Forecast-driven facility location model for pre-positioning relief goods in preparation for strong typhoons

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Forecast-driven facility location model for pre-positioning relief goods in preparation for strong typhoons

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Executive Summary

The Philippines experiences a high number of natural disasters every year. Annually, the Philippines is exposed to an average of 20 typhoons, five of which are potentially destructive (de la Cruz, 2016). Lack of typhoon-resilient infrastructure leaves the country vulnerable and leads to loss of life and destruction of property. This was highlighted to the global community when typhoon Haiyan struck the Philippines in 2013 and left 6,300 casualties.

There has been a growing interest in pre-positioning resources to increase preparedness (Rawls and Turnquist, 2010; Davis, Samanlioglu, Qu, and Root, 2013; Rodríguez-Espíndola, Albores, and Brewster, 2018). Pre-positioning ensures that the goods are located closer to the impacted communities which enables for a more efficient response. However, pre-positioning also comes with additional warehouse, shipping and commodity costs.

Pre-positioning for strong typhoons is a big challenge in the field of humanitarian logistics, especially with the inherent uncertainty of the typhoon path. Forecast data provide insight as to which area is affected and also provide an idea on the expected impact of the typhoon. Moreover, the forecasts provide a time frame that serves as lead time for decision makers to preposition relief goods in the area depending on the projected typhoon strength and impact.

In previous pre-positioning studies such as Gobaco, Lahoz, Ng, and Sy (2016), Galindo Pacheco and Batta (2015), and Davis et al. (2013), the pre-positioning is done over a defined geographic area where the lead time with respect to the incoming typhoon is the same across all points of the network. In reality, however, different points in the network experience different lead times, and this is not adequately captured by previous pre-positioning models.

To address the research gaps, an iterative methodology is designed. The aim is to answer the main research question: *How to determine the robust pre-positioning strategy in preparation for a typhoon, where forecast information is updated periodically?*

A brief description of the iterative methodology is as follows: First, an ensemble of typhoon tracks is generated based on the weather forecast data. Then, the generated tracks are used to determine potential damage scenarios and estimated lead times at each point in the network. Characteristics of the damage scenarios include demand estimation, supply point damage, and delays in the transportation network. The results of the computational exercise for damage scenarios and lead times are used as inputs to determine the optimal pre-positioning actions for each damage scenario. Then, the solution for each scenario are evaluated across all the other potential scenarios, and the robust solution of pre-positioning action is chosen. Finally, based on decision theory, a choice is made whether to execute a pre-positioning action or wait for forecast over the next period.

Test cases based on the track of Typhoon Haiyan in 2013 were designed to evaluate the performance of the pre-positioning configuration generated from the iterative methodology. Three strategies and two robustness metrics were evaluated. Results show that the best strategy is to implement the robust pre-positioning configuration at the last period possible. It happens when the difference between the lead time and the time for pre-positioning is less than 6 hours, which is the time between two successive forecast periods. This allows to take advantage of the decrease in uncertainty with each successive forecast, which leads to better pre-positioning outcomes.

Insights from this study show that the methodology can be implemented at various levels of administration of disaster response in the Philippines, be it in provincial, regional, and multi-regional level. Furthermore, results from the implementation of the iterative methodology over a large network allows for pre-positioning at different periods at different points on the network based on the lead time at each location. Finally the choice of robustness criteria, signal to noise ratio and minimax regret, did not generate conclusive results as to which option performs better.

The main scientific contributions of this study are as follows: 1) Design of an iterative methodology that utilizes ensemble forecast to generate robust pre-positioning configuration and 2) Design of a facility location model that accounts for the differences in lead times across a large network.

This study presents some recommendations to the Department of Social Welfare and Development (DSWD) to improve further on the agency's performance during typhoon response operations in the Philippines. First, it needs to ensure that the amount of goods stockpiled at regional warehouses is sufficient in anticipation of strong typhoons such as Typhoon Haiyan for a pre-positioning strategy to be effective. Next, the model used in this study has the potential to support the decision-making process in the context of disaster preparedness and response and can improve the ability of the agency to increase its efficiency in responding to strong typhoons that are to come.

For further research, The damage scenarios which serve as input to the model can be improved by utilizing real time data available from weather forecast agencies such as Philippine Atmospheric, Geophysical, and Astronomical Services Administration (PAGASA). Real time information regarding not only on wind speed but also on precipitation, atmospheric pressure, landslide and flood prone areas, and storm surge warnings, etc. allow for better damage estimation which then helps in ensuring a pre-positioning strategy that is in tune with the current atmospheric situation. Also, real-time typhoon track ensembles can be obtained from forecast agencies such as Japan Meteorological Agency (JMA) to have a better gauge of an incoming typhoon's track and intensity, which also leads to better lead time estimation at each location as well as damage scenarios.

Moreover, heuristic algorithms can be used to improve the efficiency of the optimization calculations. Furthermore, aggregation of demand points can also increase the efficiency of calculations and can be used for networks that are of a larger geographical scope. Finally, the study can also be extended to explore possible cooperation on pre-positioning between different actors such as NGOs and the private sector.

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Chapter 1

Introduction

The Philippines experiences a high number of natural disasters every year. According to World Risk Report 2016, the Philippines ranks third globally on susceptibility to natural disasters (UNU-EHS, 2016). Annually, the Philippines is exposed to an average of 20 typhoons, five of which are potentially destructive (de la Cruz, 2016). Figure 1.1 shows the paths of all the typhoons in 2016 in western Pacific Ocean. Many of these typhoons have made landfall in the Philippines.

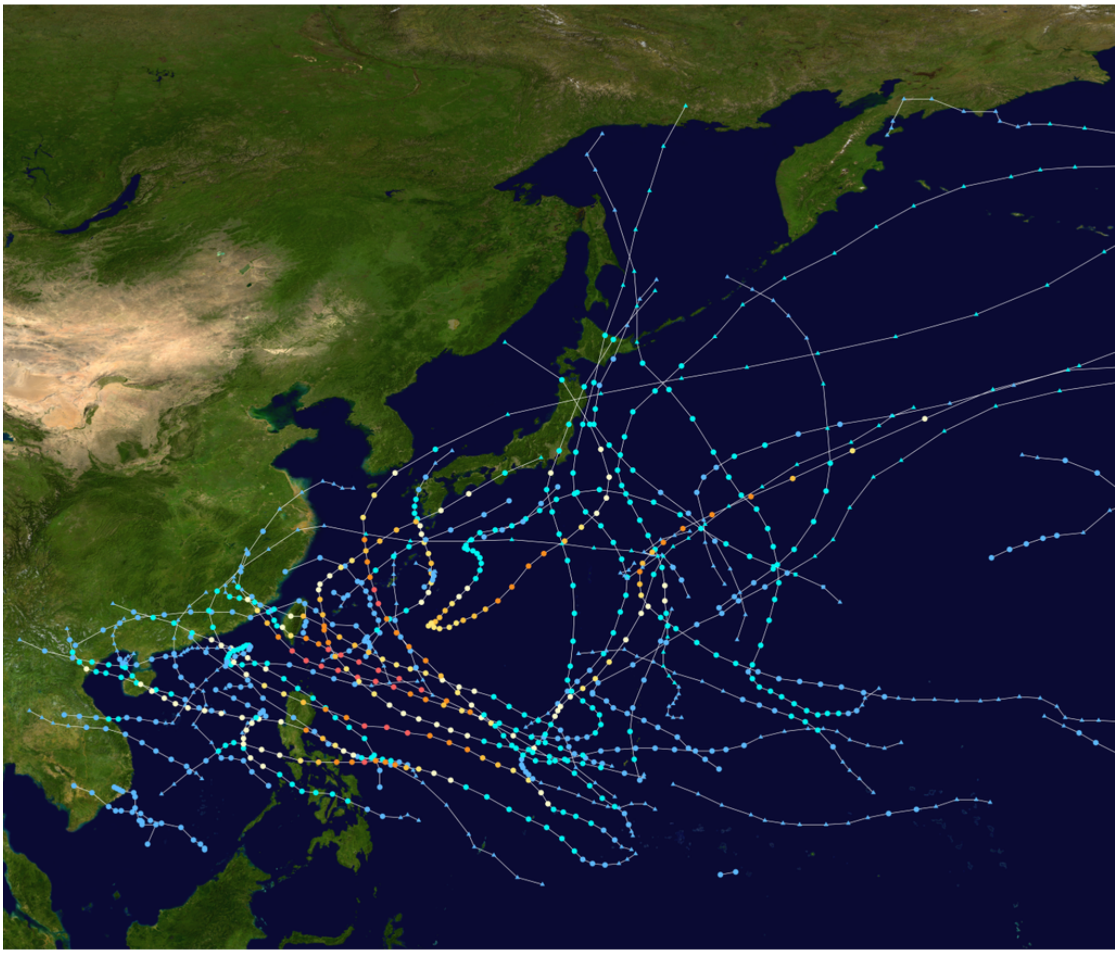


Figure 1.1: Typhoon tracks in 2016

Lack of typhoon-resilient infrastructure leaves the country vulnerable and leads to loss of life and destruction of property. Over the past four decades, typhoons that made landfall in East and Southeast Asia have intensified by 12-15% and are projected to intensify in the future

(Mei and Xie, 2016). The Philippines is projected to incur around \$300 billion in monetary damages from typhoons by 2100, which is equivalent to 86% of its GDP in 2016 (Alano and Lee, 2016).

The National Disaster Risk Reduction and Management Council (NDRRMC) is the main agency in the Philippines responsible to prepare for and respond to natural disasters. It is a coordinating body tasked to develop the National Disaster Response Plan (NDRP), which serves as the principal guide to strengthen national disaster management efforts (Bueza, 2017). Despite having an institutional framework, the government's response to extreme natural disasters has been unsatisfactory, as evidenced in the case of Typhoon Haiyan in 2013. Some reports indicate a lack of a well-coordinated response operation on the distribution of relief goods, which impacted the timeliness of the government's response (Santiago, Manuela Jr., Tan, Sañes, and Tong, 2016).

1.1 Humanitarian Logistics

Humanitarian logistics is crucial to a successful relief operation in the aftermath of a disaster. According to Thomas and Kopczak (2005), humanitarian logistics is the "function that is charged with ensuring the efficient and cost-effective flow and storage of goods and materials for the purpose of alleviating the suffering of vulnerable people." Essentially, humanitarian logistics operations are designed such that the right goods are delivered to the right place and are distributed to the right people at the right time (van Wassenhove, 2006). Supplies and personnel must be transported quickly to its intended destination to maximize survival of affected population (Afshar and Haghani, 2012). However, this could be challenging due to potential breakdown of existing functions that support the level of human existence in the area concerned, such as roads and bridges and the provision of electricity, telephones, or water (Tatham and Houghton, 2011).

The capacity and location of humanitarian responders are crucial elements of humanitarian logistics in the aftermath of a disaster. Moreover, there is also a growing interest in pre-positioning resources to increase preparedness (Rawls et al., 2010; Davis et al., 2013; Rodríguez-Espíndola et al., 2018). Pre-positioning ensures that the goods are located closer to the impacted communities which enables for a more efficient response. However, pre-positioning also comes with additional warehouse, shipping and commodity costs. Thus, it is also important to monitor the time frame and costs of prepositioning (Melito, 2014).

The term "pre-positioning" is quite broad. Agencies such as USAID perform overseas prepositioning by stockpiling food commodities near regions that historically experience high level needs for food during emergencies. These are currently located in Sri Lanka, Djibouti, UAE, South Africa, Spain, and Kenya. The time frame of deliveries for these international stockpiles are long. It is estimated that USAID's pre-positioning strategy has decreased the average delivery time for WFP by 28 days in 2009-2012, from 135 to 102 days (Melito, 2014). The long time frame may not be appropriate for an efficient response to sudden-onset disasters such as typhoons. The type of pre-positioning described in this study is smaller in geographic scope - it is the pre-positioning of goods in anticipation of a typhoon. Due to the lack of typhoon-resilient infrastructure in many areas in the Philippines, it is inevitable that many people would need immediate relief assistance in case of a strong typhoon. To ensure efficient relief response to towns that are located far away from stockpiles in regional warehouses, local distribution centers can be set up before the typhoon to efficiently respond to its aftermath.

Pre-positioning for strong typhoons is a big challenge in the field of humanitarian logistics, especially with the inherent uncertainty of the typhoon path. Thankfully, there are early warning systems designed to inform an area before a typhoon is expected to make landfall. For example, Philippine public storm warning signals are issued as early as 36 hours before a typhoon makes landfall and the forecast is updated regularly (Official Gazette of the Republic of the Philippines, 2012). Data from these forecasts can provide insights to the relevant government agencies as to which area is affected and also provide an idea on the expected impact of the typhoon. Moreover, the forecasts provide a time frame that serves as lead time for decision makers to preposition relief goods in the area depending on the projected typhoon strength and impact.

Pre-positioning for typhoon preparedness is subject not only to the uncertainties of the typhoon's characteristics at landfall but also on the impact of the typhoon in the area. The impacts of the typhoon on demand, supply, and even the availability of certain routes in the aftermath of the typhoon are also uncertain. Goods that are located close to the most devastated areas are also subject to a higher risk of destruction by the typhoon.

The aim of this thesis project is to develop a methodology that enables robust pre-positioning against strong typhoons. This is to be done in steps. First, weather forecast data is used as a starting point to generate potential typhoon tracks based on the information received at the given time period. Next, the typhoon tracks are used to determine damage scenarios, which involve the estimation of demand, supply damage, and potential delays in the transportation network. Next, an facility location model is used to determine the robust location and quantity of pre-positioned goods. Finally, a decision theory approach is used to determine whether to perform a pre-positioning action or wait for the next forecast.

1.2 Thesis Structure

This thesis is structured as follows:

- Chapter 1 presents the research background, the structure of the thesis project, and a brief overview of the case study.
- Chapter 2 provides a comprehensive review of literature related to humanitarian logistics. It delves in deeper to facility location problems and classifies them according to problem and modeling types.
- Chapter 3 presents the research gaps, the main research question, and the research subquestions to be addressed. It also elaborates on the research approach, which includes the research framework and methodology used, and describes the research flow.
- Chapter 4 explains the methodological framework in a step by step process. It also includes the illustrative problem definition and definition of relevant terms.
- Chapters 5-7 expands on the different steps of the iterative methodology. Chapter 5 focuses on scenario generation and impact estimation models. Chapter 6 elaborates on the capacitated facility location model. Chapter 7 talks about the evaluation step and the pre-positioning strategy algorithms
- Chapter 8 details the implementation of the methodology to a case study of typhoon Haiyan in the Philippines.
- Chapter 9 shows the results of the case study and compares the performance of the resulting pre-positioning configuration across different strategies and robustness metric.
- Chapter 10 discusses the results in the context of decision making in pre-positioning relief goods against strong typhoons.
- Chapter 11 shows model verification and its sensitivity to selected parameters.
- Chapter 12 presents reflections based on the iterative methodology and the challenges of its implementation in practice.
- Chapter 13 provides answers to the main research questions an provides recommendations for future work.

1.3 Case Study Overview

The Western Visayas Region in the Philippines, also known as Region VI, is comprised of three major islands with a total land area of 20,223 square kilometers. It has a population of over 6.2 million with an average annual growth rate of 1.56% from 2000 to 2005 (Department of Agriculture, 2018). It is subdivided into six provinces: Aklan, Antique, Capiz, Iloilo, and Guimaras, and Negros Occidental. The map of the region is shown in figure 1.2.

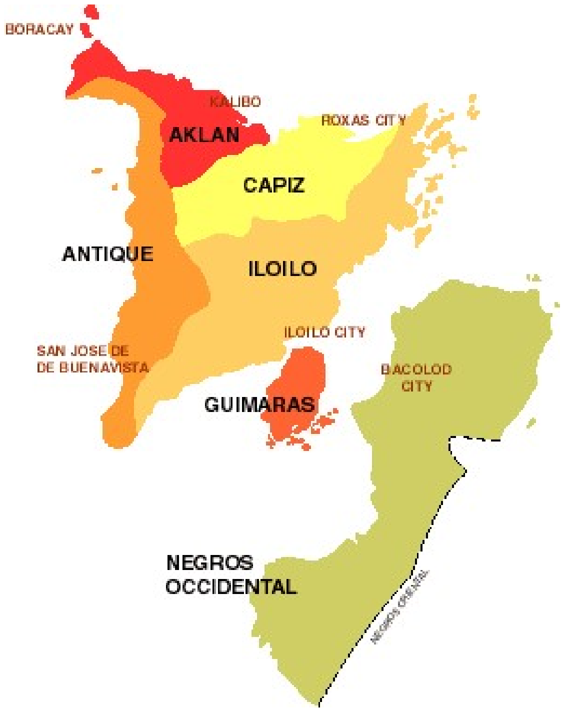


Figure 1.2: Map of Western Visayas Region, Philippines (Region VI)

The provinces are further subdivided into cities and municipalities as summarized in table 1.1. The major islands share a similar topography which is characterized by rigged hills and mountains in the interior and fertile plains and coastal lowlands that heads towards the sea (Department of Agriculture, 2018). The region also has twelve principal rivers. In the event of strong typhoons, many areas are highly susceptible to flooding and rain-induced landslides.

Table 1.1: Cities and municipalities of each province

Province	**Cities**	**Municipalities**
Iloilo	2	42
Capiz	1	16
Aklan	0	17
Antique	0	18
Guimaras	0	5
Negros Occidental	13	19
Total	**16**	**117**

The region has experienced a number of strong typhoons in the past decade. The most destructive ones include Fengshen in 2008 and Haiyan in 2013. Damages in the region from typhoon Fengshen (Frank) amounted to over PhP 1.6 billion (USD 36 million), affecting around 1.6 million people and leaving 257 people dead (PIA, 2008). Typhoon Haiyan (Yolanda) affected over 3.8 million people in the region, leaving 294 dead and over 482,000 houses damaged. The damage to the region was estimated at PhP 17.8 billion (USD 410 million) (NDRRMC, 2013).

Chapter 2

Literature Review

This chapter provides a systematic discussion of available literature related to pre-positioning relief goods. First, the literature review approach is elaborated, then the field of humanitarian logistics is explored. Then, related literature is classified based on solution method, modeling type, and problem type. This section also examines the current state of pre-positioning in the Philippines. Insights gained from the literature review is used to identify the gaps in the research domain of pre-positioning goods and also provides an insight of how the pre-positioning problems are currently tackled.

2.1 Literature Review Approach

Upon the preliminary search of papers within the humanitarian logistics realm, it was clear that the amount of research done in the field has dramatically increased over the past fifteen years. In order to describe the state of the art in the field of humanitarian logistics, there are papers published that are solely dedicated in reviewing humanitarian logistics literature. These papers provided a systematic way of classifying literature, which helped in providing an initial list of literature that is relevant to pre-positioning relief goods.

Next, a systematic literature review is conducted by searching relevant papers mainly through Google, which provides the links to the content in journals dedicated to humanitarian logistics, transportation, or operations research through academic databases such as Science Direct, Scopus, and other websites such as ResearchGate. Keywords that are used include "prepositioning", "facility location problems", "forecast-driven", and/or "robust optimization." Moreover, in articles deemed relevant to the study, the reference list is also explored to obtain more relevant studies.

Finally, an examination of websites related to the pre-positioning in the Philippines is also explored. This involves going through various government reports in disaster response and preparedness, disaster preparedness and response plans, government memorandums, and also various websites of government agencies related to pre-positioning.

2.2 Literature Reviews in Humanitarian Logistics

Literature reviews conducted in recent years aimed to provide an insight on the state of the art in humanitarian logistics research and identify gaps and trends for future research (Kunz and Gerald Reiner, 2012; Leiras, Brito, Queiroz Perez, Rejane Bertazzo, Tsugunobu, and Yozinaki, 2014; Overstreet, Hall, Hanna, and R. Kelly, 2011; Anaya-Arenas, Renaud, and Ruiz, 2014; Chiappetta Jabbour, Amorim Sobreiro, Lopes de Sousa Jabbour, de Souza Campos, Barberio Mariano, William, and Renwick, 2017; Bealt and Mansouri, 2018). For example, Kunz et al. (2012) used qualitative and quantitative content analysis process to examine existing literature to identify most studied topics in humanitarian logistics.

Other studies developed research frameworks for literature review. Leiras et al. (2014) developed a framework through qualitative and quantitative content analysis. Anaya-Arenas et al. (2014) used a systematic and scientific methodology to consolidate published research works in an objective and transparent way. Chiappetta Jabbour et al. (2017) developed a systematized approach by applying a system of codes and classifications to relevant literature on humanitarian logistics. Bealt et al. (2018) focused on a systematic review of literature related to community participation in humanitarian logistics activities. These literature review studies provided a good starting point in understanding the state of the art in humanitarian logistics and in identifying studies that are relevant to developing a robust pre-positioning strategy in the Philippines.

To identify most relevant articles to the study, a set of criteria is defined based on the studies of Kunz et al. (2012), Leiras et al. (2014), and Anaya-Arenas et al. (2014) and are summarized as follows:

- **Type of Disaster.** According to van Wassenhove (2006), there are four types of disasters as shown in Table 2.1 classified based on its speed of start (sudden-onset vs. slow-onset) and cause (natural vs. man-made). Based on this classification, the articles deemed relevant to the study are those that pertain to natural, sudden-onset disasters.

Table 2.1: Types of Disasters (van Wassenhove, 2006)

	Natural	**Man-made**
Sudden-onset	Earthquake Hurricane Tornadoes	Terrorist Attack Coup d'Etat Chemical Leak
Slow-onset	Famine Drought Poverty	Political Crisis Refugee Crisis

- **Phase of Disaster Management.** Altay and S. Walter G. (2006) outlines the four typical activities of disaster operations management, which are mitigation, preparedness, response, and recovery. Mitigation involves measures that improve resilience to a disaster - either to prevent the onset or reduce its impacts. Preparedness activities involve getting personnel and equipment ready before the onset of a disaster. Once a disaster strikes, the activities in the immediate aftermath are included in the response activities while long-term developments after a disaster are included in recovery activities (Leiras et al., 2014). As this study involves designing a preparedness strategy, literature considered relevant mainly involve activities in the preparedness and some in the response phases.
- **Research Topic and Method.** Relevant literature use analytical methods to determine optimal facility location for relief goods pre-positioning. According to Boonmee, Arimura, and Asada (2017), facility location problems can be classified according to solution method (exact or heuristic), modeling types (deterministic, dynamic, stochastic, and robust), and problem type (minisum, set covering, maximal covering and minimax). All of the different facility location problem types are to be explored in the literature review.

2.3 Facility Location Problems in Humanitarian Logistics

In reviewing literature related to pre-positioning, it became clear that the most relevant literature are related to facility location problems. In the aftermath of a typhoon, the locations of warehouses, distribution centers, shelters, and hospitals are crucial for an efficient response operation. The decision on where to locate these facilities can be determined using optimization problems. This section summarizes different facility location problems in literature and what solution methods and modeling types are used.

Solution Method

There are two main approaches used to solve facility location problems: exact and heuristic. Exact algorithms are used to find the optimal solution to a problem. However, many facility location problems are NP-hard, where the time to solve the problem increases exponentially with respect to problem dimensions. To address this issue, heuristic algorithms are employed because it takes less time. However, the results are sub-optimal compared to exact algorithms (Boonmee et al., 2017).

Exact algorithms have been used extensively in humanitarian logistics facility location problems. Afshar et al. (2012) designed an exact algorithm to model a network structure of integrated logistics operations that is in compliance with FEMA's logistics structure. Balcik and Beamon (2008) developed a variant of the maximal covering location model to determine the number and location of distribution centers and the amount of relief supplies needed to address the needs of people affected by earthquakes. Khayal, Pradhananga, Pokharel, and Mutlu (2015) designed a model of a distribution plan for dynamically changing demand over different periods. These studies, among others, have used exact algorithms to solve a problem within reasonable time. However, a common recommendation is to use heuristic algorithms to efficiently solve larger problems.

Commonly used heuristic algorithms in facility location problems include genetic algorithms, tabu search algorithm, greedy algorithms, and locate-allocate heuristics. Comes, Schätter, and Schultmann (2013) used a greedy algorithm to solve an uncapacitated facility location problem and determine robust locations of health care centers for the 2010 earthquake in Haiti. Jia, Ordóñez, and Dessouky (2007) developed a genetic algorithm, locate-allocate heuristic, and Lagrangean relaxation heuristic to propose solution approaches for facility locations of medical supplies in response to a large scale emergency in Los Angeles within a short computational time. Salman and Yücel (2015) used a tabu search algorithm to select facility locations and maximize total expected demand. For more information on heuristic algorithms, Zheng, Chen, and Ling (2015) provides a comprehensive review on the state-of-the-art of evolutionary algorithms in the realm of humanitarian logistics.

Given the small size of the case study network, an exact solution method is used for this study. In the future, if the case study network is expanded, then heuristic algorithms can be considered.

Problem Type

Facility location problems come in different types depending on the problem context. The most common problem types according to Boonmee et al. (2017) are shown below including examples from literature.

- **Minisum.** The minisum facility location problem selects or locates P facilities and minimizes cost (time, distance, transport cost) between the facility and the demand point it caters to (Boonmee et al., 2017). It is similar to the p-hub median problem defined by Campbell (1996). Many studies have focused on minisum problems, particularly on reducing transportation costs from supply to demand locations. Rawls et al. (2010) used a two-stage stochastic mixed integer program (SMIP) to provide a pre-positioning strategy for hurricanes and made a case study application on the Gulf Coast area of the US. The objective function of the model involved minimizing the transportation cost of supplies from the facility location to the demand points. Verma and Gaukler (2015) compared two models to choose the locations of disaster response facilities for an earthquake. The first is a deterministic model that incorporates distance-dependent damages. The second is a stochastic programming model that incorporates the damage intensity as a random variable. The formulation of the objective function involves minimizing expected transportation costs of goods over all disaster scenarios. Davis et al. (2013) developed a two-stage stochastic linear programming model to determine how to preposition relief goods based on the forecast of a hurricane. The first stage involves decision on prepositioning and the second stage involves response. The objective function includes prepositioning costs, redistribution costs between supply nodes, and distribution costs from supply to demand nodes.

- **Set Covering.** According to Boonmee et al. (2017), set covering problem involves selecting the minimum number of facilities to cover all demand points. Hale and Moberg (2005) combined a set covering problem with FEMA's *Disaster Management Guide* to design a decision process to identify secure site locations in times of disasters. Hu, Yang, and Xu (2014) developed a non-dominated sorting algorithm to solve a bi-objective model and increase the emergency coping capacity during earthquakes. The two objectives are to minimize total evacuation distance and minimize the number of shelters.

- **Maximal Covering.** Maximal covering problem sets the number of facilities to P and maximizes the number of demand nodes covered within a certain distance (Boonmee et al., 2017). Murali, Ordóñez, and Dessouky (2012) used maximal covering location problem to identify locations to open where medicines should be handed out as response to a potential bio-terror attack in Los Angeles County. A loss function was used to account for distance-sensitive demand and chance-constraints were used to address demand uncertainty. Jia et al. (2007) determined facility locations of medical supplies in response to large scale emergencies using a maximal covering problem. A genetic algorithm, a locate-alocate, and a Lagrangean relaxation heuristic were developed to solve the problem in an efficient manner.

- **Minimax.** Minimax facility location problem minimizes the maximum distance between supply and demand nodes given P facilities. It is also known as the P-center problem (Boonmee et al., 2017). Ye, Zhao, Xi, and Dessouky (2015) propose an extension of the p-center model, called emergency warehouse location problem (EWLP), to minimize the loss resulting from disasters. EWLP was then solved using a variable neighborhood search (VNS) based heuristic algorithm. In comparison to current emergency warehouse location planning, the solution generated can incur huge savings meanwhile guaranteeing that resources are delivered on time. The minimax facility location problem can also structured to minimize worst system performance. Paul and Hariharan (2012) used a minimax problem formulation to minimize the social cost (fatality cost plus cost of maintaining a stockpile) in receiving and allocating Strategic National Stockpile assistance from the Center for Disease Control and Prevention (CDC) in the United States.

Based on these problem types, minisum is considered the most appropriate in this study. In the case of pre-positioning in the Philippines, the amount of resources available is limited. Thus, the minisum approach helps provide the most efficient approach based on limited resources.

Modeling Type

According to Boonmee et al. (2017), there are four main models that are used in facility location problems: deterministic, dynamic, stochastic, and robust. Each of the four main modeling types is described with corresponding uses in literature.

- **Deterministic.** The deterministic type of facility location problems involve the selection or location of facilities (warehouse, distribution centers, etc.) by determining input parameters (number of affected individuals, location, capacity, fixed cost), with all parameters being known and constant over time (Boonmee et al., 2017). The deterministic problem formulation is the basis for the dynamic, robust, and stochastic models. There are many studies on facility location that only involve deterministic optimization. Abounacer, Rekik, and Renaud (2014) used an epsilon-constraint method to solve a three-objective optimization problem and generate the exact Pareto front. The three objectives are to minimize total transportation duration of relief goods, minimize the number of responders required to operate open facilities, and to minimize non-covered demands. A deterministic optimization approach was used since decisions need to be taken immediately after the disaster with whatever information is available. The study also assumes that request for products are estimated by experts based on their experience and assessment of the disaster situation.

- **Dynamic.** Dynamic facility location problems involve multiple time periods where demand points, environmental factors, operating costs, and number of facilities may change (Boonmee et al., 2017). Khayal et al. (2015) designed a model for selection of temporary distribution facilities for a disaster that has changing demand over different periods. The proposed minimizes logistics and deprivation costs of relief distribution for all time periods. This allows for augmentation from central supply locations in case demand for goods exceeds the supply at a temporary distribution facility. Afshar et al. (2012) developed an integrated model at the operational level that describes logistics operations in response to natural disaster that is in compliance the complex logistics structure of the US Federal Emergency Management Agency (FEMA). It involves finding optimal facility location for four levels of temporary facilities and incorporates a dynamic vehicle routing problem and multi-modal transportation problem.

- **Stochastic.** Stochastic optimization involves assigning a probability distribution to uncertain parameters (Boonmee et al., 2017). Rawls et al. (2010) used a two-stage stochastic mixed integer program (SMIP) to provide a pre-positioning strategy for hurricanes and made a case study application on the Gulf Coast area of the US. SMIP accounts for uncertainty in demand, survival of pre-positioned stocks, and transportation network availability after an event. This model was extended to account for service quality constraints, which includes 1) confidence level value that denotes there is sufficient supply in the network to meet all demands and 2) ensure that the distance of supply movement is less that a specified limit (Rawls and Turnquist, 2011). Salmerón and Apte (2010) designed a two-stage, stochastic, mixed integer prepositioning optimization (PO) model. the first stage includes decisions to expand resources such as warehouses, medical facilities, and ramp spaces. The second stage involves logistical decisions including transportation and delivery of required commodities.

- **Robust.** Robust optimization is used for problems where some parameters are uncertain. Uncertain parameters are characterized by discrete scenarios or continuous ranges (Boonmee et al., 2017). Vargas Flores, Lauras, Okongwu, and Dupont (2015) used robust optimization by designing a humanitarian supply chain that would perform best based on 12 probable scenarios of earthquakes in Peru. The probability of occurrence of each scenario is estimated based on the historical data of past crises. Bozorgi-Amiri, Jabalameli, and Al-e-Hashem (2013) developed a robust approach for facility location in Iran by considering demand, supply, procurement cost, and transportation cost to be uncertain and discretized the stochastic quantities to constitute distinct earthquake scenarios. These scenarios and corresponding probabilities are determined by experts and disaster planners based on previous calamities and known geological faults. Das and Hanaoka (2013) also used robust optimization on locating relief distribution centers for an earthquake in Bangladesh and robustness was also characterized by assigning probabilities to four different earthquake scenarios.

Given the recent exposure of the Philippines to some of the strongest typhoons globally, robust optimization is ideal. The definition of a robust solution used in this study is as defined by (Comes et al., 2013): "the alternative that performs relatively well when compared to further alternatives across a wide range of scenarios." This study utilizes forecast data as the reference point from which different impact scenarios are derived. Then, the robust solution is defined into two different ways. The first definition is the one that exhibits the best performance among all the different alternatives based on a wide range of scenarios. The second definition is the one that exhibits the minimum maximum regret, which is the one that performs the closest to the optimal solution at each scenario.

Objective Functions in Facility Location Models

Among the most common objective functions used in facility location problems involve minimizing costs. This ranges from transportation/distribution costs (Chang, Tseng, and Chen, 2007; Khayal et al., 2015; Rawls et al., 2010; Rawls et al., 2011; Rawls and Turnquist, 2012; Verma et al., 2015), or cost-related objectives such as distance between supply and demand nodes (Abounacer et al., 2014; Hu et al., 2014; Uichanco, 2015) and response time/efficiency (Comes et al., 2013; Manopiniwes and Irohara, 2016a). There are studies that also account for the cost of opening facilities (Chang et al., 2007; Hu et al., 2014) and maintenance/storage costs of pre-positioned inventories (Manopiniwes and Irohara, 2016b). Moreover, there are studies that account for penalty costs for delays (Khayal et al., 2015) or unmet demand (Rawls et al., 2011).

