FOOD, TRUCK, SEVER	0.2850788
X(NDC1, LDC1, POD4, WATER, AIR, MEDIUM	0.7045989E-01
X(NDC1, LDC1, POD4, WATER, TRUCK, MEDI	0.7365728E-01
X(NDC1, LDC1, POD4, FOOD, AIR, MILD)	1.000000
X(NDC1, LDC1, POD4, FOOD, AIR, SEVERE)	1.000000
X(NDC1, LDC1, POD4, FOOD, TRUCK, MEDIU	0.9263427
X(NDC1, LDC1, POD4, FOOD, TRUCK, SEVER	1.000000
X(NDC1, LDC1, POD4, MEDI, AIR, MEDIUM)	0.9295401
X(NDC1, LDC1, POD4, MEDI, TRUCK, MILD)	1.000000
X(NDC1, LDC1, POD5, FOOD, AIR, MILD)	1.000000
X(NDC1, LDC1, POD5, FOOD, AIR, MEDIUM)	1.000000
X(NDC1, LDC1, POD5, FOOD, AIR, SEVERE)	1.000000
X(NDC1, LDC1, POD5, FOOD, TRUCK, MILD)	0.7372762
X(NDC1, LDC1, POD5, FOOD, TRUCK, MEDIU	1.000000
X(NDC1, LDC1, POD5, FOOD, TRUCK, SEVER	0.3934150
X(NDC1, LDC1, POD5, MEDI, TRUCK, MILD)	0.2627238
X(NDC1, LDC1, POD5, MEDI, TRUCK, SEVER	0.6065850
X(NDC1, LDC2, POD2, WATER, AIR, MILD)	1.000000
X(NDC1, LDC2, POD2, WATER, AIR, MEDIUM	0.1122918E-02
X(NDC1, LDC2, POD2, WATER, AIR, SEVERE	0.1078282E-02
X(NDC1, LDC2, POD2, WATER, TRUCK, MILD	0.4812487
X(NDC1, LDC2, POD2, WATER, TRUCK, SEVE	1.000000
X(NDC1, LDC2, POD2, FOOD, AIR, MEDIUM)	0.9988771
X(NDC1, LDC2, POD2, FOOD, AIR, SEVERE)	0.8626258E-02
X(NDC1, LDC2, POD2, MEDI, AIR, SEVERE)	0.9902955
X(NDC1, LDC2, POD2, MEDI, TRUCK, MILD)	0.5187513
X(NDC1, LDC2, POD2, MEDI, TRUCK, MEDIU	1.000000
X(NDC1, LDC2, POD3, WATER, AIR, MEDIUM	0.9972795
X(NDC1, LDC2, POD3, WATER, TRUCK, MILD	0.1267849
X(NDC1, LDC2, POD3, WATER, TRUCK, MEDI	1.000000
X(NDC1, LDC2, POD3, FOOD, AIR, MILD)	1.000000
X(NDC1, LDC2, POD3, FOOD, AIR, MEDIUM)	0.2720522E-02
X(NDC1, LDC2, POD3, FOOD, TRUCK, SEVER	1.000000
X(NDC1, LDC2, POD3, MEDI, AIR, SEVERE)	1.000000
X(NDC1, LDC2, POD3, MEDI, TRUCK, MILD)	0.8732151
X(NDC1, LDC2, POD4, FOOD, AIR, MILD)	1.000000
X(NDC1, LDC2, POD4, FOOD, AIR, MEDIUM)	1.000000
X(NDC1, LDC2, POD4, FOOD, AIR, SEVERE)	1.000000
X(NDC1, LDC2, POD4, FOOD, TRUCK, MEDIU	1.000000
X(NDC1, LDC2, POD4, FOOD, TRUCK, SEVER	1.000000
X(NDC1, LDC2, POD4, MEDI, TRUCK, MILD)	1.000000
X(NDC1, LDC2, POD6, WATER, AIR, MILD)	1.000000
X(NDC1, LDC2, POD6, WATER, AIR, MEDIUM	1.000000
X(NDC1, LDC2, POD6, FOOD, AIR, SEVERE)	0.9916289
X(NDC1, LDC2, POD6, FOOD, TRUCK, MILD)	0.8064736
X(NDC1, LDC2, POD6, FOOD, TRUCK, MEDIU	1.000000

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X( NDC1, LDC2, POD6, FOOD, TRUCK, SEVER        1.000000
X( NDC1, LDC2, POD6, MEDI, AIR, SEVERE)       0.8371101E-02
X( NDC1, LDC2, POD6, MEDI, TRUCK, MILD)       0.1935264
