Modeling of Stock Pre-positioning and Distribution Planning to Support Disaster Relief Response

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Modeling of Stock Pre-positioning and Distribution Planning to Support Disaster Relief Response

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Chapter 1

Introduction

1.1 Overview

Research in the area of Disaster Operations Management (DOM) has gained more popularity in recent years. As defined by Altay and Green (2006), disaster operations are set of activities that are performed before, during, and after a disaster with the goal of preventing loss of human life, reducing its impact on the economy, and returning the state of normalcy. Based on this definition, preventing loss of human life can be considered as the most important goal and indicator that determine the success of the operations itself. As stated by Galindo and Batta (2013), the International Federation of Red Cross and Red Crescent Societies (IFRC) records some of the most memorable destructive events related to disasters which include the World Trade Canter attacks in 2001, the earthquake and tsunami in Indonesia in 2004, hurricane Katrina in 2005, and the Haiti earthquake in 2010. The IFRC estimates there are 1,105,352 casualties, and 2,550,272,267 of affected people. These numbers increase every time a new major disaster strikes, such as the Tohoku earthquake and tsunami in 2011, and the most recent one, the Nepal earthquake in 2015. The massive numbers of casualties and people affected by these disasters indicate the urge and importance of studies in the area of DOM.

Altay and Green (2006) mention that there are four programmatic phases in disaster management: mitigation, preparedness, response, and recovery. According to a review conducted by Galindo and Batta (2013), the authors stated that response phase, followed by preparedness phase and then mitigation phase are found to be the most common types of research contributions in DOM between the timeframe 2005–2010. They also mention that DOM has become a highly active field in OR/MS, which means that the diverse OR/MS techniques, including facility location analysis, stock pre-positioning analysis, and transportation planning or routing problems may be applied to the different stages of DOM.

Natural disaster such as earthquake or tsunami however, is notorious for its uncertainty factors. Even in this modern age, it is very difficult or nearly impossible to predict the exact time of occurrence of a disaster and the extent of the area hits by a disaster. According to Beamon (2004), this research area has additional complexity and unique challenges since the demand is unpredictable and suddenly occurs in large amounts with short lead times for a wide variety of supplies. There are also high stakes associated with the timeliness of deliveries and the lack of resources in terms of supply, people, technology, transportation capacity, and money. Therefore, it is very challenging to conduct researches in the area of DOM, particularly researches related to disaster logistics. Thus, in this thesis, preparedness phase is set to be the main focus, while optimization methods are used in developing new models of stock pre-positioning and distribution (routing) problems. The models are particularly developed to help the government and/or decision maker to prepare and response quickly as the disaster strikes.

In this chapter, we will introduce and discuss the concepts of disaster logistics, stock pre-positioning and distribution (routing) problem. Additionally, we will present literatures related to DOM that impact and contribute to our research. This chapter is organized as follows: In section 1.2, we will introduce the basic concept of disaster relief logistics. In section 1.3, we will discuss the concept of stock pre-positioning problem in order to support emergency response and present the concept of an extended model of stock pre-positioning by taking facility disruptions into account. In section 1.4, we will discuss the concept of distribution (routing) planning. In section 1.5, we will present the motivation of our study and a brief concept of optimization modeling in stock pre-positioning and distribution planning. In section 1.6, we define the objective of this thesis. In section 1.7, we present the outline of this thesis.

1.2 Disaster Relief Logistics

Disasters are inevitable. Natural disasters (such as earthquake, tsunami, flood, hurricane, etc), man-made disasters (such as war, terrorism, etc), disease and extreme poverty at any point in time are to be found somewhere in the world (Maspero and Ittmann, 2008). Disaster Operations Management (DOM) covers these large areas of disaster classification. The most important goal of DOM is to prevent or minimize human suffering and loss of human life.

As defined by Altay and Green (2006), and Galindo and Batta (2012), there are four main phases of DOM: 1. Mitigation phase, 2. Preparedness phasee, 3. Response phase, and 4. Recovery phase. Each phase has it own unique challenges which need to be planned and programmed carefully. Figure 1.1 shows the details of each phase. In this thesis, we focus on preparedness phase, more specifically on developing strategies of emergency planning in the event of a natural disaster. Emergency planning in this context is strictly related to disaster relief logistics planning.

In a workshop with humanitarian organizations, Thomas and Mizushima (2005) define humanitarian or disaster logistics as the process of planning, implementing and controlling the efficient, cost-effective flow and storage of goods and materials, as well as related information, from the point of origin to the point of consumption for the purpose of meeting the end beneficiary's requirements. The characteristics of disaster logistics are presented by Beamon (2004) in Fig. 1.2. Compared to its counterpart, commercial logistics which has a relatively stable demand patterns and well-defined information, disaster logistics seem much more complex and agile.

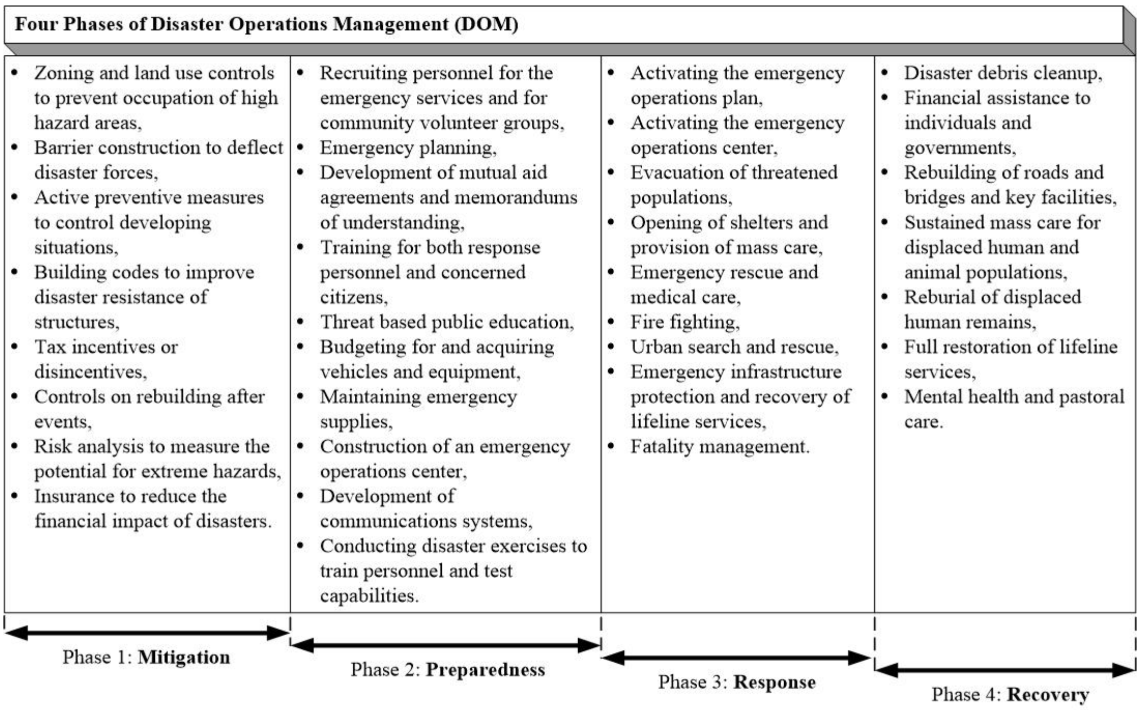

Figure 1.1 Four Phases of DOM (Altay and Green, 2006)

Decker (2013) mentions that the decision makers in disaster relief operations are facing complex problems of the unknown and unpredictability in the humanitarian sector. They don't know when, where, what, how much, where from and how many times demand is required in the early days of the post disaster response. These thoughts raise an alarm to continue the work of improving disaster relief planning and management. The methods on how to provide relief supplies and distribute them quickly and efficiently to the affected areas are some of the important issues in DOM that needs to be discussed further.

In essence, disaster relief planning also depends on the availability of budgets. Without enough budgets provided by the governments and/or non-government sectors, the operations will face many obstacles; one of them is the shortage of critical items to be transported to specific disaster areas. But unfortunately, not all governments in all countries can provide enough budgets to support emergency relief response. In such cases, some scenarios are needed to be developed and analysed prior to the disasters.

Humanitarian or Disaster Relief Logistics	
Demand Pattern	Demand is generated from random events that are unpredictable in terms of timing, location, type, and size. Demand requirements are estimated after they are needed, based on an assessment of disaster characteristics.
Lead Time	Approximately zero lead times requirements (zero time between the occurrence of the demand and the need for the demand), but the actual lead time is still determined by the chain of material flow.
Distribution Network Configuration	Challenging due to the nature of the unknowns (locations, type and size of events, politics, and culture), and "last mile" considerations.
Inventory Control	Inventory control is challenging due to the high variations in lead times, demands, and demand locations.
Information system	Information is often unreliable, incomplete or non-existent.
Strategic Goals	Minimize loss of life and alleviate suffering.
Performance Measurement System	Primary focus on output performance measures, such as the time required to respond to a disaster or ability to meet the needs of the disaster (customer satisfaction).
What is "Demand"?	Supplies and people.

Figure 1.2 Characteristics of disaster relief logistics (Beamon, 2004)

1.3 Stock Pre-positioning in DOM

1.3.1 Background

Galindo and Batta (2012) review that mathematical programming is still the most preferred methodology in DOM. Basically, there are three major issues that have been discussed by most of the papers focus in mathematical models related to disaster logistics operations. One of the most important issues is stock pre-positioning problem.

Stock pre-positioning involves preparing critical relief supplies in strategic locations and determining the amount of demand to be released in disaster areas. Hale and Moberg (2005) mention that rather than waiting passively for a situation of crisis to occur somewhere in the world to launch humanitarian operations, it is better to show pro-activity by mobilizing supplies or other material and non-material resources in anticipation. According to Beamon (2004), many issues are need to be focused in pre-positioning stage; including budget limitation, limited number of distribution centers and limited capacity for each distribution center. In addition, the demand is uncertain. Once the disaster happens in one location, demand is requested, and demand must be transported efficiently into the disaster area. Because in disaster relief case, the demands are lumpy and occur suddenly, that the locations are completely unknown until the demand occurs.

In some cases, where the distribution center has not yet existed, it is necessary to determine the best location of each distribution center, the optimum number of distribution center that needs to be opened, and the maximum capacity of each distribution center. OR/MS technique such as facility location analysis can be applied to deal with these problems. Hale and Moberg (2005) suggest that emergency supplies need to be located in a manner as to not be vulnerable to attack. But, they need to be close to the areas to which they are assigned to serve. Therefore, it may fall in dilemma: how is the best way to locate an emergency resource within the supply chain to serve specific areas without being vulnerable itself.

Recently, literatures related to stock pre-positioning in DOM are increasing and can be found conveniently. The work of Balcik and Beamon (2008) integrate facility location and inventory decisions. Their model integrates facility location and inventory decisions. They consider multiple items, and captured budgetary constraints and capacity restriction of distribution centers. They also provide the simulation of pre- and post-disaster relief funding on relief system’s performance. Another work by Mete and Sabinzky (2010) proposes a two stage stochastic programming approach for disaster preparedness which is consist of warehouse selection and inventory decisions, and transportation plans and demand satisfaction decisions. Instead of using the traditional OR/MS techniques, some authors prefer to build new heuristic algorithms and solve the problems using tools such as CPLEX, C++ or C# (Murali et al., 2012; Lin et al., 2011; Sha and Huang, 2012; Verma and Gaukler, 2015).

1.3.2 Stock Pre-positioning under Facility Disruptions

There are many potential threats that can lead to facility disruptions. Disaster, either natural or man-made disaster, is one of the threats that can cause serious breakdown of logistics systems. In a special case of stock pre-positioning model when it takes facility disruptions into account, further investigations of the probability of occurrence of a disaster and the probability of a disruptions scenario are needed.

Although papers related to this specific topic are still limited, recently, several authors have managed to publish some interesting papers that focus on logistics design under the risk of facility disruptions. For example, Qin et al. (2013) create a fortification planning model for capacitated logistics systems in a two-stage stochastic mixed-integer programming framework. In their model, the operating facilities are susceptible to accidental disruptions. Once a facility is hit by disruptions, the disrupted facility is completely inoperable throughout its entire recovery time so that customers assigned to it must be emergently reassigned to any non-disrupted facility that has enough excess capacity to accommodate the additional demand. They estimate the probability of disruptions scenario by historic data and forecast of experts. They also use one specific parameter to indicate whether a facility is hit in some scenarios. If a facility fails, this specific parameter is equal to 1 and otherwise 0. To solve the large-scale problems, they use alternative methods based on decomposition (D2-BAC) and run the model on CPLEX.

Another work presented by Hatefi and Jolai (2014) propose a robust and reliable mixed-integer programming model for an integrated forward-reverse logistics (IFRL) network design, which simultaneously takes uncertain parameters and facility disruptions into account. The authors use a robust criterion to obtain the reliable counterpart model of the IFRL network. In their model, a set of facilities may be simultaneously disrupted in each scenario. The augmented robust are developed to control the reliability of the proposed model among disruption scenarios. Furthermore, two alternatives objective functions are considered, which minimize the expected scenario costs and the nominal costs. The problems are solved using GAMS/CPLEX.

Sawik (2014) recently presents the coordinated supplier selection, order quantity allocation and customer order scheduling for single and multiple sourcing strategies to optimize worst-case performance of a supply chain under various types of disruption risks. The author stated that the suppliers are located in different geographic regions and the supplies are subject to different types of disruptions. For any combination of suppliers hit by different types of disruptions, a formula for calculating the corresponding disruption probability is developed. The obtained combinatorial stochastic optimization problem is formulated as mixed-integer program with conditional value-at-risk as a measure. The computational experiments are preformed using the AMPL programming language and run by CPLEX and Gurobi solvers.

1.4 Distribution Planning in DOM

Two key issues in the immediate response stage correspond to: 1) the design of relief distribution systems focuses on the flow of relief supplies into a disaster affected zone, and 2) the design of evacuation systems (Khrisnamurty et al., 2013). Rachaniotis et al. (2013) state that for humanitarian organizations, setting up an efficient supply chain in general and more specifically a last mile distribution network is always a complex operation after a man-made or a natural disaster.

Unlike logistics managers in the private sector, humanitarians face difficulties due to their operations' nature. In addition, even with accurate data, both demand and supply can vary significantly during the response operation period. Unexpected events also force resources to move out of one operation field and head off to another, even overnight.

Rachaniotis et al. (2013) also mention that the first three days after the disaster are crucial and during them supplies arrive to the operation field by air, by land or by sea from abroad as quickly as possible. Then, during the next three months approximately, it is a balancing effort between effectiveness in helping people and minimizing cost, considering that development programs operations may continue in parallel. de La Torre et al. (2012) state that disaster relief presents many unique logistics challenges, with problems including damaged transportation infrastructure, limited communication and coordination of multiple agents. The authors review several papers related to disaster relief routing and found that a common trend in making allocation decisions is to prioritize the needs of the most vulnerable populations.