Some studies criticize having a cost minimization objective, as it is deemed limited and inappropriate for relief distribution networks (Anaya-Arenas et al., 2014). It is contended that minimizing logistic costs is appropriate for commercial activities but not for humanitarian logistics operations, where the primary goal is to allocate limited resources to mitigate human suffering (Holguín-Veras, Pérez, Jaller, Van Wassenhove, and Aros-Vera, 2013). This may be true in the response phase, however, investing in preparedness phase could lead to reduction of cost in the subsequent response phase while achieving the same or even better levels of service. Pre-positioning efforts of UNICEF and WFP on internationally-sourced emergency supplies have yielded ROI's in the range of 1.6-2.0 and average time savings of 14 to 21 days (Meerkatt, Kolo, and Renson, 2015).

Other studies incorporate deprivation costs as part of the objective function. Deprivation cost is defined as "the economic valuation of human suffering associated with a lack of access to a good or service" (Holguín-Veras et al., 2013). Holguín-Veras et al. (2013) argued that "proxy approaches", such as maximum headways between deliveries and minimum delivery amounts, do not properly capture human suffering. The resulting deprivation cost function is monotonic, non-linear, and convex with respect to deprivation time. Deprivation costs have been used in inventory-allocation distribution models (Pérez-Rodríguez and Holguín-Veras, 2016) and facility location models (Cotes and Cantillo, 2018).

Fairness/equity is also used as part of the objective function. Ransikarbum and Mason (2014) used a maximin approach for the objective function to maximize the minimum percentage of satisfied demand. The percentage of demand satisfied was used as a surrogate measure for fairness. Zhan, Liu, and Ye (2013) used expected total unmet demands to represent equity in relief resource allocation. Rodríguez-Espíndola et al. (2018) used the minimization of maximum unfulfillment as a measure of equity. Huang, Smilowitz, and Balcik (2012) used three metrics to measure equity: 1) maximum pairwise difference between service levels 2) standard deviation between service levels and 3) a convex disutility function to minimize disutility-weighted arrival time.

Many studies also expressed facility location problems using multiple objective functions. Ransikarbum et al. (2014) used three objective functions: 1) maximize fairness, 2) minimize unsatisfied demand, and 3) minimize total network costs and normalized the objective functions using a linear normalization technique to allow comparisons between different criteria. Barzinpour and Esmaeili (2014) used goal programming approach to prioritize between the three objective functions used, and these goals are derived from expert judgment of municipal authorities. Abounacer et al. (2014) used an epsilon-constrained method for a three-objective optimization problem and proved that it generates the exact Pareto front provided the problem has at least two integer and conflicting objectives.

Based on the problem tackled in this study, three objectives are considered. First is to maximize the amount of demand that is satisfied. In the context of the decision-maker, the primary reason for augmentation by DSWD is to ensure that that the relief goods first are able to reach the people in need. To maximize the coverage of relief goods, this objective also ensures that the number of goods that are destroyed during the typhoon is also minimized. The next main objective is to ensure that the response is efficient. The act of pre-positioning effectively brings the goods closer to the potentially affected area before it even gets affected, which allows for a faster response than for all the goods to come from a distant main warehouse facility. The third objective function ensures that the operations are the most cost-effective. This involves the cost of pre-positioning (transportation of relief goods from the main distribution center to the local distribution centers) as well as setup costs for the distribution centers.

Since a lot of studies deem that cost-based approaches are inappropriate for humanitarian logistics operations, the approach in obtaining the optimized solution should ensure that the minimization of cost does not come at the expense of either efficiency or demand coverage. Thus, a hierarchical approach is proposed. The objective that comes at first priority is the maximization of demand, then efficiency of operations, and then finally the cost. The hierarchical approach is also seen in other multi-objective models in humanitarian logistics, such as the study of Liberatore, Ortuño, Tirado, Vitoriano, and Scaparra (2012), where a hierarchical model is used for the optimization of recovery operations in a case study on the Haiti 2010 earthquake.

Forecast-Driven Prepositioning Models

There are studies found in literature that are forecast-driven pre-positioning models. In this study, forecast-driven pre-positioning is defined as models that account for the regular intervals of forecast updates to derive the optimal conditions for pre-positioning.

Galindo Pacheco et al. (2015) designed a model to determine the location and amount of goods pre-positioned based on forecast data. The study used stochastic programming that is based on a Markovian approach. The Markovian approach assumes that forecast in the next time period depends only on the current forecast. With the Markovian transition probability matrix, the potential attributes of the hurricane at landfall (intensity, location of landfall, and time of landfall) can be defined along with its corresponding probabilities. This is the basis for which the scenarios are defined and evaluated at a certain point in time given the most recently available forecast data. Decision theory is then used to evaluate the different approaches for resource deployment.

Gobaco et al. (2016) also uses decision theory to determine the decision of whether to pre-position at the current time period or wait for more information. A series of models were developed: Model A (perfect information model), B (optimal pre-positioning under uncertainty), B_0 (calculates cost of getting more information), and C (decision model on whether to pre-position). Additionally, Gobaco et al. (2016) also considers the potential reduction of capacity of transport links. Furthermore, Gobaco et al. (2016) also uses multiple objective functions which are linearized through linear physical programming (LPP).

Studies done on pre-positioning relief goods either assume that the lead time is given, such as 48 hours (Davis et al., 2013; Uichanco, 2015), or are assumed the same throughout the network (Galindo Pacheco et al., 2015; Gobaco et al., 2016). This study extends the work done on forecast-driven pre-positioning models to account for differences in lead time at each supply point. Thus, pre-positioning decisions can be done at different times over the network based on the forecast trajectory of the typhoon.

Moreover, the construction of different scenarios for this study is based on a generated ensemble of typhoon tracks at a given time period based on the forecast data. This allows to get an insight on the behavior of the typhoon over the planning horizon. Therefore, the impacted area is going to be different for unique forecast typhoon tracks. The forecast lead times at each point will also differ for typhoon tracks of different trajectories. This allows for a model construction that captures a robust pre-positioning decision on a large network impacted by a typhoon.

Chapter 3

Research Questions and Approach

The ultimate goal of this thesis project is to design a pre-positioning strategy that is suitable for the Western Visayas Region in the Philippines. To achieve this goal, research gaps are first identified based on the literature review. From the research gaps, the main research question and subsequent research subquestions are defined. The research methods to answer each research subquestion are also discussed in detail. Finally, research flow diagram, which illustrates the research design into concrete steps, is presented.

3.1 Research Gaps

The assumptions and considerations for pre-positioning are very context specific. Studies on pre-positioning that are focused on case studies in the continental USA may not be appropriate for the Philippines. This section will focus on the gaps in current literature to adequately capture the strategy needed in the Philippine context and will also identify technological developments in recent years that could provide valuable data to improve the state of pre-positioning in the Philippines.

The main source of input information for pre-positioning relief goods is mainly weather forecasts and its anticipated impact on the network. This is evident in previous works explored in literature. For example, Davis et al. (2013) partitioned the warehouse network of southern US whether it is impacted or not based on forecast information 48 hours prior to landfall. Supplies were then reallocated between impacted and non-impacted warehouses based on the weather forecast, and the allocation was determined based on the estimated demand for relief supplies and also the estimated destruction of supply points.

Many studies that focus on disaster preparedness involve pre-positioning of relief goods over a contiguous landmass. The Philippines, however, is an archipelago of more than 7,000 islands, and thus the relief network has added complexity. Pre-positioning efforts between different islands could be hindered either by cost, time, and/or access constraints. Transportation via the sea take considerable time and can be limited depending on the strength of the typhoon. For instance, no vessel is allowed to sail when a Public Storm Warning Signal (PSWS) Number 1 or higher is issued within the origin, intended route, and the destination of the vessel (PCG, 2013a).

Another factor that should be considered when pre-positioning in the Philippines is the potential disruption of transport links between different municipalities in the aftermath of the typhoon. Floods or accumulated debris may cause delays in road travel, such as shown in figure 3.1 (Maitem, 2013). Bridges may also be destroyed by a big flood during a typhoon. These situations present more difficulties to deliver humanitarian aid efficiently to those impacted by the typhoon.

There are studies that incorporate network damage into facility location problems. For example, Salman et al. (2015) modeled the impact of an earthquake on network links to maximize demand coverage over all possible network configurations. Taking network damage into consideration provides a more realistic approach in identifying locations where you need to pre-position

Figure 3.1: Impassable road in the aftermath of Typhoon Haiyan in Tacloban City, Philippines

relief goods. For example, if a link is forecast to be inaccessible when the storm hits (due to flooding or rain-induced landslide), then goods can be pre-positioned based on alternate routes to ensure access to relief goods within the first 72 hours.

With an incoming typhoon, forecast information regarding a typhoon is regularly disseminated by the designated government agency to decision makers and also to the general public. In the Philippine context, new forecast information is made available every six hours. Technological advancements in the Philippines such as the near-real time dissemination of hazard-related information by the University of the Philippines (UP) Project NOAH (Nationwide Operational Assessment of Hazards) and the regular publication of disaster related situation reports by the Disaster Response Operations Monitoring and Information Center (DROMIC) under the Department of Social Welfare and Development (DSWD) opens new opportunities for disaster preparedness strategies. As typhoons could take a few days before making landfall, this gives decision makers lead time for pre-positioning relief goods. Optimization models could be utilized to generate the best pre-positioning/re-positioning strategy of supplies based on forecast information. For example, relief supplies can be augmented at a certain location if the newer typhoon forecast indicates a higher demand for relief goods.

Current pre-positioning activities in the Philippines show a disproportionate amount of pre-positioning compared to the actual impacts of the typhoon - perhaps accounting for stronger typhoons that are expected to come over the entire duration of the typhoon season. However, maintaining many storage facilities over a long period of time incur huge costs. These costs can be streamlined by taking advantage of the regular updating of forecast information and pre-positioning in response to the expected damage to be brought by the typhoon. This way, the additional costs of storage can be minimized without compromising response efficiency.

Few studies explore regular updating of forecast information and use it in pre-positioning supplies in preparation of a coming typhoon (Gobaco et al., 2016; Galindo Pacheco et al., 2015). For example, the study by Galindo Pacheco et al. (2015) involve stochastic programming and decision theory to determine the best time for starting pre-positioning activities. This study will also use periodically issued forecast data to determine the optimal pre-positioning strategy. The pre-positioning decision will be based not only on expected impacts on demand, supply, and transport link delays but also on how much lead time is available to the decision maker.

In previous pre-positioning studies such as Gobaco et al. (2016), Galindo Pacheco et al. (2015), and Davis et al. (2013), the pre-positioning is done over a defined geographic area where the lead time with respect to the incoming typhoon is the same across all points of the network. In reality, however, different points in the network experience different lead times, and this is not adequately captured by previous pre-positioning models.

The key contribution of this study is to explore a different scenario design which allows the development of an facility location model that accounts for the differences in lead times across the network. Thus, the pre-positioning decisions can be optimized to enable earlier pre-positioning at points where the typhoon is projected to hit first.

As the path of the typhoon is uncertain, the approach used in this study allows an almost dynamic scenario construction, which updates the scenarios considered as soon as new forecast is available. The optimization calculations performed over the scenarios, along with the evaluation of each solution across the different scenarios generates a solution that exhibits scenario-based robustness at a given time period. Then, based on the decision-maker's strategic preferences, and considering the lead times for each location, pre-positioning actions can be executed.

A robust strategy is very important in the Philippine context especially that the country has experienced some of the most devastating typhoons globally over the past decade and how the trend of extreme weather occurrences are more likely to increase in the future. A model which accounts for varying lead times across the network allows for a more responsive preparedness phase and a more efficient response phase. A visualization of the iterative approach used in this study is shown in figure 4.3 in the methodology section.

3.2 Research Relevance

The main goal of this research is to provide a tool that helps with the decision-making process in pre-positioning relief goods in anticipation of an incoming typhoon. Currently, a huge focus of DSWD is on the response phase, which is the augmentation of relief goods in areas where the typhoon has already hit. However, the different layers of the supply chain structure can sometimes hinder in the efficiency of the response, even when the goods are readily available. Current protocols on disaster response is that first, if a barangay or village is affected by the typhoon and the needs for relief goods are high, then it has to go first request assistance to the municipal level, then the provincial level, and then to the regional and national level. This study takes on the perspective of the regional level, and to determine the strategic locations in the context of the incoming typhoon that will allow efficient response in all parts of the region that are potentially affected.

This study also aims to provide the ability to generate insights based on the results of the forecast data. It allows the decision-maker within DSWD to have an idea of the potential impacts of the typhoon before it comes, as well as the different potential scenarios that can arise. The tool used in this study can be used to emphasize more data-driven decision making in conjunction with previous experience and knowledge of local circumstances.

Moreover, the methodology used in this thesis project can provide insights especially on managing the pre-positioning of relief goods over a large network. It allows for prioritization of tasks based on regular forecast updates in order to determine where to pre-position at which time. It also allows for the decision-maker to carefully scrutinize the decision between pre-positioning early or waiting for more accuracy in the succeeding forecasts.

3.3 Research Question

Based on the research gaps discussed, the main research question for this proposal is stated below:

How to determine the robust pre-positioning strategy in preparation for a typhoon, where forecast information is updated periodically?

In order the address the main research question, the following research sub-questions are included:

1. How to generate an ensemble of potential typhoon tracks based on forecast data? (RSQ1)
2. How to estimate the impact of a typhoon track scenario on a network, particularly on demand of relief goods, supply destruction, and transport delays? (RSQ2)
3. How can the robust pre-positioning configuration be determined based on many potential damage scenarios? (RSQ3)
4. How to determine when to make the pre-positioning decision given different lead times at different points in the network? (RSQ4)

RSQ1. Generation of potential typhoon tracks

Potential typhoon tracks at each period need to be investigated in order to have a gauge of how the typhoon will behave over time. This way, the potential behavior of a typhoon over the selected network can be estimated. The generation of typhoon tracks is determined from forecast data.

RSQ2. Defining damage scenarios based on typhoon track ensemble

Once the potential typhoon tracks are generated, its corresponding impact on the network need to be estimated. In this study, particular aspects that are focused on are impact on demand of relief goods, supply points which are destroyed, and transport segments which experiences delays. The resulting damage scenarios can provide important input information to determine the robust pre-positioning configuration.

RSQ3. Robust pre-positioning configuration based on damage scenarios

One of the key aspects of this study is to determine the optimal pre-positioning configuration based on a certain damage scenario. Then, given a range of potential damage scenarios, the robust configuration is the solution that performs well over the scenarios analyzed.

RSQ4. When to make the pre-positioning decision

Given the robust configuration, there needs to be a trigger as to when a pre-positioning decision has to be performed. Given the strategic preferences of the decision maker and the differences in lead times across different points in the network, there needs to be a clear indication of when a robust solution needs to be implemented.

3.4 Research Methods

The research sub-questions are addressed through different methods. A summary of the methods used is shown in table 3.1. This study is predominantly quantitative, employing many of the techniques found in literature such as building optimization models for facility location problems.

Table 3.1: Summary of methods to be used for each research subquestion

Research Subquestion	**Method**
RSQ1 Generation of Typhoon Track Ensemble	Markov Transition Probability Matrix, Monte-Carlo Sampling
RSQ2 Determining Damage Scenarios	Impact Estimation Models in Literature
RSQ3 Robust Pre-positioning Configuration	Optimization Model based on Facility Location Problems, Scenario-Based Robustness
RSQ4 When to Implement Pre-positioning Decision	Decision Theory

- The main idea of RSQ1 is to generate an ensemble of typhoon tracks, which serve as potential scenarios based on forecast data. The ensemble of typhoon tracks is generated through the use of Monte-Carlo sampling with the aid of Markov Transition Probability Matrices, which were generated given historical data in the area observed.

- For RSQ2, the impacts of the typhoon need to be estimated based on the typhoon track. The estimated impact will be the corresponding input to the optimization models. In order to estimate the impacts, an extensive review of literature needs to be conducted. Existing methods of impact estimation (demand, supply damage, transport network delays) needs to be evaluated to determine the most appropriate estimation method.

- To determine the robust pre-position configuration for RSQ3, first, an optimization model needs to be designed to determine the optimal pre-positioning configuration for each scenario. Then, the optimal pre-positioing configuration for each scenario needs to be evaluated across all potential scenarios to determine the scenario-based robust solution.

- Finally, to decide when to implement the pre-positioning decision for RSQ4, it is important to account for the differences in lead times across the network, among other strategic considerations of the decision maker. These strategic considerations are captured through decision theory algorithms, which provides the decision on whether to perform a pre-positioning decision or wait for the next forecast.

Research Flow Diagram

The research flow diagram, shown in figure 3.2, illustrates the research design into concrete steps. It also gives a logical process flow for this project. It shows in which sections will the research questions be addressed as well as its corresponding methods.

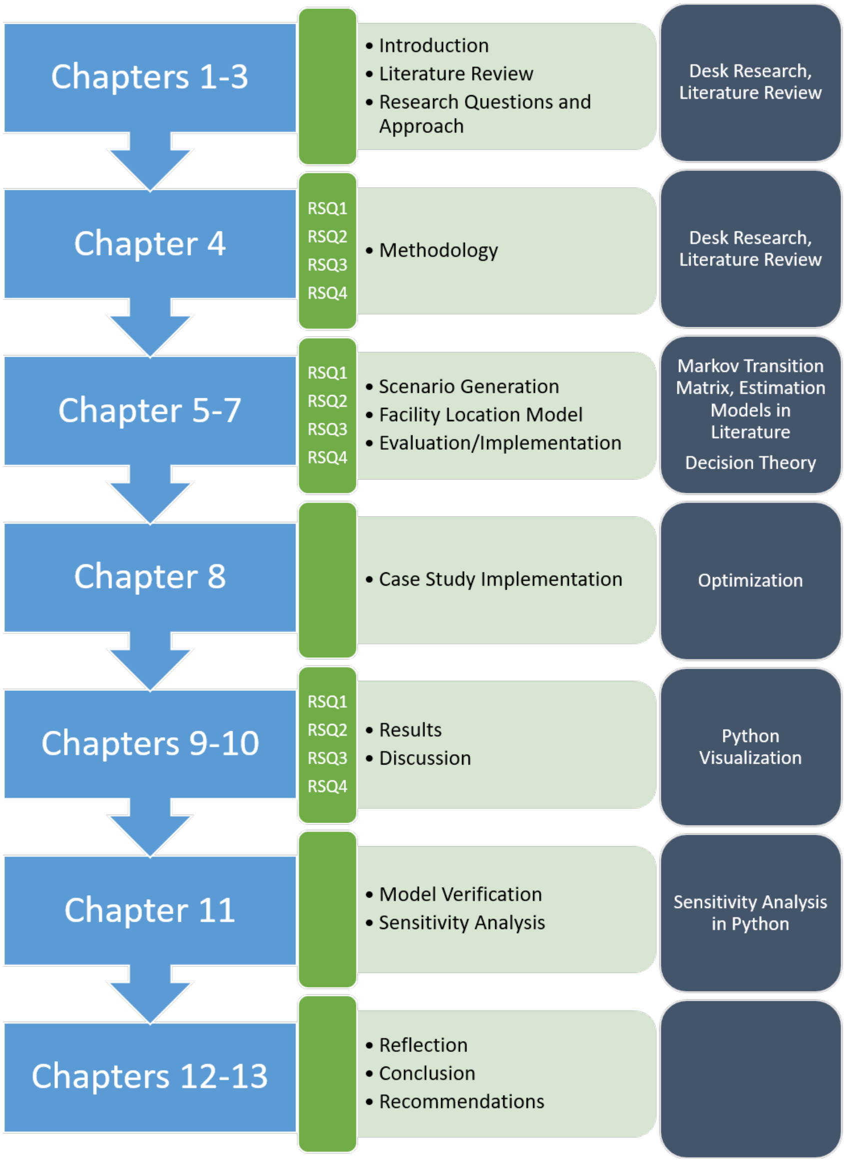


Figure 3.2: Research flow diagram

Chapter 4

Methodology

This chapter focuses on the design of an iterative approach that aims to address each of the research sub-questions. It shows the step by step iterative process from the issuance of forecast data to finally implementing a pre-positioning action. Moroever, it also provides an explanation regarding how the iterative approach is implemented across multiple periods. To aid in the understanding in the terms used in this chapter, definition of key terms is included in Appendix A. This chapter also includes an illustrative definition of the problem.

4.1 Illustrative Problem Definition

Suppose you have a network of twelve points that is going to be hit by the typhoon as shown in figure 4.1A. According to the forecast, when the typhoon hits the network, each point is going to have a demand for relief goods after the typhoon has hit. The relief goods are intended for the immediate necessities of the people after the typhoon has hit and not for long term relief. Each point is going to be defined as a demand point (DP)

Suppose you have a Regional Distribution Center (RDC), which is symbolized by a green square shown in figure 4.1A. It is a permanent facility that contains a stockpile of relief supplies. It is located at (1,2). Suppose that any supply facility can only efficiently service DPs that are located maximum of two segments away. This means that in this network the RDC is not capable of efficiently providing the relief goods for all the DPs. The DPs served by the RDC are colored green, as shown in figure 4.1B.

To increase the number of DPs covered, suppose that a temporary Local Distribution Center (LDC) can be set up to service other DPs. It is represented by a yellow triangle in figure 4.1B. To ensure maximum coverage, the optimum location of the LDC must be determined. In this example case, it will be either (4,2) and (3,2). The yellow DPs in figure 4.1B are the ones that are served by the LDC after the typhoon strikes.

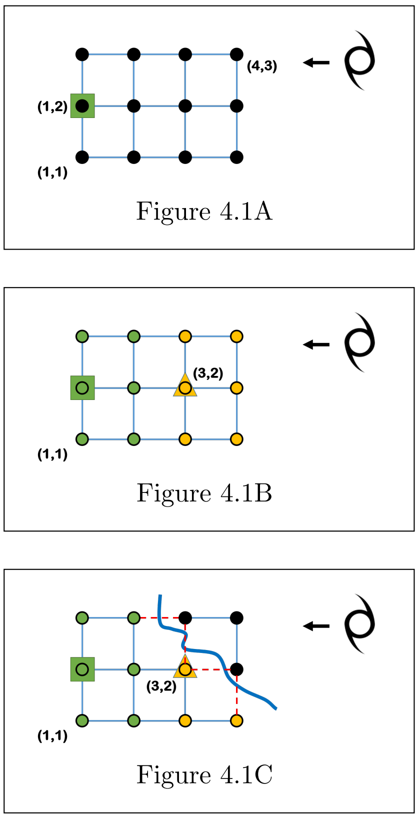


Figure 4.1: Visualization of Problem Setup (I)

Suppose there is a river that passes through the network, as shown in figure 4.1C. Based on the typhoon forecast, there is a high chance for the river to be flooded, which could render the roads along its path flooded, which can cause a lot of delay for relief goods delivery. The flooded roads are shown as red dashed lines. If the roads are flooded, the three points in the top right corner are the network will not be serviceable based on the current set-up as shown in figure 4.1C.

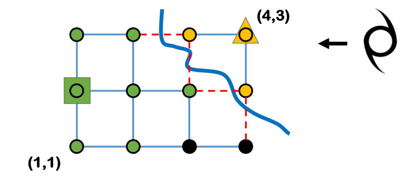


Figure 4.2D

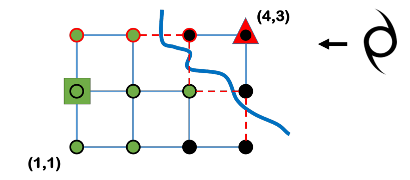


Figure 4.2E

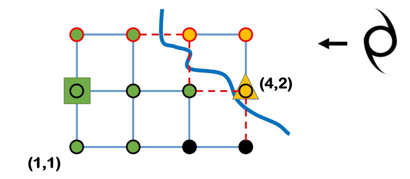


Figure 4.2F

Figure 4.2: Visualization of Problem Setup (II)

In order to maximize coverage, it is better to place the LDC to (4,3). This means, that at this configuration, only two points will not be served instead of three. This configuration is shown in figure 4.2D. Note that although the road could be impassable in the response phase (after the typhoon hits), in the pre-positioning phase, the road network is still fully intact. Thus, goods can be pre-positioned at the LDC at (4,3).

Suppose also that in the same scenario, the typhoon is expected to be extremely destructive. This turns the topmost DPs in the network to have a red border, which means that if an LDC is placed there, there is a high chance of it being destroyed. If an LDC is destroyed, then the relief goods located at the LDC are considered unusable. If the LDC is kept at (4,3), then the LDC will be damaged, as shown in figure 4.2E. However, if the LDC is placed at (4,2), as shown in figure 4.2F, then the coverage is maximized.

4.2 Two-Stage Facility Location Problem

The problem described is essentially a two-stage facility location problem. First, there is an available stock of relief goods at the RDC. The RDCs are usually large warehouses operated by the regional government for the intention of distributing relief goods in case a disaster strikes. For this case, these goods are shipped to LDCs in anticipation of a typhoon. LDCs are temporary storage facilities which then distribute the relief goods to the demand points.

Based on the illustrative description of the problem, the goal of the problem owner is to find the optimal location of the LDC and how much goods it should contain. This decision is based on the latest forecast information received by the problem owner. The forecast data provides ideas of what may happen to the network at typhoon landfall. Based on the forecast, different scenarios of the typhoon's impact on the network are designed. Thus, the forecast data gives the problem owner an estimate of how much goods are expected to be demanded at each DP, which links in the network may have delays, and at which locations are potentially at high risk of damage based on the typhoon path (and thus not viable locations to establish LDCs).

At a given point in time, based on impact scenarios generated from the latest forecast, a capacitated facility location model can be done to determine the optimum location and amount of supplies at each LDC. This model is called model **P1** and it has the following objectives in order of hierarchy:

1. Maximize demand coverage

2. Minimize average travel time per unit of relief good

3. Minimize total costs

It is important to recognize that the typhoon forecast is subject to uncertainty. The characteristics of the typhoon (maximum wind speed, time until landfall, location at landfall) are still highly uncertain even when using the most advanced forecasting equipment and models available. However, the forecast data provides the problem owner a starting point and narrows down the expected behavior of the typhoon. This behavior can be inferred based on historical data. For example, a very strong typhoon with wind speeds of about 350 km/h that is expected to make landfall within 12 hours is very unlikely to have wind speeds of 15 km/h at landfall.

Moreover, there is value in waiting for newer forecasts, as later forecasts provide more accuracy, which could then lead to a better estimation of its impact on the network, and consequently, a better pre-positioning action. However, waiting for later forecasts decreases the amount of lead time available for pre-positioning. In preparation for the typhoon, the LDC needs to be setup, and it takes time to transport goods from the RDC and open an LDC. It is also important to consider that the solution obtained is robust. This means that given a current forecast (and its uncertainty), the chosen solution can perform relatively well compared to other alternatives across all the different scenarios that may happen.

4.3 Iterative Approach to Determine Pre-positioning Action

Based on the problem formulation described in section 4.1, an iterative process is designed for this study, as shown in figure 4.3. It shows the step by step process to follow starting from the initial forecast data until all the pre-positioning actions get implemented. The iterative approach entails the generation of scenarios based on forecast data, which then serve as input for the optimization model.

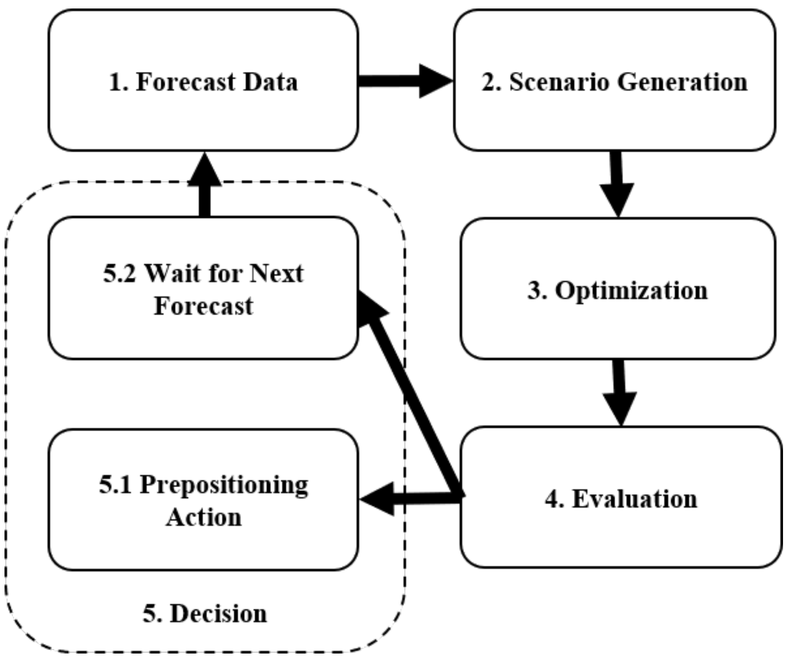


Figure 4.3: General process flow to determine pre-positioning action

1. **Forecast Data.** Once a typhoon is formed in the Northwestern Pacific basin, weather forecast agencies such as the Japan Meteorological Agency are required to issue forecast information periodically until dissipation of the typhoon. The formation serves as the

trigger for the start of the iterative approach, and the forecast data serves as one of the key sources of data for scenario generation.

2. **Scenario Generation.** The characteristics of a typhoon from its formation until its dissipation is inherently uncertain, thus there is an overwhelmingly high number of possibilities of typhoon behavior over time. Weather forecast agencies use simulation models to forecast the behavior of the typhoon and try to capture the uncertainty through a forecast cone. In order to capture the uncertainty, potential typhoon tracks are generated based on forecast data. Individual typhoon tracks serve as input to generate potential damage scenarios in the network. Due to limitations in time and computational power, only a limited number of scenarios can be analyzed.

3. **Optimization.** For each damage scenario, an multi-objective optimization model based on a capacitated facility location problem is used to determine the optimal feasible pre-positioning action. This model is named model P1. Based on the damage scenario, P1 results to a configuration as to where to pre-position goods and how much is needed at each location. P1 uses a lexicographic or hierarchical approach, which means that the objectives are ranked in a decreasing order based on priority. In a hierarchical approach, the objective with the highest priority is first optimized, then the objective with the second-highest priority is optimized given that that value of the first objective remains optimal (Gutjahr and Nolz, 2015). The same procedure is then repeated for the next priority level.

4. **Evaluation.** As there are multiple scenarios at a given period, and since each scenario has a solution based on model P1, each solution needs to be evaluated to determine the robust solution at the given period. For this, a modified version of model P1 is used, named model P2, which evaluates how a candidate solution for a given scenario performs under a different scenario. P2 also uses the same hierarchical optimization approach as P1 but uses different metrics to characterize robustness: 1) best performance across all scenarios and 2) regret based, which is the solution that exhibits the smallest maximum regret.

5. **Decision.** The Decision step in the approach consists of two parts: 5.1 is to conduct a pre-positioning action, while 5.2 waits for the next forecast. At this stage, the problem owner is presented with the robust solution given the scenarios available at each period. Based on the strategic preferences of the decision maker, it is possible to either not pre-position at all, pre-position everything, or pre-position only at specific locations and wait for an updated forecast for the other locations.

4.4 Iterative Approach Across Multiple Periods

The iterative approach as described in section 4.3 details the steps needed to be taken at each period. However, the planning horizon by which the pre-positioning actions can be implemented extends over multiple periods - which starts from the formation of the typhoon until goods can no longer be pre-positioned. This section describes the multi-period process by which the iterative approach is implemented on.

At the first period, it is assumed that a typhoon has formed and that all the goods are still stockpiled at the RDC. This is defined as the initial condition which is used as in input for the optimization model. Then, based on the forecast, the iterative approach described on the previous section. Notice that the fifth step of the approach involves making a decision as to whether to pre-position or not. The decision choices involved results to a tree-like structure as shown in figure 4.4.

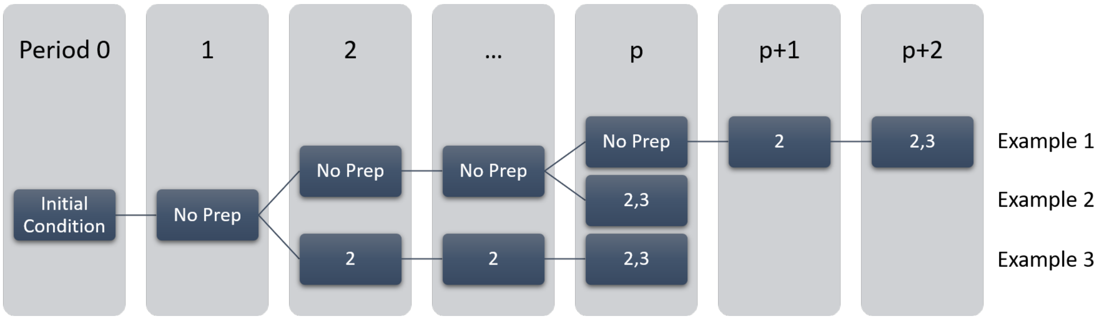


Figure 4.4: Decisions across multiple periods

Figure 4.4 shows three different examples of a how the decision making process is implemented over different periods. The numbers in the top row show the different time periods, while the data in the rectangle shows which facility is opened at each period (or none at all). Notice that all the three examples end in the same configuration (2,3). However, this does not necessarily mean that the three examples will perform the same in the event of a typhoon.