X( NDC1, LDC3, POD2, WATER, AIR, SEVERE       0.1078282E-02
X( NDC1, LDC3, POD2, WATER, TRUCK, MILD        1.000000
X( NDC1, LDC3, POD2, WATER, TRUCK, MEDI        1.000000
  X( NDC1, LDC3, POD2, FOOD, AIR, MILD)        1.000000
X( NDC1, LDC3, POD2, FOOD, AIR, SEVERE)       0.9978434
X( NDC1, LDC3, POD2, FOOD, TRUCK, SEVER        1.000000
X( NDC1, LDC3, POD2, MEDI, AIR, MEDIUM)        1.000000
X( NDC1, LDC3, POD2, MEDI, AIR, SEVERE)       0.1078282E-02
 X( NDC1, LDC3, POD3, WATER, AIR, MILD)        1.000000
X( NDC1, LDC3, POD3, WATER, AIR, MEDIUM        1.000000
X( NDC1, LDC3, POD3, WATER, AIR, SEVERE        1.000000
X( NDC1, LDC3, POD3, WATER, TRUCK, MILD       0.4928603
X( NDC1, LDC3, POD3, WATER, TRUCK, MEDI        1.000000
X( NDC1, LDC3, POD3, MEDI, TRUCK, MILD)       0.5071397
X( NDC1, LDC3, POD3, MEDI, TRUCK, SEVER        1.000000
X( NDC1, LDC3, POD5, WATER, TRUCK, MEDI        1.000000
X( NDC1, LDC3, POD5, FOOD, AIR, MEDIUM)        1.000000
X( NDC1, LDC3, POD5, FOOD, AIR, SEVERE)        1.000000
X( NDC1, LDC3, POD5, FOOD, TRUCK, MILD)       0.7304341
  X( NDC1, LDC3, POD5, MEDI, AIR, MILD)        1.000000
X( NDC1, LDC3, POD5, MEDI, TRUCK, MILD)       0.2695659
X( NDC1, LDC3, POD5, MEDI, TRUCK, SEVER        1.000000
X( NDC1, LDC3, POD6, WATER, AIR, MEDIUM       0.1163345
X( NDC1, LDC3, POD6, WATER, TRUCK, MILD       0.3174792
  X( NDC1, LDC3, POD6, FOOD, AIR, MILD)        1.000000
X( NDC1, LDC3, POD6, FOOD, AIR, SEVERE)       0.9916289
X( NDC1, LDC3, POD6, FOOD, TRUCK, MILD)       0.5661863
X( NDC1, LDC3, POD6, FOOD, TRUCK, MEDIU        1.000000
X( NDC1, LDC3, POD6, FOOD, TRUCK, SEVER        1.000000
X( NDC1, LDC3, POD6, MEDI, AIR, MEDIUM)       0.8836655
X( NDC1, LDC3, POD6, MEDI, AIR, SEVERE)       0.8371101E-02
X( NDC1, LDC3, POD6, MEDI, TRUCK, MILD)       0.1163345
  X( NDC2, LDC1, POD1, WATER, AIR, MILD)      0.6193681
X( NDC2, LDC1, POD1, WATER, TRUCK, MEDI        1.000000
X( NDC2, LDC1, POD1, WATER, TRUCK, SEVE       0.5180364E-01
  X( NDC2, LDC1, POD1, FOOD, AIR, MILD)       0.3806319
X( NDC2, LDC1, POD1, FOOD, AIR, MEDIUM)        1.000000
X( NDC2, LDC1, POD1, FOOD, AIR, SEVERE)        1.000000
X( NDC2, LDC1, POD1, FOOD, TRUCK, MILD)        1.000000
X( NDC2, LDC1, POD1, FOOD, TRUCK, SEVER       0.9481964
X( NDC2, LDC1, POD4, WATER, AIR, MEDIUM       0.7045989E-01
X( NDC2, LDC1, POD4, WATER, AIR, SEVERE        1.000000
X( NDC2, LDC1, POD4, WATER, TRUCK, MEDI       0.7365728E-01