Hamedi et.al. (2012) formulate routing and scheduling of humanitarian supply transportation to minimize the total cost which is composed by travel time, travel distance, risk exposure and risk accumulation costs. The authors also consider the reliability, cost, average response time and the arrival time of the first vehicle (in this case, the authors use trucks to deliver supplies to demand points) to make an optimum plan of the deployment of disaster response fleet. They suggest that the response time may increase rapidly if some routes become partially or completely unavailable due to the uncertainty in road conditions.

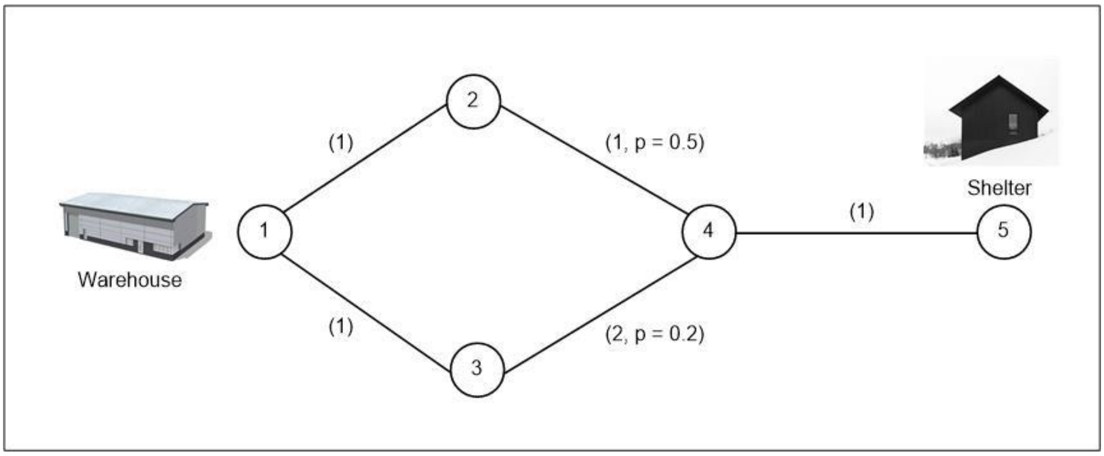

Figure 1.3 A simple humanitarian response network (Hamedi, 2012)

Figure 1.3 shows the sample network illustration. In this figure, two disaster response vehicles (trucks) need to ship supplies from the origin node 1 to destination node 5. The authors state that when all links are available (not damaged by the disaster), the cost of path 1-2-4-5 is 3 and the cost of path 1-3-4-5 is 4. Hence, it is easy for the decision maker to choose the shortest path for truck deployment. By considering probability of link failure, the model becomes more complex. The authors then assume that the link failure probabilities in their model are independent. These failures cannot be discovered in advance.

Lin et al. (2011) develop a multi-objective logistics model that considers a muti-item, multi-period, multi-vehicle, soft time windows and split delivery strategy. In their model, a multi-objective tour based integer-programming formulations is constructed. Minimization of the total unsatisfied demand (particularly for critical items), the total travel time for all tours, the total travel time for all vehicles and the difference in the satisfaction rate between nodes, become the objectives of their model. To aggregate the multi-objective formulations to a single objective formulation, they apply the weighted sum method. They also propose two strategies to overcome the difficulties in solving problem with large-scale numbers of tours.

The first strategy is to use only a subset of all possible tours iteratively to solve the model, while the second strategy allows the whole problem to be decomposed into several sub-problems and be solved in parallel. The first strategy is built based on a Genetic Algorithm (GA), while a decomposition and assignment heuristic approach is proposed for the second strategy. Based on this study, we realize that a distribution (routing) problem with massive numbers of tours can be very difficult to deal with. Thus, building a proper algorithm can be necessary in order to solve the problem.

Abounacer et al. (2014) focus their study on the response stage for the logistic feature, more specifically on two relevant issues: location and transportation. The location problem focuses on designing a network for distributing humanitarian aid (e.g., food, water, survival equipment and medical goods), while the transportation problem discusses the distribution of humanitarian aid from Humanitarian Aid Distribution Centers (HADC) to demand points. Since both problems are solved simultaneously, the problem is then considered as a location-transportation problem.

Therefore, the authors present a multi-objective emergency location-transportation problem with three main objectives: to minimize the sum of all transportation durations, to minimize the number of agents needed to operate the opened HADCs, and to minimize the total uncovered demand. An epsilon-constraint method is proposed to solve the problem.

1.5 Motivation of the Study

1.5.1 Motivation of the Study of Optimization Models in Stock Pre-positioning

Balcik and Beamon (2008) develop a model which is a variant of the maximal covering location model. Their model determines the number and locations of distribution centers in a relief network and the amount of relief supplies to be stocked at each distribution. Their mathematical models however, do not include a set of potential response time of a distribution center to provide service in the specific disaster area.

Few years later, the work of Lee et.al. (2011) includes this set of potential response time into the model. Their model simultaneously determines the decision of distribution centers to cover a single disaster area and the amount of supplies to be stocked in each distribution center. By using their model, the result of the proportion of relief demand satisfied for one of the critical items is zero due to its higher price and larger size per unit compared to another items. In a real system, this zero result is not acceptable since some amounts of critical items should be stored in distribution centers. In order to solve this problem, in this thesis we propose a new two-stage mathematical model. Stage I is to minimize the lower bound of the proportion of unsatisfied relief demand, while Stage II is to maximize the amount of critical items covered in each distribution center by inputting the optimum results of stage I. The details of this work can be seen in Chapter 2.

In addition, we apply our model to Indonesia and perform sensitivity analysis by changing the value of its important parameter. Meanwhile, some authors focus on minimizing the costs; Lin et al. (2011) build a multi-objective logistics model with one of the objectives is to minimize the penalty cost of unsatisfied demand; Mete and Zabinsky (2010) present a warehouse selection and inventory decisions model that minimize the total cost of operating warehouses.

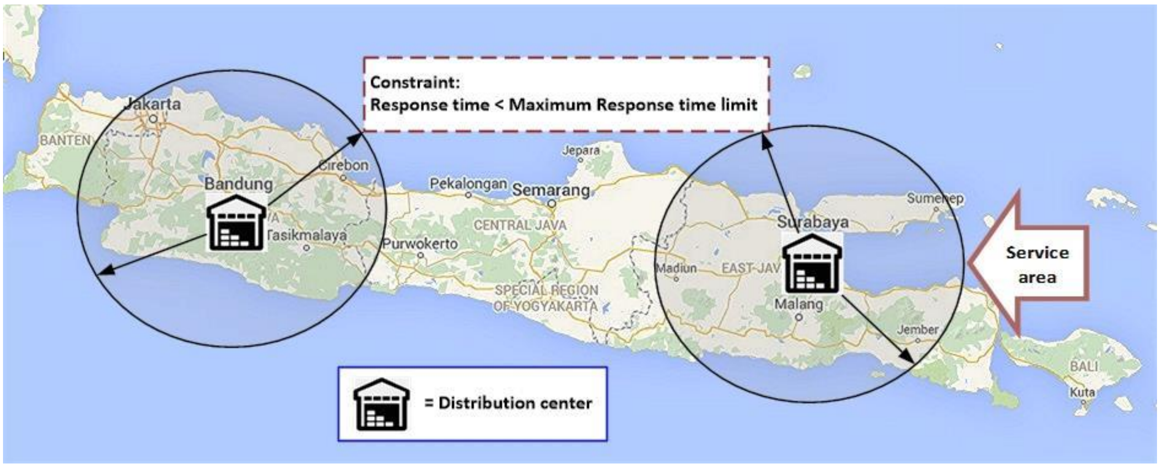

Figure 1.4 Time constraint: the assignment of service area for each distribution center

In our models, the distribution centers have been established by the government. Therefore, it is not necessary to build another new distribution center(s). First, we need to focus on determining the service area for each distribution center by considering the time limitation. Time limitation here denotes the maximum response time limit for each vehicle available in a distribution center to reach a specific disaster area. This maximum response time limit is determined by the governments and/or decision makers, and it has to be set wisely in order to minimize the loss of human life.

Figure 1.4 illustrates the concept of this time constraint where a distribution center can only serve disaster areas that located within the range of a given maximum response time limit. Instead of using time limitation as a constraint, Verma and Gaukler (2015) use distance limitation in their model which presents the two location models for large-scale emergencies that consider the impact of a disaster to the disaster response facilities and the population centers in surrounding areas.

There are some parameters that are crucial in this stock pre-positioning model. One of them is the availability of budgets. Either pre-disaster or post-disaster budget, both have important roles in determining the final results. Pre-disaster budget commonly used to purchase items to be stocked in distribution centers, to purchase vehicles, to build distribution centers, to operate distribution centers, and so on, while post-disaster budget is used to fund all activities occur during the actual emergency response following a disaster. In some cases, these budgets (or costs) can be the main focus of study.

In some of our stock pre-positioning models, we add a new parameter of the number of vehicles available in each distribution center. This parameter can be crucial since the less the number of vehicles available, the less the number of critical items can be distributed to disaster area(s). We also add the expected satisfied relief demand in a specific disaster area as a parameter. This parameter forces the number of critical items to be sent to a specific disaster area is no less than its pre-determined number. Other important parameters are probability of occurrence of earthquake in a disaster area, maximum capacity of each distribution center, unit volume of each item, expected demand in each disaster area, unit weight of each item, maximum weight capacity of a vehicle and the criticality weight for each item.

In some cases, stock pre-positioning model is combined with transportation model. This joined model can give better support to the government's emergency response plan since it simultaneously generates several outputs, such as the number of items to be stocked in distribution centers and the amount of items to be delivered to each disaster area. This joined model also gives more outcomes to be analysed. Thus, in chapter 3, we extend the stock pre-positioning model presented in chapter 2 and develop a new stock pre-positioning model that considers transportation planning problem into account.

Chapter 4 presents the extended stock pre-positioning model that has been developed in chapter 3. In this chapter, we propose a new stock pre-positioning model to support emergency relief response under facility disruptions. By considering the disruption of one or more facilities (distribution centers), the model become more realistic to be applied to the real system. Some of the optimization tools that can to be used to solve the problems are GAMS, LINGO, LINDO, AMPL and Gurobi.

1.5.2 Motivation of the study of Optimization Models in Distribution Planning

The transportation of emergency relief supplies has constantly been a great challenge for years. In terms of distribution of disaster relief, various uncertainty factors such as road conditions following a disaster and the amount of emergency supplies required to be sent to the affected area is difficult to predict. In most cases, compared to using helicopter, ground vehicles such as trucks are still preferable to deliver supplies to affected areas. Normally, the decision-maker should make a quick decision whether to send a group of fully-loaded vehicles through certain routes based on incomplete information of road conditions shortly after a disaster strikes, or wait in order to gain more reliable information. Once the decision is made, it can risk human lives and health.

Chapter 5 discusses further details of our distribution model. In this proposed model, we consider transportation and vehicle purchase budgets as constraints. We realize that the governments in developing countries such as the Philippines, Indonesia or Bangladesh, who often experience disasters such as earthquakes, floods and typhoons, do not really have large budget to be allocated for emergency response. Most of these countries highly rely on NGO, INGO or even assistance from the governments of developed countries. In the field, for example in some parts of Indonesia, the local government often reduces the number of vehicles to be deployed to disaster areas quickly after a disaster occurs. Some local governments don't even have enough budgets to purchase or add new vehicles. Our intention is that this proposed model can be applied not only to the developed countries, but also to the developing countries.

Hamedi et al. (2012) address humanitarian response planning for a fleet of vehicles with reliability considerations. The authors focus on minimizing the total cost which is composed by travel distance, travel time, risk exposure and risk accumulation costs, with and without considering the probability of route failure. This method is interesting. But rather than just focus on route probability, we also focus on route availability for all possible scenarios. More precisely, first, we generate all possible scenarios based on route availability and then we calculate the probability of route available for each scenario. By analysing route availability for all possible scenarios, we are able to adapt our model to all possible situations that will occur in the real system.

Ukkusuri and Yushimito (2008) develop an approach to disaster pre-positioning problems that account for the routing of vehicles and possible disruptions in the transportation network. This means the graph has a probability of failure for some pre-selected edges. While the authors focus on finding the best location to pre-position inventories, our model which considers a single existing distribution center, focuses on maximizing the amount of each item to be delivered to the affected areas using a certain number of vehicles in a specific period of time. In addition, not only considering a single routing problem period as appear in the pre-positioning model of Ukkusuri and Yushimito (2008), we propose a multi-period distribution model. The situation of route recovery can be considered in this multi-period distribution model. Hence, our model is more realistic to be applied to the real system.

To develop a distribution model that can demonstrate a large-scale observation to all possible scenarios, an algorithm is built to generate all possible path combinations. This algorithm gives results of the available routes and the probability of route availability for each scenario. These results are become the two important parameters for the next stage of mathematical modeling that will be solved using an optimization method. In this case, the mathematical model is formulated as a mixed-integer programming (MIP) model which is built to maximize the amount of each item to be delivered to disaster area(s). Other parameters to be considered are number of demand, costs (including transportation and vehicle purchasing cost), maximum capacity of a vehicle, unit weight of each item, criticality weight of each item and budgets availability. The complete discussion of this work is presented in Chapter 5 of this thesis.

1.6 Objective of the Thesis

There are four works will be discussed in each of the next four consecutive chapters. The first work develops a stock pre-positioning model with an objective to obtain the maximum number of expected relief demand covered by the existing distribution centers by preventing the result of zero proportion of relief demand satisfied under budget constraints. The second work extends the previous stock pre-positioning model that has been developed in the first work. This study considers multi-items, multi-vehicles and multi-periods with the objective to maximize the expected relief demand covered by distribution centers by considering the transportation constraints into the model.

The third work is an extension of the previous model that has been developed in the second work. This study proposes a stock pre-positioning model under facility disruptions that considers multi-items, multi-vehicles, and multi-periods. The objective is to maximize the expected relief demand covered by distribution centers by considering the transportation problem and facility disruption scenarios into the model.

The fourth work develops an independent distribution model of emergency relief supplies. The objective of this study is to simultaneously determine the maximum amount of relief supplies sent to disaster areas and the optimum number of vehicles required in distribution center by considering route availability.

Each of this study is provided with case study or illustration. Each of this study also performs sensitivity analysis by modifying the number of some important parameters or demonstrates a large-scale observation of all potential scenarios. The objective of this thesis in general is to determine the optimum amount of critical items to be covered in distribution centers and/or to be distributed to disaster area(s) in order to support the governments and decision makers to prepare and respond quickly as a disaster strikes.

1.7 Outline of the Thesis

The outline of this thesis is described as follow: In chapter 2, a stock pre-positioning model to obtain the maximum number of inventory stocked, while at the same time preventing the result of zero proportion of a single item type stored in distribution centers is developed. In this model, a new variable of proportion of unsatisfied relief demand is introduced. The proposed model is then applied to Indonesia, a disaster prone country located in Southeast Asia. The sensitivity analysis is performed to show the effect of different upper bound of the proportion of unsatisfied relief demand.