The main difference as to why the three different examples (leading to the same configuration) are implemented over different periods is due to the pre-positioning strategy as well as the choice of robustness metric. At the beginning of each period, the iterative process is implemented, which results to a suggested configuration that is robust and feasible based on the information available at that period. The robustness choice also impacts which configuration is chosen. The pre-positioning strategy algorithm decides as to whether the configuration is not to be implemented at all (as shown in period 1 for all three examples), partially (as shown in period 2 for example 3), or fully (as shown in period p for example 2).

Although the same sites are selected in the end, it does not guarantee that all three examples will perform the same when the typhoon arrives. The reason is that they operate under different estimations of damage scenarios. For instance, example 3 pre-positions at 2 based on the information at period 2, whereas example 1 does the same under period p+1. Since example 1 pre-positions at a later period, it has a benefit of getting improved accuracy of the damage scenarios by which the pre-positioning decision is based. Thus, example 1 is highly likely to have the quantity of goods that is closer to the amount that is demanded when the typhoon arrives.

Another important thing to note is that one of the main assumption for this project is that any pre-positioning action that is executed is considered final and irreversible. It corresponds to the reality that a pre-positioning action consumes considerable time and resources given a very short lead time, thus re-pre-positioning is neither practical, nor cost-effective, nor feasible. This is reflected in figure 4.4 in example 3, where the pre-positioning at facility 2 is kept until period p, when pre-positioning action is also performed at facility 3. This also means that the previous action is taken into account for future pre-positioning decisions.

Chapter 5

Scenario Generation

One of the important aspects of this thesis is the scenario generation. It provides the link between the initial forecast data and turns it into valuable input that is useful for the optimization model. In this section, the scenario generation step is unpacked into different steps. First, the characteristics of the forecast data is described. Then, the method for which forecast tracks are generated is elaborated. Finally, the impact estimation models are described which leads to the damage scenarios. The steps to determine the damage scenario is shown in figure 5.1

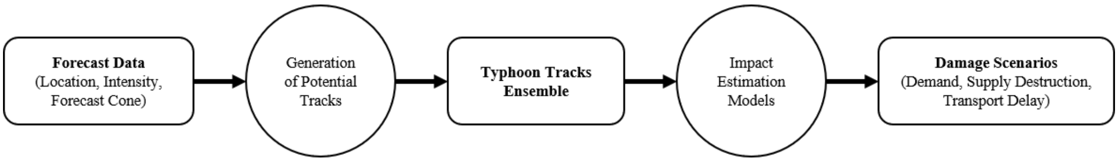


Figure 5.1: Process flow for scenario generation

5.1 Forecast Data

The first step in the pre-positioning process is obtaining forecast data. The Regional Specialized Meteorological Center (RSMC) in Tokyo is responsible for providing information regarding typhoons in the western Pacific Ocean. Typhoon forecasts and warnings focused in the Philippine Area of Responsibility are obtained via the Philippine Atmospheric, Geophysical, and Astronomical Services Administration. An example of a forecast is shown in figure 5.2. A typhoon forecast includes the following information:

1. **Forecast Hour.** Each typhoon forecast includes expected characteristics of the typhoon for select forecast hours over the next five days. These forecast hours are at 0, 12, 24, 36, 48, 72, 96, 120 h. The typhoon forecast also indicates at which forecast hour is the typhoon expected to make landfall. It is indicated as "INLAND" in figure 5.2. Note that if the forecast indicates that the center of the typhoon is inland after 48h, it means that the typhoon expected to make landfall between 36h and 48h.

2. **Longitude and Latitude.** For each forecast hour, the expected position of the center of the typhoon is described.

3. **Intensity.** The expected maximum wind speed of the typhoon is also described at each forecast hour.

```
FORECAST POSITIONS AND MAX WINDS

INIT  09/0300Z 22.1N  77.7W  140 KT 160 MPH
 12H  09/1200Z 22.6N  79.1W  140 KT 160 MPH
 24H  10/0000Z 23.3N  80.6W  135 KT 155 MPH
 36H  10/1200Z 24.5N  81.4W  130 KT 150 MPH
 48H  11/0000Z 26.5N  81.9W  115 KT 130 MPH...INLAND
 72H  12/0000Z 31.6N  83.8W   50 KT  60 MPH...INLAND
 96H  13/0000Z 35.0N  87.0W   25 KT  30 MPH...INLAND
120H  14/0000Z 35.5N  87.5W   20 KT  25 MPH...POST-TROP/INLAND
```

Figure 5.2: Forecast Information for Hurricane Irma at 2300 08 Sep 2017

The planning horizon for this study starts with the formation of the typhoon. Starting with typhoon formation, forecasts are issued every six hours, which marks the beginning of each period.

5.2 Generation of Potential Typhoon Tracks

This step is aimed at addressing RSQ1, which is to generate an ensemble of potential typhoon tracks based on forecast data.

Forecast information are generated at each time period to update the public regarding the behavior of the typhoon. A typhoon track is highly uncertain, and thus there are many ways by which the typhoon can behave over time. A forecast cones is generated by weather forecast agencies using models based on historical data and projected atmospheric conditions. The forecast cone gives the decision maker an idea of how the typhoon may behave over time. For this study, the forecast data is used as a reference point to generate an ensemble tracks which represent different possible tracks for the current typhoon.

In practice, the Japan Meteorological Agency uses a Typhoon Ensemble Prediction System (TEPS) for the North Pacific Ocean and South China Sea. TEPS is used to help define the probability circle radius of typhoons Fukuda (2018) and Yamaguchi, Sakai, Kyoda, Komori, and Kadowaki (2009). Ensemble predictions for typhoons are established every six hours. In 2017, the General Ensemble Prediction System (GEPS) is introduced to combine TEPS with other models to achieve an efficient use of computational resources and produces an ensemble size of 27 (Tokuhiro, 2017). Another model, the Global Spectral Model (GSM), is also used to generate intensity forecasts.

Ideally, historical data of the track ensembles can be used to generate the different damage scenarios for this study. Unfortunately, historical data of the individual results of TEPS/GEPS and GSM is difficult to obtain, and thus for the purposes of computational exercises in this study, an alternative way of generating typhoon tracks is used.

To generate the different potential tracks, a modified approach patterned from the studies of Galindo Pacheco et al. (2015) and Czajkowski and Woodward (2010) was used. Czajkowski et al. (2010) modeled hurricane forecasts as a Markovian process, which assumes that the forecast in the next period depends only on the current period. This study differs in Czajkowski et al. (2010) and Galindo Pacheco et al. (2015) in that this study models not the forecast data, but the typhoon behavior as a Markovian process. The main assumption is that the behavior of a typhoon in the next period is dependent only on the current period. This allows for simulation of typhoon tracks as a Markov chain, and the projected typhoon behavior is defined by the probability distribution in a Markov transition probability matrix.

To generate the Markov transition probability matrices, the best track data of typhoons in the western Pacific Ocean was obtained from Japan Meteorological Agency. The database contained information of typhoon tracks from 1951 until April 2018. Two Markov transition probability matrices were generated - one on intensity and one on location.

To generate the transition probability matrix for intensity, shown in table 5.1, the typhoon intensity at each period was compared to the succeeding one. For example, if the intensity at period p was at 40 knots, and became 50 at p+1, then 1 was added to the table at row 40, column 50. The rows were then normalized to obtain the likelihood of a typhoon intensity in the next period, given the intensity at the current period. Data was gathered on all typhoon paths since 1951, and the resulting transition probability matrix is shown in table 5.1. To aid in the interpretation of the table, the row shows the intensity at period p, and the percentage of occurrence of a certain intensity at p+1 is shown at each of the columns. The intensity values in table 5.1 are shown in knots.

To generate the transition probability matrix for location, the same principle applies as with intensity. For location, however, there are two parameters: latitude and longitude. The general idea is to generate all the possibilities of the location of the typhoon at the next period if its currently located at point A. To do this, the coordinates of the typhoons to be analyzed were rounded to the nearest 0.5 degree. Then, the study space was determined based on the tracks of the typhoons that has entered the Philippine Area of Responsibility since 1951. The resulting study space is a grid with partitions at every 0.5 degree spanning from the coordinates 4.5 to 27.5 degrees latitude and from 112.5 to 159 degrees longitude. The result is a 4-dimensional matrix, which was constructed with the aid of MultiIndex DataFrames in python. With reference to the grid, the matrix can be interpreted as: if the typhoon is located at a certain point in the grid at period p, what are the probabilities of the typhoon landing at each point in the grid at period p+1.

The potential typhoon tracks were generated as a Markov chain with the aid of the two transition probability matrices. The generated tracks, however, have to fall within the forecast cone. The forecast data, as shown in figure 5.2, gives the location of the center of the typhoon at specific forecast hours. A 2/3 probability circle is drawn at each location, which shows where the typhoon center is supposed to land at that forecast hour 67% of the time based on historical data. Each forecast hour has a specified radius, which differs depending on the region (Eastern Pacific, Eastern Pacific, North Atlantic, etc.). A review of the 2016 and 2017 probability circle radii by Fukuda (2018) categorizes the radii according to forecast time, direction, and speed of the tropical cyclone. To ensure consistency, the largest probability-circle radii at each forecast hour was used. An extract of the probability-circle radii table from Fukuda (2018) is shown in table 5.2. In generating potential tracks, it was ensured that at a specific forecast hour, the distance between the generated track and the forecast data point does not exceed the radii of the corresponding probability circle.

Table 5.1: Markov transition probability matrix for maximum wind speed (%). Wind speed values are in knots (kt)

p \ p+1	**0**	**35**	**40**	**45**	**50**	**55**	**60**	**65**	**70**	**75**	**80**	**85**	**90**	**95**	**100**	**105**	**110**	**115**	**120**	**125**	**130**	**135**	**140**
0	87	11	2	1	0	0	0																
35	9	53	30	7	1	0	0																
40	3	8	52	30	6	1	0																
45	2	2	9	52	29	6	1	0	0														
50	0	1	3	11	48	30	6	1	0		0												
55	0		1	3	11	49	28	8	1	0	0		0										
60	0			1	4	11	43	29	10	1	0												
65	0		0	0	2	4	13	40	31	8	2	0	0										
70			0		0	1	4	10	50	22	10	1	1	0									
75				0			1	4	13	53	21	7	2	0	0								
80					0	0	0	2	4	14	54	17	7	1	1		0						
85							0	0	1	3	15	60	15	5	1		0						
90								0	0	1	6	15	57	13	6	0	1				0		
95									0	0	1	4	20	56	15	2	0						
100										0	1	1	7	15	63	8	4		0	0			
105											1		2	7	21	53	11	5					
110											0		2	0	13	9	68	4	3				
115															2	9	16	63	7	2			
120															2		22	5	66	2			2
125																11	22		11	56			
130																			33		67		
135																							
140																				100			

Table 5.2: Probability-circle radii of typhoons as of January 2016

Forecast Time (h)	Probability-circle radii (nm)
12	85
24	130
48	210
72	325
96	425
120	500

Based on the forecast at period p, the typhoon tracks generated form an ensemble of forecasts, each of which represent a scenario s. Based on the given forecast data as a starting point, Monte-Carlo simulation is used to generate the potential tracks based on the probabilities given in the transition probability matrices described in the previous section. Each track is used to generate a damage scenario, which is elaborated in the next section.

5.3 Impact Estimation Models

This step aims to address RSQ2, which is to estimate the impact of typhoon behavior on a network, particularly on demand of relief goods, supply destruction, and transport delays.

For each scenario s, there is a corresponding impact to the network, resulting into damage scenarios. Damage scenarios serve as the input for the optimization models. The main factor used for damage calculations in this study comes from wind profile calculations, which is derived from the typhoon intensity. The models used in this step were derived from the ones used in different studies and other assumptions, which are elaborated in this section. The impact estimation models are used in this study serve as inputs for the computational exercise done in the case study and do not adequately capture the entirety of the projected impacts of an incoming typhoon.

Wind Profile Model

A multivariate regression model used by Uichanco (2015) to analyze the impacts of seven West Pacific typhoons that affected the Philippines from 2008-2015 show a very strong relationship between the fraction of population impacted by a typhoon and the observed wind speed. The regression model was analyzed on a municipal level in the Philippines. Thus, in modeling impacts of the typhoon with respect to demand, the wind profile of the typhoon is estimated based on its intensity. The approach used in this study is the one used by (Uichanco, 2015), which is a three-parameter wind profile model based on the distance of a point from the typhoon's center.

W_{max}	Maximum wind speed (Intensity of the typhoon)
R_{max}	Radius at which maximum wind speed occurred
B	Radial width of wind at maximum speed
r_j	Distance between point j and the center of the typhoon
$W(r_j)$	Wind profile at r_j

$$W(r_j) = W_{max}\sqrt{\left(\frac{R_{max}}{r_j}\right)^B e^{\left(1-\left(\frac{R_{max}}{r_j}\right)^B\right)}} \tag{5.1}$$

To allow for consistency between calculations, the wind profile of each track is assumed to follow equation 5.1.

To have a better understanding of the impact estimation based on wind profile, consider figure 5.3. Assume that the intensity of the typhoon correlates with the size of the typhoon icon. Figure 5.3 shows a typhoon track for three periods, with each succeeding period having greater intensity. Given this scenario, the typhoon is expected to impact objects A, B, and C. Object B will experience the largest impact, as it will be located along the typhoon track at peak intensity. Object C, on the other hand, will experience an intensity closer to the intensity at the second period, so it will be less impacted than object B. Finally, object A will experience the impact based on the maximum wind speed it experiences, dependent on its distance from the typhoon track and the intensity of of the typhoon at that point.

It is important to note that the wind profile on its own cannot adequately capture other impacts of a typhoon such as storm surges, landslides, floods, etc. The wind profile is merely used as a tool to estimate potential damage scenarios which will are then used as inputs for the optimization model.

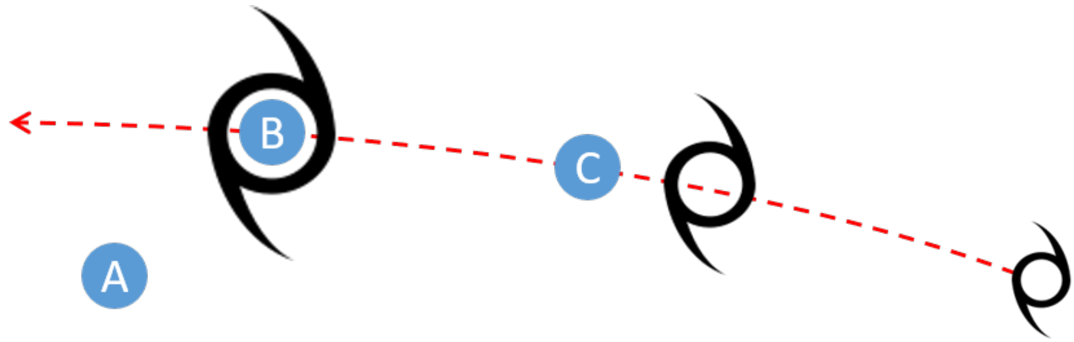


Figure 5.3: Impact estimation illustration

Demand Model

The demand at point j is calculated based on the wind profile at demand point j through the equation below.

D_j Amount demanded at demand node j
N_j Population at node j

$$D_j = N_j \times \min(1, 0.004W(r_j)) \tag{5.2}$$

As different points over the course of the typhoon track will generate different wind profiles at point j, the maximum wind speed experienced by j over the whole typhoon trajectory is used for demand calculations.

To define the impacted area of the typhoon, there are two important parameters to be considered. For a typhoon, R33 is the radius that experiences 32.9 m/s winds (118.44 kph), which is close to the threshold of Tropical Cyclone Warning Signal 3 in the Philippines (121 kph) and Category 1 of the Saffir-Simpson Hurricane Wind Scale (119 kph). RMW is the radius that experiences the maximum winds. Based on the wind profile equation, if the typhoon has a maximum intensity higher than 118.44 kph, the RMW < R33.

In this study, demand points only generate demand if the maximum wind intensity that the point experiences is equal to or greater than 118.44 kph. This is in accordance to wind impact assessment of PAGASA, which states that at Signal 3, "majority of light material houses may be unroofed or destroyed" (Official Gazette of the Republic of the Philippines, 2012). Thus, along the trajectory of the typhoon, if the typhoon has a maximum wind intensity that is greater than 118.44 kph, all the objects that fall within the R33 will experience a surge in demand.

Damage to LDCs

If the winds exceed 185 kph, the typhoon belongs to Tropical Cyclone Warning Signal 4 in the Philippines. According to Official Gazette of the Republic of the Philippines (2012), at these winds, many large trees may be uprooted, and most residential and institutional buildings of mixed construction may be severely damaged. Thus if an LDC experiences winds corresponding to Signal 4, it is assumed that it becomes inoperative after the typhoon. Therefore, based on the wind profile, all the points that fall within the RMW of the typhoon at points where the intensity is greater than 185 kph is considered inoperative, and all the relief goods it contains are considered unusable.

Road Delays

When a typhoon with very strong winds causes destruction to property and uproots trees and other vegetation, this can create obstructions in the road network which lead to delays in the response phase of the operation. For this study, if a both points at the end of a segment experiences wind speeds higher than 185 kph, then it is assumed that the segment will experience delay in the response operation. Thus, segments that are located between two inoperative supply points are considered to incur delays.

5.4 Damage Scenario

A damage scenario is generated based on each track in the ensemble for a given period. A damage scenario consists of the amount of demand at each DP, the locations which are damaged, and road segments that incur delays are identified. This damage scenario serve as input to the optimization models P1 and P2, which are elaborated in the next section. A visualization of the damage scenario is shown in figure 5.4.

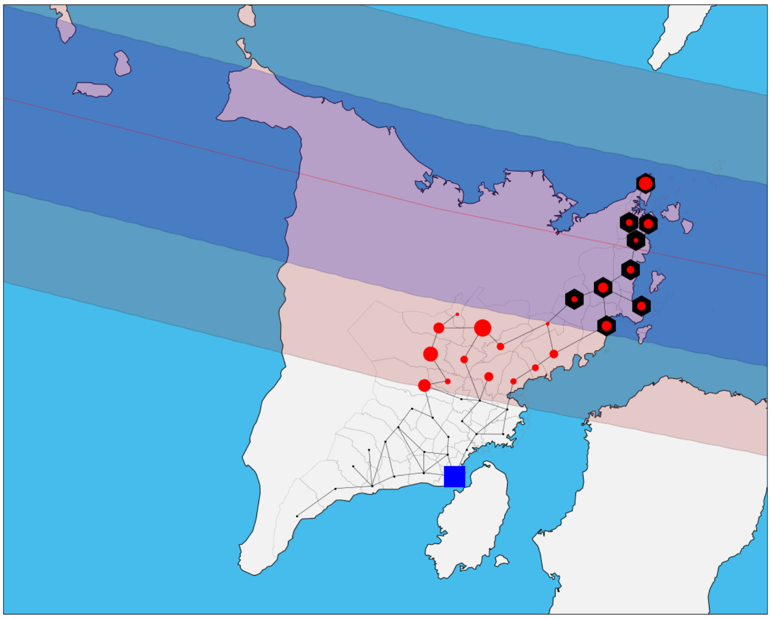


Figure 5.4: Example visualization of damage scenario

As seen in figure 5.4, the track of the typhoon is shown as a red line. The inner band represents the area where the RMW has impacted, and the outer band represents the area impacted by R33. It shows the amount demanded in red circles, and the size of the circle shows the quantity demanded at each location. The blue square indicates the location of the RDC. The black hexagons that fall within the RMW band are the locations where the LDCs are considered inoperative and cannot be used for pre-positioning. The segments between the hexagons are the segments which will incur delay in the response phase.

Chapter 6

Capacitated Facility Location Model

This chapter aims to address RSQ3, which is to determine the robust pre-positioning configuration based on potential damage scenarios. This chapter also unpacks the optimization step referred to in figure 4.3.

Based on the damage scenario, a capacitated facility location model is used to determine the optimum location of LDCs and how much goods should each one contain. This section outlines the assumptions made for the model, and elaborates the structure of model P1. The process flow is shown in figure 6.1. Appendix A provides the definition of the key terms used in this section.

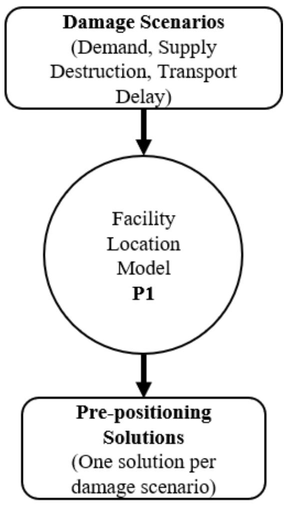


Figure 6.1: Process flow for the optimization step

6.1 Model Assumptions

In designing model P1, it is first important to identify the assumptions considered in building the model. This helps to scope the problem and identify the key variables and parameters that need to be defined. The assumptions for this study are as follows:

1. **Forecast Accuracy.** The forecast accuracy of a typhoon's characteristics increases for each succeeding time period with respect to a point location. The expected track of the typhoon is defined by the forecast cone, where the center of the typhoon is expected to remain 67% of the time (NHC, 2018a). An example of a forecast cone is shown in figure 6.2. For this study, the damage scenarios are based on plausible typhoon tracks, which are bound by the cone of uncertainty at the given time period. Any generated forecast track is

limited to a maximum of 120 hours, which is based on the longest forecast hour provided in the forecast.

2. **Scenarios.** The potential scenarios are generated based on the forecast data at a given period. The initial position and intensity of the typhoon is the same as that in the forecast data. Based on that initial position and intensity, potential tracks of the typhoon are generated. The potential tracks are bound by the forecast cone. As done in practice by the JMA, the number of tracks generated at each period is constant, which means that the number of potential scenarios evaluated does not decrease with each succeeding time period. The main reason for this is that the forecast trajectory of a typhoon is limited to 120 hours ahead. Thus, in dealing with a large network, a typhoon may not yet reach other parts of the network that are far from the typhoon. There is therefore a possibility that the damage scenario does not take into account a part of the network that is further away from the forecast track. Even so, the first assumption regarding the increasing accuracy of typhoon still holds (with respect to a point location), since if you consider a point location, a later forecast period provides more accuracy as to whether the location is going to be hit or not. This holds true even when the number of scenarios generated per period is constant.

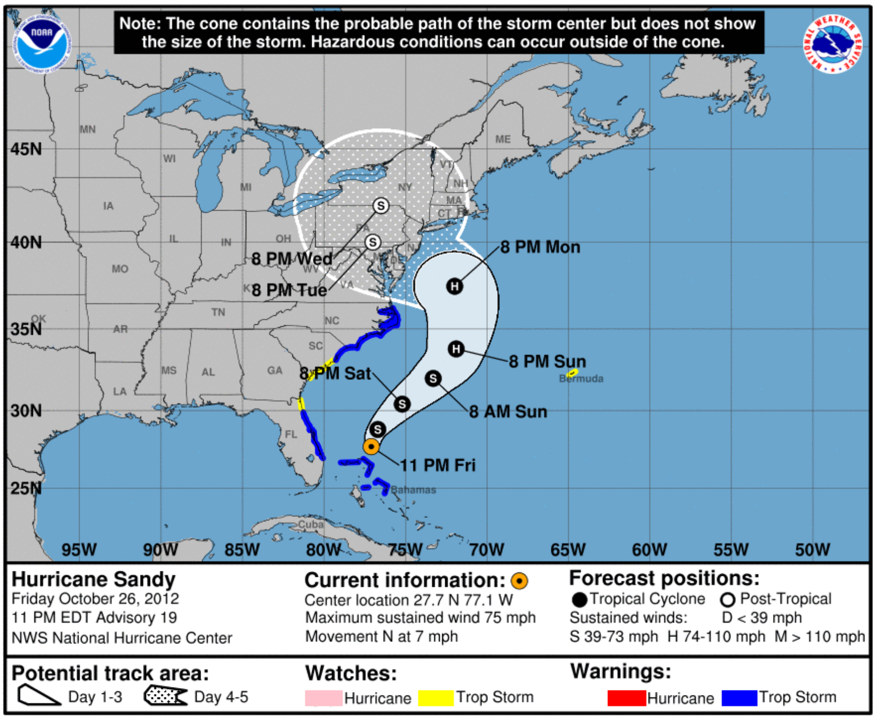


Figure 6.2: Forecast Cone of Hurricane Sandy 26 October 2012 11 PM (NHC, 2018a)

3. **Calculation of Demand, Supply, Network Damage -** Based on each potential typhoon track, the impacts on DPs, LDCs, and the road network is determined. The impacts on the network are calculated as a function of the typhoon's maximum wind speed and distance from the typhoon center. The models used for determining the network damage is explained in detail in section 5.

4. **Demand Points (DPs).** If a DP is impacted by the typhoon with an intensity greater than 118 kph, then demand of relief goods is expected. The candidate locations of DPs are fixed and given. The set of DPs affected for each scenario is dependent on the projected track of the typhoon.

5. **Local Distribution Centers (LDCs).** The LDCs serve as temporary distribution facilities which supply relief goods to the demand points after the typhoon strikes.

- There is a limited number of LDCs that can be set up. Only one LDC can be set up for each municipality.
- The candidate locations for LDCs are fixed and given. The set of candidate locations of the DPs are also potential candidate locations of LDCs.
- The capacity of an LDC is fixed and given.
- If an LDC is at the same location as the DP, there is no transportation cost incurred for delivering relief goods.
- If a certain scenario projects the LDC to be destroyed, then it becomes inoperative and cannot deliver the goods it contains to the DPs.
- There is a fixed set-up cost for each LDC. The time to set up each LDC is also fixed.

6. **Regional Distribution Center (RDC).** The RDC serves as the main supply facility where all the goods to be pre-positioned are sourced from.

    - There is only one RDC per region. The location of the RDC is permanent and given.
    - The RDC supplies the goods used for pre-positioning to different LDCs.
    - The amount of goods in an RDC is given and its capacity is also defined.

7. **Paths.** Certain segments incur delay if it is impacted by the typhoon. A segment incurs delay if the both ends of the segment falls within the RMW of the typhoon, which is equal to 1.5 times the normal travel time through the segment. The delay in the transportation also increases the transportation costs. The calculation of the total transportation time from point A to point B is based on the shortest route determined using the Djikstra algorithm. The shortest path calculation also accounts for the delays specific to each scenario.

8. **Pre-positioning Supply Chain Structure.** The RDC, LDCs, and DPs follow the supply chain structure shown in figure 6.3.

    - The RDC is the main source of relief goods. The relief goods are pre-positioned to the different LDCs in the pre-positioning phase.
    - During the response phase, relief goods only flow one way from SPs to the DPs.
    - Due to the short lead times, no re-pre-positioning is allowed.

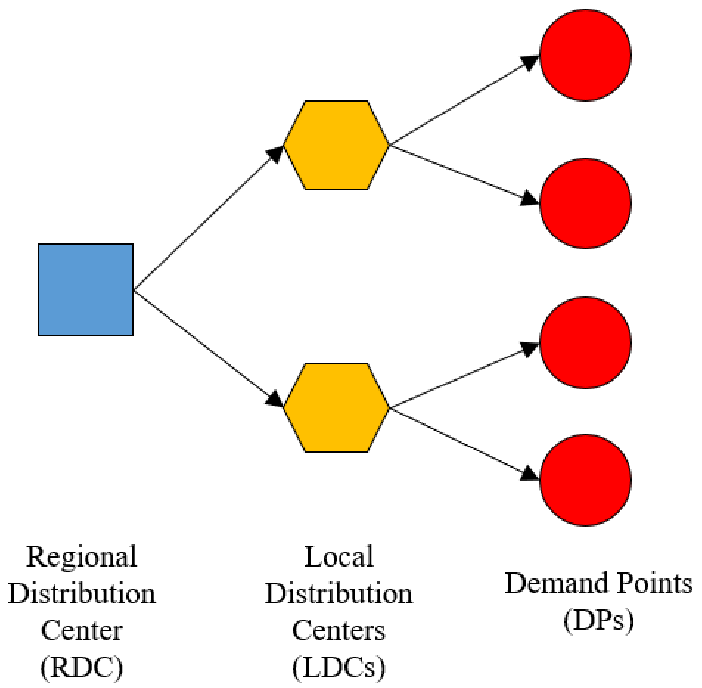


Figure 6.3: Humanitarian Logistics Supply Chain Structure

9. **Phases of Disaster Management.** This study deals with two phases of disaster management:

    - Pre-positioning (Preparedness) Phase - This involves moving goods from the RDC to the different LDCs. These action only take place within the pre-positioning phase.
    - (Immediate) Response Phase - this phase concerns the activities that happen right after the typhoon has struck. In this study, the only response activities considered are those that are conducted within 72 hours after the typhoon has hit an area. Only the goods at surviving SPs are to be distributed to DPs. Long term response operations are not taken into account.

10. **Pre-positioning decision**. A pre-positioning action is only considered feasible if the amount of time that it takes to conduct the pre-positioning action is less than the lead time.

11. **Transportation.** The following assumptions are made regarding transportation:

    - There is a fixed transportation cost per unit distance for each segment type.
    - There is a single type of vehicle used (truck) for the transportation of goods over land and also a single type of ro-ro ship used for transportation of goods over water. Ro-ro vessels are designed to carry wheeled cargo such as trucks.
    - Transportation costs are evaluated per unit of relief good based on the total distance from node a to b.
    - Transportation costs do not change from one period to another.
    - Operational activities such as scheduling and routing are not considered in this study
    - The road segments do not have a maximum capacity.

12. **Relief Goods.** - A unit of relief good is a family food pack (FFP), which contains food items which can sustain a family of five for two to three days.

13. **Finite Relief Goods** - In this study, the amount of goods to be pre-positioned are considered finite. The task of the decision maker is to determine how to best pre-position the amount of goods available without consideration for the inflow of goods that may happen at later stages. Thus, there is no penalty cost associated with any unfulfilled demand or a post-disaster expedited cost to fulfill all demand.

6.2 Model P1 Formulation

Model P1 provides the optimal pre-positioning setup based on the damage scenario s generated at period p. It performs the calculations based on the projected track of a typhoon, giving the optimum location and amount of relief goods at each candidate LDC if the typhoon is to follow the projected trajectory over the next 120 hours. It also ensures that pre-positioning at the optimum locations identified are feasible based on the calculated lead time at each location.

Model P1 is a capacitated facility location model with multiple objective functions. There are parameters that are particular to each scenario, or to each period, each of which are indicated with the superscript p or s accordingly. Other parameters that do not have superscripts are considered the same throughout all periods and scenarios. The input information required for P1 include the demand calculated at each DP, which LDCs are inoperative, which road links will cause delays, as well as other cost parameters. The output of P1 constitute a suggestive layout for the decision maker. The decision variables are labeled with subscript p^*, which means that it is for the optimum configuration based on the data at period p. It provides the suggested flow of relief goods among supply points, the quantity of goods to be pre-positioned at each supply point, and the expected flow of relief goods from the supply points to the demand points.

There are three objectives for P1 which are evaluated in order of hierarchy as presented below:

1. **Maximize Demand.**The first objective is the maximization of demand coverage. It ensures that if there is sufficient supply, all the demand points must be satisfied. This objective also minimizes the amount of supplies destroyed, as destroyed goods are not able to satisfy demand. Moreover, it also minimizes the amount of supplies to be pre-positioned at locations where the lead time exceeds the amount of time available for pre-positioning, as these goods are considered unusable to satisfy expected demand.

2. **Minimize Response Time.** The second objective function concerns the minimization of the average travel time per unit of relief good in the response phase. This objective function ensures that after all the demand has been satisfied, the model optimizes for which configuration can this be achieved with the most efficiency.

3. **Minimize Cost.** The third objective is to minimize the total cost of operations. This includes the cost in the pre-positioning phase (delivery and setup of LDCs) and the corresponding response phase, which is the distribution of the goods to the allocated DPs.

Sets, Parameters, and Decision Variables for Model P1

Table 6.1 summarizes all the notations used for the sets, parameters, and decision variables used in the formulation of model P1.