  X( NDC2, LDC1, POD4, FOOD, AIR, MILD)       0.9820737
X( NDC2, LDC1, POD4, FOOD, TRUCK, MILD)        1.000000
X( NDC2, LDC1, POD4, FOOD, TRUCK, MEDIU       0.9263427
  X( NDC2, LDC1, POD4, MEDI, AIR, MILD)       0.1792627E-01
X( NDC2, LDC1, POD4, MEDI, AIR, MEDIUM)       0.9295401
X( NDC2, LDC1, POD4, MEDI, TRUCK, SEVER        1.000000
  X( NDC2, LDC1, POD5, FOOD, AIR, MILD)        1.000000
X( NDC2, LDC1, POD5, FOOD, AIR, MEDIUM)        1.000000
X( NDC2, LDC1, POD5, FOOD, TRUCK, MILD)       0.7304341
X( NDC2, LDC1, POD5, FOOD, TRUCK, MEDIU        1.000000
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X( NDC2, LDC1, POD5, FOOD, TRUCK, SEVER       0.8689012
X( NDC2, LDC1, POD5, MEDI, AIR, SEVERE)        1.000000
X( NDC2, LDC1, POD5, MEDI, TRUCK, MILD)       0.2695659
X( NDC2, LDC1, POD5, MEDI, TRUCK, SEVER       0.1310988
X( NDC2, LDC2, POD2, WATER, AIR, MEDIUM       0.1122918E-02
X( NDC2, LDC2, POD2, WATER, AIR, SEVERE       0.1078282E-02
X( NDC2, LDC2, POD2, WATER, TRUCK, MILD       0.5187513
X( NDC2, LDC2, POD2, WATER, TRUCK, MEDI       0.3221949E-01
  X( NDC2, LDC2, POD2, FOOD, AIR, MILD)        1.000000
X( NDC2, LDC2, POD2, FOOD, AIR, MEDIUM)       0.9988771
X( NDC2, LDC2, POD2, FOOD, AIR, SEVERE)       0.9978434
X( NDC2, LDC2, POD2, FOOD, TRUCK, MEDIU       0.3924042E-01
X( NDC2, LDC2, POD2, FOOD, TRUCK, SEVER        1.000000
X( NDC2, LDC2, POD2, MEDI, AIR, SEVERE)       0.1078282E-02
X( NDC2, LDC2, POD2, MEDI, TRUCK, MILD)       0.4812487
X( NDC2, LDC2, POD2, MEDI, TRUCK, MEDIU       0.9285401
 X( NDC2, LDC2, POD3, WATER, AIR, MILD)       0.1129144
X( NDC2, LDC2, POD3, WATER, AIR, MEDIUM       0.1360261E-02
X( NDC2, LDC2, POD3, WATER, AIR, SEVERE       0.1680948E-02
X( NDC2, LDC2, POD3, WATER, TRUCK, SEVE        1.000000
  X( NDC2, LDC2, POD3, FOOD, AIR, MILD)       0.2477811
X( NDC2, LDC2, POD3, FOOD, AIR, MEDIUM)       0.9986397
X( NDC2, LDC2, POD3, FOOD, AIR, SEVERE)       0.9983191
X( NDC2, LDC2, POD3, FOOD, TRUCK, MILD)        1.000000
X( NDC2, LDC2, POD3, FOOD, TRUCK, MEDIU        1.000000
  X( NDC2, LDC2, POD3, MEDI, AIR, MILD)       0.6393046
X( NDC2, LDC2, POD4, WATER, TRUCK, SEVE        1.000000
  X( NDC2, LDC2, POD4, FOOD, AIR, MILD)       0.5975423E-02
X( NDC2, LDC2, POD4, FOOD, AIR, MEDIUM)        1.000000
X( NDC2, LDC2, POD4, FOOD, TRUCK, MILD)        1.000000
X( NDC2, LDC2, POD4, FOOD, TRUCK, MEDIU        1.000000