In chapter 3, we extend the previous model that has been developed in Chapter 2. This new model of stock pre-positioning simultaneously generates the maximum proportion of relief demand covered in distribution centers and the maximum amount of relief demand distributed from multiple distribution centers to a single disaster area within a certain period of time. The proposed model is applied to the same real system as in the previous chapter with some upgrades of the data. Sensitivity analysis is conducted by modifying the number of available vehicles and the total planning period in order to improve the results of proportions of relief demand satisfied.

In chapter 4, we develop a new model that integrates the decisions of the maximum proportion of relief demand covered in distribution centers, the maximum amount of relief supplies delivered to a single disaster area and the number of optimum vehicle available in distribution centers. This model is an extension of the previous model that has been proposed in chapter 3. This new model takes the risk of facility disruptions into account and is applied to Indonesia as a case study. All potential disruption scenarios are generated and analysed to improve the proportions of relief demand satisfied.

In chapter 5, we present a distribution model that considers a single distribution center, multiple disaster areas, homogenous fleet of vehicles, multi-items and multi-periods. This study integrates the transportation plans and demand satisfaction decisions by considering route availability. To understand this proposed model better, an illustration that demonstrates a large-scale observation to all possible scenarios is given.

In chapter 6, the results of this thesis are summarized and possible future works are discussed.

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Chapter 2

Stock Pre-positioning Model with Unsatisfied Relief Demand Constraint to Support Emergency Response

2.1 Introduction

In this chapter, we study a two-stage stock pre-positioning model to prevent the zero proportion of relief demand satisfied of disaster areas. This chapter is organized as follows: First, we introduce the literatures related to this study and state the objective of our study. Second, we formulate the two-stage mathematical model. Third, we describe the real system and the data used in this model. Finally, we present the computational results of the proposed model and provide the sensitivity analysis to show the effect of different upper bound of the proportion of unsatisfied relief demand.

2.2 Literature and Objective

Disaster management covers large area of disasters classification. Amin and Markus (2008) mention that disasters are classified to natural disasters and technological disasters, or complex emergencies. Disaster Management that covers natural disasters, including earthquake, is required to identify hazard prone and formulate actions that should be prioritized. In the previous year, Whybark (2007) explains the importance of the management of disaster relief inventories. The author also describes the characteristic of disaster relief inventories and shows the significant differences between disaster relief and enterprise inventories. As mentioned in Chapter 1 section 1.3, pre-positioning is one of the major issues to be concerned in disaster logistics operations. Pre-positioning involves preparing critical relief supplies in strategic locations and determining the amount of demand to be released in disaster areas.

Literature related to stock pre-positioning problem have been observed. Ozbay and Ozguven (2007) concern an efficient and quick-response humanitarian inventory management model which can determine the safety stock that will prevent disruptions at a minimal cost. While almost at the same time, Tovia (2007) builds an emergency response model (ERM) that can be used to evaluate response capabilities, to assess the logistics challenges in the event of natural disaster, specifically hurricane, and to perform what-if analysis on the threat of a weather disturbance system. Chang *et al.* (2007) apply the data processing and network analysis functions of the geographic information system to estimate the possible locations of rescue demand points and the required amount of rescue equipment for flood emergency logistics.

Three years later, Gatignon et al. (2010) evaluate the decentralized supply chain's performance in responding to humanitarian crises through an analysis of the International Federation of the Red Cross (IFRC)'s operations during the Yogyakarta earthquake in 2006. Just by a year, Lin et al. (2011) propose a complex logistics model for disaster relief operations. They focus on minimization of total penalty cost of unsatisfied demand, especially for high priority items, and provide a real-world earthquake scenario.

Raftani-Amiri et al. (2010) conduct a multi-period supply network research. They consider multiple food products with time windows on condition that the customer will be served only by one supplier in different time periods. Later, Kähkönen (2011) demonstrates that a proper case study can be conducted in the research field of supply management. The author also emphasizes how the validity and reliability of the case study can be evaluated. Ozguven and Ozbay (2013) develop a humanitarian emergency management framework based on the real-time tracking of emergency supplies and demands through the use of RFID technology integrated. They concern a multi-commodity stochastic humanitarian inventory management model (MC-SHIC) to determine the optimal emergency inventory levels at the minimal cost.

The previous work of Lee et al. (2011) simultaneously determine the decision of distribution centers to cover a single disaster area and the amount of supplies to be stocked in each distribution center. They carefully consider the response time needed for each existing distribution center to serve one or more disaster areas. In their model, the distribution centers have been established by the government and each distribution center is located in a single disaster area. By using their model, the result of the proportion of item type G (tent) is zero due to its higher price or larger size per unit compared to another items. The result eventually changes (no longer zero) when maximum response time is increased rapidly and each budget is multiplied by ten.

Changing the budgets, however, is inappropriate since the budgets are predetermined by the government. In a real system, this result of zero proportion of some critical items could not be tolerated. To support emergency relief response, all critical items should have some amounts to be stocked in distribution centers.

To solve this problem, we propose our new two-stage model. In order to obtain the maximum number of inventory stocked, while at the same time preventing the result of zero proportion of a single item type stored in distribution centers, a new variable of proportion of unsatisfied relief demand is introduced. In the first stage, we use an approach to minimize the lower bound of the proportion of unsatisfied demand of each item under given budgets. Furthermore, we generate the upper bound of the proportion of unsatisfied demand. In the second stage, by using the optimum results from the previous stage as inputs, we maximize the total expected relief demand satisfied by considering the new variable of the proportion of unsatisfied demand.

This proposed model is applied to the same real system as in the previous work of Lee et al. (2011), by also maintaining the same data estimation for each parameter. The objective of this study is to obtain the maximum number of expected relief demand covered by the existing distribution centers by preventing the result of zero proportion of relief demand satisfied under budget constraints.

2.3 Model Formulation

Each distribution center is located in a single disaster area, and each distribution center can provide service in one or more disaster areas. The same assumption is also used in this model that the earthquake will not occur at the same time in multiple disaster areas.

Data set:

i = disaster area;

j = distribution center;

J^i = distribution center j that provide service in disaster area i;

k = item type.

Parameters:

T_{ij} expected time to satisfy relief demand in disaster area *i* from distribution center *j* (hour),

δ_i maximum response time limit to perform emergency response in disaster area *i* (hour),

u_k upper bound of the proportion of unsatisfied relief demand of item type k ($u_k = Z_k + (1 - Z_k) * m_k$), where $Z_k < u_k < 1$ and $0 < m_k < 1$,

m_k degree of importance of item type k; where $m_k = m,\ \forall k$,

P_i probability of occurrence of earthquake in disaster area *i*,

d_{ik} expected demand for item type *k* in disaster area *i* (unit),

U_j capacity of distribution center *j* (m^3),

γ_k unit volume of item type *k* (m^3),

B_0 pre-disaster budget ($),

B_1 post-disaster budget ($),

g_{jk} unit cost of acquiring item type *k* at distribution center *j* ($/unit),

c_{ijk} unit cost of shipping item type *k* from distribution center *j* to demand point *i* ($/unit),

w_k criticality weight for item type *k*; $\sum_k w_k = 1$ and $w_k \geq 0$,

M a very large positive number.

Decision variables:

f_{ijk} proportion of item type *k* relief demand satisfied by distribution center *j* that provide services in disaster area *i*,

N_{ik} proportion of unsatisfied relief demand of item type *k* in disaster area *i*,

Z_k the lower bound of the proportion of unsatisfied relief demand of item type *k*,

Q_{jk} units of item type *k* stored at distribution center *j*,

a_{ij} set of potential response time of distribution center *j* that will provide service in disaster area *i* (a_{ij}= 1; if expected time *T* is no bigger than maximum response time limit, 0 otherwise),

X_{ij} set of potential distribution center *j* to provide service in disaster area *i* (X_{ij}= 1, if distribution center *j* provides service in disaster area *i*, 0 otherwise).

2.3.1 Stage I: Generating Lower Bound of the Proportion of Unsatisfied Demand

As discussed in Chapter 1 section 1.5.1, the distribution centers have been established by the government. Therefore, it is not necessary to build another new distribution center(s) or to determine the location of new distribution center(s). Each distribution center is assigned to provide services to one or more disaster areas that located inside the range of a given maximum response time limit.

The problem consists of two stages. In this first stage, we derive the following problem (1-k) for each item type k in {1, 2,…, k}.

Objective function

$$Min = Z_k. \tag{2.1}$$

Constraints:

$$\sum_{k\in K} f_{ijk} \le MX_{ij}, \qquad \forall i\epsilon I, j\epsilon J, \tag{2.2}$$

$$\sum_{j\in J} f_{ijk} = 1 - N_{ik}, \qquad \forall i\epsilon I, k\epsilon K, \tag{2.3}$$

$$N_{ik} \le Z_k \qquad \forall i\epsilon I, \tag{2.4}$$

$$f_{ijk} d_{ik} \le Q_{jk}, \qquad \forall i\epsilon I, j\epsilon J, k\epsilon K, \tag{2.5}$$

$$\sum_{k\in K} \gamma_k Q_{jk} \le U_j, \qquad \forall j\epsilon J, \tag{2.6}$$

$$\sum_{j\in J} \sum_{k\epsilon K} Q_{jk} g_{jk} \le B_o, \tag{2.7}$$

$$\sum_{k\epsilon K} \sum_{j\epsilon J} d_{ik} c_{ijk} f_{ijk} \le B_1, \quad \forall i\epsilon I, \tag{2.8}$$

$$f_{ijk} \ge 0, \qquad \forall i\epsilon I, j\epsilon J, k\epsilon K, \tag{2.9}$$

$$N_{ik} \ge 0, \qquad \forall i\epsilon I, k\epsilon K, \tag{2.10}$$

$$a_{ij} T_{ij} \le \delta_i, \qquad \forall i\epsilon I, j\epsilon J, \tag{2.11}$$

$$a_{ij} \ge X_{ij}, \qquad \forall i\epsilon I, j\epsilon J, \tag{2.12}$$

$$\sum_{j\in J} X_{ij} \ge 1, \qquad \forall i\, \epsilon I, i \ne j, \tag{2.13}$$

$$a_{ij} \in (0,1), \qquad \forall i\epsilon I, j\epsilon J, \tag{2.14}$$

$$X_{ij} \in (0,1), \qquad \forall i\epsilon I, j\epsilon J. \tag{2.15}$$

The objective function (2.1) minimizes lower bound of the proportion of unsatisfied relief demand of each item type. Constraint set (2.2) ensures the amount of supplies sent to satisfy relief demand that only exists when the distribution center provides service in designated disaster areas. Constraint set (2.3) means that the actual demand is equal to the amount of satisfied relief demand summed with the amount of unsatisfied relief demand in a specific disaster area. Constraint set (2.4) assures that the proportion of unsatisfied relief demand does not exceed the desired lower bound limit. Constrain set (2.5) requires the inventory level at a single distribution center that is no smaller than the maximum amount of demand. Constraint set (2.6) guarantees that the amount of inventory kept at any distribution center does not exceed its capacity. Constraint set (2.7) requires that the preparedness expenditures related to provision of logistics for basic needs in emergency does not exceed the pre-disaster budget. Constraint set (2.8) means that the transportation costs to mobilize resources are less than the expected post-disaster budget. Constraint set (2.9) describes the non-negativity constraint on the proportion of demand satisfied. Constraint set (2.10) describes the non-negativity constraint of the proportion of unsatisfied demand. Constraint set (2.11) guarantees that the existing distribution center can only provide service in specific disaster area if the expected time to satisfy relief demand is no bigger than the maximum response time limit. Constraint set (2.12) guarantees that a distribution center will not provide service in specific disaster area if the expected time to satisfy relief demand is bigger than the maximum response time limit. Constraint set (2.13) assures that at least one distribution center will provide service in any disaster area. Constraint sets (2.14) and (2.15) define the binary variable of potential response time and service area for each distribution center, respectively.

2.3.2 Stage II: Maximizing the Total Expected Relief Demand Satisfied of Disaster Areas

Next, in the second stage, the objective function (2.16) is now maximizing the total expected relief demand covered by the existing distribution centers, while constraint set (2.4) is needed to be modified. Since the value of optimal lower bound of the proportion of unsatisfied relief demand has been generated in the first stage, we should be able to determine the value of the upper bound of the proportion of unsatisfied relief demand, where $u_k = Z_k + (1 - Z_k) * m_k$ and $Z_k < u_k < 1$. The new constraint set (2.19) guarantees that the proportion of unsatisfied relief demand in each disaster area is smaller than the desired upper bound limit. In spite of these two changes of objective function (2.16) and constraint set (2.19), other constraints are remaining the same as described in section 2.3.1.

Objective function:

$$Max = \sum_{i\in I}\sum_{k\in K}\sum_{j\in J^i} p_i d_{ik} w_k f_{ijk}. \qquad (2.16)$$

Modified constraints:

$$\sum_{k\in K} f_{ijk} \le MX_{ij}, \qquad \forall i\epsilon I, j\epsilon J, \qquad (2.17)$$

$$\sum_{j\epsilon J} f_{ijk} = 1 - N_{ik}, \qquad \forall i\epsilon I, k\epsilon K, \qquad (2.18)$$

$$N_{ik} \le u_k, \qquad \forall i\epsilon I, k\epsilon K. \qquad (2.19)$$

$$f_{ijk} d_{ik} \le Q_{jk}, \qquad \forall i\epsilon I, j\epsilon J, k\epsilon K, \qquad (2.20)$$

$$\sum_{k\in K} \gamma_k Q_{jk} \le U_j, \qquad \forall j\epsilon J, \qquad (2.21)$$

$$\sum_{j\epsilon J}\sum_{k\epsilon K} Q_{jk} g_{jk} \le B_o, \qquad (2.22)$$

$$\sum_{k\epsilon K}\sum_{j\epsilon J} d_{ik} c_{ijk} f_{ijk} \le B_1, \quad \forall i\epsilon I, \qquad (2.23)$$

$$f_{ijk} \ge 0, \qquad \forall i\epsilon I, j\epsilon J, k\epsilon K, \qquad (2.24)$$

$$N_{ik} \ge 0, \qquad \forall i\epsilon I, k\epsilon K, \qquad (2.25)$$

$$a_{ij} T_{ij} \le \delta_i, \qquad \forall i\epsilon I, j\epsilon J, \qquad (2.26)$$

$$a_{ij} \ge X_{ij}, \qquad \forall i\epsilon I, j\epsilon J, \qquad (2.27)$$

$$\sum_{j\epsilon J} X_{ij} \ge 1, \qquad \forall i \,\epsilon I, i \ne j, \qquad (2.28)$$

$$a_{ij} \in (0,1), \qquad \forall i\epsilon I, j\epsilon J, \qquad (2.29)$$

$$X_{ij} \in (0,1), \qquad \forall i\epsilon I, j\epsilon J. \qquad (2.30)$$

It is necessary to provide an adjustment to the model to be used in the real system. The constraint sets (2.13) and (2.26) are changed to:

$$\sum_{j\in J} X_{ij} \ge 2, \qquad \forall i \,\epsilon I_1, \qquad (2.31)$$

$$\sum_{j\in J} X_{ij} \ge 1, \qquad \forall i \,\epsilon I_0. \qquad (2.32)$$

Constraint set (2.31) assures that at least two distribution centers will provide services in disaster area that already has one existing distribution center (I_1), while constraint set (2.32) assures that at least one distribution center will provide service in disaster area with zero existing distribution center (I_0).