Table 6.1: List of Notations for Model P1

Sets	
I	Set of all supply nodes (RDC + LDC). $h, i \in I$ are indices
J	Set of demand nodes. $j \in J$ is an index
Parameters	
m_{hi}	Transportation time from supply node h to supply node i
c_{hi}	Transportation cost per unit of relief good from supply node h to supply node i
Q_i^p	Quantity of goods at supply node i at period p
S_i^s	Binary value equal to 1 if supply node i is usable (not damaged) at scenario s.
$u_{o,i}$	Time required to open LDC i
$c_{o,i}$	Cost to open LDC i
cap_i	Capacity of LDC i
x_{ii}^p	Binary value equal to 1 if supply node i is open at period p
c_{ij}^s	Transportation cost per unit of relief good from i to j at scenario s
m_{ij}^s	Transportation time per unit of relief good from i to j at scenario s
D_j^s	Quantity demanded at node j for scenario s; $j \in J$
F_{ii}^s	Lead time for pre-positioning at LDC i; $i \in I$
F_{ij}^s	Lead time for pre-positioning at i if i is allocated to j at scenario s. If DP j is allocated to SP i, then the lead time is the minimum time the typhoon hits either i or j.
P_i^p	Binary value equal to 1 if the amount of goods pre-positioned at i is already finalized by start of period p. This value is also 1 if $F_{ii}^s = 0$.
E^p	Refers to the costs incurred already by period p. At period p there may have been goods pre-positioned already which was incurred in previous periods.
Decision Variables	
$y_{hi}^{p*,s}$	Flow of goods from supply node h to supply node i at optimum configuration based on scenario s
$x_{ii}^{p*,s}$	Binary value equal to 1 if supply node i is to be opened for pre-positioning at optimum configuration based on scenario s; 0 otherwise
$y_{ij}^{p*,s}$	Flow of goods from supply node i to demand node j at optimum configuration based on scenario s
$x_{ij}^{p*,s}$	Binary variable equal to 1 if demand node j is allocated to supply node i at optimum configuration based on scenario s.

Objective Functions

$$\text{Max} \qquad Z_1^{p*,s} = \sum_{i\in I}\sum_{j\in J} y_{ij}^{p*,s} \tag{6.1}$$

Equation (6.1) maximizes total quantity of demand satisfied for scenario s.

$$\text{Min} \qquad Z_2^{p*,s} = \sum_{i\in I}\sum_{j\in J} y_{ij}^{p*,s} m_{ij}^s \tag{6.2}$$

Equation (6.2) minimizes the cumulative travel time by all relief goods. Thus, it also reduces the average travel time per unit of relief good.

$$\text{Min} \qquad Z_3^{p*,s} = \sum_{h\in I}\sum_{i\in I} c_{hi} y_{hi}^{p*,s} + \sum_{i\in I}(1 - x_{ii}^p) x_{ii}^{p*,s} c_{o,i} + \sum_{i\in I}\sum_{j\in J} c_{ij}^s y_{ij}^{p*,s} \tag{6.3}$$

Equation (6.3) minimizes the total costs. The first two terms are associated with the pre-positioning stage: the first term evaluates the cost of transport between supply nodes and the second term calculates the opening cost of each LDC. The final term minimizes the expected cost in the response phase - from delivering from the LDC/RDC to the specific DPs.

Subject To

$$\sum_{i\in I} y_{ij}^{p*,s} \le D_j^s \qquad \forall j \in J \tag{6.4}$$

Equation (6.4) Ensures that the flow of goods at node j from all supply nodes is not greater than the amount demanded at j for scenario s

$$m_{hi} x_{ii}^{p*,s} + (1 - x_{ii}^p) x_{ii}^{p*,s} u_{o,i} \le (1 - x_{ij}^{p*,s}) F_{ii}^s + x_{ij}^{p*,s} F_{ij}^s \qquad \forall h, i \in I, j \in J \tag{6.5}$$

Equation (6.5) Ensures that the pre-positioning action is feasible given the lead time. This includes transport of goods between supply nodes and set up time for a new LDC. The lead time depends whether or not i is allocated to node j. If i is allocated to node j, then F_{ij}^s needs to be considered. If not, then the lead time at LDC i, F_{ii}^s should be used.

$$\sum_{j\in J} y_{ij}^{p*,s} \le Q_i^p + \sum_{h\in I}(y_{hi}^{p*,s} - y_{ih}^{p*,s}) \qquad \forall i \in I \tag{6.6}$$

Equation (6.6) Ensures that there is enough quantity of supply at node i to deliver to node j.

$$\sum_{h\in I} y_{ih}^{p*,s} \le Q_i^p \qquad \forall i \in I \tag{6.7}$$

Equation (6.7) Ensures that there is enough quantity of supply at node i to deliver to another supply node h

$$\sum_{j\in J} y_{ij}^{p*,s} \le x_{ii}^{p*,s} cap_i \qquad \forall i \in I \tag{6.8}$$

Equation (6.8) Ensures that the quantity of goods delivered from LDC i to DPs does not exceed the capacity of the LDC.

$$y_{ij}^{p*,s} \le M * x_{ij}^{p*,s} \qquad \forall i \in I, j \in J \tag{6.9}$$

Equation (6.9) Ensures that the DP j is served only if j is allocated to i.

$$y_{hi}^{p*,s} \leq M * (1 - P_h^p)(1 - P_i^p) \qquad \forall h, i \in I \tag{6.10}$$

Equation (6.10) Ensures that no supply goods are transferred to/from a location where the pre-positioning action is already considered final

$$y_{hi}^{p*,s} \leq M * S_i^s \qquad \forall h, i \in I \tag{6.11}$$

Equation (6.11) Ensures that no goods are pre-positioned to a node that is inoperable for scenario s

$$x_{ij}^{p*,s} \leq S_i^s \qquad \forall i \in I, j \in J \tag{6.12}$$

Equation (6.12) Ensures that no goods are distributed to demand nodes if there is supply at node i but is considered inoperable at scenario s

$$y_{ij}^{p*,s}, y_{hi}^{p*,s} \in \mathbb{Z}^+ \qquad \forall i \in I, j \in J \tag{6.13}$$

$$x_{ij}^{p*,s}, x_{ii}^{p*,s} \in \{1, 0\}, \qquad \forall i \in I, j \in J \tag{6.14}$$

Equations (6.13) and (6.14) describe the domain of variables

6.3 Modeling Approach: Hierarchical Optimization

In hierarchical optimization, each objective is assigned a priority. Optimization is performed in the order of priority. In hierarchical optimization, optimizing for a lower priority objective is done without degrading the attained objective values of higher priority objectives.

For model P1, the objective functions are evaluated in the following order: Maximize Demand, Minimize Response Time, and Minimize Cost. Therefore response time minimization is not evaluated at the expense of compromising maximum demand, and also cost is minimized without compromising efficiency (minimum response time).

The modeling approach is chosen due to a few reasons. First is due to the preference of the decision maker. According to the interview conducted, demand maximization, efficiency, and cost are three important objectives. However, efficiency of operations is key, however, it is contingent to the assumption that all goods are located in a safe place. The least important objective is cost. Transforming these statements into the model results to the hierarchical approach as described. Firstly, it ensures that all the goods are located in a safe place and that it is able to reach the maximum amount of people. Next, it ensures that the goods are located at places where the response phase is most efficient, regardless of pre-positioning costs. Finally, the total cost is minimized while achieving the same level of efficiency.

Another reason for the selection of the hierarchical optimization approach is due to the assumption that the goods located at the RDC is finite. Thus, the decision maker can only pre-position the relief goods that are at his disposal. In this case, there is no penalty cost associated with destroyed goods and there is also no cost associated with expedited post-disaster delivery. The delivery of goods not accounted for in the pre-positioning phase is outside the scope of this project. Thus, in dealing with finite amount of goods, there is a tendency of another objective to perform better at the expense of another objective, which may result to non ideal scenarios. For example, configuration A performs much more efficiently (low average response time), however this may be due to the destruction of half the goods, leading to only half the goods to deliver in the response phase. Another case would be to not pre-position, as this would not incur the costs associated with pre-positioning but it will definitely incur a higher response time.

Chapter 7

Determining the Robust Solution and Decision Implementation

The previous chapter discusses how the capacitated facility location model identifies the optimal configuration for scenario s at a given period p. This chapter focuses on explaining in detail the final two steps: evaluation and decision. First, it describes how the robust solution is evaluated among all the different solutions identified. Then, It also describes the algorithms which decide as to whether the robust solution is implemented at a given period, or to wait for the next period.

The process flow for the evaluation step is shown in figure 7.1.

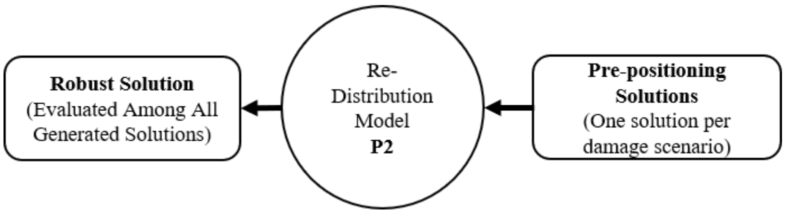


Figure 7.1: Process flow for the evaluation step

7.1 Model P2 - Redistribution Model

For all the tracks generated representing the possible scenarios s at period p, there are the same number of solutions as there are scenarios. To determine the robust solution among all the solutions presented, Model P2 is used. P2 is similar to P1, except that it takes $y_{hi}^{p*,s}$ as an input parameter instead of a decision variable. Model P2 is effectively a re-distribution model. It determines the optimum distribution of goods during the response phase given a pre-positioning configuration. It has the same objective functions as P1, and uses the same optimization approach to evaluate the performance of a solution over a specific scenario.

Model P2 is then used to evaluate the performance of $y_{hi}^{p*,s}$ over all the scenarios generated to assess its general performance. In order words, it answers the question: if the optimal pre-positioning solution for scenario A was performed across all the other scenarios, how will it perform?

Model P2 does not use the constraints exclusively used for $y_{hi}^{p*,s}$ at P1, such as equations (6.6), (6.7), and (6.10). Also, the amount of damaged goods can also be calculated if the solution for scenario A is performed under the conditions at scenario B. This is shown through equation (7.1), assuming that solution from scenario A is evaluated under scenario B.

$$\sum_{h \in I} y_{hi}^{p*,A} S_i^B \qquad \forall i \in I \tag{7.1}$$

Moreover, through equation (6.5), model P2 does not allow the re-distribution of goods if the pre-positioning action is not completed before the onslaught of the typhoon. As such, there are two ways by which relief goods are not re-distributed: 1) if the goods are located in places where the typhoon's impact renders the LDC inoperative and 2) if the goods to be pre-positioned at a certain location cannot complete the pre-positioning process before the arrival of the typhoon.

As each track at period p is generated using Monte-Carlo sampling using the Markov transition probability matrices, it is assumed that each scenario generated has equal likelihood of happening. The performance of each candidate solution across all scenarios was determined.

As not all scenario parameters are the same, such as the total amount of goods demanded at each scenario, the performance of a solution was evaluated in relation to the scenario parameters. Therefore, instead of comparing the "amount of goods delivered" for each scenario, it is instead changed to "% of demand covered" at each scenario. The performance of each candidate solution across all scenarios is defined based on its average performance.

The evaluation across all different scenarios can take a lot of computational time. If there are a scenarios, then the number of evaluations that need to be performed are a^2. This is the limiting factor that defines how many scenarios are generated in the first place.

7.2 Determining the Robust Solution

McPhail, Maier, Kwakkel, Giuliani, Castelletti, and Westra (2018) defined a number of robustness metrics used to measure the performance of a system, such as expected value metrics, metrics of higher-order moments, regret-based metrics, and satisficing metrics. All these metrics measure robustness in different ways, and thus, it is worth to explore each of them to determine which metric results to a better performance in this study. Each of the robustness metrics are discussed in this section, and the elaboration of which robustness metrics are used is motivated.

- **Expected Value Metrics.** This metric suggests that a solution is robust if it reaches an expected level of performance across a range of scenarios. In this study, there is no indication of an expected level of performance with regards to pre-positioning goods. Therefore, this metric is not appropriate to use in this study.
- **Metrics of Higher-Order Moments.** The performance of a solution can be evaluated over a range of metrics, such as variance. This provides information on how a solution performs over a wide range of scenarios. This is similar to the statistical or density based family of robustness metrics as described by Kwakkel, Eker, and Pruyt (2016). In the study of Kwakkel et al. (2016), the signal to noise metric is used, which is based on the intuition that a robust solution has a good expected value with limited standard deviation. It is defined through the following equation, where x is a candidate solution:

$$SN_x = \begin{cases} (\mu_x + 1)(\sigma_x + 1), & \text{minimization} \\ (\mu_x + 1)/(\sigma_x + 1), & \text{maximization} \end{cases} \tag{7.2}$$

  Where μ is the mean performance over the set of scenarios and σ is the standard deviation. The +1 is included to handle cases where the μ and σ is close to 0. In this study, this metric is used to evaluate the robustness of solution x across the different scenarios and in comparison to all the alternative solutions.
- **Regret Based Metrics.** Regret is defined as the difference between the performance of a solution x in a given scenario and the performance of the ideal solution for that scenario. Another way of measuring robustness is to determine the maximum regret of each solution across all scenarios. The solution that has the smallest maximum regret performs as closely as possible to the optimal solution at each scenario. The minimax regret is evaluated using the following set of equations.

$$R(s,x) = \text{P2}(s,x) - \text{P2}(s, ideal) \tag{7.3}$$

$$R_{max}(s,x) = max(R(s,x)) \qquad \forall s \in S \tag{7.4}$$

where x is a candidate solution evaluated in scenario s and S is the set of scenarios available. The regret values are evaluated separately for each objective.

- **Satisficing Metrics.** These metrics involve an acceptable performance threshold. Alternatives are considered robust if they have acceptable performance relative to the threshold. Similar to expected value metrics, there is no acceptable performance threshold available, thus this robustness metric is not used.

Among the four types of robustness metrics, two are used to identify the robust solution for this study: signal to noise ratio and minimax regret. The two robustness metrics are applied for each of the resulting values of the three objective functions as a result of the evaluation under P2. To determine the robust solution at period p, the hierarchical approach is applied similar to Model P1. Thus, for each period, there can be two different robust solutions.

7.3 Pre-positioning Strategy Algorithms

This section aims to address RSQ4, which is how to determine when to make the pre-positioning decision given different lead times at different points across the network. The pre-positioning strategy algorithms form the core of the decision step, which is shown in figure 7.2. This section discusses the motivation behind the choice of strategy algorithms and how each one is structured.

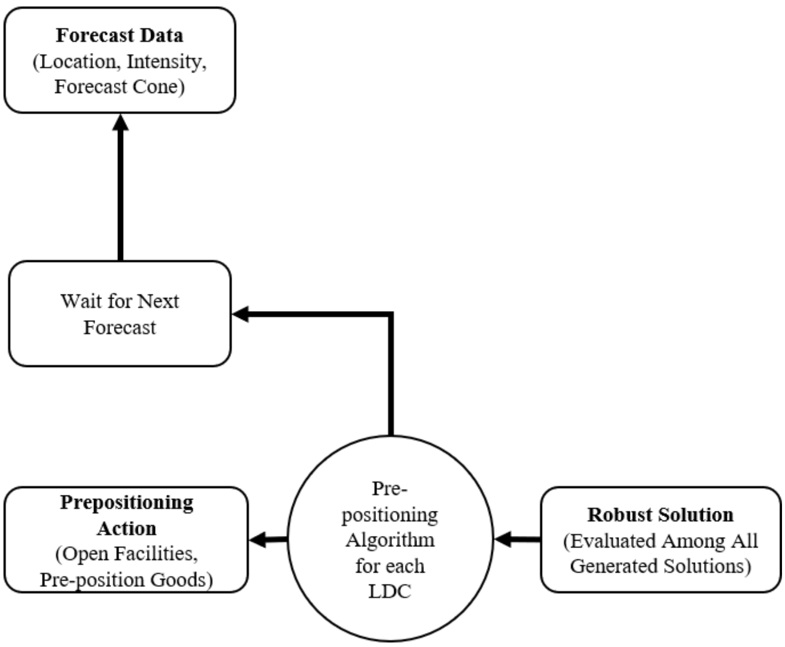


Figure 7.2: Process flow for the decision step

Figure 7.2 shows that after the robust solution is found for period p, the choice on whether to make the pre-positioning decision or not rests with the decision maker. The pre-positioning strategy is the algorithm which the decision-maker uses to decide whether to perform a pre-positioning action at period p or wait for succeeding forecasts.

Forecast-based pre-positioning found in literature provide decision models that are based on costs. For the study of Gobaco et al. (2016), the motivation is that waiting to gain newer forecast information comes at an expense of incurring expedited cost due to the rushing of pre-positioning action on shorter lead times. The expediting costs are expressed as a factor multiplied to the cost of pre-positioning at current time period. The decision whether to pre-position or not depends based on the preference of the decision maker in consideration of the projected costs to be incurred if the current optimal configuration is to be implemented in the next period. However, important questions arise in this type of approach especially in dealing with a large network. First, in a large network where the lead times can vary from one place to another, how does the expediting factor differ? Also, how much lead time is expected before pre-positioning actions start to be rushed and thus incur expedited costs? Due to these questions left unanswered, this study does not have a strategy that is based on projected costs and assume that pre-positioning costs remain the same across all time periods before the typhoon strikes.

Another pre-positioning study that use cost-based decision model is Galindo Pacheco et al. (2015). The study by Galindo Pacheco et al. (2015) uses a single objective function based on cost, which includes pre-positioning costs, response cost, penalization costs for affected units at destroyed SPs, cost for surplus units at SPs, cost for unsatisfied demand, in-transit units at landfall, and acquisition costs of goods. The decision model evaluates the total cost associated with implementing the pre-positioning decision now based on the possible scenarios at the current period and waiting to implement the pre-positioning decision over the next time period (less lead time). If the cost difference between pre-positioning now and waiting exceeds the maximum cost the decision maker is willing to bear, then the pre-positioning is conducted at the current time period. This decision model can be problematic as technically, the decision-maker is willing to compromise the efficiency of the response as long as it falls within the cost tolerance of the decision-maker. This could render feasible configurations available at earlier time periods to be infeasible at later time periods. Moreover, it can be difficult to assess as to which part of the objective function contributes most to the projected cost increase thus the decision maker may not be completely aware of which component contributes the most to the increased value of the objective function.

The three pre-positioning strategies evaluated for this study focuses solely on lead time. It aims to show the differences in the performance during the response phase if lead times are considered differently. The first strategy is to not pre-position at all. The second strategy is a common feature across different studies on pre-positioning against tropical cyclones - which is to conduct the positioning action is conducted when the minimum lead time is less than 48 hours. Finally, the third strategy is the one introduced for this study, which is to implement the pre-positioning at a given location only at the last moment that is possible. The three different strategies is elaborated in further detail below.

1. **No pre-positioning at all.** For this case, the performance will be evaluated based on sourcing all the goods from the RDC. This will provide an insight as to whether pre-positioning goods can actually improve the performance in the response phase.

2. **Start pre-positioning when minimum lead time at any point i across all scenarios is less than 48 hours.** The approach of using a constant lead time throughout the network of 48 hours is used by a few studies such as (Davis et al., 2013). The justification for using 48h stems from the NHC issuing a hurricane watch if tropical storm force winds are predicted to make landfall in an area within 48h.

   (a) At period p, if there exists scenarios where $\sum_{j \in J} D_j^s > 0$, solve for P1 and P2 to obtain the robust solution at p, which is symbolized with the superscript $p*, robust$.

   (b) If at period p, equation (7.5) holds true for any supply node i, it means that the minimum lead time across all scenarios is less than 48 hours, and all the pre-positioning actions as suggested by $p*, robust$ needs to be executed. This is demonstrated by setting $P_i^p = 1$ for all $i \in I$. Thus all pre-positioning actions are considered final at p.

$$min(F_{ij}^s \qquad \forall j \in J, s \in S) <= 48 \tag{7.5}$$

   (c) Execute equation (7.6) to show the amount of goods at i for the robust solution.

$$Q_i^{p*,final} = Q_i^p + P_i^p \sum_{h \in I} y_{hi}^{p*,robust} \qquad \forall i \in I \tag{7.6}$$

   (d) Repeat step (a) for the next period until equation (7.5) holds. It means that the optimization is to be done at each period until the minimum landfall time at any point i is less than 48 hours.

3. **Pre-position at the last period possible.** This is to perform pre-positioning action at node i when the difference between the time it takes to pre-position at supply node i and the minimum lead time available at node i is less than 6 hours. This ensures that the pre-positioning can happen at different supply points i at different periods p.

   (a) At period p, if there exists scenarios where $\sum_{j\in J} D_j^s > 0$, solve for P1 and P2 to obtain the robust solution at p, which is symbolized with the superscript $p*, robust$.

   (b) If at period p, equation (7.7) holds true for node i, then this means that the difference between the minimum lead time across all scenarios and the time to pre-position at i is less than 6 hours, and thus cannot wait for the next forecast. Thus, set $P_i^p = 1$ to mean that the pre-positioning decision is considered finalized by the beginning of period p, and will hold true for all succeeding periods.

$$min(F_{ij}^s \forall j \in J, s \in S) - (x_{hh}^p(1 - x_{hh}^{p*,robust})u_{c,h} + m_{hi}x_{ii}^{p*,robust} + (1 - x_{ii}^p)x_{ii}^{p*,robust}u_{o,i}) \leq 6 \tag{7.7}$$

   (c) Execute equation (7.8) to show the amount of goods at i at $p+1$

$$Q_i^{p+1} = Q_i^p + P_i^p \sum_{h\in I} y_{hi}^{p*,robust} \qquad \forall i \in I \tag{7.8}$$

   (d) Using new parameters obtained from period p, repeat steps (a) and (b) and (c) for the next periods until the equation (7.9) holds. If equation (7.9) holds, it means that for all i in the network, $Q_i^p = Q_i^{p*,final}$ It also means that, either all the possible pre-positioning actions are finalized or the landfall time across all the supply nodes is 0 and no additional pre-positioning action can take place.

$$Q_i^{p+1} = Q_i^p * P_i^p \qquad \forall i \in I \tag{7.9}$$

The three decision strategies will be used to determine the time to implement the pre-positioning action in anticipation of an incoming typhoon, specifically typhoon Haiyan. Historical data from formation to dissipation of typhoon Haiyan was obtained and will serve as the periodical forecasts for which the different pre-positioning strategy algorithms will be implemented. The implementation of these strategies is discussed in more detail in the following chapter.

Chapter 8

Case Study Implementation

This chapter details the implementation of the iterative methodology described in chapter 4 to a case study in the Philippines. First, it gives an introduction of the network to be analyzed and also gives an overview of the current state of preparedness that are already in place. Finally, it details the actual implementation of the iterative method based on the case-specific parameters.

8.1 The Network: Western Visayas Region

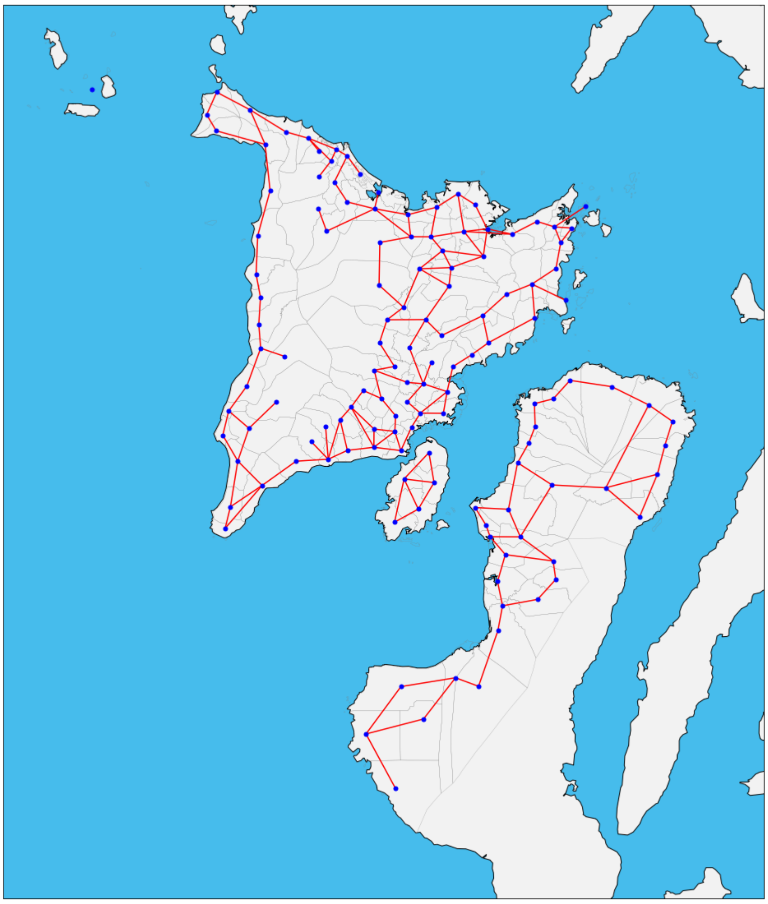


Figure 8.1: Western Visayas Road Network

The Western Visayas Region experiences typhoons every year. A visualization of the network for the region is shown in figure 8.1. Each blue point corresponds to the location of the administrative capital of each municipality. These points serve as the candidate locations of both DPs and LDCs that can be impacted in the event of a typhoon. Red segments illustrate the main highways that connect the different municipalities.

When a strong typhoon strikes, there is potential damage to parts of the network that results to a surge in demand for relief goods at DPs, destruction of LDCs, and delays in some road segments. The pre-positioning supply chain structure follows figure 6.3. The regional warehouse, located in Iloilo City, serves as the main source of relief goods in the region. The Department of Social Welfare and Development Field Office VI serves as government agency in charge of pre-positioning relief goods.

The Philippine Area of Responsibility (PAR) is the designated area where PAGASA monitors occurences of typhoons (PCG, 2013b). The area is shown in figure 8.2. Once a weather disturbance enters PAR and is expected to make landfall, PAGASA is mandated to issue weather bulletins every six hours. This provides information for DSWD-VI to prepare for the typhoon.

Figure 8.2: Philippine Area of Responsibility

Experience from Typhoon Haiyan in 2013 shows that the region has suffered tremendous damage from the resulting typhoon track. This case study explores how the iterative methodology as described in chapter 4 and shown in figure 4.3 could help DSWD Field Office VI in pre-positioning of relief goods in anticipation of Typhoon Haiyan. This study aims to maximize the coverage of demand in the early response phase, ensure the efficiency of response, and minimize the cost of response once maximum demand is covered.

The planning horizon starts at 06:00h November 3, 2013 based on the first data point of the historical forecast data available from National Oceanic and Atmospheric Administration (NOAA). The planning horizon ends at the last forecast data point, at 00:00h November 12, 2013.

8.2 State of Disaster Preparedness in the Philippines

After the devastation of Typhoon Haiyan in 2013, there was an increased effort from the government to mitigate potential impacts of a disaster. For example, when a typhoon is projected to impact the country, the national coordinating agency disseminates relevant information to core agencies and potentially impacted areas to aid in pre-disaster planning (Uichanco, 2015).

The 2014 National Disaster Response Plan (NDRP) is the government's response to hydro-meteorological hazards. It divides the coordinating agencies and organizations into eight response clusters which were patterned to the Cluster Approach of the United Nations (Office of Civil Defense, 2014). The cluster that covers relief goods pre-positioning is the Food and Non-Food Items Cluster. It is led by the DSWD and is in charge to validate all pre-positioned resources on at all field offices and at the provincial, city, and municipal levels (Office of Civil Defense, 2014). Figure 8.3 shows the different levels by which the Disaster Risk Reduction and Management Structure (DRRM) operates and the structure of the management council is shown in figure 8.4.

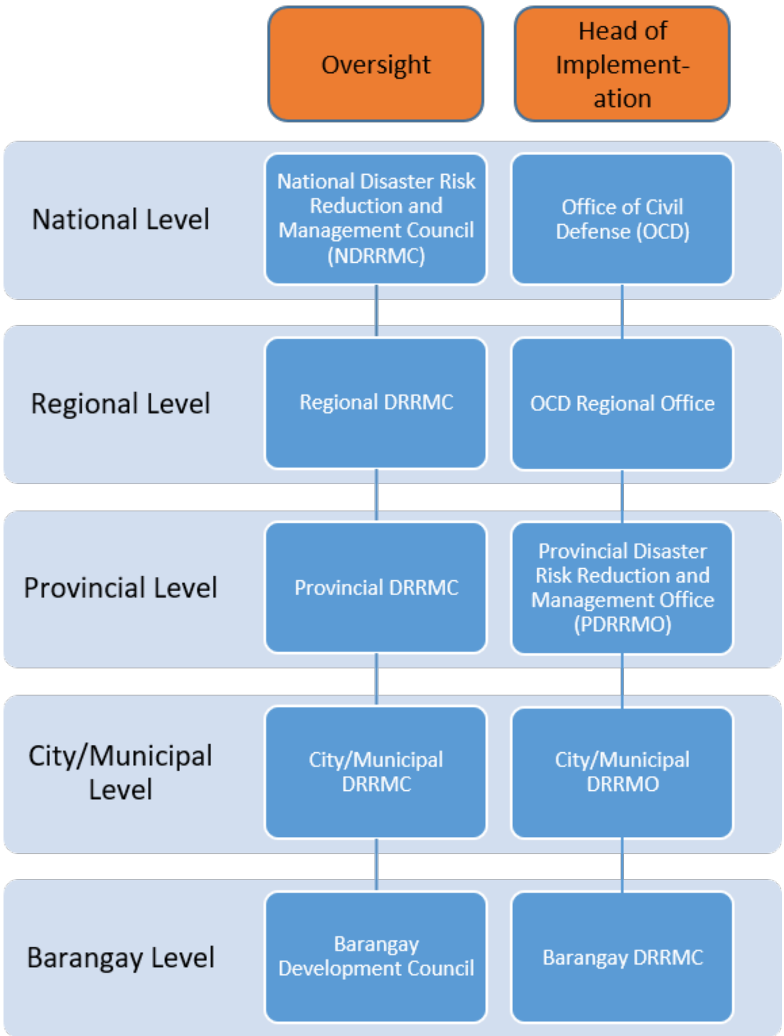


Figure 8.3: Disaster Risk Reduction and Management Structure (Office of Civil Defense, 2014)

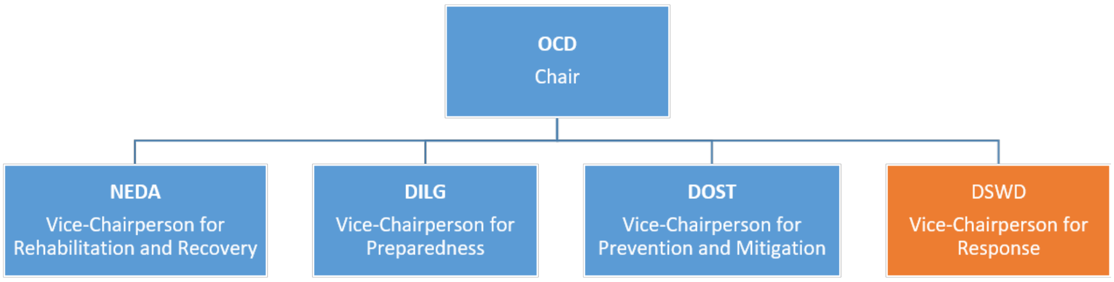


Figure 8.4: National Disaster Risk Reduction and Management Council (Office of Civil Defense, 2014)

Pre-positioning efforts in their jurisdiction are entirely the responsibility of the local government units. The Joint Memorandum Circular No. 2013-1 by NDRRMC, DBM, and DILG (2013) stipulates that local government units must set aside not less than five percent of estimated revenue from regular sources to support disaster risk management activities, which includes disaster preparedness programs such as stockpiling of basic emergency supplies. Furthermore, the National Disaster Preparedness Plan was in created in 2015 to develop and implement comprehensive response policies, plans, and systems at the national and local level. One of the response preparedness tasks is the preparation of stockpiles and pre-positioned resources, which is guided by an integrated platform for assessment, simulation, forecasting, and monitoring (NDRRMC, 2015).

Early Warning Systems and Risk Assessments

Information fragmentation can lead to ineffective dissemination of risk information in the Philippines. Different institutions are in charge of disseminating risk information. Examples of institutions involved are:

- Philippine Atmospheric, Geophysical and Astronomical Services Administration (PAGASA). PAGASA is the Philippine institution tasked to provide timely, accurate, and reliable weather related information and services. It provides weather forecasts and flood warnings against hydrometeorological hazards and risks (PAGASA, 2018).
- The Mines and Geosciences Bureau (MGB) is the institution mandated to conduct geoscientific surveys, which includes vulnerability assessments particularly on landslide risks (MGB, 2018).
- The National Mapping and Resource Information Authority (NAMRIA) is in collaboration with the United Nations Development Program (UNDP) and Government of Australia Australian Aid (AusAID) to develop hazard maps for different natural disasters (NAMRIA, 2018).