  X( NDC2, LDC2, POD4, MEDI, AIR, MILD)       0.9940246
X( NDC2, LDC2, POD4, MEDI, AIR, SEVERE)        1.000000
X( NDC2, LDC2, POD6, WATER, AIR, SEVERE       0.1247056
X( NDC2, LDC2, POD6, WATER, TRUCK, MILD       0.7988553
X( NDC2, LDC2, POD6, WATER, TRUCK, MEDI       0.1163345
X( NDC2, LDC2, POD6, WATER, TRUCK, SEVE       0.1163345
  X( NDC2, LDC2, POD6, FOOD, AIR, MILD)        1.000000
X( NDC2, LDC2, POD6, FOOD, AIR, MEDIUM)        1.000000
X( NDC2, LDC2, POD6, FOOD, AIR, SEVERE)       0.8669233
X( NDC2, LDC2, POD6, FOOD, TRUCK, MILD)       0.8481013E-01
X( NDC2, LDC2, POD6, MEDI, AIR, SEVERE)       0.8371101E-02
X( NDC2, LDC2, POD6, MEDI, TRUCK, MILD)       0.1163345
X( NDC2, LDC2, POD6, MEDI, TRUCK, MEDIU       0.8836655
X( NDC2, LDC2, POD6, MEDI, TRUCK, SEVER       0.8836655
 X( NDC2, LDC3, POD2, WATER, AIR, MILD)       0.1964497E-02
X( NDC2, LDC3, POD2, WATER, AIR, MEDIUM       0.9955083
X( NDC2, LDC3, POD2, WATER, AIR, SEVERE       0.1078282E-02
X( NDC2, LDC3, POD2, FOOD, AIR, MEDIUM)       0.4491671E-02
X( NDC2, LDC3, POD2, FOOD, AIR, SEVERE)       0.9978434
X( NDC2, LDC3, POD2, FOOD, TRUCK, MILD)       0.1582004E-01
X( NDC2, LDC3, POD2, FOOD, TRUCK, MEDIU        1.000000
X( NDC2, LDC3, POD2, FOOD, TRUCK, SEVER       0.5000000
  X( NDC2, LDC3, POD2, MEDI, AIR, MILD)       0.9980355
X( NDC2, LDC3, POD2, MEDI, AIR, SEVERE)       0.1078282E-02
X( NDC2, LDC3, POD2, MEDI, TRUCK, MILD)       0.9841800
X( NDC2, LDC3, POD2, MEDI, TRUCK, SEVER       0.5000000
 X( NDC2, LDC3, POD3, WATER, AIR, MILD)       0.9382354E-02
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X( NDC2, LDC3, POD3, WATER, AIR, SEVERE        0.9966381
X( NDC2, LDC3, POD3, WATER, TRUCK, MILD        0.1267849
  X( NDC2, LDC3, POD3, FOOD, AIR, MILD)        0.1504438
X( NDC2, LDC3, POD3, FOOD, AIR, SEVERE)        0.3361896E-02
  X( NDC2, LDC3, POD3, MEDI, AIR, MILD)        0.8401739
X( NDC2, LDC3, POD3, MEDI, AIR, MEDIUM)         1.000000
X( NDC2, LDC3, POD3, MEDI, TRUCK, MILD)        0.8732151
X( NDC2, LDC3, POD3, MEDI, TRUCK, MEDIU         1.000000
X( NDC2, LDC3, POD3, MEDI, TRUCK, SEVER         1.000000
X( NDC2, LDC3, POD5, WATER, AIR, MEDIUM        0.9834958
  X( NDC2, LDC3, POD5, FOOD, AIR, MILD)         1.000000
X( NDC2, LDC3, POD5, FOOD, AIR, MEDIUM)        0.1650419E-01
X( NDC2, LDC3, POD5, FOOD, TRUCK, MILD)        0.7274757
X( NDC2, LDC3, POD5, FOOD, TRUCK, MEDIU         1.000000
X( NDC2, LDC3, POD5, FOOD, TRUCK, SEVER        0.2992462