2.4 Data Construction

Indonesia, a developing country that is located in Southeast Asia and is considered as an earthquake-prone country, becomes the main focus in this study. At the end of year 2012, there are 33 provinces existing in Indonesia, which in this study are considered as the 33 disaster areas. In October 2010, the Indonesian governments have distributed some logistics and equipments in 16 disaster-prone areas in order to support disaster preparedness. In this study, these 16 disaster-prone areas are considered as the locations for 16 temporary existing distribution centers. Figures 2.1 and 2.2 show the map of 33 disaster areas and the location of 16 temporary distribution centers, while Table 2.1 shows the details of disaster areas, distribution centers, and item types.

The distribution centers are located in 16 different disaster areas. In this case, a distribution center serves one or more disaster areas and one disaster area is possibly served by one or more distribution centers. Commonly, disaster relief consists of many items. The items needed are very diverse and difficult to be accurately satisfied. In this study, the items are limited up to nine critical item types. These nine items are the most priority items and need to be available in each distribution center.

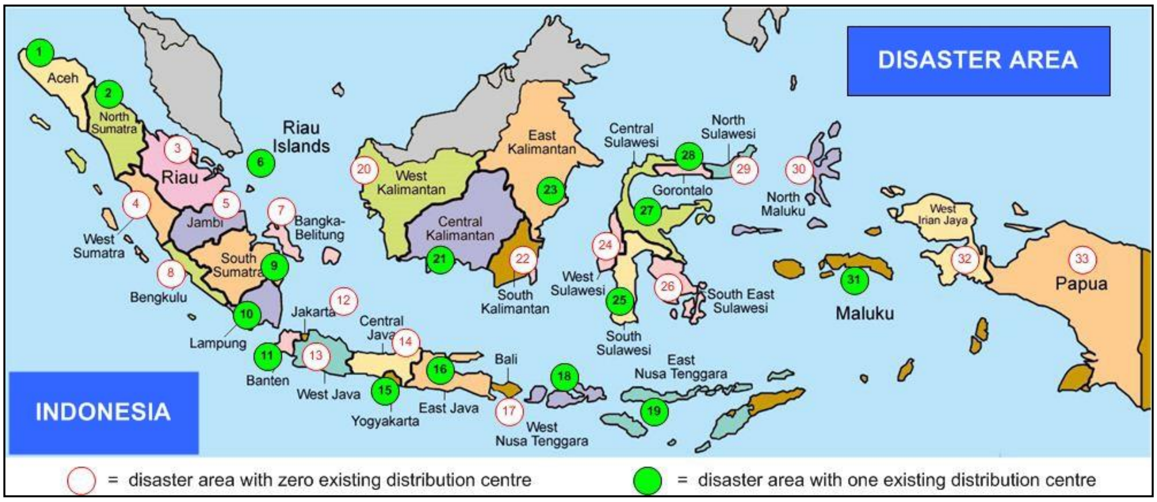

Figure 2.1 Map of 33 disaster areas

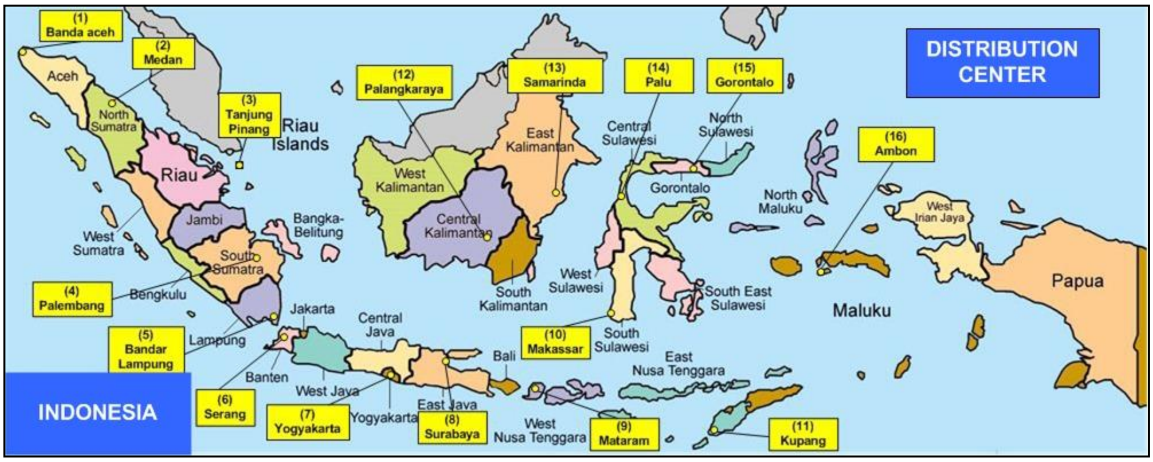

Figure 2.2 Location of 16 temporary distribution centers

Table 2.2 depicts the data estimation. The data used in this model is extensive and some of it is very difficult to be determined. Hence, for the sake of simplicity, we use approximation and/or assumption to determine some of the data. The approximate distance from a distribution center to an affected area is easily obtained by using the application of distance measurement tools provided by Google maps. Figure 2.3 shows the example of distance calculation from the distribution center 7 (Yogyakarta) to disaster area 17 (Bali) provided by Google maps. Related to the calculation of expected response time, helicopters are used to transport each item to the affected area. The expected loading time is set to be 2 hours (the same for each item). The maximum response time limit is set to be 8 hours, while in the reality this number is flexible, depends on the government policy.

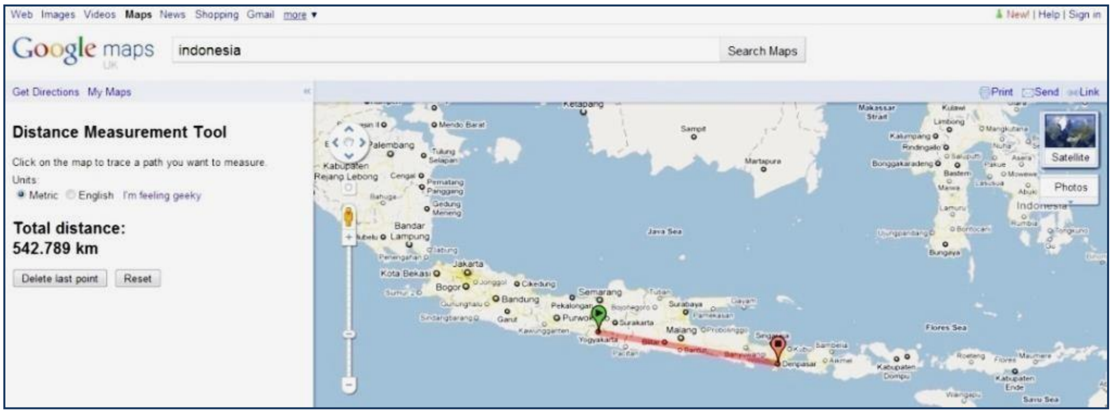

Figure 2.3 Distance measurement provided by Google maps (http://maps.google.com)

Table 2.1 Data set

Number of disaster area: 33	1. Aceh* 2. North Sumatra* 3. Riau* 4. West Sumatra 5. Jambi 6. Riau Island 7. Bangka-Belitung 8. Bengkulu 9. South Sumatra* 10. Lampung* 11. Banten* 12. Jakarta 13. West Java	14. Central Java 15. Yogyakarta* 16. East Java* 17. Bali 18. West Nusa Tenggara* 19. East Nusa Tenggara* 20. West Kalimantan 21. Central Kalimantan* 22. South Kalimantan	23. East Kalimantan* 24. West Sulawesi 25. South Sulawesi* 26. South East Sulawesi 27. Central Sulawesi* 28. Gorontalo* 29. North Sulawesi 30. North Maluku 31. Maluku* 32. West Papua 33. Papua
Number of distribution center: 16	1. Banda Aceh 2. Medan 3. Tanjung Pinang 4. Palembang 5. Bandar Lampung	6. Serang 7. Yogyakarta 8. Surabaya 9. Mataram 10. Makassar	11. Kupang 12. Palangkaraya 13. Samarinda 14. Palu 15. Gorontalo 16. Ambon
Number of item type: 9	A. Medicine (box) B. Instant food (box) C. Rice (per 50 Kg sack)	D. Drinking water (box) E. Blanket (unit) F. Clothes (packet)	G. Tent (unit) H. Mat (unit) I. Lantern lamp (unit)

*) Disaster area with one existing distribution center

The probability of earthquake for each disaster area is estimated based on the principal of 6 earthquake zones of Indonesia. These 6 earthquake zones are studied by Irsyam et al. (2010) with the result shown in Fig. 2.4. Indonesia population in year 2010 is used for the demand estimation. The capacity of each distribution center is obtained by assuming the dimension of each distribution center = 100*100*12 = 120,000 m^3. Normally, only 70% space is used for the storage. Hence, the capacity of each distribution center is 84,000 m^3.

Criticality weights are obtained by classifying all items into two groups: primary and secondary items. Primary items are set to have bigger priorities compared to secondary items. Primary items are medicine, instant food, rice, drinking water, clothes and tent, while secondary items are blanket, mat and lantern lamp. Score of 1 is given to each of primary item, while score of 0.5 is given to each of secondary item. The criticality weight of each item is calculated by dividing the criticality score of each item by the total of criticality weight of all items.

Table 2.2 Data estimation

Expected response time	(distance from distribution center to the affected area (Km)) / vehicle speed (Km/hr)) + (expected loading time (hr))
Maximum response time	Expected to be 8 hours since the earthquake (the same for each disaster area)
Probability of earthquake	Calculated based on the frequency of earthquake hit each disaster area during 2005-2010. The earthquake magnitude varies between 1.0 to 9.0 Mw.
Amount of demand	Estimated from the total population of each province in 2010.
Criticality weight	(Weight of each item type / total weight) Weight of item type A to I = 0.13, 0.13, 0.13, 0.13, 0.07, 0.13, 0.13, 0.07 and 0.07, respectively.
Volume	Unit volume of item type A to I = 0.019 m, 0.054 m^3, 0.020 m^3, 0.054 m^3, 0.009 m^3, 0.112 m^3, 0.200 m^3, 0.0562 m^3 and 0.006 m^3, respectively.
Distribution center capacity	84,000 m^3 (the same for each distribution center)
Unit cost of acquiring relief items	Purchase cost of item type A to I, respectively = $364.162, $5.780, $0.925, $3.699, $6.936, $11.561, $751.445, $8.671 and $8.092. respectively (1 USD = Rp. 8,650).
Unit cost of shipping from distribution center to the affected area	(Expected response time (hr)) x (Kerosene needed (litre/hour)) x 2 (round trip)
Maximum pre-disaster budget available	$857,317,919.075
Maximum post-disaster budget available	$116,589,595.375

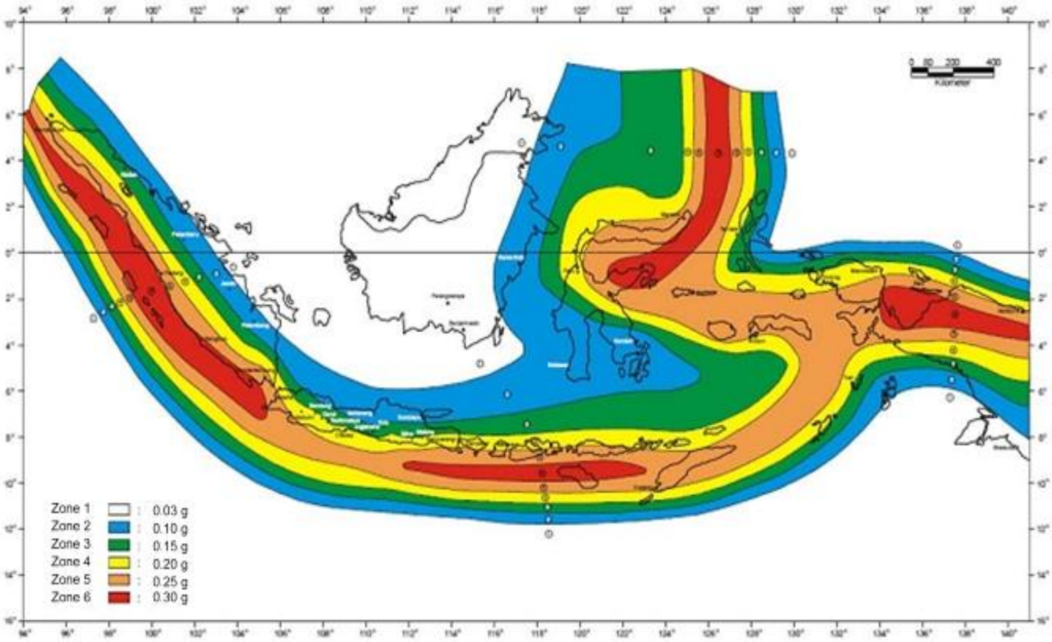

Figure 2.4 Indonesia's earthquake map (Irsyam et al., 2010)

Unit cost of acquiring relief item is estimated from the purchase price of each item. To calculate the unit cost of shipping, it is necessary to assume the maximum load of helicopter. The maximum load of medium size of helicopter can be assumed to be 6.23 m^3 for one way trip. It is also important to be noticed that pre-disaster and post-disaster budgets are predetermined by the government. In this study, maximum pre-disaster and post-disaster budgets are adapted from the budget allocation for preparedness and emergency response programs in year 2010-2014 estimated by the Indonesian government (Republic of Indonesia. Indonesian National Board for Disaster Management, 2010).

2.5 Computational Results and Analysis

LINGO 8.0 is used for finding the optimal solutions with the mathematical model presented in section 2. All experiments solving each problem are tested on a personal computer with an intel® Core^{TM} 2 Duo CPU 2.93GHz and 2.00 GB of RAM. The computation time of all the test problems is less than 1 minute.

At first, we run the model which minimizes lower bound of the proportion of unsatisfied relief demand of each item type as described in section 2.3.1. This model runs under pre-disaster budget of USD 857,317,919.08; post-disaster budget of USD 116,589,595.38; maximum response time of 8 hours; and capacity of each distribution center of 84,000 m³. The results of lower bound of proportion of unsatisfied demand are (for item type A to I): 0.949, 0.000, 0.277, 0.000, 0.000, 0.791, 0.851, 0.000 and 0.000, respectively.

The results of grouping service area for each distribution center with maximum 8 hours of response time are shown in Fig. 2.5 and 2.6 (refer to chapter 1, section 1.5.1. for the concept of generating service areas for each distribution center). Figure 2.5 shows that distribution center 12 (Palangkaraya), due to its strategic location, can serve up to 28 disaster areas. On the contrary, distribution center 1 (Banda Aceh) can serve only 9 disaster areas. Figure 2.6 shows that disaster area 23 (East Kalimantan) can be served by the maximum number of 14 distribution centers, while disaster area 33 (Papua), due to its remote location, can only be served by 1 distribution center.