The Climate Change Commission (CCC) is coordinating with the relevant institutions to create a platform to integrate information from the relevant institutions (CCC, 2018). A similar effort is currently being implemented by the University of the Philippines (UP) Project NOAH (Nationwide Operational Assessment of Hazards). UP Project NOAH aims to reduce the catastrophic impacts of extreme sudden-onset natural disasters by undertaking research in disaster science as well as having a comprehensive and multidisciplinary hazard assessments (NOAH, 2018).

Near Real Time Hazard Information Dissemination

UP Project NOAH has a Web-GIS tool that can be accessed through the link: `http://noah.up.edu.ph/`. It uses cutting-edge technologies and collaborates with multiple stakeholders to develop systems, tools, and technologies that can be used to mitigate the impacts of natural disasters such as typhoons (Lagmay, Racoma, Aracan, Alconis-Ayco, and Saddi, 2017). According to Lagmay et al. (2017), its capabilities are:

- Estimation of rainfall probability
- Weather and water level sensors
- Light Detection and Ranging (LiDAR) and radar-derived topography
- 1-D and 2-D flood simulations and crowd sourcing of flood events
- Landslide inventory, simulations, and monitoring
- Storm surge simulations and hazard maps
- Mapping platform mashups and the world wide web

Meteorological data gathered using the technologies mentioned are displayed in the UP Project NOAH website. It allows near real-time access to data for decision-makers as well as the general public (Lagmay et al., 2017). Examples of data that can be generated from the Project NOAH website is a landslide hazard map of Western Visayas as shown in figure 8.5

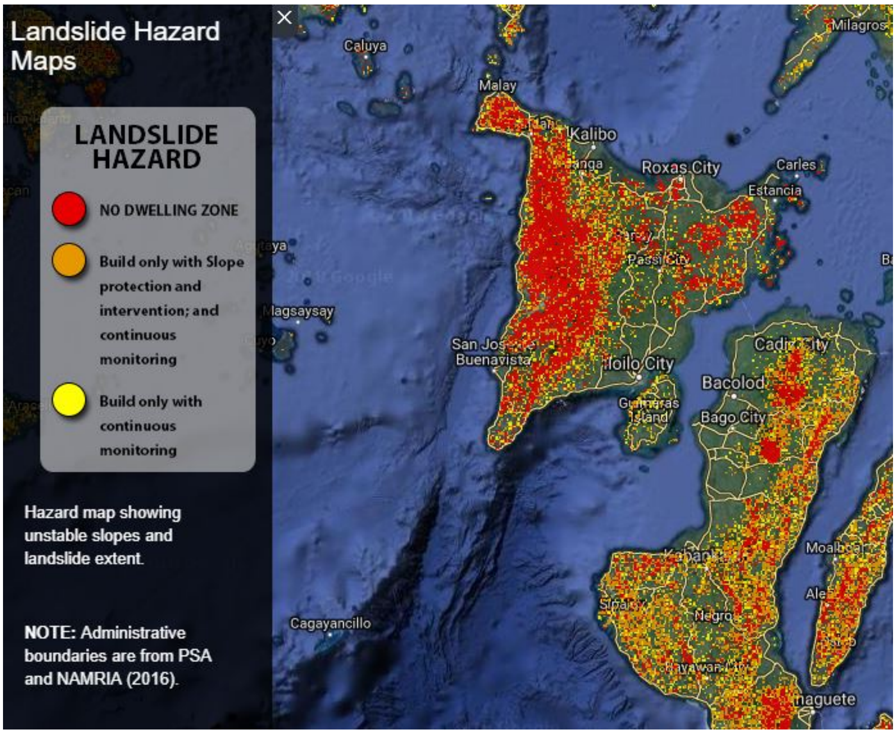


Figure 8.5: Landslide Hazard Map of Western Visayas Region, Philippines (Region VI)

Current Pre-positioning Practices

Pre-positioning activities conducted for the recent Typhoon Maliksi, formed on 4th of June 2018, gave an insight on the pre-positioning practices conducted by DSWD based on the reports published by DROMIC. Through its virtual operations center (Virtual OpCen), the amount of stockpiles at each regional warehouses can be seen as shown in figure 8.6. The Virtual OpCen also has a list of multiple pre-determined locations in each municipality (schools, gymnasiums, government buildings, etc.) to serve as temporary evacuation centers once a strong typhoon hits (DROMIC, 2018c).

Figure 8.6: Regional Stockpiles as of 14 June 2018 (DROMIC Website)

Moreover, in an event of a typhoon, DROMIC publishes regular reports on the tropical storm. In the report, it shows the weather bulletin, the results of the Predictive Analytics for Humanitarian Response, status of pre-positioned resources (stockpile and standby funds), and the situation and preparedness actions undertaken at each region (DROMIC, 2018a).

The Predictive Analytics for Humanitarian Response provides a regional estimate of the Family Food Packs (FFPs) required and its corresponding cost based on the number of poor families affected on the regions that will receive intense rainfall for the next 72 hours. DROMIC provides a visualization on the regularly published reports such as shown in figure 8.7 (DROMIC, 2018a).

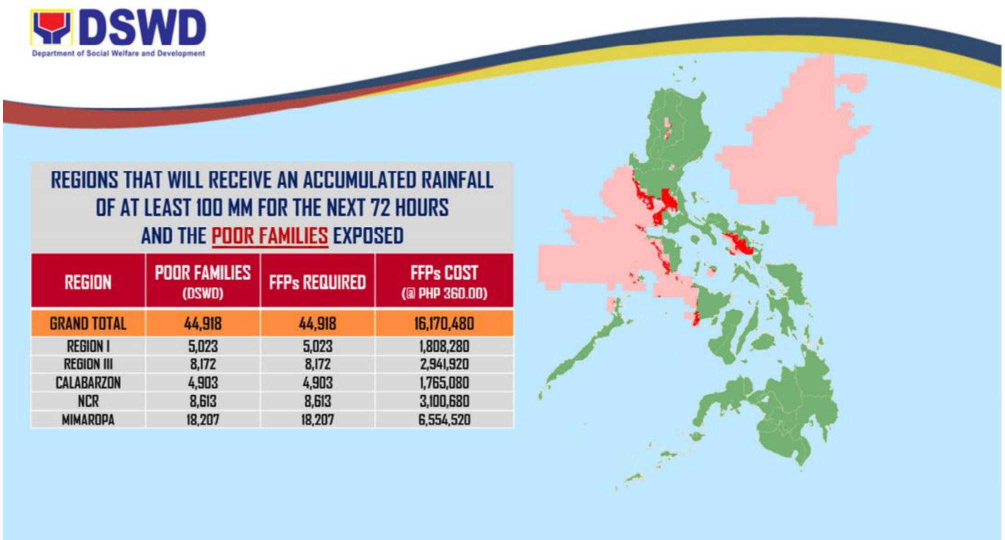


Figure 8.7: Estimated required FFPs per region as of 10 June 2018

Additionally, DROMIC reports provide a breakdown of the status of pre-positioning. Not only does it show the amount of FFPs that are stored in different regional warehouses, it also shows the amount of pre-positioned goods that are located in different municipalities. The amount of goods pre-positioned per region, and the corresponding affected people for typhoon Maliksi is shown in table 8.1 (DROMIC, 2018a; DROMIC, 2018b).

Table 8.1: Prepositioned Goods and Affected Population for Typhoon Maliksi

Region	FFPs Prepositioned Outside Regional Warehouses (10 June 2018)	Affected Population (11 June 2018)
NCR	0	0
CAR	0	0
I	3,400	0
II	27,750	0
III	5,500	93
CALABARZON	1,520	0
MIMAROPA	24,788	0
V	8,800	0
VI	1,000	0
VII	7,016	0
VIII	8,700	0
IX	2,209	0
X	9,021	0
XI	7,511	0
XII	0	0
CARAGA	5,646	0
ARMM	0	0
Total	**112,861**	**93**

Based on the situational reports, it seems that the estimated amount of FFPs required as shown in figure 8.7 does not necessarily translate to the actual affected population shown in table 8.1. Also, The amount of goods prepositioned outside of regional warehouses seem very disproportionate to the eventual affected population. This could be due to the fact that June usually marks the start of the typhoon season, and that the pre-positioning may account for stronger typhoons that are expected to come through the rest of the year.

Overall, the overview of the pre-positioning actions conducted currently in the Philippines provides insight on how to structure the problem as well as to identify the crucial assumptions with regards to building the pre-positioning model. It also helped in identifying research gaps as described in section 3.1.

8.3 Implementation of the Iterative Methodology

As discussed in the previous chapters, the expanded version of the framework used for this study is shown in figure C.1. This section expands on the implementation of each of the steps with details specific to the case study in the Philippines.

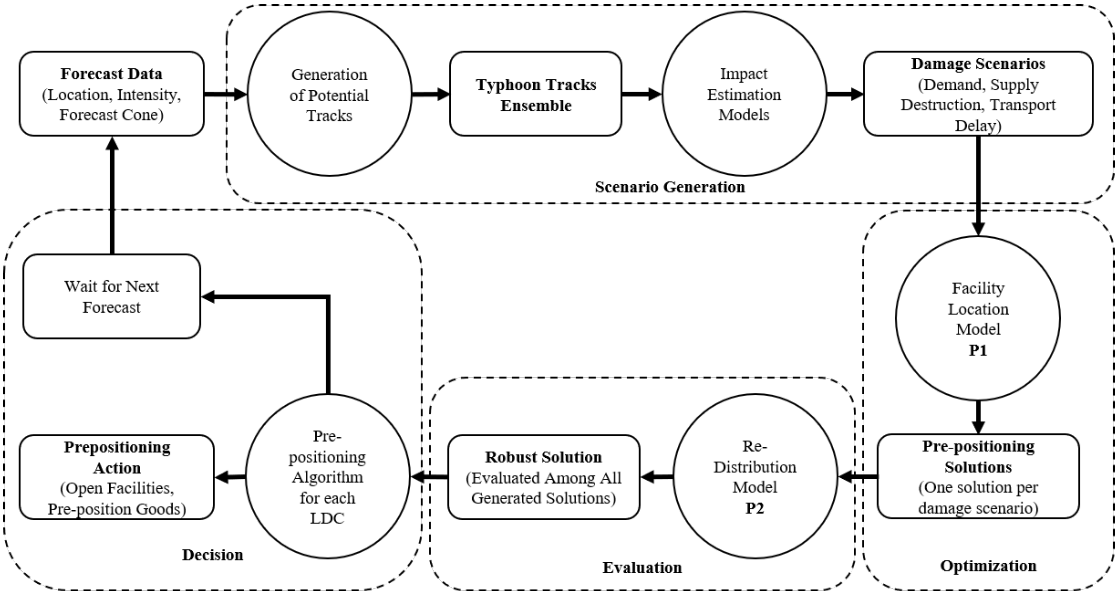


Figure 8.8: Disaster Risk Reduction Management Structure (NDRRMC, 2015)

Step 1. Forecast Data

Historical forecast data for Typhoon Haiyan was obtained from the forecast archive of the NOAA website. As explained in section 5.1, at each period, the coordinates and intensity at each forecast hour are given. An example of this data can be shown in figure 8.9. The coordinates are in degrees and the intensity is given in miles per hour.

Time of Forecast: 201311030600

Forecast Hour	Latitude	Longitude	Intensity
0	6.4	156	25
12	6.7	153.6	35
24	7.1	150.8	45
36	7.7	148.4	55
48	8.2	145.3	65
72	9.2	139.9	85
96	10.1	133.8	105
120	11.5	127.7	120

Figure 8.9: Forecast Information for Typhoon Haiyan at 06:00H November 3, 2013

Forecast information tables were downloaded from the NOAA website through the use of Beautiful Soup package in python 3.0. Each table serves as the forecast information at a given time period, and serves as the basis for the generation of potential typhoon tracks in the following section.

Step 2. Scenario Generation

Generation of Potential Typhoon Tracks

The values from the forecast data from the NOAA website were converted to the units that were used for the generation of the probability matrices. For typhoon intensity, data was converted from mph to knots and rounded to the nearest 5 knots. For location parameters, the coordinates were rounded to the nearest 0.5 degree. Then, with the use of the Markov Transition Probability Matrices for intensity and typhoon location, Monte Carlo Sampling was done in python to generate potential tracks for each period. 100 typhoon tracks were generated for each forecast period from period 0 to period 23 (last period when Typhoon Haiyan was within the Philippine Area of Responsibility). The number of samples can be increased for better accuracy, but cost additional computational time especially in the evaluation phase. For the track generation, it was ensured that all the tracks fell within the forecast cone at each period, by ensuring that the distance of the typhoon track at each forecast hour is less than the corresponding forecast radius. Both forecast and generated tracks data were truncated once the typhoon is out of the Philippine Area of Responsibility to reduce computational time. An example of a sample track in comparison to forecast data is shown in table 8.2

Table 8.2: Comparison of forecast data and generated track

	Forecast			**Generated Track**		
Forecast Hour	**Latitude**	**Longitude**	**Intensity**	**Latitude**	**Longitude**	**Intensity**
0	8.5	133.0	130	8.5	133.0	130
6				8.5	131.0	120
12	9.5	129.5	125	9.0	130.0	110
18				9.0	128.5	100
24	10.5	126.0	115	9.5	127.5	105
30				9.5	126.5	105
36	11.5	122.0	105	10.0	125.0	105
42				11.0	122.5	95
48	12.5	118.5	100	11.0	121.0	95

The resulting ensemble of tracks is a list of DataFrames generated in python. This list serves as the input for the damage estimation models, which is explained in the next section. The 100-member ensembles over 23 periods generated for typhoon Haiyan was used for all the different test cases in this study to ensure consistency.

Impact Estimation Models

The impact of a given track is estimated across the network, which results to a damage scenario as shown in table 8.3. As a track is essentially a set of points at different forecast hours, it was necessary to interpolate between the points to have a better gauge of demand at each point in the network. For this study, five equidistant points were inserted between two consecutive points of any generated track. Moreover, the tracks were truncated to only include the points where it is located in the Philippine Area of Responsibility, as these are the only points that would generate demand. The selected track points were evaluated across all the different points in the network to estimate demand, which LDC locations are potentially destroyed (value of 0) and how much lead time is left for pre-positioning at each location. Note that the municipalities that do not experience a surge in demand are not strongly impacted by the typhoon and thus do not have values for lead time. However, the corresponding lead time of a LDC, should it be placed in an area that is not impacted by the typhoon, is dependent on the DPs it serves in the response phase.

The calculations for travel distances (and also delays) is done mainly by inputting all the data points into a graph through the NetworkX library in python. If both points at the end of an edge is a destroyed LDC, then the edge incurs a delay of 1.5 times the current travel time. The shortest travel time between two points is then calculated by implementing the Djikstra algorithm on the graph. A table which evaluates the shortest travel time between any two points is generated. The corresponding travel costs are also calculated based on the shortest path obtained.

Table 8.3: Example of estimated impacts of a given track

Municipality	Latitude	Longitude	FFP Demand	LDC	Lead Time (h)
AJUY	11.2	123.0	4814	1	18
ALIMODIAN	10.9	122.4	0	1	
ANILAO	11.0	122.7	2525	1	18
BADIANGAN	11.0	122.5	2371	1	18
BALASAN	11.5	123.1	3085	0	18
BANATE	11.0	122.8	2847	1	18
BAROTAC NUEVO	10.9	122.7	0	1	
BAROTAC VIEJO	11.1	122.9	4111	1	18
BATAD	11.4	123.1	2000	0	18
BINGAWAN	11.2	122.6	1322	1	18
CABATUAN	10.9	122.5	0	1	
CALINOG	11.1	122.5	5306	1	18
CARLES	11.6	123.1	6194	0	12

Step 3. Optimization

Based on the inputs obtained from the damage scenarios, the optimization model P1 was run to generate the optimal solution for each scenario. The model was constructed using the python wrapper for Gurobi Solver, gurobipy. Results of model P1 is shown per scenario in a DataFrame such as in table 8.4, where the results of each objective function is shown, and accordingly the amount of goods to be pre-positioned at each LDC for the optimum solution. Columns labeled 1,2, and 3 are the identifiers for each LDC.

Table 8.4: Example results of Model P1

Scenario	Total Demand	Demand Fulfilled	Supplies Destroyed	Ave Response Time	Cost	Total Facilities	Facility		
							1	2	3
1									
2									
...									
n									

Step 4. Evaluation

Similar to P1, model P2 was also constructed using gurobipy and implemented in python. The decision variables for the optimal solution for each scenario were saved and were used as inputs for P2 in order to evaluate how each solution performs at all the different scenarios. The performance of each scenario is evaluated as well as the corresponding robustness metrics (signal to noise ratio (SN) and minimax regret), which helps determine the optimal solution. The results are summarized in a table with the format shown in table 8.5.

Table 8.5: Example table for results of Model P2

Sol	%Demand Fulfilled (SN)	Average Response Time (SN)	Total Cost (SN)	% Demand Fulfilled (Minimax)	Average Response Time (Minimax)	Cost Difference (Minimax)
1						
2						
...						
n						

The robustness criteria are evaluated in a hierarchical manner, as described in section 7.2. Depending on the robustness criteria, the robust solution at a given period is determined.

Step 5. Decision

The pre-positioning strategy algorithms are also programmed in python. Depending on the strategy chosen, the program implements the corresponding strategy algorithm, which determines whether the pre-positioning actions are performed at period p. If a pre-positioning decision is implemented, it subsequently updates the input parameters, such as the resulting quantity of goods at each LDC, and this is then used as input for model P1 at period $p + 1$. If at period p, all the goods in the RDC are pre-positioned based on the robust configuration, then the iterative process ends.

8.4 Experimental Design

A series of experiments were conducted to determine the pre-positioning actions to be conducted in anticipation of typhoon Haiyan. As previously described, 100 potential tracks are generated at each period for 23 periods. The same input tracks are used for all the test cases examined. All cases start at p = 0.

Four test cases were examined. Different test cases were used to see how the methodology can be implemented at different levels of governance. Case 1 and 2 focus on a provincial level. Case 3 focuses on a regional level. Case 4 focuses on an inter-regional level. Figure 8.10 shows the different geographical scope for each case. Cases 1 and 2 focuses on the red area. Case 3 has a wider scope and involves the red + blue area. Finally, case 4 covers the red + blue + green area.

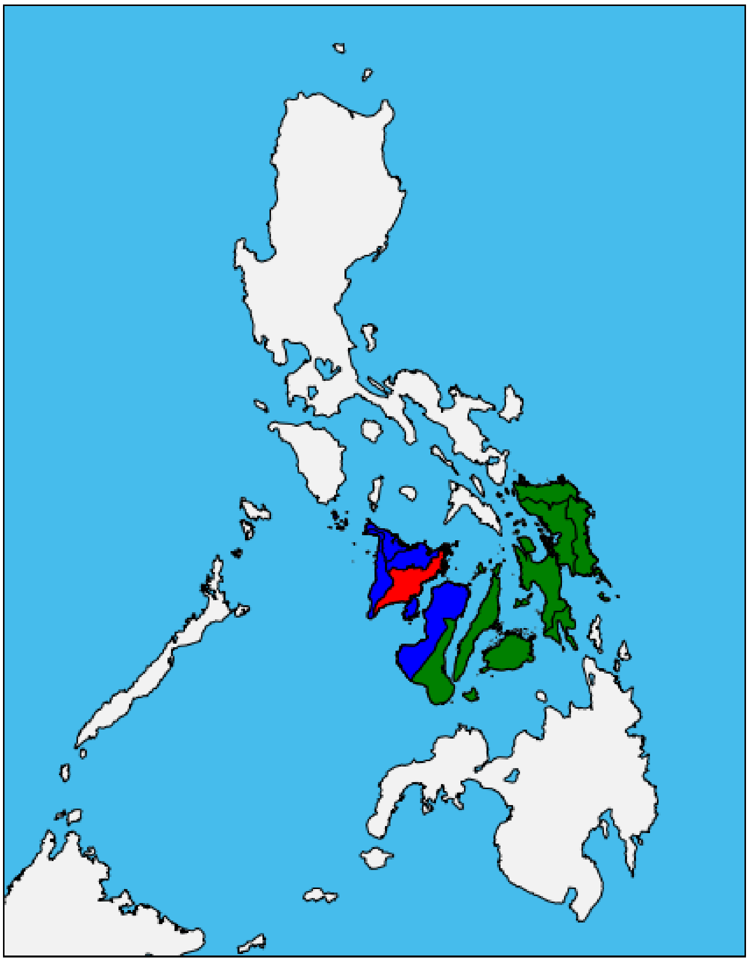


Figure 8.10: Geographical scope of the test cases

As different cases have an increased geographical scope, the number of DPs/LDCs to be considered also increases if a municipal level is considered. A higher number of candidate DPs/LDCs increases computational time dramatically. In order to be feasible given the short lead time, levels of aggregation are proposed. The aggregation of DPs/LDCs is summarized in table 8.6.

Table 8.6: DP/LDC aggregation for test cases

	Scope	**RDC**	**DPs/LDCs**	**DP/LDC Aggregation**	**DP/LDC Location**
Case 1	Provincial	1	43	Municipal	Town Center
Case 2	Provincial	1	43	Municipal	Town Center
Case 3	Regional	1	18	Legislative District	Central Municipality
Case 4	Multi-Regional	3	16	Provincial	Provincial Capital

The iterative methodology is applied on the four cases and the robust solution is determined based on the two robustness metrics (SN and Minimax Regret). The robust solutions are determined for the three different strategies at each case.

For each case, simulations are performed to assess the performance of all combinations of pre-positioning strategies and choice of robustness metric against the actual path of typhoon Haiyan. The performance of each solution is shown in section 9.

8.4.1 Processing Times

All of the experiments done for this project were conducted using a laptop with Intel Core i5-6300U CPU @ 2.4 GHz and 16.0 GB RAM. In contrast to what would be done in practice, damage scenarios and the resulting shortest path calculations were calculated for all scenarios of the 23 periods prior to the optimization runs. As the damage scenarios are a significant part of the computation that needs to be done before the optimization and evaluation models can be performed, these are also shown in table 8.7.

Table 8.7: Processing times evaluating 100 scenarios over 23 periods

	Scope	**DP/LDC**	**Processing Time For All Periods (min)**			
			Scenario Generation		**Optimization + Evaluation**	
			Damage Scenario	**Shortest Path**	**Robustness Metric**	
					SN	**Minimax**
Case 1	Provincial	43	32.22	6.37	92.99	93.11
Case 2	Provincial	43	32.22	6.37	96.38	95.72
Case 3	Regional	18	18.66	0.67	20.69	20.66
Case 4	Multi-Regional	16	16.82	0.35	33.32	33.45

Results of the run times show that the higher the number of candidate DP/LDC, the higher the corresponding processing times for scenario generation and optimization and evaluation steps. However, it is not the case for case 3 and 4, where even as case 4 has less DP/LDC candidate points, it still incurred a higher run time. The reason for this is the wider geographical coverage of Case 4 that result to more scenarios where there is high level of demand and also supply point damage.

The model run times are highly relevant since the decision maker has very limited time to implement the pre-positioning action. Thus, the model run time must be much shorter than the time difference between two successive forecast advisories, which is 6 hours. The longest cumulative run time in this study (including scenario generation, optimization, and evaluation) for 100 typhoon tracks across all 23 periods is 2 hours, 14 minutes, and 58 seconds. The efficiency of the run time suggests that the methodology can be feasibly implemented in practice, given that a laptop of the same computing power is available.

There are important caveats however that need to be considered when it comes to run time. Although there are 100 typhoon tracks that are analyzed for each period, only the scenarios that generate demand and damage to LDCs are considered. Thus, if one forecast track shows a weaker intensity, or the direction of the typhoon path is outside the covered area, then these scenarios do not generate any demand in the network. Therefore, the behavior in the case of typhoon Haiyan is that the computational time increases the closer the typhoon is to the affected region, as more scenarios generate demand and supply damage. In practice, in the case of an incoming typhoon, GEPS generates an ensemble size of 27 for each period (Tokuhiro, 2017). Thus, in practice, a lower starting ensemble size could result to even faster computational times.

Chapter 9

Results

This chapter details the performance results of implementing the iterative methodology in anticipation of Typhoon Haiyan. First, the results of the different combinations of pre-positioning strategies and robustness metric under the different test cases are shown. Then, the performance of the robust solutions under the given time period is evaluated. Finally, frequently chosen facility locations for each test case are elaborated.

9.1 Performance under Typhoon Haiyan

The performance results under typhoon Haiyan are split into the different test cases. As explained previously, the first and second cases are of the same geographical scope (provincial level), the second case covers a regional scope, and finally an inter-regional scope is considered. The different combinations of robustness metrics and pre-positioning strategies are compared with the performance of the ideal solution, which is the solution to be implemented if there is perfect information regarding the behavior of the typhoon.

Case 1: Pre-position at Provincial Level, Operating at Maximum Capacity

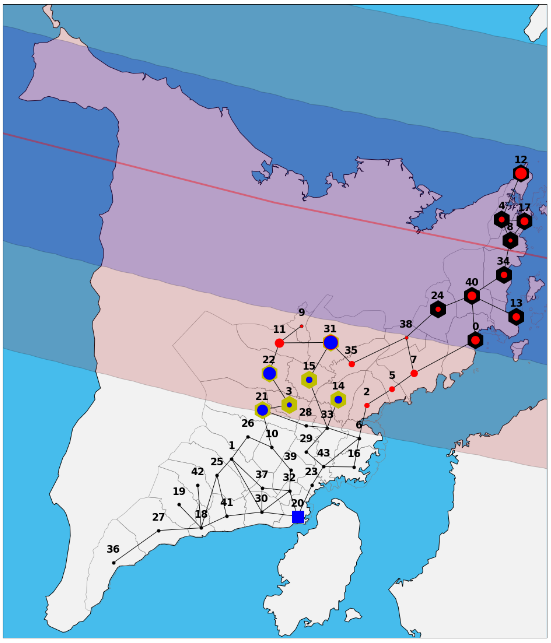
The summary of results based on the first case are summarized in table 9.1. Table 9.1 shows the performance of each pre-positioning strategy when subjected to typhoon Haiyan. Case 1 reflects the performance of different strategies when it operates at the actual maximum capacity at the DSWD regional warehouse, which is at 30,000 FFPs. The total estimated amount of goods demanded for the track of typhoon Haiyan is at 85,716 FFPs for the whole Iloilo Province. The regional capacity only amounts to 35% of the total goods demanded.

Table 9.1: Summary of Performance for Case 1

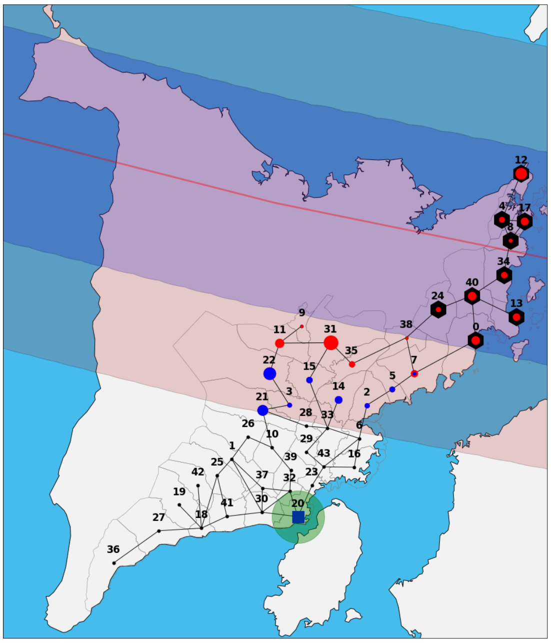
Strategy	Robustness Criteria	% Demand Supplied	Goods Destroyed	Ave Travel Time (min)	Cost (PHP)	Open Facilities
Perfect Information	N/A	35.00	0	0.00	286,955	6
1	N/A	35.00	0	44.66	84,550	1
2	SN/Minimax	35.00	0	44.66	84,550	1
3	SN	35.00	0	36.44	120,879	2
3	Minimax	35.00	0	17.70	219,976	5

To understand table 9.1 a visual representation of the actual location of the pre-positioned goods is shown in figure 9.1. The red line that goes across the subfigures shows the track of typhon haiyan. The bands represent the affected area based on the typhoon trajectory. The inner band represent the area that experience a heavy damage. Within this area, candidate LDCs are considered inoperative in the early response phase, as shown by the black hexagons.

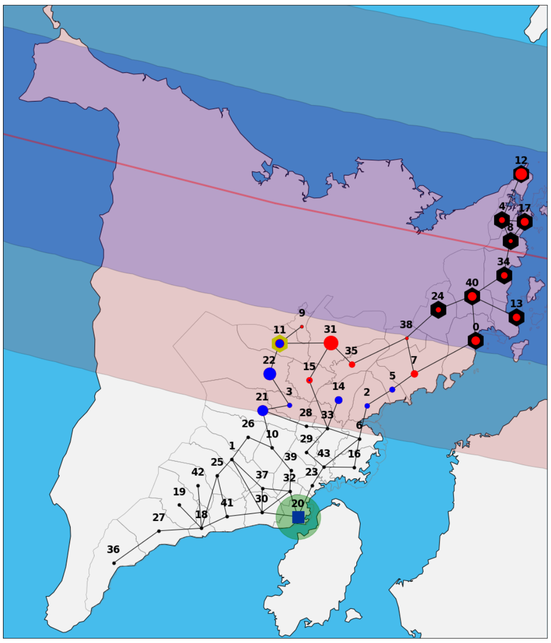
The red circles represent the amount of goods demanded in an area, which is scaled depending on the quantity of demand. The blue circles represent the satisfied demand in the response phase, and the remaining unstatisfied demand remains red. The yellow hexagons show the LDC locations and the blue squares show the locations of the RDCs. Each yellow hexagon contain pre-positioned goods, which are typically in green. In some cases, such such as in Figure 9.1 (a), the green circles may not be visible, because the amount stocked is equivalent to the amount demanded at that LDC location. If there is overstock at an LDC, then a larger green circle is seen. The numbers next to the locations show the identifier of each LDC location.



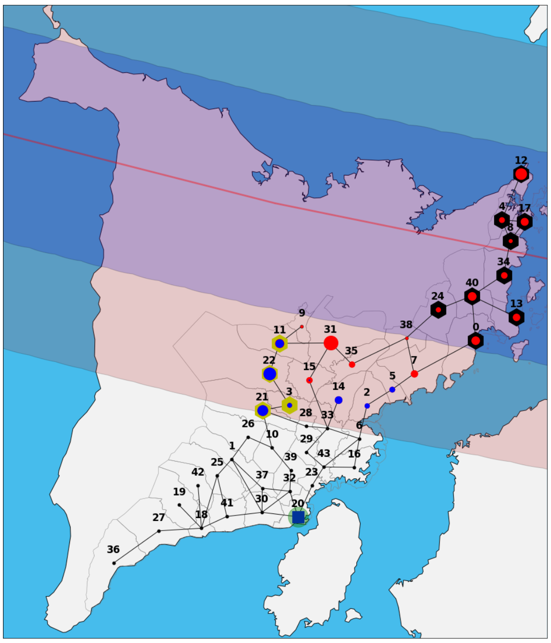
(a) Case 1: Perfect Information



(b) Case 1: Strategy 2, Robustness Metric: Signal to Noise Ratio & Minimax Regret



(c) Case 1: Strategy 3, Robustness Metric: Signal to Noise Ratio



(d) Case 1: Strategy 3, Robustness Metric: Minimax Regret

Figure 9.1: Visualization of Pre-positioning for Case 1

The configuration for the ideal solution is shown in figure 9.1 (a). It shows that given perfect information, 6 facilities (1 RDC, 5 LDCs) need to be established to have the best performance in terms of demand maximization, response time, and cost. This results to an average travel time of goods to 0, which means that the goods are pre-positioned where the demand is expected post-disaster, leading to an average travel time of 0. This results to a total cost of 286,955 PHP, which is the highest cost among all the different strategies explored.

Strategy 1, or the no pre-positioning strategy, shows that if you only keep the goods in the RDC and not perform any pre-positioning at all, all the goods can still be delivered, leading to a 100% amount of demand supplied. However, this comes at a higher average travel time of 44.66 minutes per good. Finally, even though the transportation time is higher which results to higher transportation cost, the total cost incurred is still much less than all the other alternatives, as the fixed cost associated with additional open facilities are much higher compared to the total transportation cost of 30,000 FFPs.

Strategy 2, which is to pre-position 48 hours before expected impact, leads to the same configuration as Strategy 1. Also, both robustness metric yield the same solution for this strategy. This could be due to many scenarios available at the 48h mark result to an expected demand at the demand node at same location as the RDC, which is also the most populated area in the province covered. However, in comparing to the actual track of typhoon Haiyan, the RDC location did not generate demand according to the impact estimation models.