X( NDC2, LDC3, POD5, MEDI, AIR, SEVERE)         1.000000
X( NDC2, LDC3, POD5, MEDI, TRUCK, MILD)        0.2725243
X( NDC2, LDC3, POD5, MEDI, TRUCK, SEVER        0.7007538
X( NDC2, LDC3, POD6, WATER, TRUCK, SEVE         1.000000
  X( NDC2, LDC3, POD6, FOOD, AIR, MILD)         1.000000
X( NDC2, LDC3, POD6, FOOD, AIR, MEDIUM)         1.000000
X( NDC2, LDC3, POD6, FOOD, AIR, SEVERE)        0.1749322
X( NDC2, LDC3, POD6, FOOD, TRUCK, MILD)        0.9085060
X( NDC2, LDC3, POD6, FOOD, TRUCK, MEDIU         1.000000
X( NDC2, LDC3, POD6, MEDI, AIR, SEVERE)        0.8250678
X( NDC2, LDC3, POD6, MEDI, TRUCK, MILD)        0.9149400E-01
 X( NDC3, LDC1, POD1, WATER, AIR, MILD)        0.9958020E-01
X( NDC3, LDC1, POD1, WATER, AIR, SEVERE         1.000000
X( NDC3, LDC1, POD1, WATER, TRUCK, SEVE        0.5180364E-01
  X( NDC3, LDC1, POD1, FOOD, AIR, MILD)        0.9004198
X( NDC3, LDC1, POD1, FOOD, AIR, MEDIUM)         1.000000
X( NDC3, LDC1, POD1, FOOD, TRUCK, MILD)         1.000000
X( NDC3, LDC1, POD1, FOOD, TRUCK, MEDIU         1.000000
X( NDC3, LDC1, POD1, FOOD, TRUCK, SEVER        0.9481964
X( NDC3, LDC1, POD4, WATER, AIR, MEDIUM        0.7886203
X( NDC3, LDC1, POD4, WATER, TRUCK, MEDI        0.6317136
  X( NDC3, LDC1, POD4, FOOD, AIR, MILD)        0.5975423E-02
X( NDC3, LDC1, POD4, FOOD, AIR, SEVERE)         1.000000
X( NDC3, LDC1, POD4, FOOD, TRUCK, MILD)         1.000000
X( NDC3, LDC1, POD4, FOOD, TRUCK, MEDIU        0.1439176
  X( NDC3, LDC1, POD4, MEDI, AIR, MILD)        0.9940246
X( NDC3, LDC1, POD4, MEDI, AIR, MEDIUM)        0.2113797
X( NDC3, LDC1, POD4, MEDI, TRUCK, MEDIU        0.2243688
X( NDC3, LDC1, POD4, MEDI, TRUCK, SEVER         1.000000
 X( NDC3, LDC1, POD5, WATER, AIR, MILD)         1.000000
X( NDC3, LDC1, POD5, WATER, AIR, SEVERE        0.7760719
X( NDC3, LDC1, POD5, WATER, TRUCK, MILD        0.8131447E-01
X( NDC3, LDC1, POD5, FOOD, AIR, SEVERE)        0.2239281
X( NDC3, LDC1, POD5, FOOD, TRUCK, MILD)        0.6101455
X( NDC3, LDC1, POD5, FOOD, TRUCK, SEVER        0.8689012
X( NDC3, LDC1, POD5, MEDI, AIR, MEDIUM)         1.000000
X( NDC3, LDC1, POD5, MEDI, TRUCK, MILD)        0.3085401
X( NDC3, LDC1, POD5, MEDI, TRUCK, MEDIU         1.000000
X( NDC3, LDC1, POD5, MEDI, TRUCK, SEVER        0.1310988
X( NDC3, LDC2, POD2, WATER, AIR, MEDIUM         1.000000
X( NDC3, LDC2, POD2, WATER, AIR, SEVERE        0.9999372
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