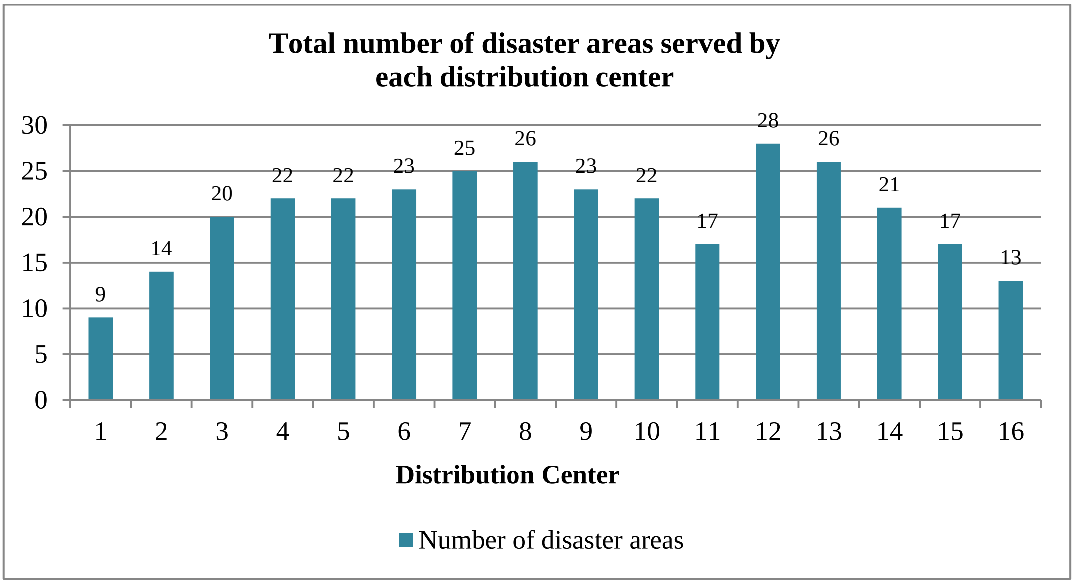

Figure 2.5 Number of disaster areas that served by a single distribution center

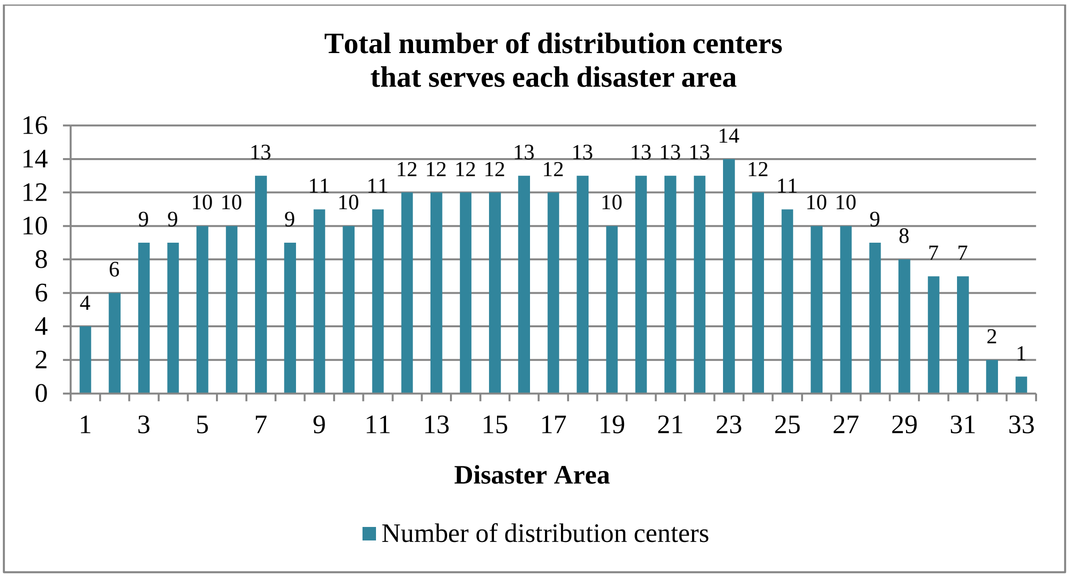

Figure 2.6 Number of distribution centers that serves the same disaster area

Furthermore, by using the results of lower bound of proportion of unsatisfied demand as inputs, we continue to the second stage of model formulation as described in section 2.3.2. As we mentioned earlier, this study focuses on how the new variable of the proportion of unsatisfied relief demand will improve the final result of preventing the zero proportion of a single item type stored in distribution centers. Hence, scenario for sensitivity analysis by changing the upper bound of the proportion of unsatisfied relief demand under given budgets (denoted by u_k) is performed. As can be seen in Table 2.3, the upper bound of each item type depends on government policy, which is assumed to vary from 0.780 to 0.999.

Table 2.3 Scenarios for sensitivity analysis

Scenario	Degree of Importance of All Item Types (m_k)	Upper Bound of the Proportion of Unsatisfied Relief Demand of Item Type A to I (u_k)
1	0.780	0.989; 0.780; 0.841; 0.780; 0.780; 0.954; 0.967; 0.780; 0.780
2	0.800	0.989; 0.800; 0.855; 0.800; 0.800; 0.958; 0.970; 0.800; 0.800
3	0.850	0.992; 0.850; 0.892; 0.850; 0.850; 0.969; 0.978; 0.850; 0.850
4	0.900	0.995; 0.900; 0.928; 0.900; 0.900; 0.979; 0.985; 0.900; 0.900
5	0.999	0.999; 0.990; 0.993; 0.990; 0.990; 0.998; 0.999; 0.990; 0.990

Table 2.4 Average proportion of satisfied and unsatisfied relief demand for each item type

	Sce-nario	Objective Function Value	Item Type								
			(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)	(I)
Average Proportion of Satisfied Relief Demand	1	16,703,300	0.353	0.865	0.876	0.865	0.911	0.595	0.318	0.821	0.938
	2	17,053,820	0.362	0.850	0.893	0.848	0.919	0.589	0.296	0.810	0.938
	3	17,532,810	0.377	0.832	0.906	0.833	0.934	0.576	0.232	0.793	0.954
	4	17,707,590	0.396	0.813	0.911	0.824	0.934	0.591	0.159	0.734	0.988
	5	17,955,520	0.438	0.798	0.919	0.801	0.934	0.591	0.016	0.677	0.988
Average Proportion of Unsatisfied Relief Demand	1	16,703,300	0.647	0.135	0.124	0.135	0.089	0.405	0.682	0.179	0.062
	2	17,053,820	0.638	0.150	0.107	0.152	0.081	0.411	0.704	0.190	0.062
	3	17,532,810	0.623	0.168	0.094	0.167	0.066	0.424	0.768	0.207	0.046
	4	17,707,590	0.604	0.187	0.089	0.176	0.066	0.409	0.841	0.266	0.012
	5	17,955,520	0.562	0.202	0.081	0.199	0.066	0.409	0.984	0.323	0.012

By changing the upper bound of the proportion of unsatisfied demand, we get the new results of the average proportion of satisfied relief demand. As shown in Table 2.4, there are no zero results or zero proportions of satisfied relief demand for each item type. This means, all item types are stored in distribution centers, including item type G, although it has larger volume and higher price compared to another items. This new result is quite different from the previous work conducted by Lee, et al. (2011), where the amount of item type G stocked in distribution centers is zero (no stock). By applying this new model, the limitation can be eliminated.

The previous model generates an objective function value of 17,979,240, while in the new model the number varies between 16,703,300 to 17,955,520. The number is smaller compared to the number generated by the previous model, but this smaller number covered each item type stored in distribution centers. This means the new model is preferable to be applied in the real systems.

Due to budget limitations, the average proportion of each item type cannot even reach 1.00. To increase the total proportion of satisfied relief demand, or to decrease the total proportion of unsatisfied relief demand, the government needs to upgrade their budgets (for some developing countries, this plan is difficult to be realized). In spite of this limitation, we consider scenario 1 as the best scenario because most of its critical items have lower proportion of unsatisfied relief demand compared to other scenarios.

Also, we noticed that the bigger the upper bound of the proportion of unsatisfied relief demand inputted, the bigger the value of objective function resulted.

2.6 Conclusion

In this study, we propose a new emergency model of stock pre-positioning that focuses on preventing the result of zero proportion of a single item type stored in distribution centers. This two-stage stock pre-positioning model is formulated as a linear programming with assumptions that the earthquake will not occur at the same time in multiple disaster areas and the demand is deterministic. The first stage of model formulation: generating lower bound of the proportion of unsatisfied demand, is specifically developed to improve the previous model built by Lee et.al. (2011). This first stage aims to prevent the zero proportions of some items stocked in distribution centers. The optimum results of stage I are used as inputs in stage II. Next, the second stage of model formulation: maximizing the total expected relief demand satisfied of disaster areas, is developed to determine the maximum amount of items stocked in distribution centers.

This proposed model is applied to a real case with 33 disaster areas and 16 temporary existing distribution centers in Indonesia. Sensitivity analysis is provided by changing the parameter of upper bound of the proportion of unsatisfied relief demand for each item. The results of each scenario provided by sensitivity analysis show a significant improvement compared to the previous results of single-stage model presented by Lee et.al. (2011). By adding a new variable of proportion of unsatisfied relief demand, the amount of each item type stocked in distribution centers, including item type G (tent) which has higher price and larger size per unit compared to another items, is no longer zero. The bigger the value of upper bound of the proportion of unsatisfied relief demand for each item inputted, the bigger the average proportion of satisfied relief demand resulted. These results are acceptable, based on the government policy that requires the availability of each critical item type in distribution centers. For a long-term planning in an effort to perform emergency response efficiently, the government is encouraged to make a better preparation and invest more budgets.

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Chapter 3

Emergency Response Model of Stock Pre-positioning with Transportation Constraints

3.1 Introduction

In this chapter, we study a stock pre-positioning model that integrates the decisions of the maximum proportion of relief demand covered in distribution centers and the maximum amount of relief supplies delivered to a single disaster area within a certain period of time. This chapter is organized as follows: First, we mention the literature related to this study and define the objective of our study. Next, we build the proposed mathematical model. Afterward, we present the real system and the data used in this model. Finally, we run the model and analyze the computational results of different scenarios generated by changing the number of helicopters available in a distribution center, or by adding more periods to the set.

3.2 Literature and Objective

Pre-positioning involves preparing critical relief supplies in strategic locations and determining the amount of demand to be released in disaster areas. The main objective of the study of disaster management is to minimize or prevent the loss of human life. Based on this objective, the delivery of relief supplies to the affected area within a relatively short period of time becomes one of the crucial factors to be considered. Opit et al. (2013) develop a stock pre-positioning model to obtain the maximum number of expected relief demand covered by the existing distribution centers by preventing the zero proportion of relief demand satisfied.

Their stock pre-positioning model however, does not consider the transportation planning into the model. This limitation leads us to extend the model by adding a new variable of amount of each item to be delivered from distribution centers to a specific disaster area. This new model captures budgetary constraints, capacity restrictions of distribution centers, and vehicles availability in each distribution center. This model is developed to support an emergency disaster relief response in the event of an earthquake.

There are numbers of studies that focus in the area of Disaster Operations Management (DOM). Galindo and Batta (2013) survey the recent OR/MS research in DOM. Their survey shows that mathematical programming is the most preferred methodology, while response stage is the most preferred problem to be focused. Balcik and Beamon (2008) develop a model that determines the number and locations of distribution centers in a relief network and the amount of relief supplies to be stocked at each distribution center. Mete and Sabinzky (2010) propose a two stage stochastic programming approach for disaster preparedness.

Papers related to transportation problems also have been discussed in literatures. Lin et al. (2011) develop a multi-objective integer programming model for delivery of prioritized items in disaster relief operations. Zhang et al. (2012) design a heuristic algorithm based on linear programming and network optimization to efficiently solve the optimal allocation of emergency resources problem. Hamedi et al. (2012) consider the reliability of a route into their routing and scheduling of humanitarian supply transportation model. Abounacer et al. (2014) propose a multi-objective emergency location-transportation problem for disaster response. Edrissi et al. (2013) propose a plan for retrofitting transportation link to ease access to the affected areas, and locating and equipping emergency response centers.

Although the above studies discuss facility location, stock pre-positioning and/or transportation planning problem, none of the above studies propose a stock pre-positioning model that simultaneously generates the maximum proportion of relief demand covered in distribution centers and the maximum amount of relief demand distributed from multiple distribution centers to a single disaster area within a certain period of time. By integrating these two decisions into a single model, the new model will become more reliable to be applied to the real system. The objective of this study is to maximize the expected relief demand covered by distribution centers by considering the transportation constraints into the model.

3.3 Model Formulation

In this new model, first, we need to determine the service area for each distribution center. By grouping service area for each distribution center, the total travel time of the first wave of delivery is guaranteed to be less than the maximum response time limit. The optimum results of the assignment of each distribution center to a number of disaster areas will be used as an input in the mathematical model presented in stage I. Stage I is developed to prevent zero results of the proportion of relief demand satisfied. Additionally, the optimum results of stage I will be used as an input in stage II. Stage II determines the maximum amount of relief demand to be covered by each distribution center. Figure 3.1 depicts the stages for solving this model.

In this model, we assume that the earthquake will not occur at the same time in multiple disaster areas, which means each distribution center will not be able to provide service to multiple disaster areas at the same time. The unit of time within planning period is called normal service period (t), where $\bar{T} = \{1,2,3,\ldots,\bar{t}\}$, and $\bar{t}$ is the total number of normal service period. One unit of time can be 1 hour, 8 hours, or even 1 day. If the service time of a vehicle exceeds the planning period, the activity will be considered as a delayed service period, $\bar{S} = \{1,2,3,\ldots,\bar{s}\}$, where $\bar{s}$ is the total number of delayed service period. Delayed service is allowed within a certain limit of time.

Let I = {1, 2, 3,…,$\bar{\imath}$} be the set of disaster areas, and J = {1, 2, 3,…, $\bar{\jmath}$} be the set of distribution centers. Let J^i be the set of distribution centers that provide service in disaster area *I*, $i \in I$. Let K = {1, 2, 3…, $\bar{k}$} be the set of item types, and V = {1, 2, 3,…, $\bar{v}$} be the set of vehicle types. Given disaster area *I* and distribution center *j*, let V_j^i be the set of vehicles available in distribution center *j* to provide service in disaster area *I*, $i \in I$, $j \in J$. In this model, the distribution centers have been established by the government.