Strategy 3, which is to pre-position at the last minute possible, resulted to the best course of action among the different pre-positioning strategies regardless of the robustness metric. It results to pre-positioning to more facilities and incur more cost (mainly due to setup costs of LDCs), however, both solutions of strategy 3 performed better than strategy 1 and 2 in terms of efficiency. In terms of robustness metric for strategy 3, minimax regret performs better than signal-to-noise ratio. The minimax regret solution has a higher number of facilities, which results to a lower average travel time per good of 17.70 minutes.

It is worth noting that the calculated demand for case 1 exceed the amount of FFPs available at RDC more than twice, with the stockpile only capable of meeting 35% of the demand even at the ideal solution. A lower amount of stockpile leads to a lower number of LDCs to operate, which decreases the risk of pre-positioning at places where the goods can be destroyed. This is evident in table 9.1, where the performance of each strategy based on percentage of demand supplied is on par with the solution with perfect information.

To have a better evaluation of the performance of the proposed methodology, another case is explored such that the amount of goods in the RDC is higher than the amount demanded. This allows for the establishment of more LDCs, which could then result to a higher chance that some of the chosen facilities can be destroyed by the typhoon.

Case 2: Pre-position at Provincial Level, Operating at Higher than Maximum Capacity

The summary of results for the second case are summarized in table 9.2. The same network is chosen for Case 2 and Case 1, and the only difference is that the amount of goods located at the RDC is increased from 30,000 to 100,000 FFPs. This could be possible through renting of additional warehouses to increase the current capacity. The total demand of goods for this case is 85,716 FFPs, which means that the supply is 16.67% higher than the demand. This also means that there are more goods available for pre-positioning, which increases the number of LDCs that are chosen for pre-positioning. This trend is evident in the solutions shown in table 9.2. Also, the visualization for the configuration for the different cases is shown in figure 9.2.

Table 9.2: Summary of Performance for Case 2

Strategy	Robustness Criteria	% Demand Supplied	Goods Destroyed	Ave Travel Time (min)	Cost (PHP)	Open Facilities
Perfect Information	N/A	100	0	32.80	960,162	16
1	N/A	100	0	84.94	459,407	1
2	SN/Minimax	98	16204	94.64	1,069,492	11
3	SN	100	4186	74.26	1,041,505	15
3	Minimax	100	8445	60.07	1,374,793	24

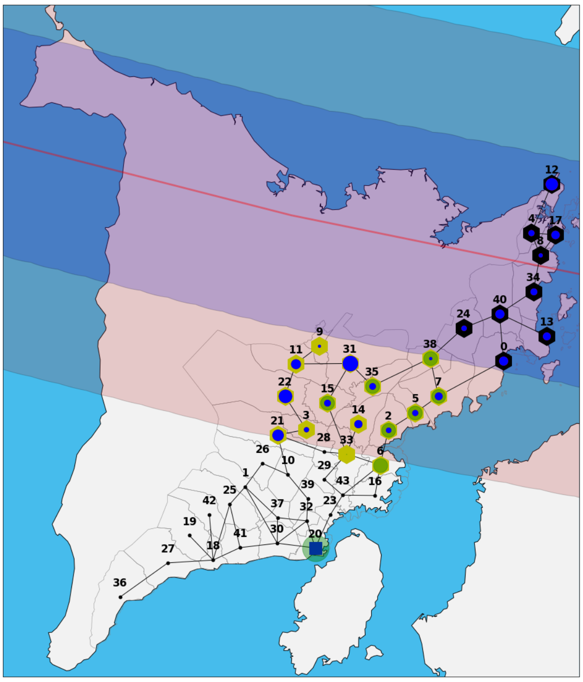
Based on the figure in table 9.2, the number of open facilities increased across the board. It also shows that most of the circles in this case are blue, which means that there is sufficient goods to satisfy the amount demanded given the track of typhoon Haiyan. It is also noticed that for the ideal scenario, the LDC locations that are closest to the heavily damaged area are filled with goods to ensure that the average travel time in the response phase is low. This is shown by the green circles that are larger than the blue circles, seen in facilities 15, 35, and 38 in Figure 9.2 (a). However, given the limited capacity of an LDC at 7,500 goods, the goods are spread out across a few municipalities while still taking into account that the response phase should be most efficient.

Similar to that of Case 1, results in case 2 shows that Strategy 3 performs the best across all the different strategies. Strategy 3 ensures that 100% of the goods demanded is satisfied, and results to the most efficent response regardless of the choice of robustness metric. It is interesting to note that for both results of strategy 3, even though there are goods that are destroyed, the excess amount of goods available at the RDC ensures that there are enough goods to satisfy the total amount demanded. This presents the value of having enough or even excess goods in anticipation of strong typhoons.

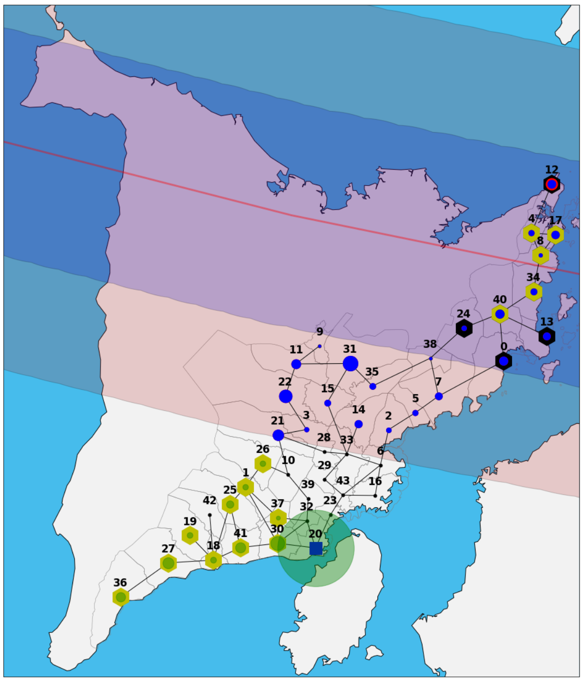
The result of Strategy 2 shows a huge danger of pre-positioning. It shows the possibility that wrongly pre-positioning may even make the decision-maker worse-off than not pre-positioning. Strategy 2 results to a total of 16,204 goods destroyed, and despite the excess amount of goods in the RDC, the percentage of demand that is supplied only amounts to 98%. As seen in figure 9.2, few LDCs opened such as 45, 34, 8, 4, and 17 are located in the heavily damaged area, which means that the goods pre-positioned there are not usable in the response phase. Moreover, most of the chosen LDC locations are clustered at the lower part of map, which is much farther to the affected area than the RDC. This means that the average response time is much slower than not pre-positioning at all, which is evident in table 9.2. The results of strategy 2 stresses the importance of waiting for more accurate forecast data, as more accuracy allows for performance that is much closer to the ideal scenario.

When it comes to the choice of robustness metric, results from case 2 show that the minimax regret solution performs better then the signal-to-noise ratio as shown in Strategy 3. Although the minimax solution has a higher amount of goods destroyed, the % of demand supplied is at 100%, which is on par with the performance of the signal-to-noise ratio and the ideal solution. Then, the average travel time in the response phase for the minimax solution is better than the SN solution, at 60.07 and 74.26 minutes respectively. Since the evaluation for the best solution is on a hierarchical fashion, then the minimax solution is considered the best solution for Case 2.

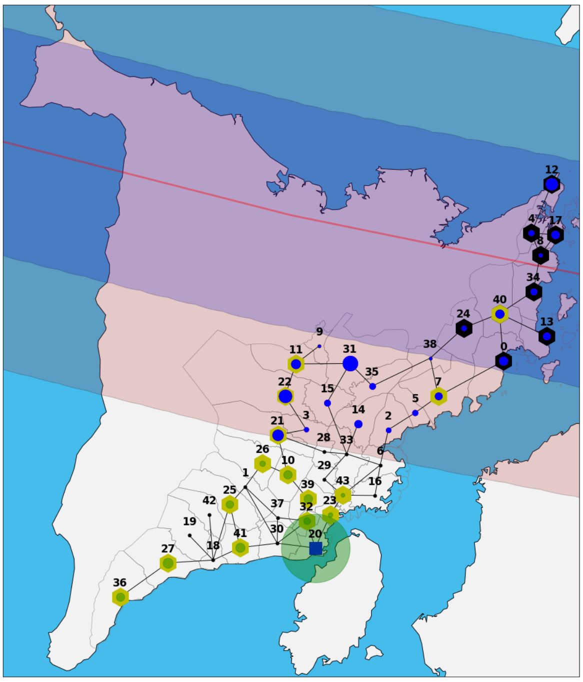
Cases 1 and 2 illustrate the applicability of the iterative methodology to determine the pre-positioning strategy at a provincial level. It is also important to see how the pre-positioning strategy works on a larger geographic scope. However, in working with the same level of data aggregation, working on a larger geographic scope dramatically increases the number of DPs/LDCs to be considered. Thus, covering large networks results to much slower processing times, which can compromise the timely delivery of the proposed pre-positioning configuration. To allow for a larger network coverage without compromising processing times, the next test case is explored where DPs/LDCs were aggregated from a municipal level to legislative districts. The results of this aggregation is shown in the next section.



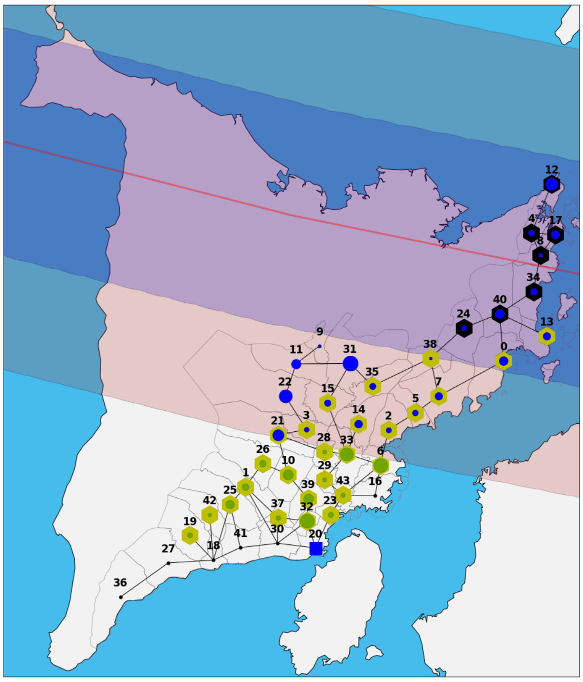
(a) Case 2: Perfect Information



(b) Case 2: Strategy 2



(c) Case 2: Strategy 3, Robustness Metric: Signal to Noise Ratio



(d) Case 2: Strategy 3, Robustness Metric: Minimax Regret

Figure 9.2: Visualization of Pre-positioning for Case 2

Case 3: Preposition at Regional Level with DP Aggregation

The province of Iloilo, which was used for Case 1 and 2, had a total of 43 candidate DP/LDCs. The Western Visayas Region is comprised of six provinces, one of which is the Iloilo province. This region contains a total of 143 municipalities and cities. To make calculations efficient, and to be able to perform the iterative methodology over the larger network at a reasonable time, the DP/LDC points were aggregated.

One of the potential aggregation of different municipalities is on a district level as shown in figure 9.3. It partitions the whole region into 17 legislative districts, which dramatically decreases processing time while covering a larger area. The municipalities or cities that are located centrally in the district were chosen as the candidate location for the SP and DP. The locations that are selected are shown in Appendix B.

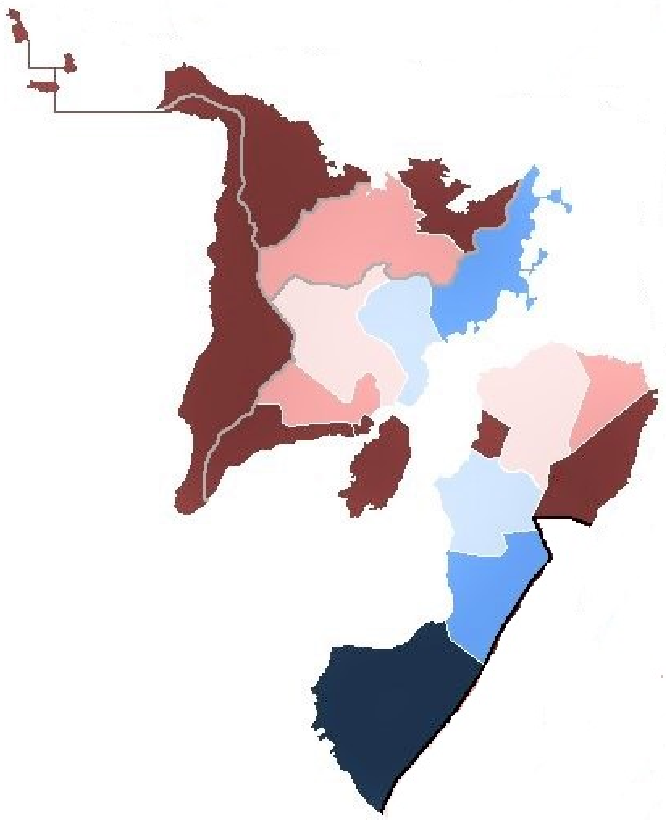


Figure 9.3: Map of the Legislative districts in Western Visayas Region

Due to the aggregation, the candidate locations are now not municipalities, but rather districts. To facilitate similar assumptions throughout the study, a single facility for each municipality is assumed. Thus, the resulting capacity of each district for pre-positioning is equivalent to the number of municipalities/cities within the district times the capacity of one facility. The aggregation lessens the number of DPs to be considered, however, it only gives the total number of goods to be pre-positioned at each district. Thus, it does not provide clarity as to how the goods will be distributed in each district for pre-positioning.

The initial amount of goods to pre-position for Case 3 is 300,000 goods, while the total demand for the region is estimated at 313,147. This results to an upper limit of 95.80% of demand supplied, if all the goods are delivered. This ensures that more facilities are chosen and the performance of the different strategies can be compared.

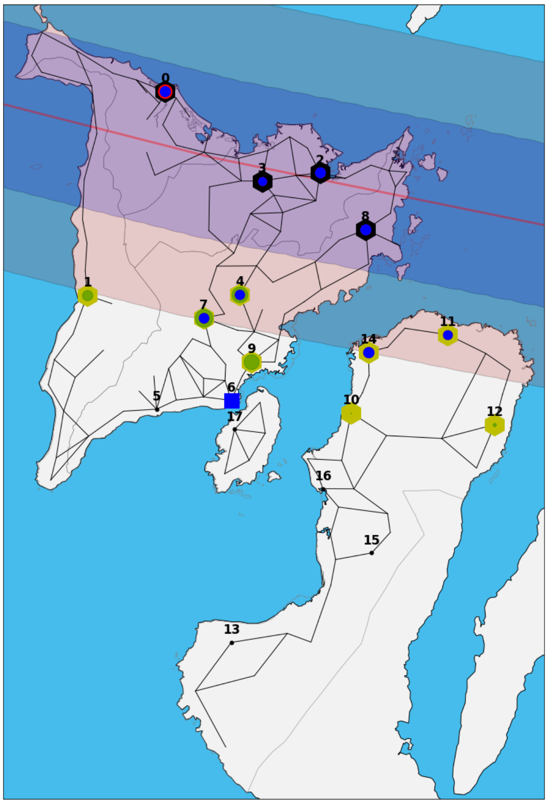
The results for case 3 are shown in table 9.3 with the corresponding visualization shown in figure 9.4. It shows that the designed methodology can also be applied at a larger network. Similar to Case 1 and 2, Strategy 3 performed better than Strategy 2, which further reinforces the value of waiting for more forecast information to reduce the risk of wrongly pre-positioning. Both solutions for strategy 2 has placed LDCs in the extremely damaged area, which resulted to destruction of goods, thus leading to a much lower amount of goods supplied. It is very interesting to note that Strategy 1 dominates over the other two Strategies, which means that for this case, the performance would have been better if no pre-positioning was done at all.

Table 9.3: Summary of Performance for Case 3

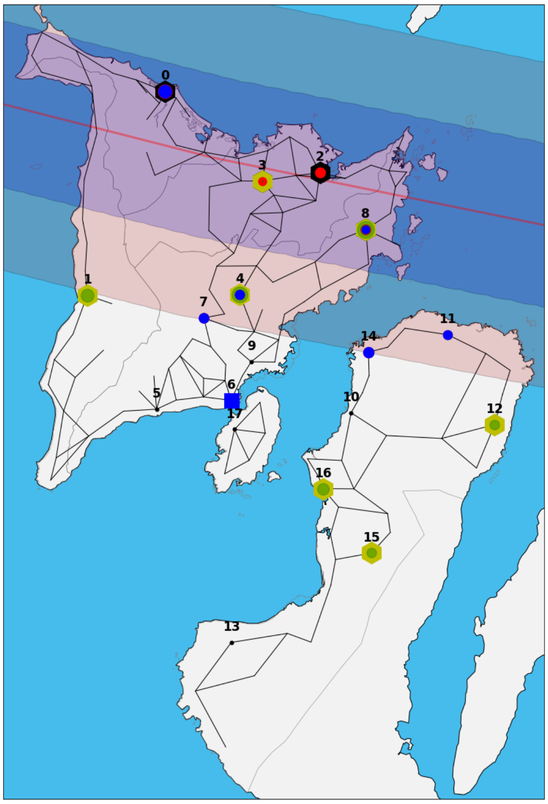
Strategy	**Robustness Criteria**	**% Demand Supplied**	**Goods Destroyed**	**Ave Travel Time (min)**	**Cost (PHP)**	**Open Districts**
Perfect Information	N/A	95.80	0	57.01	3,174,773	8
1	N/A	95.80	0	124.88	2,637,672	1
2	SN	73.26	70,575	102.71	4,632,350	5
2	Minimax	63.99	99,614	80.44	3,331,895	6
3	SN/Minimax	95.80	0	150.04	5,587,816	8

For the robustness metric, the signal-to-noise ratio solution performed better than the minimax solution, especially for strategy 2. This is in contrast to the findings in the previous cases, where the minimax solutions showed equal or better performance.

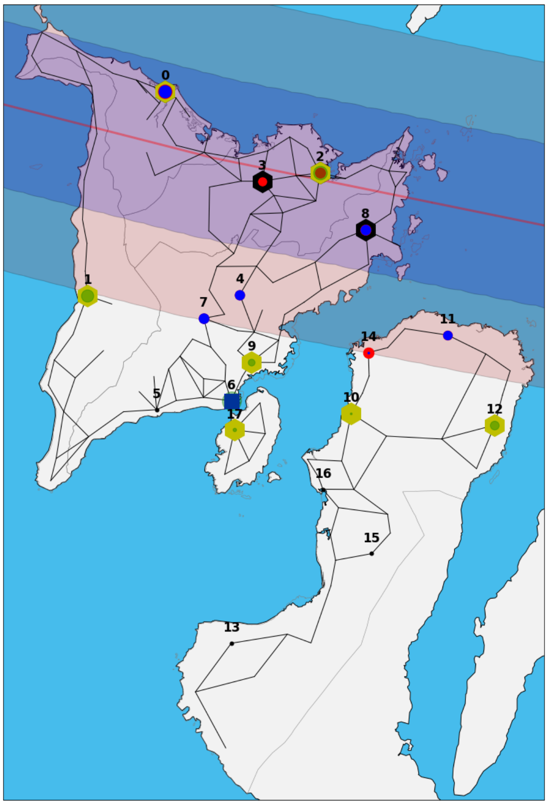
Case 3 operates at the regional level, which is a larger scope than that of Case 1 and 2. However, in reference to the path of an incoming typhoon, it was found that the pre-positioning actions were all activated at the same period. This means that the area considered is not large enough to demonstrate the capability of the model to design a strategy that works across larger networks, where the lead time at each point may differ. Thus another case is explored, which deals with a multi-region network.



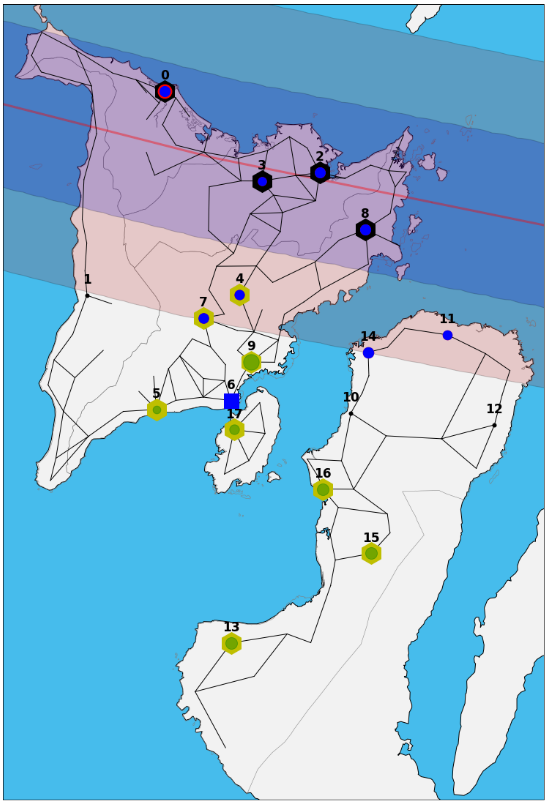
(a) Case 3: Perfect Information



(b) Case 3: Strategy 2,Robustness Metric: Signal to Noise Ratio



(c) Case 3: Strategy 2, Robustness Metric: Minimax Regret



(d) Case 3: Strategy 3, Robustness Metric: Minimax Regret & Signal to Noise Ratio

Figure 9.4: Visualization of Pre-positioning for Case 3

Case 4: Preposition at Multi-Regional Level with DP Aggregation

In pre-positioning for a multi-region level, the three chosen regions were the ones that were impacted the most by Typhoon Haiyan, which are Regions VI, VII, and VIII. In this case, a municipal or district level of aggregation will result to a much higher amount of LDC/DP locations. Thus for this case, a provincial level of aggregation is proposed. The capital of each province serves as its main DP/LDC point, which then distributes the goods across the municipalities in each province. Since there are three regions involved, there are also three RDCs for this case.

The same assumptions for Case 3 regarding capacity are considered for Case 4. The capacity of each province is equal to the sum of the capacities of its component municipalities. At this level of aggregation, the total amount demanded was 315,027 and the amount stockpiled at each RDC was 100,000, resulting to a maximum of 95.23% of demand supplied if all goods are delivered.

Table 9.4: Summary of Performance for Case 4

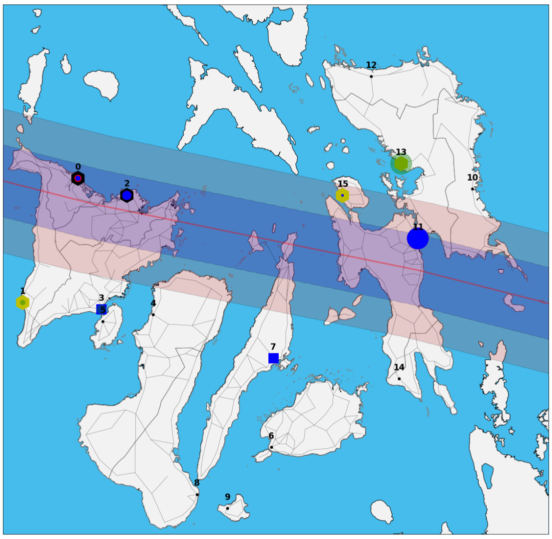
Strategy	Robustness Criteria	% Demand Supplied	Goods Destroyed	Ave Travel Time (min)	Cost (PHP)	Open Provinces
Perfect Information	N/A	95.23	0	121.51	7,661,722	4
1	N/A	63.49	100,000	310.18	5,336,615	2
2	SN/Minimax	40.90	171,166	216.78	7,356,903	3
3	SN	94.29	2,962	346.41	12,900,020	3
3	Minimax	95.23	0	197.37	12,026,219	5

As seen in figure 9.5, the resulting demand was highest at province 11, which is the location of Tacloban City. Province 11 is also the location of the RDC for Region VIII. Thus, the goods that are initially stockpiled at this location will be destroyed if not moved elsewhere before the impact of the typhoon. This is evident in terms of the performance of Strategy 1 (no pre-positioning), where 100,000 goods are destroyed, as shown in table 9.4. This situation is not seen in the previous cases explored.

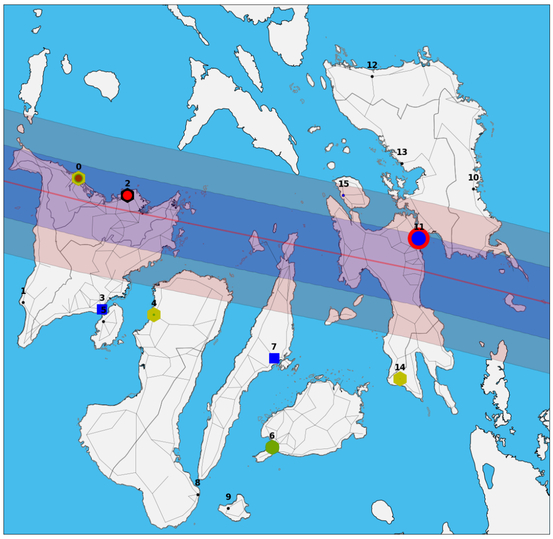
In terms of performance under typhoon Haiyan, strategy 3 shows better performance than strategies 1 and 2, based on the figures shown in table 9.4. Regardless of robustness metric, the % of demand supplied is close to the solution given perfect information. Strategy 2 has considerably a much lower performance than strategy 1, as shown in table 9.4 and also visually represented in figure 9.5. It keeps goods at province [11], which is the RDC that is destroyed, and also pre-positions at province [0] which is also destroyed by the typhoon.

With regards to the robustness metric, the minimax solution performs better in this case. The minimax solution for strategy 3 results to less goods destroyed, and a much lower average travel time of 197.37 minutes in contrast to 346.41 minutes for the signal-to-noise ratio solution.

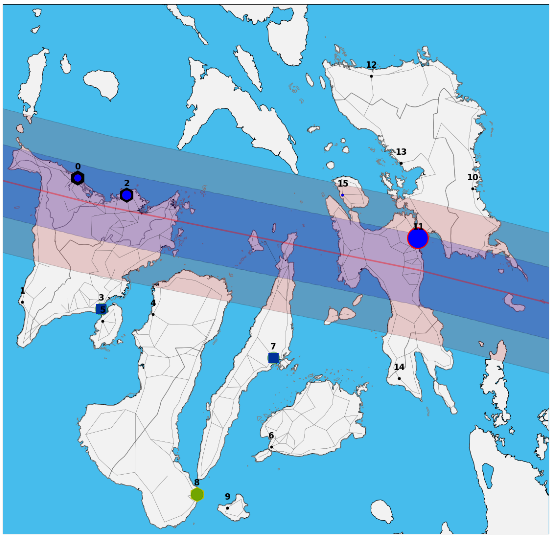
As case 4 deals with a multi-region network, its geographical scope is much larger than case 1,2, and 3. The wider geographical scope allows for pre-positioning across multiple periods, which cannot be clearly expressed by only looking at figure 9.5. Thus, the next sections deal with the multi-period pre-positioning as well as the performance of the pre-positioning actions over time.



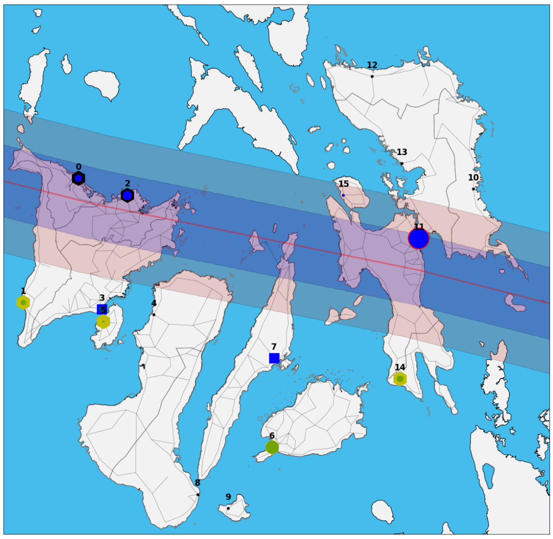
(a) Case 4: Perfect Information



(b) Case 4: Strategy 2, Robustness Metric: Signal to Noise Ratio / Minimax Regret



(c) Case 4: Strategy 3, Robustness Metric: Signal to Noise Ratio



(d) Case 4: Strategy 3, Robustness Metric: Minimax Regret

Figure 9.5: Visualization of Pre-positioning for Case 4

9.2 Performance Over Time Period

The iterative methodology is implemented across all the different periods from the formation of the typhoon until all the goods are pre-positioned. A new forecast cone is generated every period, which means that a new typhoon track ensemble is also generated. As for the case of typhoon Haiyan, it is now known that the track will eventually hit the network analyzed, however, during the anticipation of the typhoon, this is highly uncertain in the earlier stages. This is reflected in the total number of scenarios that generate demand in the network as seen in figure 9.6.

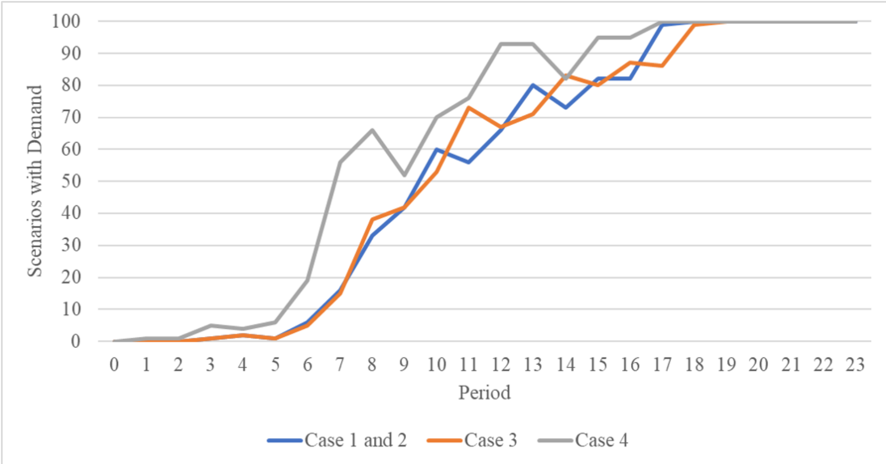


Figure 9.6: Number of Scenarios that Generate Demand per Period

Figure 9.6 shows an increasing trend in the number of scenarios that generate demand. In the early stages of the typhoon, it may be the case that the typhoon is not strong enough, or its trajectory does not pass the network analyzed at all. In these instances, the track will not generate a corresponding damage scenario, thus it is eliminated from the scenarios analyzed.

The candidate solutions generated per period are based on the damage scenarios generated at that period. As the typhoon gets closer, there is a higher chance that the tracks follow the eventual path of the typhoon, however, it may not always be the case. As the probabilities of each step in the typhoon track are generated based on historical typhoon tracks, the ensemble mean of the forecast tracks may differ greatly from the actual typhoon path. Thus, the performance of the robust solution can fluctuate over time, as seen in figure 9.7.

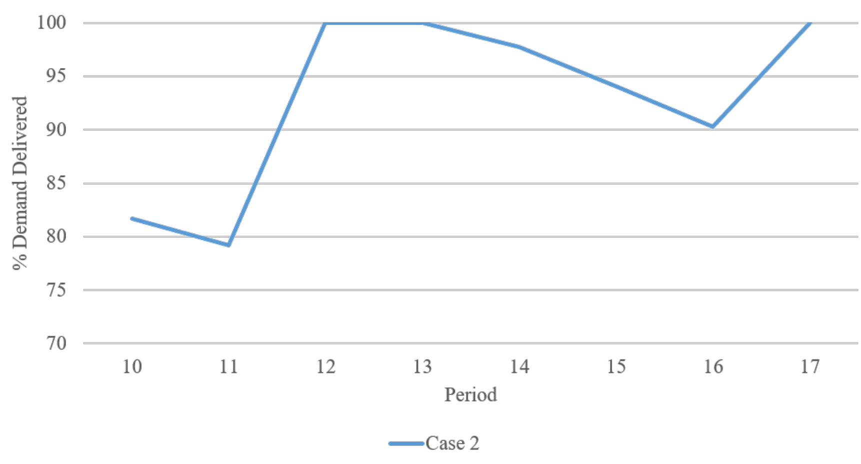


Figure 9.7: Performance of Strategy 3 in Case 2 across different periods

9.3 Pre-positioning Across a Large Network

In a multi-region level such as in Case 4, the lead times across the different points in the network can vary such that the pre-positioning action can be done across multiple periods. This is true for the minimax regret solution of strategy 3, as shown in figure 9.8.