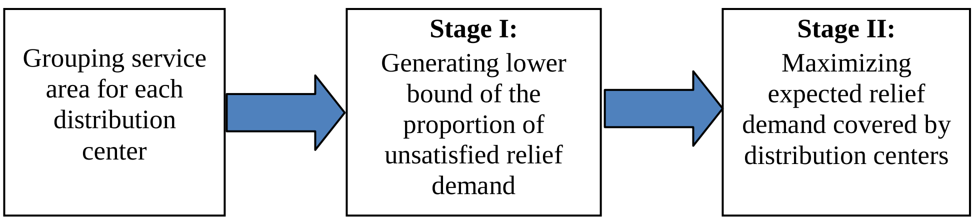

Figure 3.1 Stages of problem solving

Table 3.1 Parameters and decision variables

Parameters :	
u_k	upper bound of the proportion of unsatisfied relief demand of item type *k*, $k \in K$,
m_k	degree of importance of item type k; where $m_k = m,\ k \in K$,
X_{ij}	potential distribution center *j* to provide service in disaster area *I*, $i \in I$, $j \in J^i$,
Y_{ijvt}	potential vehicle *v* available in distribution center *j* to provide service in disaster area *i* at period *t*, $i \in I, j \in J^i, v \in V_j^i, t \in \bar{T} \cup \bar{S}$,
P_i	probability of occurrence of earthquake in disaster area *i*, $i \in I$,
d_{ik}	expected demand for item type *k* in disaster area *I* (unit), $i \in I$, $k \in K$,
U_j	capacity of distribution center *j* (m^3), $j \in J$,
γ_k	unit volume of item type *k* (m^3), $k \in K$,
B_0	pre-disaster budget ($),
B_1	post-disaster budget ($),
g_{jk}	unit cost of acquiring item type *k* at distribution center *j* ($/unit), $j \in J$, $k \in K$,
C_{ijkv}	unit cost of shipping item type *k* from distribution center *j* to demand point *i* by vehicle *v* ($/unit), $i \in I, j \in J, k \in K, v \in V$,
w_k	criticality weight for item type *k*; $\sum_k w_k = 1$ and $w_k \geq 0$, $k \in K$,
M	large positive number,
DC_j	cost of operating a single distribution center, $j \in J$,
β_k	unit weight of item type *k* (Kg), $k \in K$,
CW_v	the maximum weight capacity of vehicle *v* (Kg), $v \in V$,
EL_{ik}	expected satisfied relief demand of item type *k* in disaster area *i* ; $EL_{ik} \leq 1$, $i \in I, k \in K$,
n_{ijv}	number of vehicle *v* available in distribution center *j* to provide service in disaster area *I*, $i \in I$, $j \in J$, $v \in V$.
Decision Variables:	
f_{ijk}	proportion of item type *k* relief demand satisfied by distribution center *j* that provide services in disaster area *I*,
N_{ik}	proportion of unsatisfied relief demand of item type *k* in disaster area *I*,
Z_k	the lower bound of the proportion of unsatisfied relief demand of item type *k*,
Q_{jk}	units of item type *k* stored at distribution center *j*,
A_{ijkvt}	amount of item type *k* to be delivered from distribution center *j* to disaster area *I* by vehicle *v* in period *t*.

First, we need to determine the potential distribution center *j* to provide service in disaster area *i* (denoted by X_{ij}). Each distribution center is located in a different disaster area, and each of it provides service to one or more disaster areas located inside the range of a given maximum response time limit. X_{ij}= 1, if distribution center *j* provides service in disaster area *i*, 0 otherwise, where $i \in I$, $j \in J^i$. To cover the possibility of losing a distribution center, at least two distribution centers will provide services in disaster area with one existing distribution center. X_{ij} is determined by considering the expected response time and the maximum response time limit for each vehicle to reach a specific disaster area.

Next, the potential vehicle *v* available in distribution center *j* to provide service in disaster area *I* at period *t* (denoted by Y_{ijvt}), is determined. Y_{ijvt}= 1, if vehicle *v* in distribution center *j* provides service to disaster area *i* at period *t*, 0 otherwise, where $i \in I, j \in J^i, v \in V_j^i, t \in \bar{T} \cup \bar{S}$. Also, in this model we assume that the earthquake hit at period 0. The response is immediately started at period 1. In order to support emergency response, our model encourages each vehicle to provide service as soon as possible. The first response (first wave) is considered as an important event in this study. Table 3.1 shows the parameters and decision variables.

3.3.1 Stage I: Generating Lower Bound of the Proportion of Unsatisfied Relief Demand

In order to prevent zero results of the proportions of relief demand satisfied, firstly, we need to generate the lower bound of the proportion of unsatisfied relief demand for each item (denoted by Z_k).

Objective function:

$$Min = Z_k. \tag{3.1}$$

Constraints:

$$\sum_{k \in K} f_{ijk} \leq MX_{ij}, \qquad \forall j \epsilon J, i \epsilon I, \tag{3.2}$$

$$\sum_{j \epsilon J} f_{ijk} = 1 - N_{ik}, \qquad \forall i \epsilon I, k \epsilon K, \tag{3.3}$$

$$N_{ik} \leq Z_k, \qquad \forall i \epsilon I, k \epsilon K, \tag{3.4}$$

$$f_{ijk} d_{ik} \leq Q_{jk}, \qquad \forall j \epsilon J, i \epsilon I, k \epsilon K, \tag{3.5}$$

$$\sum_{k \in K} \gamma_k Q_{jk} \leq U_j, \qquad \forall j \epsilon J, \tag{3.6}$$

$$\sum_j (DC_j + \sum_{k \epsilon K} Q_{jk} g_{jk}) \leq B_o, \tag{3.7}$$

$$\sum_{j \in J} \sum_{k \in K} \sum_{v \in V} \left(C_{ijkv} \left(\sum_{t \in \bar{T}} A_{ijkvt} + \sum_{m=\bar{t}+1}^{\bar{t}+\bar{s}} A_{ijkvm}\right)\right) \leq B_1, \qquad \forall i \epsilon I, \tag{3.8}$$

$$\sum_{j \in J} \sum_{k \in K} \sum_{v \in V} \left(\sum_{t \in \bar{T}} A_{ijkvt}\right) \geq EL_{ik} d_{ik}, \forall i \epsilon I, k \epsilon K, \tag{3.9}$$

$$\sum_{v \in V} \left(\sum_{t \in \bar{T}} A_{ijkvt} + \sum_{m=\bar{t}+1}^{\bar{t}+\bar{s}} A_{ijkvm} \right) = f_{ijk} d_{ik} , \ \forall j \epsilon J, i \epsilon I, k \epsilon K, \quad (3.10)$$

$$\sum_{k \in K} \beta_k A_{ijkvt} \leq n_{ijv} CW_v, \ \forall v \epsilon V, j \epsilon J, i \epsilon I, t \epsilon \overline{T} \cup \bar{S}, \quad (3.11)$$

$$A_{ijkvt} \leq M \, Y_{ijvt} , \forall v \epsilon V, j \epsilon J, i \epsilon I, k \epsilon K, t \epsilon \overline{T} \cup \bar{S}, \quad (3.12)$$

$$A_{ijkvt} \geq 0, \qquad \forall v \epsilon V, j \epsilon J, i \epsilon I, k \epsilon K, t \epsilon \overline{T} \cup \bar{S}, \quad (3.13)$$

$$f_{ijk} \geq 0, \qquad \forall j \epsilon J, i \epsilon I, k \epsilon K, \quad (3.14)$$

$$N_{ik} \geq 0, \qquad \forall i \epsilon I, k \epsilon K. \quad (3.15)$$

The objective function (3.1) minimizes lower bound of the proportion of unsatisfied relief demand of each item type. Constraint set (3.2) states the assignment of service area for each distribution center. Constraint set (3.3) means that the actual demand is equal to the amount of satisfied relief demand summed with the amount of unsatisfied relief demand. Constraint set (3.4) assures that the proportion of unsatisfied relief demand does not exceed the desired lower bound limit. Constrain set (3.5) ensures that the amount of demand is smaller than the inventory level on distribution centers. Constraint set (3.6) imposes the capacity restrictions on distribution centers. Constraint sets (3.7) and (3.8) state the maximum budget of pre- and post-disasters. Constraint set (3.9) forces the amount of items delivered within normal service period to reach the desired level of satisfied relief demand. Constraint set (3.10) imposes the total amount of items delivered to be equal to the amount of inventories stocked in distribution centers. Constraint set (3.11) assures that the maximum load of each vehicle is not exceeding its weight capacity. Constraint set (3.12) ensures that certain type of vehicles may only deliver items to specific disaster areas. Constraint set (3.13) guarantees that the amount of items to be delivered exists when the delivery is provided within normal or delayed service period. Constraint sets (3.14) and (3.15) describe the non-negativity constraints.

3.3.2 Stage II: Maximizing Expected Relief Demand Covered by Distribution Centers

Next, in stage II, we need to determine the value of the upper bound of the proportion of unsatisfied relief demand (denoted byu_k), where $u_k = Z_k + (1 - Z_k) * m_k$, $Z_k < u_k < 1$, and $0 < m_k < 1,\ \forall k \epsilon K$ (value of Z_k has been generated in Stage I).

Objective function:

$$Max\ =\ \sum_{i\in I}\sum_{k\in K}\sum_{j\in J^i} p_i d_{ik} w_k f_{ijk}. \qquad (3.16)$$

Constraint:

$$N_{ik} \leq u_k,\ \ \forall i \epsilon I, k \epsilon K. \qquad (3.17)$$

The objective function (3.16) is now maximizing the total expected relief demand covered by the existing distribution centers. Constraint set (3.4) is now replaced by constraint set (3.17) that guarantees the proportion of unsatisfied relief demand in each disaster area is smaller than the desired upper bound limit. In spite of these two changes, other constraints are remaining the same (refer to Stage I, section 3.3.1).

3.4 Data Construction

Similar to the previous studies conducted in Chapter 2, we also apply this new model to Indonesia, an earthquake-prone country that is located in the pacific ring of fire. To improve the results, we update the number of disaster areas from 33 to 34 (based on 34 provinces existed in Indonesia since late 2012). Number of temporary distribution centers is 16. Figures 3.2 and 3.3 show the map of 34 disaster areas and the location of 16 temporary distribution centers. We use large amount of data to be inputted into the new model. For the sake of simplicity, we use assumptions to some data which are found difficult or nearly impossible to be obtained. The complete data set is presented in Table 3.2, while Table 3.3 describes the data estimation.

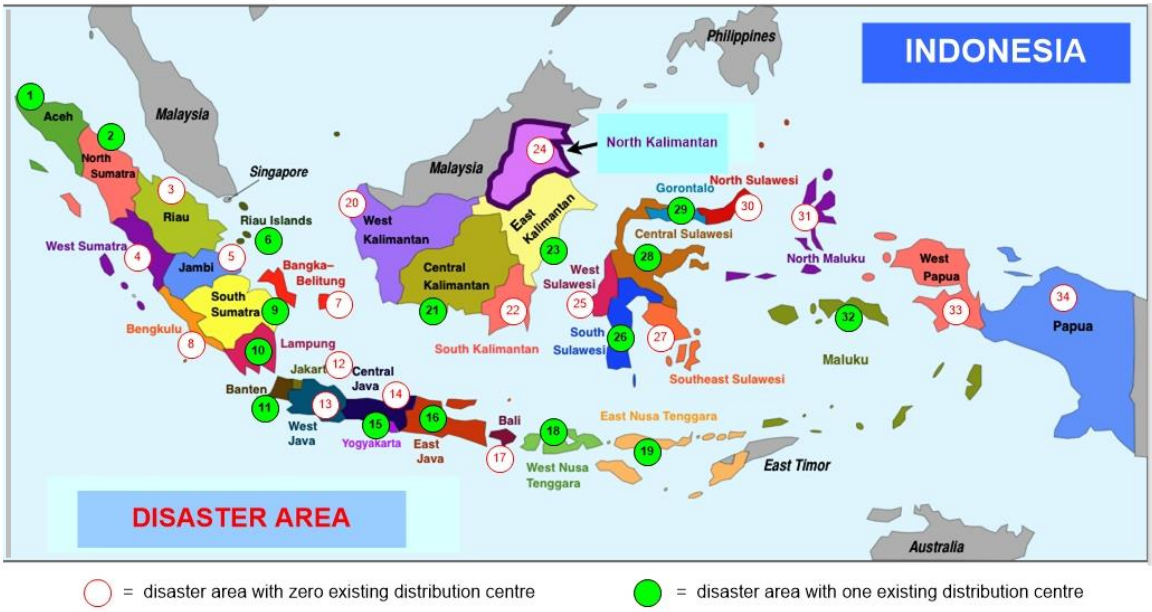

Figure 3.2 Map of 34 disaster areas

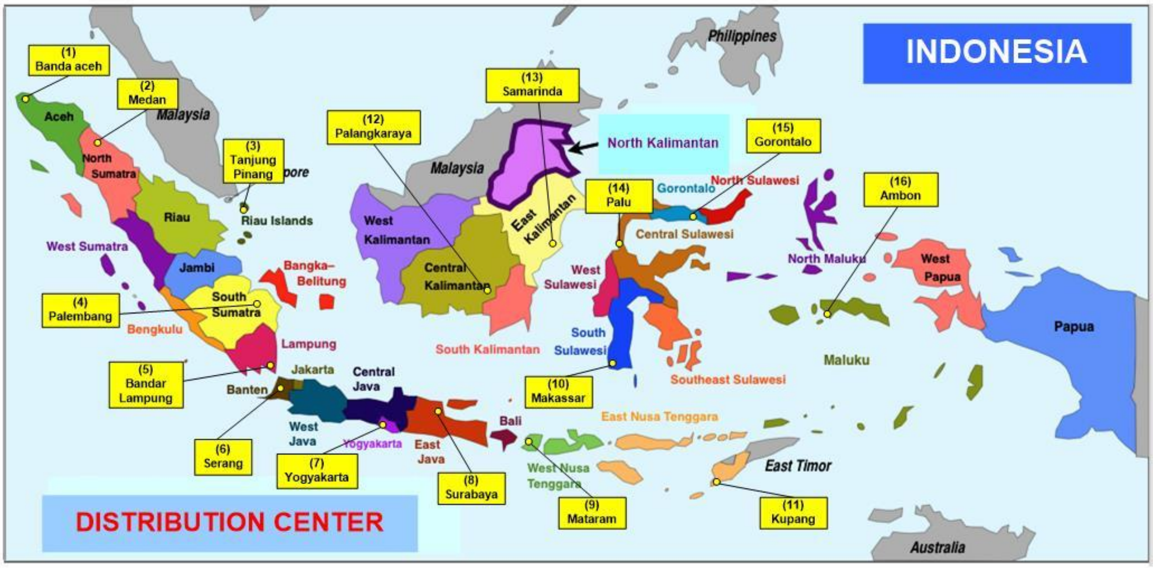

Figure 3.3 Location of 16 temporary distribution centers

We run our model under four normal service periods and two delayed service periods, which is equal to 72 hours (1 period = 12 hours). In the field, these numbers are flexible, depends on the government policy. Disaster relief items needed, including consumable and inconsumable items, are very diverse. As described in chapter 2 section 2.4, we narrow the item up to nine critical item types. We consider that these nine items hold the highest priority and need to be covered by the existing distribution centers. Maximum pre-disaster and post-disaster budgets are adapted from the budget allocation for preparedness and emergency response programs in year 2010-2014 (Republic of Indonesia. Indonesian National Board for Disaster Management, 2010).

Two types of vehicle are available in each distribution center, truck and helicopter. Trucks can only be used to deliver items in the area that is connected to the mainland. To deliver items between two different islands without any available roads access, helicopters are used as a main transport. Helicopter will provide service every period, while truck will provide service every two-period. In this study, the data of the size and speed of helicopter has been updated.

Table 3.2 Updated data set

Disaster area		
1. Aceh*	12. Jakarta	23. East Kalimantan*
2. North Sumatra*	13. West Java	24. North Kalimantan
3. Riau*	14. Central Java	25. West Sulawesi
4. West Sumatra	15. Yogyakarta*	26. South Sulawesi*
5. Jambi	16. East Java*	27. South East Sulawesi
6. Riau Island	17. Bali	28. Central Sulawesi*
7. Bangka-Belitung	18. West Nusa Tenggara*	29. Gorontalo*
8. Bengkulu	19. East Nusa Tenggara*	30. North Sulawesi
9. South Sumatra*	20. West Kalimantan	31. North Maluku
10. Lampung*	21. Central Kalimantan*	32. Maluku*
11. Banten*	22. South Kalimantan	33. West Papua
		34. Papua
Distribution center		
1. Banda Aceh	6. Serang	11. Kupang
2. Medan	7. Yogyakarta	12. Palangkaraya
3. Tanjung Pinang	8. Surabaya	13. Samarinda
4. Palembang	9. Mataram	14. Palu
5. Bandar Lampung	10. Makassar	15. Gorontalo
		16. Ambon
Item type		
A. Medicine (box)	D. Drinking water (box)	G. Tent (unit)
B. Instant food (box)	E. Blanket (unit)	H. Mat (unit)
C. Rice (per 50 Kg sack)	F. Clothes (packet)	I. Lantern lamp (unit)

*) Disaster area with one existing distribution center

Table 3.3 Updated data estimation

Expected response time (hr)	(distance from dist. center to the affected area (km)) / vehicle speed (km/hr)) + (expected loading time (hr)).
Maximum response time (hr)	Expected to be 12 hours (the same for each disaster area).
Probability of earthquake	Calculated based on the frequency of earthquakes hit each disaster area during 2005-2013. The earthquakes magnitude varies between 1.0 to 9.0 Mw.
Amount of demand	Assumed to be 1% of the total population of each province in year 2010 (which means only 1% of the total population in each disaster area will be affected by the earthquake and need to be treated immediately).
Criticality weight	(Criticality weight of each item type / total weight) Weight of item type A to I = 0.133, 0.133, 0.133, 0.133, 0.067, 0.133, 0.133, 0.067 and 0.067, respectively.
Volume (m^3)	Unit volume of item type A to I = 0.018, 0.054, 0.020, 0.054, 0.009, 0.112, 0.200, 0.056 and 0.006, respectively.
Weight (Kg)	Unit weight of item type A to I = 5, 4, 25, 18, 0.5, 5, 40, 5 and 0.25, respectively.
Distribution center capacity (m^3)	Dimension of each dist. center is assumed to be 100 x 100 x 12 = 120,000 m^3. Normally, only 70% space is used for the storage. The capacity of each dist. center is 84,000 m^3 (the same for each distribution center).
Cost of operating a distribution Center ($)	Assumed to be $6,100/5 years (the same for each distribution center). This number is calculated based on the approximation of the cost of electricity used to run a single distribution center.
Unit cost of acquiring relief items ($)	Purchase cost of item type A to I = $364.162, $5.780, $0.925, $3.699, $6.936, $11.561, $751.445, $8.671 and $8.092, respectively (1 USD = IDR 11.500).
Unit cost of shipping ($)	(Expected response time (hr)) x (fuel needed (liter/hr)) x 2 (round trip).
Expected satisfied relief demand	Range from 0.006 to 0.12 (based on the size of population in each disaster area).
Number of vehicles available	3 helicopters and 10 trucks (assumed to be the same at each distribution center).
Maximum weight capacity of a vehicle	4,100 kg for each helicopter and 14,000 kg for each truck.
Maximum budgets available ($)	Pre-disaster budget = $857,317,919.075 and post-disaster budget = $116,589,595.375.

The probability of earthquake for each disaster area is estimated based on a study conducted by Irsyam et al. (2010) that discuss the principal of 6 earthquake zones of Indonesia as shown in previous chapter (refer to Figure 2.4, chapter 2, section 2.4).

Since the demand is deterministic, Indonesia population in year 2010 is used for the estimation. In this case, however, we use only as big as 1% of the total population for the demand estimation. This means, we assume that only 1% of the total population in each disaster area will be affected by the earthquake and needs to be treated immediately. Operating cost for each distribution center is determined by calculating the approximate total cost of running a single-medium-size of distribution center for 5 years long (Indonesian government reviews their budget allocation every 5 years).

Criticality weights, as explained in Chapter 2 section 2.4, are obtained by classifying all items into two groups: primary and secondary items. Primary items are medicine, instant food, rice, drinking water, clothes and tent, while secondary items are blanket, mat and lantern lamp. Score of 1 is given to each of primary item, while score of 0.5 is given to each of secondary item. The criticality weight of each item is calculated by dividing the criticality score of each item by the total of criticality weight of all items.

Expected satisfied relief demand (denoted by EL_{ik}) is set based on its item type and disaster area. We assume, the bigger the population in a disaster area, the smaller the value of expected satisfied relief demand is determined. To prevent constraint violation which will lead to infeasible results, each value of the expected satisfied relief demand is set to be quite small, range from 0.006 to 0.12. This means, at least 0.6% to 12% of a total of each critical item will be delivered to a single disaster area within normal service period. The rest of the items will be delivered within delayed service period.

3.5 Computational Results and Analysis

The mathematical model presented in section 3.3 is coded on GAMS 24.1.3 and run by CPLEX 12.5.1.0 solver on an intel® Core^{TM} i7-3770 Dual Processor with 24 GB RAM and 3.40 GHz CPU. The computation time of each test problem is less than 1 minute. The first stage model runs under the estimation data compiled in Table 3.3. The results of the lower bounds of proportion of unsatisfied relief demand (for item type A to I) are: 0.181, 0.000, 0.890, 0.316, 0.000, 0.181, 0.383, 0.000 and 0.000, respectively.

Table 3.4 Scenarios

Scenario	Number of vehicles available (Helicopter = H, Truck = T)	Planning period (Normal service = N, Delayed service = D)
S1	H = 3, T = 10 (for each distribution center)	N = 4, D = 2
S2	H = 4, T = 10 trucks (for distribution center 12, Palangkaraya) and H = 3, T = 10 (for the rest of distribution centers)	N = 4, D = 2
S3	H = 4, T = 10 (for distribution center 13, Samarinda) and H = 3, T = 10 (for the rest of distribution centers).	N = 4, D = 2
S4	H = 3, T = 10 (for each distribution center)	N = 6, D = 2

Next, in stage II, the value of degree of importance of each item type (denoted by m_k) is set to be 0.85. Hence, the upper bounds of item type A to I are: 0.877, 0.850, 0.984, 0.897, 0.850, 0.877, 0.907, 0.850 and 0.850, respectively. By inputting these upper bound values, along with lower bound values that have been generated in stage I into the model, we generate the objective function value of stage II as big as 23,785.240. This result indicates no zero proportion of satisfied relief demand occurs, even for demand with high-priced and large-sized such as tent.

In this model, the number of relief demand to be satisfied is set at 1% of the total population. If we drastically increase this number, the result will become infeasible due to the limited number of vehicles available in distribution centers. Thus, the constraint of vehicles availability has proven to be the most restrictive constraint in this case study, as if we add one vehicle (helicopter) in a single distribution center, the proportion of relief demand satisfied will increase. To show the importance of this constraint, we provide some scenarios as shown in Table 3.4 with the sensitivity analysis shown in Table 3.5.

Scenarios 2 and 3 (refer to Table 3.4) are performed by adding one vehicle (helicopter) in a single distribution center that provides services to the most disaster areas. In that case, distribution center 12 (Palangkaraya) that serves 33 disaster areas (minus Papua), and distribution center 13 (Samarinda) that also serves 33 disaster areas (minus Aceh) are selected to perform the sensitivity analysis. We add one helicopter to Palangkaraya (scenario 2) and one helicopter to Samarinda (scenario 3).

As can be seen in Table 3.5a, the objective values of scenarios 2 and 3 show a slight improvement compared to the objective function value of scenario 1. Due to the difference of the size of population to be served by each distribution center, Palangkaraya is expected to serve bigger population than Samarinda. We assume that the bigger the population in disaster areas, the smaller the desired level of satisfied relief demand (denoted by EL_{ik}) to be determined.

Table 3.5 Results and sensitivity analysis

A. Objective function value

S1	S2	S3	S4
23,785.240	23,900.885	23,936.166	26,128.657

B. Average proportion of relief demand satisfied

	Item Type								
Scenario	(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)	(I)
S1	0.027	0.029	0.015	0.023	0.029	0.027	0.013	0.025	0.029
S2	0.027	0.029	0.015	0.023	0.029	0.027	0.014	0.025	0.029
S3	0.027	0.029	0.015	0.023	0.029	0.027	0.014	0.025	0.029
S4	0.028	0.029	0.017	0.026	0.029	0.028	0.014	0.026	0.029

C. Total amount of item delivered to disaster areas within normal service period (hundred thousand unit)

	Item Type								
Scenario	(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)	(I)
S1	734.635	219.811	526.907	267.938	1,866.378	745.646	65.271	72.266	78.285
S2	766.819	233.137	534.170	294.048	1,700.692	743.199	66.929	86.907	134.007
S3	814.908	232.250	530.191	286.581	1,821.067	714.373	64.343	122.818	123.798
S4	1,071.471	302.781	766.382	368.582	1,828.584	853.373	77.288	127.038	143.380

D. Total amount of item delivered to disaster areas within delayed service period (hundred thousand unit)

	Item Type								
Scenario	(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)	(I)
S1	772.357	256.947	223.782	114.592	517.416	669.427	10.990	142.666	120.364
S2	835.229	243.621	226.675	94.413	683.103	686.630	11.065	131.642	64.641
S3	785.485	244.508	229.670	101.880	562.727	722.031	13.652	95.730	74.851
S4	747.488	173.977	240.132	82.338	555.210	647.327	12.904	106.286	55.269

Therefore, the objective function value of scenario 2 is expected to be slightly smaller than the objective function value of scenario 3 although the values of the average proportions of relief demand satisfied for both scenarios are the same (refer to Table 3.5b). The average proportion of relief demand satisfied for each item is calculated by considering the probability of occurrence of earthquake in each disaster area (refer to Table 3.5b).

Several scenarios run by adding one truck to a single disaster area. In this case, we realize that the result of the objective function value remains the same. On the contrary, by adding one helicopter, which is fast and able to deliver critical items between islands within long distance, will slightly improve the objective function value. Tables 3.5c and 3.5d describe the total amount of items to be transported to disaster areas within normal and delayed service periods. Both tables display another slight improvement of the results of scenarios 2 and 3 compared to scenario 1. Refer to Constraint set (3.9) in section 3.3.1, we encourage each item to be transported immediately to the specific disaster area following an earthquake. Therefore, the total amount of items transported within normal service period as shown in Table 3.5c, reaches the desired level of satisfied relief demand.

Since the implementation of scenarios 2 and 3 require additional supply of budgets to purchase a new vehicle, sensitivity analysis by changing the planning period (refer to Table 3.4, scenario 4) is also provided. In this scenario, the normal service period is set to be 6 periods. Compared to other scenarios, it is confirmed that by adding more periods to the set, the proportions of relief demand satisfied are improving. Additionally, by adding more periods to the set also mean that some people affected by the earthquake will experience a longer waiting time to receive the critical relief items.

3.6 Conclusion

This study proposes a new stock-prepositioning model that simultaneously generates the maximum proportion of relief demand covered in distribution centers and the maximum amount of relief demand distributed to a single disaster area within a certain period of time. This new model is intended to support the governments in planning for emergency preparedness and disaster relief.

In this model, we assume that the earthquake will not occur at the same time in multiple disaster areas, the demand is deterministic, and there are two types of vehicles available in each distribution centers: helicopter and truck, where trucks can only deliver items to the area that is connected to the mainland. New variable of the amount of each item to be delivered from distribution centers to a specific disaster area is introduced to this model. First, each distribution center is assigned to serve some disaster areas that located within the range of pre-determined maximum response time limit. Next, as have been discussed in Chapter 2, the first stage model is built to prevent the zero proportions of items stocked in distribution centers. The second stage model is developed to determine the maximum items covered in distribution centers by inputting the optimum results of the first stage model.

Compared to the previous model presented in Chapter 2, this new model offers more outputs and restrictions to be analyzed. To verify the model, a case study with 34 disaster areas and 16 existing distribution centers in Indonesia is conducted (the data of disaster areas is updated to the current circumstances). Sensitivity analysis by performing different scenarios by changing the number of helicopters available in a distribution center, or by adding more periods to the set are provided. The results show by adding one helicopter, which is able to deliver items between islands and is faster than truck, to a certain distribution center slightly improved some of the proportions of relief demand satisfied. Therefore, for the better results, we suggest the central or local government to increase the number of vehicles (in this case, helicopter) available at each distribution center. Although we apply our model to Indonesia as a real system, this model is applicable to any other system facing an earthquake threat.

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Chapter 4

Pre-positioning of Emergency Relief Supplies under Facility Disruptions

4.1 Introduction

In this chapter, we study a stock pre-positioning model under facility disruptions that integrates the decisions of the maximum proportion of relief demand covered in distribution centers, the maximum amount of relief supplies delivered to a single disaster area and the number of optimum vehicle available in distribution centers. This chapter is organized as follows: First, we introduce the literatures related to this study and state the objective of our study. Second, we develop the two-stage mathematical model formulation. Third, we construct the data used as inputs in this model. Finally, we present and analyze the computational results of all potential disruption scenarios.

4.2 Literature and Objective

The aftermath of a natural disaster such as earthquake is always difficult to be predicted. Certain areas that located close to the epicenter of the earthquake may suffer major damages including loss of facility (distribution center) that is used to store the supplies for emergency relief response. Once a distribution center is disrupted (collapse), many people affected by the earthquake will not be able to receive the critical items needed for survival immediately. This means more people will suffer and even loss their life. This issue motivates us to extend the previous stock pre-positioning model developed by Opit and Nakade (2015a), as have been discussed in Chapter 3, to a new model that considers all potential scenarios of facility disruptions.

Papers related to stock pre-positioning and transportation planning models have been discussed in literature, such as one written by Rawls and Turnquist (2010) that presents a two-stage stochastic mixed integer program which provides an emergency response pre-positioning strategy. Lin et al. (2011) develop a multi-objective integer programming model for delivery of prioritized items in disaster relief operations. Mete and Zabinsky (2010) develop a two stage stochastic programming approach for disaster preparedness which consists of warehouse selection, inventory decisions, transportation plans and demand satisfaction decisions. Opit and Nakade (2015b) present a transportation model of emergency relief supplies by considering route availability at a specific period of time.