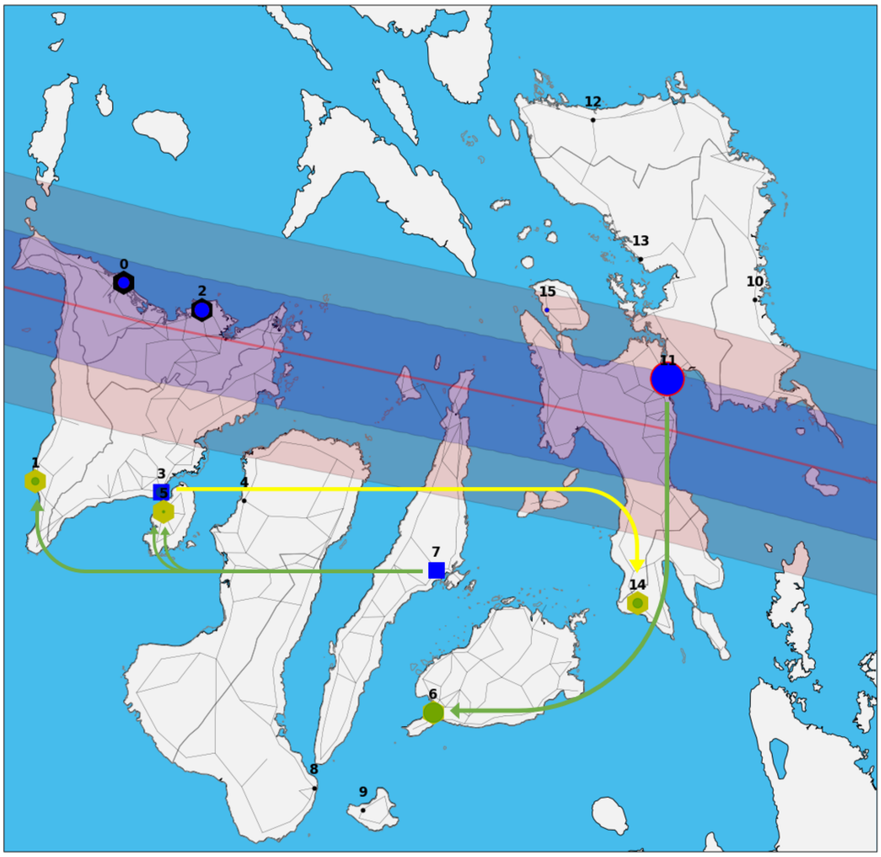


Figure 9.8: Pre-positioning of Strategy 3, Minimax Regret Solution in Case 3 across different periods

The yellow arrow indicate the pre-positioning action that was done in period 14, and the green arrows indicate the actions at period 15. In period 14, the solution that obtained the minimax regret show a high level of demand at province [11], which exceeds the capacity of the RDC at [11]. Thus goods were shipped from province [3] to [14]. Even though there were other pre-positioning actions available from the robust solution at period 14, they were not executed yet since there was still time available to wait for the next forecast.

The solutions from period [15] are then analyzed taking into account that the goods are already being shipped from [3] to [14] based on the previous period. Then, based on the updated tracks of 15, it was highly likely that [11] is to be hit with extreme damage, thus the goods were shipped out of [11] to facility [6]. Moreover, extreme damage is now also expected at [0] and [3], thus, RDC at [7] shipped goods to facilities [1,3,5]. This final configuration now results to 0 goods destroyed with an average delivery time of 197.37 minutes. It is important to note that the pre-positioning actions that were executed at a certain period may not complete the action on the same period. The pre-positioning action only has to be complete before the arrival of the typhoon.

Chapter 10

Discussion

In this chapter, the results presented in the chapter 9 are discussed in the context of decision making in pre-positioning relief goods against strong typhoons. The motivation behind the suggestions of choices of strategy and robustness metric are discussed. Then, the impacts of different parameters on the results are also discussed.

10.1 Choice of Strategy, Robustness Metric, and Scope

Choice of Strategy

The strategic choices on pre-positioning presented in this thesis all relate to lead time. It shows the value of waiting for more information regarding the forecast data and its impact on the resulting pre-positioning solution. It is clear from all the cases analyzed that strategy 3, which is to wait for the last moment available, exceeds the performance of strategies 1 and 2. It generally results to more goods that are located in a safe area, and also a more efficient response phase compared to the other strategies. However, it can be more costly as more LDCs are opened.

Given the context of the scenarios generated for this thesis project, it shows that in all cases, there is a danger of pre-positioning at the wrong places which can heavily impact the performance under the actual typhoon. Pre-positioning at a location where eventually is heavily damaged by the typhoon can yield to a lower performance. In some cases, such as case 4 in this study, it resulted to a worse performance than to not pre-position at all.

Thus, in practice, it is recommended to implement strategy 3. First, DSWD needs to determine the robust feasible configuration based on the estimated impact of the typhoon given the lead times at each point of the network. Then, compare the lead time versus the time it takes for each pre-positioning action. If the pre-positioning action can still wait for the next period, then it is not implemented. However, if the difference between the time it takes to pre-position and the lead time at the point is less than six hours, then the pre-positioning action must be performed immediately.

Choice of Robustness Metric

Based on the results from the different cases explored, the choice of robustness metric generally leads to a different configuration. This is more evident in the results of strategy 3. However, sometimes both choice of robustness metric lead to the same solution.

For the cases where the robust solutions are different, there is no conclusive evidence as to which criteria performs better. For Cases 1, 2, and 4, the minimax regret performs better, but not in case 3. The impacts of the choice of robustness metric could be further explored through analyzing its performance on different intensities and tracks of typhoons. The preference of the decision maker and the attitude towards uncertainty can also help motivate the choice for the robustness metric. If the decision maker is more risk-averse, then the minimax regret solution is more appropriate.

Evaluating for the robust solution, regardless of the robustness metric, would already be a step up from a pre-positioning based on a deterministic forecast. Although computationally more expensive, evaluating for the robust solution accounts for the inherent uncertainty that is present in the forecast.

Choice of Geographical Scope

The choice of geographical scope highlights the applicability of the iterative methodology to various levels of administration in the context of pre-positioning. The provincial level really highlights the specific details of which municipality to pre-position, when to pre-position, and how much goods to pre-position. However, if you look at a regional level, the focus shifts to a more aggregated level. Thus, the DP/LDC points in a regional case are aggregated, where pre-positioning on a district level is prioritized. Moreover, looking at an inter-regional level, the priority even shifts to how can goods be pre-positioned across multiple provinces and how can the goods be shared across different regions. The differences in focus at various levels of administration provides a good strategy to aggregate DP/LDC points and also to make the computations feasible at a reasonable time.

The applicability of the iterative methodology at various administration levels also show the possible ways that methodological applications can be synchronized. For example, the national office of DSWD can use the model at a inter-regional level to determine how much goods to be allocated/pre-positioned at a specific province based on the estimated impacts of the typhoon. Once the provincial branch of the DSWD receives the goods, it can also use the model but on a provincial level to determine whether the goods are to be pre-positioned on specific municipalities, or are they to be stockpiled in the capital to ensure rapid response to nearby provinces.

The choice of a wider geographical scope such as the inter-regional level highlights the capability of the iterative methodology to take advantage of the differences of lead times across the network to determine at which location to pre-position at a given period. This is particularly useful in managing the flow of goods across a large network. This allows DSWD to have a birds-eye-view of the network, and not only focus on the the areas that are hit first but also allocate for locations that are going to be hit at a later point. The iterative methodology allows the readjustment of the strategy in parts of the network that are going to be hit at a later period based on the updated scenario parameters and the pre-positioning actions that are conducted earlier.

10.2 Impact of Parameters

Certain aspects of the iterative methodology are not up to the decision-maker, yet still can impact the resulting robust pre-positioning action. The impacts of some parameters are discussed in this section.

Impact of Typhoon Behavior

The behavior of the typhoon highly impacts the performance of the different robust solutions in the test cases. For instance, as seen in the ideal solutions in Cases 1-4, the LDCs chosen are closest to the heavily damaged area without being damaged. However, not all typhoons cause extreme damage, and thus will have all the candidate LDCs available for selection. This will then change the resulting performance of the different proposed solutions. For example, consider a typhoon with the same track as typhoon Haiyan, but with less intensity. In this scenario, the intensity is strong enough to generate demand, yet not strong enough to destroy the LDCs in its path. The worst performing robust solutions (the one with damaged supplies) suddenly transforms into the best performing facilities, as they are closest to the demand point locations.

Another instance where typhoon behavior influences the performance of the robust solution happens when the actual typhoon track heavily damages the RDC. In this case, solutions that keep some stocks in the RDC suffer in its performance.

Impact of Number and Capacity of LDCs

The limit to the total number of LDCs highly impacts the number of facilities that are established. Since each municipality is capable of handling 1 LDC, the configuration of the solution is such that any location that incurs demand without risking LDC damage is chosen as the location for the LDC. This is because pre-positioning to a location with demand for goods results to a travel time of 0 in the response phase. Therefore, since efficiency is at higher priority than cost, then LDC locations are opened even if there is only a small amount of goods demanded at certain locations. These locations are seen to be prioritized first before the demand in a heavily damaged area, as it would require transport for the heavily damaged area.

When catering for demand at a damaged area, the facilities that are closest to the demand area are filled to its capacity. If the capacity of the LDC is higher, then this would result to fewer facilities opened. This behavior is described further in the sensitivity analysis section.

Impact of Population

If the typhoon passes through a location with a large population, then it translates to a higher level of demand. A location that has a high demand and is at safe location for LDC setup is then likely to be opened. This is because a location with higher demand can ensure efficient transportation (essentially 0) for a larger amount of goods with a single facility. However, not all places that incur higher demand result to being selected since the pre-positioning cost also includes the cost of transportation. Thus, if a location has a large demand but is far away, it might be preferable to pre-position to multiple locations of smaller demand that are closer to the LDC - whichever configuration incurs the least total pre-positioning costs.

10.3 Discussion on the Iterative Methodology

The results as shown in chapter 9 are highly dependent on the input data that are generated through the earlier steps of the methodology. Thus it is also important to discuss how these are generated and how close or far are they to the real life scenario.

When it comes to the generated tracks, it would have been ideal to use the historical model-generated ensemble tracks as input for the damage scenarios. These ensemble typhoon tracks are used to help estimate the forecast cone. However, in the case of this thesis project, only the historical data on the forecast cone is available. Thus, the Markov Transition Probability Matrices based on historical typhoon data from 1951 are used to generate the potential tracks based on the forecast cone. These tracks are then used in the study for the purpose of computational exercises. This then leads to the question: is the reverse method used in this study good enough in approximating the ensemble tracks? One way of verifying that is by comparing the results of the number of scenarios that incur demand over time as shown in figure 9.6.

The estimation of demand and and damage to LDCs are also used for the purposes of computational exercises. It only estimates demand based on the approximate wind speeds based on the wind profile equation used by Uichanco (2015) on a study also on typhoon Haiyan. However, in reality, there are far more factors that impact the level of demand such as the level of precipitation (which can result to flooding), rain-induced landslides, and storm surges. Thus, the configuration of the demand points may not exactly coincide to the path of the typhoon. For example, heavy torrential rains in a mountainous region can cause flooding in the river mouth, which can be far from the actual typhoon path.

Moreover, another question remains: in using historical model-generated ensemble tracks, how does it impact the performance of the robust solution across the different periods, such as shown in figure 9.7? Will it result to a much clearer representation of the trade-offs between forecast uncertainty and eventual performance of the robust solution? Will it show clear distinction in the performance based on the choice of robustness metric? These questions are interesting to explore for further research.

Chapter 11

Model Verification and Sensitivity Analysis

11.1 Model Verification

In order to ensure that the model exhibit the correct results, various components and inputs of the model are verified. Table 11.1 summarizes the model verification process and shows the expected behavior of the model which were tested in python.

Table 11.1: Verification for the Facility Location Model

Model Expectation	Verification Status
Hierarchical evaluation of objective function	Confirmed
Correct calculation of transportation time	Confirmed
Correct calculation of transportation cost	Confirmed
Correct calculation of total pre-positioning time	Confirmed
Correct calculation of shortest distance	Confirmed
Correct calculation of road delay	Confirmed
Goods delivered do not exceed demand	Confirmed
Correct calculation of aggregated capacity	Confirmed
Goods are not pre-positioned in heavily impacted LDC	Confirmed
Goods are not moved when pre-positioning is final	Confirmed
Goods are not moved when lead time is 0	Confirmed
Cost from executed pre-positioning are carried over to next period	Confirmed
Initial stockpile for next period updated once pre-positioning action is carried out	Confirmed
Model stops running when all goods are pre-positioned or when final period is over	Confirmed

11.2 Parameter Assessment and Validation

Each of the parameters are checked to ensure consistency and the values are reflective of the conditions based on the case study. To aid in obtaining these parameters, interviews were conducted with a civil engineer working in the region as well as a current officer from DSWD Region VI Office.

- **Network Data.** Population data, coordinate locations of each municipality, and road distances were obtained from the datasets used in the study of Uichanco (2015). The data was obtained from publicly available databases such as the National Statistics Authority, Google Maps, and OpenStreetMap Data.

- **Transportation Time.** Transportation time between different points was determined by using the Djikstra algorithm implemented in python. The Djikstra algorithm determines the shortest path between two points in a network. The road network in Region IV is comprised of both national primary and secondary roads, where the maximum allowed speed is 60-80 kph for primary roads and 40-60 kph for secondary roads. Based on the interview done with a local civil engineer, 60 kph was the average speed used in the model. The transportation time is then obtained by dividing the shortest distance by the maximum speed.

- **Capacity of LDC.** Based on the interview with a local civil engineer, an assumption of 15 x 20m was used for the floor area which can be used to store the FFPs. Then based on the dimensions of the FFP box and a stacking height of 1.2m, the maximum capacity is determined to be 7,500 goods. The maximum capacity is assumed the same for all the different LDCs. A municipal gym typically has a basketball court which measures 28.7 by 15.2 meters. Thus there is adequate floor space for the pre-positioned goods.

- **Capacity of the RDC.** According to the interview with DSWD, the current facility in Region VI has a maximum capacity of 30,000 FFPs. This has proved inadequate during the aftermath of Typhoon Haiyan. The agency had to rent more warehouses to accommodate the massive influx of relief goods in the region.

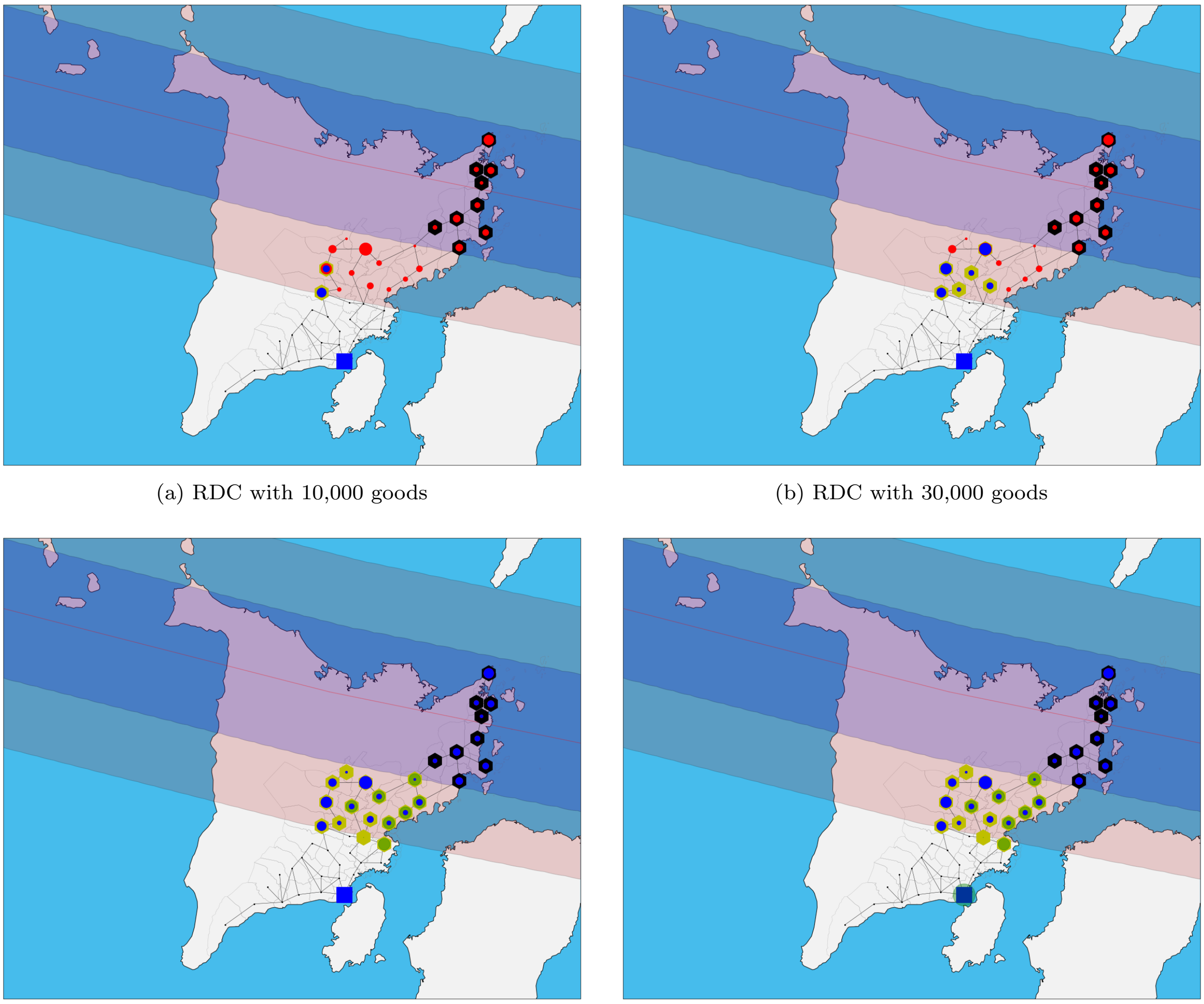
- **Opening cost and setup time of LDC.** The assumptions regarding the opening time of the LDC was made based on calculations made by the local engineer in order to set up the goods at an LDC to full capacity. It takes an estimate of 30 workers to set-up an LDC at full capacity in 8 hours. According to the officer from DSWD, the setup for distribution of relief goods are mainly done by the respective local government units (LGUs). The set-up cost is determined based on the hourly rate of the workers as well as oversight and other fixed costs per facility.

- **Limit for the number of supply facilities.** Based on the interview with the officer from DSWD, DSWD has about 5-10 staff at each municipality which forms the Quick Response Team (QRT). Therefore, DSWD regional office is able to handle 1 LDC location per municipality. Therefore, the number of LDCs setup is not limited in the model.

- **Lead Time.** The lead time was calculated based on the projected location of the typhoon at each forecast hour. Assuming linear behavior with respect to intensity and location, interpolation was done to estimate the actual time when the impacts of the typhoon can be estimated based on its wind speed. The lead time is considered as the first point by which a point experiences a demand surge. The time is also rounded down to the nearest 6 hours. Thus, if the lead time is between 6 and 12 hours, the value taken is 6 hours.

11.3 Sensitivity Analysis

Various experiments are conducted with Model P1 to determine its sensitivity to the different model parameters, and how each parameter impacts the outcome of the optimum configuration. The resulting outcomes of some of the parameters are visualized to serve as aid in the explanation. A summary of the effects of varying selected parameters are as follows:



(a) RDC with 10,000 goods

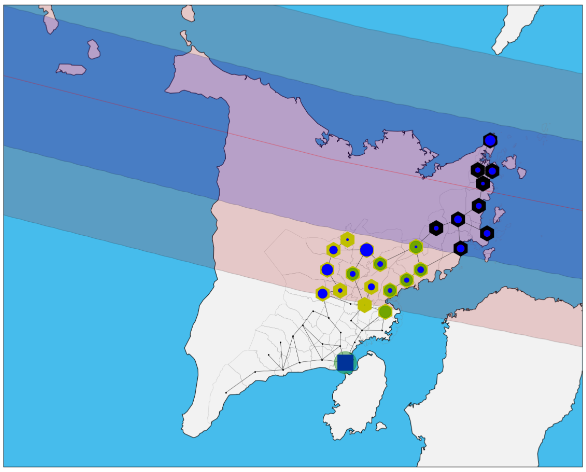
(b) RDC with 30,000 goods

(c) RDC with 85,000 goods

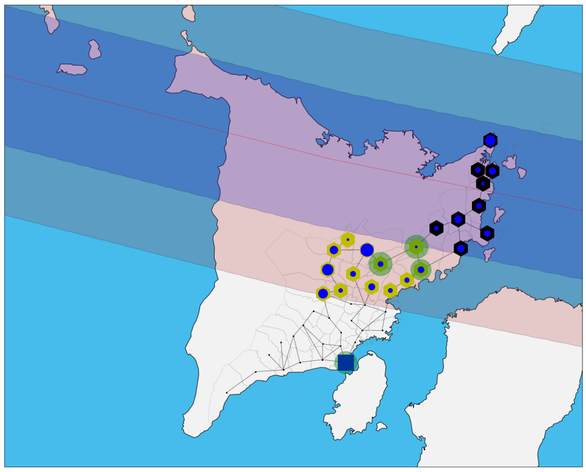
(d) RDC with 100,000 goods

Figure 11.1: Visualization of Varying Initial Supply Level

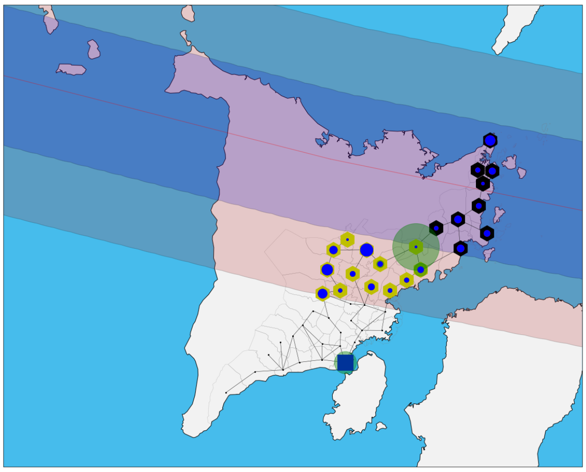
- **Initial Stockpile Level.** The initial stockpile level directly influences the number of facilities that are setup. If the initial stockpile is set to 0, then the number of operational facilities becomes 0. As the stockpile is increased, depending on the typhoon trajectory, the number of facilities used increases. As shown in Figure 11.1A, increasing the initial stockpile level to 30,000 results to an increase in the number of opened facilities to six. It is observed that as the amount of the initial stockpile is increased, the priority of the facilities being opened is a relation between the distance from the RDC as well as the quantity demanded. To reduce the number of facilities used, the ones that are opened first are the ones with larger demands. Also, it shows that the demand that is first catered is the one that is impacted and has demand, but not in the severely impacted area. Once all the demand outside the impacted region is catered to, the facilities starts to cater to the ones that are in the extremely impacted zone. This results to filling of the locations that are closest to the heavily impacted zone first, then fills the next closest one, and so on. The limit to the number of facilities used happens when the stockpile level is equal to the total amount demanded. If the stockpile exceeds demand, then the number of facilities results to the same number as if the stockpile level is equal to the total amount demanded. The excess goods are kept in the RDC.



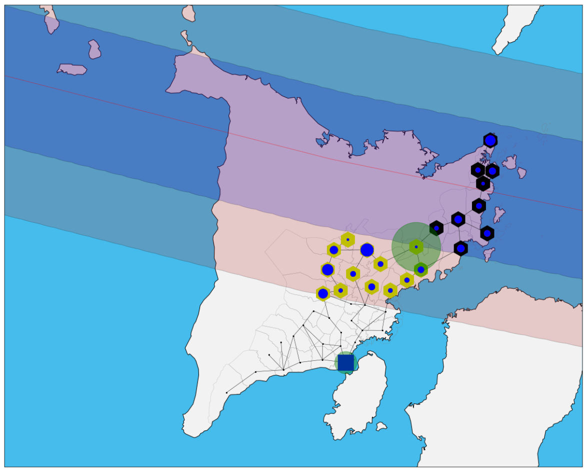
(a) capacity of 7,500 goods



(b) capacity of 15,000 goods



(c) capacity of 30,000 goods



(d) capacity of 100,000 goods

Figure 11.2: Visualization of Varying LDC Capacity

- **LDC Capacity.** Although the capacity of the LDC in this study is assumed to be constant and equal for each municipality, in Cases 3 and 4 which are aggregated, the capacity is dependent on the number of municipalities per district/province. Thus, it is also important to explore the effect of changing LDC capacity. At the scenario explored in figure 11.2, the initial amount of goods in the RDC is 100,000. Figures 11.2 a - d are consistent with the expected model behavior. Since the efficiency in the response phase is maximized regardless of cost, if there is sufficient amount of goods, a facility will be opened where a there is demand, so long as the facility is not destroyed. Increasing the capacity of the LDC will shift as many goods as possible closer to the heavily impacted area, which then decreased the number of facilities as seen from figure 11.2 a to b. Increasing the capacity further will result to most of the goods concentrated at the facility which is closest to the impacted area, as seen in 11.2 c and d.

- **Transportation Cost vs. Setup Cost.** There is a certain tradeoff with regards to the transportation and setup cost in the choice of facility location. If the set-up costs are high, then the locations with a higher demand are prioritized. This is because the response phase can remain efficient with a greater amount of goods pre-positioned without resorting to additional facilities (which incur a high cost). Moreover, if the transportation costs are high, then the locations that are closer are prioritized. The resulting configuration is always the one with the lowest total cost, so long as the higher order objectives are still attained.

- **Transportation Time and Time to Setup LDC.** Transportation time between supply nodes and the amount of time needed for setup determine whether a location is feasible for pre-positioning given a lead time. If the sum of transport time and setup time exceeds lead time at a given location, then it is considered infeasible to conduct a setup at that location. Likewise, if the sum is 0, then goods can be positioned anywhere where there is demand.

- **Typhoon Characteristics.** The typhoon trajectory and intensity directly impacts the optimum LDC configuration. If the typhoon is weak and does not generate demand, then there are no LDCs setup. If the typhoon is strong enough to generate a demand, then the LDCs are located on the points where there are goods demanded, depending on the capacity of the LDC. If the typhoon intensity is strong and causes supply damage, then goods are pre-positioned closest to the impacted area to avoid supply damage while minimizing the average travel distance of relief goods.

11.4 Model Validity

Although the model verification and sensitivity analysis show that the model performs according to the expected behavior, the validity of the model is still not guaranteed without the validation of experts. Over the course of the thesis duration, it was not possible to obtain expert opinion on the model and its applicability to pre-positioning in the Philippines. Thus, a very important step for the extension of the thesis is to consult experts in the humanitarian field in the Philippines so that they can suggest possible improvements and tweaks that would make the facility location model more in tune with reality.

To have a better gauge of the choices that were made for the facility location model, the motivations behind the choices are elaborated.

Motivation of Objective Functions

It is important to ensure that the objectives of the optimization model is aligned with the perspective of the problem owner. Thus an interview with a current officer from DSWD was conducted. According to the interview, the tagline of DSWD is *Maagap at Mapagkalingang Serbisyo*, which translates to punctual and compassionate service. Thus, response efficiency is one of the key objectives to be achieved in the model. Also, during the interview, it was indicated that demand coverage, response efficiency, and cost are all important to the problem owner. In the context of response operations, the ranking of objectives is such that first, the goods need to be safe and secure location for it to be distributed to most people, next is then that the response should be efficient, and the third is to reduce cost. This thus validates the hierarchical order of the objective functions chosen for this model.

Motivation of Constraints

In this section, the rationale behind each of the constraints are discussed. This includes references to previous studies that have used similar constraints, and if not, then the rationale behind the constraint is explained.

- **Equation 6.4.** ***Flow of goods to j should not be greater than demand at node j.*** In other pre-positioning studies, especially with a singular objective function such as cost minimization, this constraint is the other way around, where the amount of goods delivered to a node should be greater than or equal to the amount demanded (Gobaco et al., 2016; Galindo Pacheco et al., 2015). The difference lies in the assumptions. In the studies referenced, the supply of goods in the main distribution center is assumed unlimited. In this study, the assumption is that there is a limited amount of goods in the RDC which can be pre-positioned. If the same constraint is used in this study, the moment the calculated demand exceeds the amount of goods to be pre-positioned then the model becomes infeasible. The model used in this study reflects the actual situation in the case study, and considers the limited capacity of the decision-maker. In this case, the best pre-positioning is sought based on the amount of goods available. The reality in the case study is that there are people whose needs are not met in the early response phase. The augmentation of relief goods that happens after the initial response is not considered in the model. Thus, in this model, a maximization of demand is used as an objective function, and constrained such that the flow of goods to each node should not exceed demand. This allows the model to become feasible despite the shortage of supply.

- **Equation 6.5.** ***Pre-positioning action should be feasible given the lead time*** This constraint comes in various forms and is perhaps one of the most important features of forecast-based pre-positioning. The assumption is that goods can only be pre-positioned to a supply node i if the action can be completed before the typhoon strikes. This constraint is also considered in the model but in a different fashion than other studies explored in literature. In pre-positioning studies such as Galindo Pacheco et al. (2015), the lead time is defined based on the time when the hurricane makes landfall. The assumptions used by Galindo Pacheco et al. (2015) is problematic for the case study of this project for two reasons. First, as discussed previously, the landfall time used at these studies is the same across the whole network at a given period, which can only be assumed true for a small enough geographical area. Second, the NHC defines landfall as the *"intersection of the surface center of a tropical cyclone with a coastline"* (NHC, 2018[b]). It notes that the strongest winds of a tropical cyclone are not necessarily at the center, and an area can experience the strongest winds even if landfall does not occur. The methodology of this study is structured such that the lead time does not equate to landfall time, rather, the lead time is calculated based on the approximate time that a point is expected to experience wind speeds that cause a surge in demand of relief goods. This happens well before the landfall time of the typhoon. Also, since two points can have different landfall times, if a LDC is allocated to a DP, then the lead time is calculated such that it is the minimum time that the strongest winds impact either the LDC or the DP.

- **Equation 6.6.** ***Ensure enough quantity of supply at node i to deliver to node j.*** The current level of storage at SP i is defined by how much goods are there at that point initially, plus any goods it receives from other SPs minus how much goods it sends to other SPs. It is assumed that all the goods that are pre-positioned to point i are to be delivered to demand nodes, thus a separate variable to indicate storage level is not used, rather, is derived from the total amount of goods from node i delivered to demand nodes it is allocated to. Similar versions of this constraint can be found in studies of Galindo Pacheco et al. (2015), Gobaco et al. (2016), and Davis et al. (2013)

- **Equation 6.7.** ***Ensure enough initial quantity at supply node i to pre-position to other supply nodes.*** This constraint is also used by Galindo Pacheco et al. (2015), and ensures goods are only sourced from SPs that contain goods at the beginning of period p.

- **Equation 6.8.** ***Ensure that the quantity of goods sourced from an SP does not exceed its capacity.*** As the level of storage at SP i is equated to the quantity of goods it delivers to DPs, the quantity it delivers also should not exceed its capacity. This constraint is also found in the study of Galindo Pacheco et al. (2015).

- **Equation 6.9.** ***Ensure DP j is served by i only if it is allocated to i.*** This equation shows which DP is allocated to an SP based on where the goods are to be delivered in the response phase. The reason this allocation is important is that it helps defines the lead time at SP i depending on the lead time at the allocated j, as shown in Equation 5.

- **Equation 6.10.** ***Ensures that no goods are transferred to/from an SP where pre-positioning action is final.*** This constraint reflects the assumption of irreversibility of a pre-positioning action given a short lead time. This constraint also prevents re-prepositioning. Thus, if a pre-positioning action is done at period p at LDC i, goods cannot be transferred to/from that point at succeeding periods.

- **Equations 6.11 and 6.12.** ***Ensures that no goods are delivered to and from destroyed SPs***. This constraint reflects cases for scenarios where there is potential supply damage. When a SP is destroyed, then existing goods at that SP cannot be delivered to DPs, and there is no capacity to store new goods from other SPs.

- **Equations 6.13 and 6.14.** ***Domain of variables***. These are found in all types of problems to define what type of values can each variable take.

Chapter 12

Reflection

This chapter elaborates on the insights gained over the process of designing the iterative methodology as well as its potential application to the pre-positioning of relief goods in the Philippines. It discusses the impacts of some key assumptions and limitations in the model, as well as the challenges of its implementation in practice.

12.1 Reflection on Iterative Methodology

Assumptions

One of the key assumptions in the context of this research is on the irreversibility of pre-positioning actions. This has impacted the structure of the proposed solutions, where ideally one can pre-position early based on the forecast, and re-pre-position accordingly based on the new forecast obtained in the next period. However, in a practical sense, there is very limited time to pre-position for a typhoon, and pre-positioning actions can take substantial time which may encompass multiple forecast periods. It can also cause problems in its application in reality, where resources such as vehicles and manpower are scarce and re-prepositioning can cause much confusion and a feeling of wasted effort. Thus, in this study, it is assumed that once a pre-positioning action is conducted, it is considered final.

Another important assumption in this research is that the delivery trucks are always available and are capable of moving all the resources from the LDC all at once. In practice, the model should account for the availability of sufficient vehicles to ensure that a pre-positioning action is feasible. This is quite evident in cases where the solution requires pre-positioning at 15 different municipalities at a given period. Since DSWD has a presence in every municipality, this configuration can be operational. However, the implementation of pre-positioning thousands of goods across 15 different municipalities at a given period is subject to the limitation of equipment and manpower.

Limitations

One of the key limitations of this study is with regards to the run time of the facility location model. However, in practice, with a limited number of members of the ensemble in current forecast models such as GEPS (27), the facility location model can be solved in a reasonable time. The computation that can potentially cost a longer time is the damage estimation model. In this study, the damage estimation model only incorporates the surge in demand based on the highest wind speed that a location experiences. However, in reality, damage estimation especially in typhoon scenarios are much more comprehensive. For every potential damaging factor from a typhoon (storm surge, landslide, flooding, wind speed), estimation of damage scenarios for an ensemble can take considerable time.

Another limitation of the study is that it assumes that there is perfect information regarding the estimates for the damage scenarios. The quality of the solution of the model is dependent on the quality of its inputs. Thus, if key information regarding damage scenarios are missing which cannot be adequately estimated by the model, the resulting pre-positioning configuration based on a certain damage scenario can be far from optimal.

Another limitation of the iterative methodology is that it does not take into account the presence of other actors in the pre-positioning phase. Other agencies such as the Red Cross, which also has a large presence in the Philippines, can also be involved in pre-positioning goods. Moreover, the type of goods that other actors pre-position can be different (for example: sacks of rice, water, etc.) which then cause different estimates of how many people can be served with such goods.

Another limitation of the proposed methodology is that it does not account for pre-emptive evacuation measures. Learning from the experience from Typhoon Haiyan, the population are well aware of the potential catastrophe if evacuation warnings are ignored. Thus, it is possible that with good information dissemination, more people will evacuate and thus will lead to a different distribution of demand.

12.2 Challenges in Practical Implementation

The proposed iterative methodology in this research presents a step by step process on how to obtain the robust pre-positioning configuration at a given time period. The methodology is implemented to a case study of Typhoon Haiyan, which details its implementation on different administrative levels in the Philippines. Ideally, it considers the different scenarios that can happen based on the typhoon forecast in order to determine a pre-positioning configuration that is robust. This section details the potential challenges that can be encountered at each step.

As the forecast information is updated every six hours, rapid assessment of needs through the damage estimation models need to be employed. As discussed in section 12.1, this could potentially take a considerable amount of time. Moreover, this methodology requires that the decision maker is to revise the potential action plan every six hours and start the pre-positioning when it is no longer feasible to implement the pre-positioning action if the decision maker is wait for the next forecast. There can be some complications which arise in the timeliness of the implementation of the pre-positioning action. For example, there could be less people that are willing to perform pre-positioning actions if the operation is to be performed at night.

Moreover, relief goods pre-positioning is only one of the activities that are conducted in anticipation of a typhoon. Other activities include deployment of quick response teams, equipment, and medical supplies to ensure effective and efficient response. Moreover, there are also preemptive evacuation procedures that are in place. This work is done by other government agencies as well as other stakeholders in conjunction to the efforts of DSWD. Thus, it is important to consider the implementation of the iterative methodology in the context of the existing protocols that are in place in the National Disaster Response Plan.

Finally, it is very important to have an operational command center in a regional/ provincial/ municipal level to be able to coordinate with what is going on in the ground, especially for the early response phase. The scenario for which the robust solution is configured may not be the same exact scenario that will happen in reality, thus the intended recipients of the pre-positioned goods can change. In order to ensure efficiency and effectiveness of the response operations, redistribution model P2 needs to be evaluated. The implementation of the distribution of goods in the response phase will then require coordination with the higher level authority (such as provincial level) with where the stockpiles are pre-positioned (municipal level).

Chapter 13

Conclusions and Recommendations

Lessons learned from the experience with Typhoon Haiyan in 2013 emphasized the importance of disaster preparedness, particularly on pre-positioning goods before a typhoon hits. A review of literature on humanitarian logsitics and forecast-driven pre-positioning models helped identify research gaps, which led to the development of the main research question and sub-questions for this study. The main aim of this study is to design an iterative methodology to determine a robust pre-positioning strategy for relief goods in anticipation of a strong typhoon. This chapter addresses the main research questions derived from the research gaps and provides recommendations for future research directions.

13.1 Answering the Research Questions

This section revisits the research questions that are formulated in the beginning of this research. First, the research subquestions are answered, and finally the main research question is addressed.

RSQ1. How to generate an ensemble of potential typhoon tracks based on forecast data?

The first research subquestion stems from the limitation of this research to obtain historical ensemble forecast data of typhoon Haiyan. Thus, an alternative way of generating typhoon tracks is designed. First, historical data from typhoon tracks since 1951 that occurred in the West Pacific Basin were analyzed. From these tracks, a Markov transition probability matrix is generated for both intensity and location of the typhoon. The probability matrices, along with the historical forecast data of typhoon Haiyan, were used to generate the potential tracks. The initial point of the forecast data at a given period was used as a starting point of the typhoon. Then, the next instances of the location and probability were obtained based on the transition probability matrices. Finally, it was ensured that the track generated falls under the cone of uncertainty that is generated by the forecast track.

RSQ2. How to estimate the impact of a typhoon track scenario on a network, particularly on demand of relief goods, supply destruction, and transport delays?

In order to achieve the main goal of this research, it is first important to generate the potential damage scenarios for this study. A study by Uichanco (2015) utilized the wind profile of a typhoon to estimate its impact on a network. Based on this wind profile, the affected area was determined. The wind profile was used to estimate the demand at a particular demand point, and also to determine which LDCs are damaged and which roads cause delay.

RSQ3. How can the robust pre-positioning configuration be determined based on many potential damage scenarios?

For each damage scenario, a facility location model P1 was designed to simulate the pre-positioning configuration that will yield the optimal response based on the chosen objective functions. The solution for each scenario was evaluated under all the different scenarios that are available for that specific period. Robustness metrics, such as a variant of signal-to-noise ratio and minimax regret were chosen to determine the most robust alternative across all the alternatives explored.

RSQ4. How to determine when to make the pre-positioning decision given different lead times at different points in the network?

To answer this research question, three different strategies are considered. These three strategies employ different algorithms which determines whether a pre-positioning action is conducted at that period. The first strategy uses a wait-and-see approach, and does no pre-position at all. The second strategy is to pre-position once the lowest lead time for a any point in the network is less than 48 hours. Finally, the third strategy looks at the difference between the lowest lead time at each point and the time it takes to pre-position at that point. If the difference is greater than 6 hours, then there is enough time to wait for the next forecast. Otherwise, a pre-positioning action is conducted for that point.

Now it leads to the main research question:

How to determine the robust pre-positioning strategy in preparation for a typhoon, where forecast information is updated periodically?

The answer to the main research question is: through an implementation of the designed iterative methodology as shown in figure 13.1.

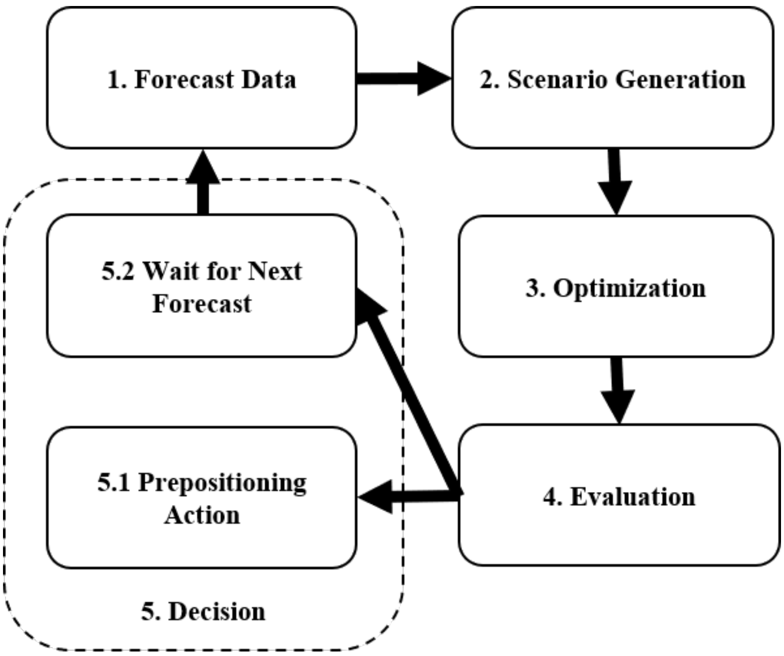


Figure 13.1: General process flow to determine pre-positioning action

First, an ensemble of typhoon tracks is generated based on the weather forecast data [Step 1]. Then, the generated tracks are used to determine potential damage scenarios and estimated lead times at each point in the network [Step 2]. Characteristics of the damage scenarios include demand estimation, supply point damage, and delays in the transportation network. The results of the computational exercise for damage scenarios and lead times are used as inputs to a capacitated facility location model to determine the optimal pre-positioning actions for each damage scenario [Step 3]. Then, the solution for each scenario are evaluated across all the other potential scenarios, and the robust solution is chosen based on the choice of robustness metric [Step 4]. Finally, based on decision theory, a choice is made whether to execute a pre-positioning action or wait for forecast over the next period [Step 5].

Test cases based on the track of Typhoon Haiyan were designed to evaluate the performance of the pre-positioning configuration generated from the iterative methodology. Three strategies and two robustness metrics were evaluated. Results show that the best strategy is to implement the robust pre-positioning configuration at the last period possible. It happens when the difference between the lead time and the time for pre-positioning is less than 6 hours, which is the time between two successive forecast periods. This allows to take advantage of the decrease in uncertainty with each successive forecast, which leads to better pre-positioning outcomes.

Insights from this study show that the methodology can be implemented at various levels of administration, be it in provincial, regional, and multi-regional level. Furthermore, results from the implementation of the iterative methodology over a large network allows for pre-positioning at different periods at different points on the network based on the lead time at each location. Finally the choice of robustness criteria, signal to noise ratio and minimax regret, did not generate conclusive results as to which option performs better.

13.2 Recommendations for DSWD

This study presents some recommendations to DSWD to improve further on the agency's performance during typhoon response operations. First, it needs to ensure that the amount of goods stockpiled at regional warehouses is sufficient in anticipation of strong typhoons such as Typhoon Haiyan for a pre-positioning strategy to be effective.

Next, the iterative methodology proposed in this study has the potential to support the decision-making process in the context of disaster preparedness and response and can improve the ability of the agency to increase its efficiency in responding to strong typhoons that are to come. The test cases also show the applicability of the model at various levels of administration. However, further validation of the model needs to be done with humanitarian logistics experts in the Philippines.

In implementing the iterative methodology, it is recommended to use the forecast ensembles generated by forecast models such as the GEPS. This ensures that the behavior off all the typhoon tracks is in accordance with the prevailing atmospheric conditions at the time of the typhoon. Moreover, more comprehensive estimations of damage scenarios based on flood, storm surge, landslides, and strong winds should be used.

Finally, the implementation of the iterative methodology should be done in accordance to the other preparedness measures such as pre-emptive evacuations. It is important to further examine to see how the methodology can fit within the framework of the national disaster response plan.

13.3 Scientific Contributions

The main scientific contributions of this study are as follows:

- **Design of an iterative methodology that utilizes ensemble forecast to generate robust pre-positioning configuration.**

The iterative methodology proposed characterizes the uncertainty of a typhoon track with the use of forecast ensembles. This approach is not explored before in literature. Also, using forecast ensembles allows for the observation of the typhoon behavior over time, which enables calculations of lead times available at each location for different scenarios. Allowing for the calculation of lead times leads to the second scientific contribution of this study, which is:

- **Design of a facility location model that accounts for the differences in lead times across a large network.**

The implication of this approach is such that pre-positioning can be done in the context of a large network, where goods can be pre-positioned at points where typhoon is projected to hit first. The rest of the goods can be pre-positioned at subsequent periods based on the difference between the lead time and the time it takes to pre-position at a given location.

13.4 Recommendations for future Work

The damage scenarios which serve as input to the model can be improved by utilizing real time data available from weather forecast agencies such as PAGASA and UP NOAH. Real time information regarding not only on wind speed but also on precipitation, atmospheric pressure, landslide and flood prone areas, and storm surge warnings, etc. allow for better damage estimation which then helps in ensuring a pre-positioning strategy that is in tune with the real situation. Moreover, there other characteristics of a municipality, such as income levels, type of materials used for houses, etc., that can also serve as helpful predictors to determine damage scenarios. Real-time information on the available locations for pre-positioning should also be considered to define the actual number of supply points which can be used for pre-positioning.

One of the main limitations of this study is using historical data to generate typhoon track ensembles at each forecast period. Using historical data becomes more unreliable especially with the ever increasing impacts of climate change. In order to account for these, real-time typhoon track ensembles can be obtained from forecast agencies such as JMA to have a better gauge of an incoming typhoon's track and intensity, which also leads to better lead time estimation at each location as well as damage scenarios.

As pre-positioning decisions need to be decided over a short period of time, it is crucial for the optimization calculations to be efficient. For future improvement, heuristic algorithms can also be used. Moreover, depending on the consideration of the decision maker, aggregation of demand points such as performed in this project can be useful to increase the efficiency of the optimization calculations. Using heuristic algorithms and aggregation of points can lead to less accurate results, therefore it is important to consider the balance between efficiency and accuracy.

As discussed in the results section, the current capacity of regional warehouses is incapable of responding effectively and efficiently to a supertyphoon like Haiyan. Thus, the study can also be extended on a national level to determine the optimum stockpile levels of permament regional warehouses in preparation of the whole typhoon season. This will help ensure adequate year-round stockpiles for forecast-driven prepositioning on a regional level.

Furthermore, forecast-driven pre-positioning can also be employed by other concerned actors such as NGO's, faith-based organizations, and charities. The study can be extended to explore possible cooperation between different actors and also deal with relief commodities other than FFPs.

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Appendix A

Definition of Terms

To aid in the clarity of the methodology section, the most commonly used terms are defined and summarized. The operational definition of some terms are specific to this study.

- **Regional Distribution Center (RDC).** The RDCs are the main storage location of the relief supplies before the occurrence of a typhoon. In pre-positioning for a single typhoon, the amount of goods available at the RDC are known. The RDCs are used as the main source of relief supplies to be pre-positioned to local distribution centers (LDC)
- **Local Distribution Centers (LDC).** The LDCs are existing structures such as gymnasiums that are re-purposed as temporary distribution centers in anticipation for an incoming typhoon. The LDCs are used in order to ensure an efficient delivery of relief goods once the typhoon strikes. The LDCs effectively reduce the delivery time of goods to the affected area.
- **Supply Points (SP).** The RDCs and the LDCs together comprise the supply points. The supply points serve as the distribution points of relief goods. The supply points deliver relief goods to Demand Points.
- **Demand Points (DP).** The DPs are locations where there is demand of relief goods after a typhoon has struck an area. This could be existing facilities such as schools that serve as temporary evacuation centers. The DPs get the relief goods needed from the supply nodes.
- **Demand.** The demand referred to in this study is the amount of relief goods needed for immediate relief in the aftermath of a typhoon. The long term demand for resources is not considered for this study.
- **Relief Goods.** A unit of relief good that is referred to for this study is a Family Food Pack (FFP), which contains food items that can sustain a family of five people for two to three days. An FFP contains six kilograms of rice, four cans of sardines, four cans of corned beef, and six sachets of coffee. An FFP is packed as a single commodity and is thus treated as a single commodity.
- **Pre-positioning Action.** A pre-positioning action is the act of moving goods between supply points in order to serve DPs more efficiently. Aside from transportation of goods, it can also involve opening and closing of supply points. A pre-positioning action can only happen before a typhoon impacts a certain area.
- **Response Action.** The response action happens after a typhoon has hit a certain area. In the context of optimization in this study, the response action is also taken into account. The location and amount of goods at each supply points will define the efficiency of the response action. Thus, in the optimization calculations in this study, the expected response action is accounted for.
- **Road/Sea Segments.** The segments serve as the path that connects adjacent points in the network. These are the paths that allows pre-positioning between supply nodes and also the response action from supply points to demand points. A path from two points in the network may comprise of more than one segment.

- **Damage Scenario.** A damage scenario is the expected impact of a projected typhoon track to the network. It is comprised of the following: the amount of demand at each of the DPs affected, the SPs destroyed (unusable), and the impacted road segments (which lead to delays). Each unique projected track has a deterministic impact on the network. Different tracks may impact a different set of demand points, supply points, and road segments.

- **Impacted Area.** A typhoon has the most impacts to the objects that are close to its path. The impacted area is the set of objects (demand points, supply points, and road segments) that are affected if a certain typhoon track is realized.

- **Typhoon Track.** A typhoon track is a set of data which shows the behavior of a typhoon over time. It is defined through its location (latitude and longitude) and intensity at a certain time. A data point of a typhoon track is defined every six hours, which is the period of time between each typhoon forecast advisory. The behavior of the typhoon is assumed to behave linearly over time between two data points. For example, if the typhoon has an intensity of 90 at t=0 and 60 at t=6, then the intensity is calculated as 75 at t=3.

- **Planning Horizon.** The planning horizon is defined as the whole time period for which a pre-positioning action is executable. In the context of this project, the planning horizon starts from the time the first forecast is issued until the last object in the network is impacted. The planning horizon is divided into time periods.

- **Time Period.** The time period is defined as the building blocks of the planning horizon. It also is the defining characteristic of when a pre-positioning action is implemented. Each time period is comprised of six hours, based on the length of time available between two forecasts. The time period is defined in terms of 0,1,2 ... n, where period = 0 is the time when the typhoon first appears in the forecast and period = 1 starts six hours after (when the next forecast data is issued).

- **Lead Time.** The lead time is defined as the amount of time available at a supply node in anticipation of the typhoon's impact. Depending on the typhoon's location, different supply nodes at the network can have different lead times. Supply nodes closer to the current location of the typhoon have shorter lead times than ones located farther away from the typhoon location. Objects that are not in the impacted area of the typhoon do not have a lead time - however, in moving relief goods between supply nodes, the lead times of the recipient supply node should be taken into account. Even if the source SP is not part of the impacted area, the goods should still be pre-positioned to an SP within the intended DP's lead time. Furthermore, the lead time and the time period can be related. For example, for a supply node that is located close to the typhoon path, if at current time period p, the lead time is 12h, then at time period p+1, the lead time is 6h, and so on. Once the lead time is 6h, then there is only 6 hours left to pre-position goods at at supply node.

- **Finalization of Pre-positioning Action.** At a given time period, the optimization model will generate the robust set of LDCs and the amount of goods to be pre-positioned in them, given the scenarios evaluated at that time period. However, these results are mainly suggestions for the decision maker. The decision maker can choose to still wait for the next period to get a more accurate forecast information. The decision maker can also decide to finalize/perform the pre-positioning action for the supply points that have much shorter lead times. The decision of whether to finalize a pre-positioning action at a certain time period is dependent on the decision maker's criteria and strategy. Given the short lead times for pre-positioning and the potentially large amount of time needed to conduct a pre-positioning action, an executed pre-positioning action is considered final and irreversible. If there are still supply points which are not finalized at the next time, then the optimization calculation again takes place and will suggest the new robust configuration of LDCs based on the new forecast and at the same time accounts for the location of the goods that are already finalized. The task of the decision maker is completed when all the supply points resulting from the optimization is finalized.

Appendix B

Network Data

The following tables are the network data points which were used for this study. Depending on the geographical scope of the analysis, the relevant municipalities/cities are selected.

Table B.1: DP/LDC Location for Case 1 and 2

Code	Municipality	Province	Region	lon	lat	District	Pop
63001000	AJUY	ILOILO	R VI	123.02	11.15	5th	47248
63002000	ALIMODIAN	ILOILO	R VI	122.39	10.85	2nd	37484
63003000	ANILAO	ILOILO	R VI	122.74	10.99	4th	27486
63004000	BADIANGAN	ILOILO	R VI	122.54	10.99	3rd	26218
63005000	BALASAN	ILOILO	R VI	123.08	11.46	5th	29724
63006000	BANATE	ILOILO	R VI	122.80	11.03	4th	29543
63007000	BAROTAC NUEVO	ILOILO	R VI	122.72	10.91	4th	51867
63008000	BAROTAC VIEJO	ILOILO	R VI	122.86	11.07	5th	41470
63009000	BATAD	ILOILO	R VI	123.11	11.41	5th	19385
63010000	BINGAWAN	ILOILO	R VI	122.57	11.19	3rd	13432
63012000	CABATUAN	ILOILO	R VI	122.49	10.88	3rd	54950
63013000	CALINOG	ILOILO	R VI	122.51	11.15	3rd	54430
63014000	CARLES	ILOILO	R VI	123.13	11.57	5th	62690
63015000	CONCEPCION	ILOILO	R VI	123.12	11.21	5th	39617
63016000	DINGLE	ILOILO	R VI	122.66	11.00	4th	43290
63017000	DUENAS	ILOILO	R VI	122.59	11.05	4th	33671
63018000	DUMANGAS	ILOILO	R VI	122.70	10.83	4th	66108
63019000	ESTANCIA	ILOILO	R VI	123.14	11.45	5th	42666
63020000	GUIMBAL	ILOILO	R VI	122.31	10.68	1st	32325
63021000	IGBARAS	ILOILO	R VI	122.25	10.74	1st	31347
63022000	ILOILO CITY	ILOILO	R VI	122.56	10.71	lone	424619
63023000	JANIUAY	ILOILO	R VI	122.47	10.98	3rd	63031
63025000	LAMBUNAO	ILOILO	R VI	122.49	11.07	3rd	69023
63026000	LEGANES	ILOILO	R VI	122.60	10.79	2nd	29438
63027000	LEMERY	ILOILO	R VI	122.92	11.23	5th	27441
63028000	LEON	ILOILO	R VI	122.35	10.81	2nd	47522
63029000	MAASIN	ILOILO	R VI	122.43	10.91	3rd	35069
63030000	MIAGAO	ILOILO	R VI	122.20	10.67	1st	64545
63031000	MINA	ILOILO	R VI	122.58	10.94	3rd	21785
63032000	NEW LUCENA	ILOILO	R VI	122.58	10.87	2nd	22174
63034000	OTON	ILOILO	R VI	122.47	10.72	1st	82572
63035000	PASSI CITY	ILOILO	R VI	122.64	11.15	4th	79663
63036000	PAVIA	ILOILO	R VI	122.54	10.77	2nd	43614
63037000	POTOTAN	ILOILO	R VI	122.64	10.93	3rd	70955
63038000	SAN DIONISIO	ILOILO	R VI	123.09	11.32	5th	33650
63039000	SAN ENRIQUE	ILOILO	R VI	122.70	11.09	4th	32422

Table B.1: DP/LDC Location for Case 1 and 2

Code	Municipality	Province	Region	lon	lat	District	Pop
63040000	SAN JOAQUIN	ILOILO	R VI	122.09	10.59	1st	51645
63041000	SAN MIGUEL	ILOILO	R VI	122.47	10.78	2nd	25013
63042000	SAN RAFAEL	ILOILO	R VI	122.84	11.16	5th	14655
63043000	SANTA BARBARA	ILOILO	R VI	122.54	10.82	2nd	55472
63044000	SARA	ILOILO	R VI	123.01	11.27	5th	46889
63045000	TIGBAUAN	ILOILO	R VI	122.38	10.71	1st	58814
63046000	TUBUNGAN	ILOILO	R VI	122.30	10.79	1st	21540
63047000	ZARRAGA	ILOILO	R VI	122.63	10.83	2nd	23693

Table B.2: DP/LDC Locations for Case 3

Code	Province	District
60416000	AKLAN	lone
60604000	ANTIQUE	lone
61912000	CAPIZ	1st
61916000	CAPIZ	2nd
67902000	GUIMARAS	lone
63020000	ILOILO	1st
63047000	ILOILO	2nd
63023000	ILOILO	3rd
63017000	ILOILO	4th
63044000	ILOILO	5th
63022000	ILOILO	lone
64505000	NEGROS OCCIDENTAL	1st
64504000	NEGROS OCCIDENTAL	2nd
64508000	NEGROS OCCIDENTAL	3rd
64525000	NEGROS OCCIDENTAL	4th
64514000	NEGROS OCCIDENTAL	5th
64507000	NEGROS OCCIDENTAL	6th
64501000	NEGROS OCCIDENTAL	lone

Table B.3: DP/LDC locations for Case 4

Code	Municipality	Province	District
60407000	KALIBO	AKLAN	lone
60613000	SAN JOSE	ANTIQUE	lone
87808000	NAVAL	BILIRAN	lone
71242000	TAGBILARAN CITY	BOHOL	1st
61914000	ROXAS CITY	CAPIZ	1st
72217000	CEBU CITY	CEBU	2 LD
82604000	BORONGAN CITY	EASTERN SAMAR	lone
67902000	JORDAN	GUIMARAS	lone
63022000	ILOILO CITY	ILOILO	lone
83747000	TACLOBAN CITY	LEYTE	1st
64501000	BACOLOD CITY	NEGROS OCCIDENTAL	lone
74610000	DUMAGUETE CITY	NEGROS ORIENTAL	2nd
84805000	CATARMAN	NORTHERN SAMAR	1st
76106000	SIQUIJOR	SIQUIJOR	lone
86407000	MAASIN CITY	SOUTHERN LEYTE	lone
86005000	CATBALOGAN CITY	WESTERN SAMAR	2nd

Appendix C

Interview Transcripts

C.1 Interview 1: DSWD Officer

The interview with the DSWD Officer is conducted in the local language Hiligaynon. The important aspects of the interview are summarized in this section.

I would like to know the capacity of DSWD VI to respond to typhoons. How many temporary facilities can the DSWD regional office manage when a typhoon hits?

The first responder is the Barangay, then the Municipal, then the Provincial. Each of them have pre-positioned goods. The Regional office only responds to the request of the LGUs that need augmentation.

So the pre-positioned goods are not necessarily provided by the regional office? According to the report I have read about Typhoon Domeng, there were a lot of goods pre-positioned outside of the Field Offices

We have our own pre-positioned goods stationed at the field office. What happens sometimes is that we are more proactive in giving food packs than the LGUs themselves. Or they request immediately that's why the pre-positioned goods from the Field Offices are distributed first.

As of now we have 30,000 pre-positioned goods. That is the required amount per field office. The preparations of the FFPs are mechanized now. There is one in the central office (Manila) and Cebu. We can produce 50,000 FFPs per day.

So how many potential facilities can serve as potential locations for pre-positioned goods in the region?

Usually municipal gyms and multi-purpose halls are used to store the goods. Sometimes, in the absence of covered gymns, schools are used if there are no evacuees present. There is always FO staff that works with the LGU personnel. We have Quick Response Teams for every town which are composed of field staff of different national programs implemented at the LGU level. But they are under the regional office.

So simultaneously, can the FO handle 1 location per municipality?

It ranges from 5-15 staff of the FO, the Quick Response Team in every LGU. Yes, the FO can handle 1 location per municipality.

When you set up a distribution center for relief goods, is there setup cost incurred?

The LGU that receives the pre-positioned goods is in charge. The FO only delivers to the operation center per LGU. The FO request trucks from the provincial level or the LGU to transport the goods to the LGU.

If the LGU has no capacity, then FO will augment right?

The province augments first before the FO.

Based on your perception, which is the most important for DSWD when it comes to relief operations: maximize the number of people helped, efficiency of operations, or minimize the cost?

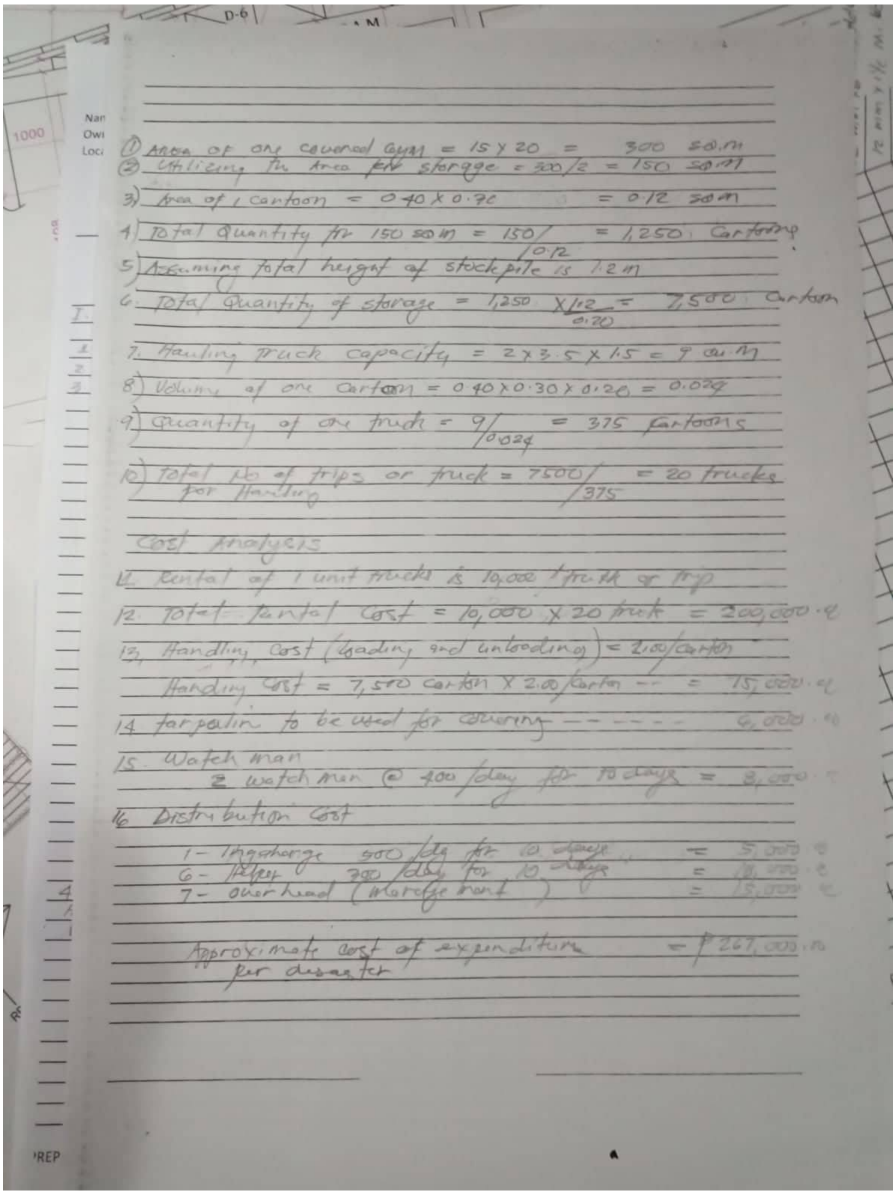
The priority is to first safekeep the goods, then its the efficiency and then last is cost. When i think about it, it goes along our tagline of "Efficient and Caring Response". I can send some materials that I have relating to the disaster response for your additional reference.

C.2 Interview 2: Civil Engineer and Contractor from Region VI

The interview was conducted in the another local language, Kinaray-a, thus the interview is translated to English.

I am trying to estimate how much relief goods can be pre-positioned in a municipal covered court. I was wondering, based on your estimate, how much goods can fit? Ballpark estimates will do.

I will try to get you an estimate on paper. Let me get back to you.


1) Area of one covered gym = 15 x 20 = 300 sq.m
2) Utilizing the Area for storage = 300/2 = 150 sq.m
3) Area of 1 cartoon = 0.40 x 0.30 = 0.12 sq.m
4) Total Quantity for 150 sq.m = 150/0.12 = 1,250 Cartoons
5) Assuming total height of stockpile is 1.2 m
6. Total Quantity of storage = 1,250 x 1.2/0.20 = 7,500 Cartoons
7. Hauling truck capacity = 2 x 3.5 x 1.5 = 9 cu.m
8) Volume of one Cartoon = 0.40 x 0.30 x 0.20 = 0.024
9) Quantity of one truck = 9/0.024 = 375 Cartoons
10) Total No. of trips or truck for Hauling = 7500/375 = 20 trucks

Cost Analysis
11. Rental of 1 unit trucks is 10,000 / truck or trip
12. Total Rental Cost = 10,000 x 20 truck = 200,000.00
13. Handling Cost (loading and unloading) = 2.00/carton
Handling Cost = 7,500 carton x 2.00/carton = 15,000.00
14 Tarpaulin to be used for covering = 6,000.00
15. Watch man
2 watch man @ 400/day for 10 days = 8,000.00
16 Distribution Cost
1 - Incharge 500/day for 10 days = 5,000.00
6 - Helper 300/day for 10 days = 18,000.00
7 - overhead (Management) = 15,000.00

Approximate cost of expenditure per disaster = ₱267,000.00

Figure C.1: Ballpark Quote Obtained from Interviewee

According to your estimates, the max capacity of the municipal gym is 7500. Is it feasible to set up 7,500 FFPs in a municipal gym within a day?

If one truck needs 6 laborers and can unload 3 trucks in one day, then you would need 42 laborers to finish the task within 8 hours.