Facility disruptions are considered into the model in these following papers. Qin et al. (2013) propose a risk mitigation combination of facility protection and emergency inventory pre-positioning policies to hedge well against accidental disruptions in the capacitated logistics systems. Akgün et al. (2015) develop an optimization model that minimizes the risk that a demand point may be exposed to because it is not supported by the located facilities. Hatefi and Jolai (2014) propose a robust and reliable model for an integrated forward-reverse logistics network design, which takes facility disruptions into account. Sawik (2014) obtains combinatorial stochastic optimization problem of suppliers hit by different types of disruptions to either minimize expected worst-case cost or to maximize expected worst-case customer service level.

All above literature provide a better understanding on developing a pre-positioning and/or transportation planning model of emergency relief supplies, with or without considering facility disruptions. As for the difference, our study integrates the decisions of the maximum proportion of relief demand covered in distribution centers, the maximum amount of relief supplies delivered to a single disaster area within a certain period of time, and the number of optimum vehicle available at a distribution center for each disruption scenario. The objective of this study is to maximize the expected relief demand covered by distribution centers by considering the transportation problem and facility disruption scenarios into the model.

4.3 Model Formulation

In this model, the temporary distribution centers have been established by the government. Each distribution center is located in a different disaster area and it is assigned to provide services to one or more disaster areas that located inside the range of a given maximum response time limit. Let S = {1, 2, 3,…, s} be the set of disruption scenarios. Let I = {1, 2, 3,…,$\bar{\imath}$} be the set of disaster areas, and J = {1, 2, 3,…, $\bar{\jmath}$} be the set of distribution centers.

Table 4.1 Parameters and decision variables

Parameters:	
u_k	upper bound of the proportion of unsatisfied relief demand of item type *k*, $k \in K$,
m_k	degree of importance of item type *k*; where $m_k = m,\ k \in K$,
P_s	probability of occurrence of earthquake for each scenario *s*, $s \in S$,
d_{ik}	expected demand for item type *k* in disaster area *i* (unit), $i \in I$, $k \in K$,
U_j	capacity of distribution center *j* (m^3), $j \in J$,
γ_k	unit volume of item type *k* (m^3), $k \in K$,
B_0, B_1	pre-disaster budget ($), post-disaster budget ($),
g_{jk}	unit cost of acquiring item type *k* at distribution center *j* ($/unit), $j \in J$, $k \in K$,
C_{ijkv}	unit cost of shipping item type *k* from distribution center *j* to demand point *i* by vehicle *v* ($/unit), $i \in I$, $j \in J$, $k \in K, v \in V$
w_k	criticality weight for item type *k*; $\sum_k w_k = 1$ and $w_k \geq 0$, $k \in K$,
DC_j	cost of operating a single distribution center, $j \in J$,
β_k	unit weight of item type *k* (Kg), $k \in K$,
CW_v	the maximum weight capacity of vehicle *v* (Kg), $v \in V$,
EL_{ik}	expected satisfied relief demand of item type *k* in disaster area *i*; $EL_{i(s)k} \leq 1$, $i \in I$, $k \in K$,
$\bar{n}_{sjv}$	maximum number of vehicle *v* available in distribution center *j* for each scenario *s*, $v \in V, j \in J$, $s \in S$.
Decision variables:	
f_{sijk}	proportion of item type *k* relief demand satisfied by distribution center *j* that provide service in disaster area *i* for each scenario *s*,
N_{sik}	proportion of unsatisfied relief demand of item type *k* in disaster area *i* for each scenario *s*,
Z_k	the lower bound of the proportion of unsatisfied relief demand of item type *k*,
Q_{jk}	units of item type *k* stored at distribution center *j*,
n_{sijv}	number of vehicle *v* available at distribution center *j* to provide service in disaster area *i* for each scenario *s*,
A_{sijkvt}	amount of item type *k* to be delivered from distribution center *j* to disaster area *i* by vehicle *v* in period *t* for each scenario *s*.

Let J_i^s be the set of distribution centers that provide service in disaster area *i* for each scenario *s* , $i \in I, s \in S$. Let I^s be the set of disaster areas hit by the earthquake for each scenario *s*, $s \in S$. Let K = {1, 2, 3…, $\bar{k}$} be the set of item types, and V = {1, 2, 3,…, $\bar{v}$} be the set of vehicle types. Let V_j^i be the set of vehicles that available in distribution center *j* to provide service in disaster area *i*, $i \in I$, $j \in J$. The unit of time within planning period is called normal service period, where $\bar{T} = \{1,2,3, \dots, \bar{t}\}$. One period can be 1 hour or even 1 day. If the service time of a vehicle exceeds the planning period, the activity will be considered as a delayed service period, where $\bar{S} = \{\bar{t}+1, \bar{t}+2, \dots, \bar{s}\}$. Table 4.1 shows the parameters and decision variables.

4.3.1 Stage I: Generating Lower Bound of the Proportion of Unsatisfied Relief Demand

This stage is developed to prevent zero results of the proportions of relief demand satisfied.

Objective function:

$$Min = Z_k. \quad (4.1)$$

Constraints:

$$\sum_{j \epsilon J_i^s} f_{sijk} = 1 - N_{iks}, \quad \forall i \epsilon I^s, k \epsilon K, s \epsilon S, \quad (4.2)$$

$$N_{iks} \leq Z_k, \quad \forall i \epsilon I^s, k \epsilon K, s \epsilon S, \quad (4.3)$$

$$\sum_{i \epsilon I^s} f_{sijk}\, d_{ik} \leq Q_{jk}, \quad \forall j \epsilon J, k \epsilon K, s \epsilon S, \quad (4.4)$$

$$\sum_{k \in K} \gamma_k Q_{jk} \leq U_j, \quad \forall j \epsilon J, \quad (4.5)$$

$$\sum_j (DC_j + \sum_{k \epsilon K} Q_{jk}\, g_{jk}) \leq B_o, \quad (4.6)$$

$$\sum_{i \epsilon I^s} \sum_{j \in J_i^s} \sum_{k \epsilon K} \sum_{v \in V_j^i} (C_{ijkv}(\sum_{t \in \bar{T}} A_{sijkvt} + \sum_{m=\bar{t}+1}^{\bar{t}+\bar{s}} A_{sijkvm})) \leq B_1, \ \forall s \epsilon S, \quad (4.7)$$

$$\sum_{j \epsilon J_i^s} \sum_{v \in V_j^i} (\sum_{t \in \bar{T}} A_{sijkvt}) \geq EL_{ik}\, d_{ik}, \quad \forall i \epsilon I^s, k \epsilon K, s \epsilon S, \quad (4.8)$$

$$\sum_{v \in V_j^i} (\sum_{t \in \bar{T}} A_{sijkvt} + \sum_{m=\bar{t}+1}^{\bar{t}+\bar{s}} A_{sijkvm}) = f_{sijk}\, d_{ik}, \quad \forall j \epsilon J_i^s, i \epsilon I^s, k \epsilon K, s \epsilon S, \quad (4.9)$$

$$\sum_{k \in K} \beta_k\, A_{sijkvt} \leq n_{sijv}\, CW_v, \quad \forall v \epsilon V_j^i, j \epsilon J_i^s, i \epsilon I^s, t \epsilon \bar{T} \cup \bar{S}, s \epsilon S, \quad (4.10)$$

$$\sum_{i \epsilon I^s} n_{sijv} \leq \bar{n}_{sjv} \quad \forall v \epsilon V, j \epsilon J, s \epsilon S, \quad (4.11)$$

$$A_{sijkvt} \geq 0, \quad \forall v \epsilon V_j^i, j \epsilon J_i^s, i \epsilon I^s, k \epsilon K, t \epsilon \bar{T} \cup \bar{S}, s \epsilon S, \quad (4.12)$$

$$f_{sijk} \geq 0, \quad \forall j \epsilon J_i^s, i \epsilon I^s, k \epsilon K, s \epsilon S, \quad (4.13)$$

$$N_{sik} \geq 0, \quad \forall i \epsilon I^s, k \epsilon K, s \epsilon S, \quad (4.14)$$

$$n_{sijv} \in \{0, 1\}, \quad \forall v \epsilon V, j \epsilon J, i \epsilon I^s, s \epsilon S. \quad (4.15)$$

The objective function (4.1) minimizes lower bound of the proportion of unsatisfied relief demand of each item type. Constraint set (4.2) means that the actual demand is equal to the amount of satisfied relief demand summed with the amount of unsatisfied relief demand. Constraint set (4.3) assures that the proportion of unsatisfied relief demand does not exceed the desired lower bound limit. Constrain set (4.4) ensures that the amount of demand is smaller than the inventory level on distribution centers. Constraint set (4.5) imposes the capacity restrictions on distribution centers. Constraint sets (4.6) and (4.7) state the maximum budget of pre- and post-disasters. Constraint set (4.8) forces the amount of items delivered within normal service period to reach the desired level of satisfied relief demand. Constraint set (4.9) imposes the total amount of items delivered to be equal to the amount of inventories stocked in distribution centers. Constraint set (4.10) assures that the maximum load of each vehicle is not exceeding its weight capacity. Constraint set (4.11) ensures that the number of vehicles placed in each distribution center is less than its maximum number available. Constraint sets (4.12), (4.13) and (4.14) describe the non-negativity constraints. Constraint set (4.15) describes the binary constraint.

4.3.2 Stage II: Maximizing Expected Relief Demand Covered by Distribution Centers

The value of the upper bound of the proportion of unsatisfied relief demand is determined, where $u_k = Z_k + (1 - Z_k) * m_k$, $Z_k < u_k < 1$, and $0 < m_k < 1$, $\forall k \epsilon K$ (value of Z_k has been generated in Stage I).

Objective function:

$$Max \ = \ \sum_{i \epsilon I^s} \sum_{k \in K} \sum_{j \in J_i^s} P_s \, w_k \, f_{ijks} \ d_{ik} \qquad (4.16)$$

Constraint:

$$N_{sik} \leq u_k, \ \ \forall i \epsilon I^s, k \epsilon K, s \epsilon S. \qquad (4.17)$$

The objective function (4.16) is now maximizing the total expected relief demand and back up inventory covered by the existing distribution centers. Constraint set (4.4) is now replaced by constraint set (4.17) that guarantees the proportion of unsatisfied relief demand in each disaster area is smaller than the desired upper bound limit. Despite these two changes, the rest of the constraints are remaining the same (refer to Stage I).

4.4 Data Construction

Indonesia remains the main focus in this case study with the total of 34 disaster areas (number of existing provinces) and 16 temporary distribution centers (refer to Chapter 3, Figures 3.2 and 3.3). Table 4.2 presents the details of disaster areas and temporary distribution centers. To solve the problem, firstly, all potential disruption scenarios are generated. In this new model, the earthquake can occur at the same time in multiple disaster areas. Once a disaster area is hit by an earthquake, the distribution center that located inside this area may or may not be disrupted. We assume that at most two neighboring disaster areas will suffer damages after they got hit by an earthquake. For example, disaster 1 has 1 neighboring area, which is disaster area 2 (refer to Figure 4.1). Thus, when an earthquake hit disaster area 1, it can cause damage to only disaster area 1 or to disaster area 1 and 2.

Therefore, if only disaster area 1 is hit by an earthquake then distribution center 1 that located inside this area may or may not be disrupted. We then generate the first two scenarios, where distribution center in disaster area 1 is disrupted (scenario 1) and not disrupted (scenario 2). Next, if disaster areas 1 and 2 hit by an earthquake then distribution centers 1 and 2 that located inside each area may or may not be disrupted at the same time. Another possibility, distribution center 2 may be disrupted while distribution center 1 is completely unaffected, and vice versa. Hence, we can generate four scenarios where only distribution center 2 is disrupted (scenario 3), only distribution center 1 is disrupted (scenario 4), both distribution centers are completely unaffected (scenario 5) and both distribution centers are disrupted (scenario 6), and so on for the next disaster area(s). Finally, we generate the total number of 118 scenarios.

Tabel 4.2 Data set

Disaster area		
1. Aceh*	14. Central Java	24. North Kalimantan
2. North Sumatra*	15. Yogyakarta*	25. West Sulawesi
3. Riau*	16. East Java*	26. South Sulawesi*
4. West Sumatra	17. Bali	27. South East Sulawesi
5. Jambi	18. West Nusa Tenggara*	28. Central Sulawesi*
6. Riau Island	19. East Nusa Tenggara*	29. Gorontalo*
7. Bangka-Belitung	20. West Kalimantan	30. North Sulawesi
8. Bengkulu	21. Central Kalimantan*	31. North Maluku
9. South Sumatra*	22. South Kalimantan	32. Maluku*
10. Lampung*	23. East Kalimantan*	33. West Papua
11. Banten*		34. Papua
12. Jakarta		
13. West Java		
Distribution center		
1. Banda Aceh	6. Serang	11. Kupang
2. Medan	7. Yogyakarta	12. Palangkaraya
3. Tanjung Pinang	8. Surabaya	13. Samarinda
4. Palembang	9. Mataram	14. Palu
5. Bandar Lampung	10. Makassar	15. Gorontalo
		16. Ambon

*) Disaster area with one existing distribution center

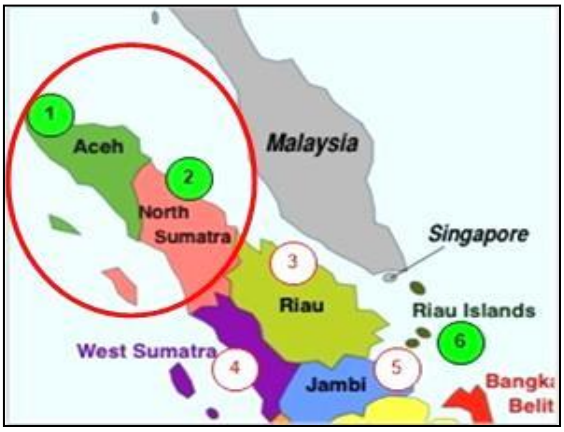

Figure 4.1 Illustration of the two neighboring disaster areas

The probability of occurrence of earthquake for each scenario (denoted by P_s) is estimated based on the probability of occurrence of earthquake in each disaster area by considering the chances (proportion) of each disaster area to be hit by an earthquake. Figure 4.2 shows the illustration on how to generate the probability of occurrence of earthquake for each combination of disaster areas 1 and 2. In this model however, we assume that the value of P_s is the same for each scenario of disaster area i hit by an earthquake. This means, the facility disruptions are not considered into the calculation of each P_s. For example, two scenarios can be generated when disaster area 1 is hit by an earthquake: Scenario 1) When the distribution center in this area is disrupted and Scenario 2) When the distribution center in this area is not disrupted. Regardless of the risk of facility disruptions, the value of P_1 and P_2 is the same, which is equal to 0.034 (refer to Figure 4.2).

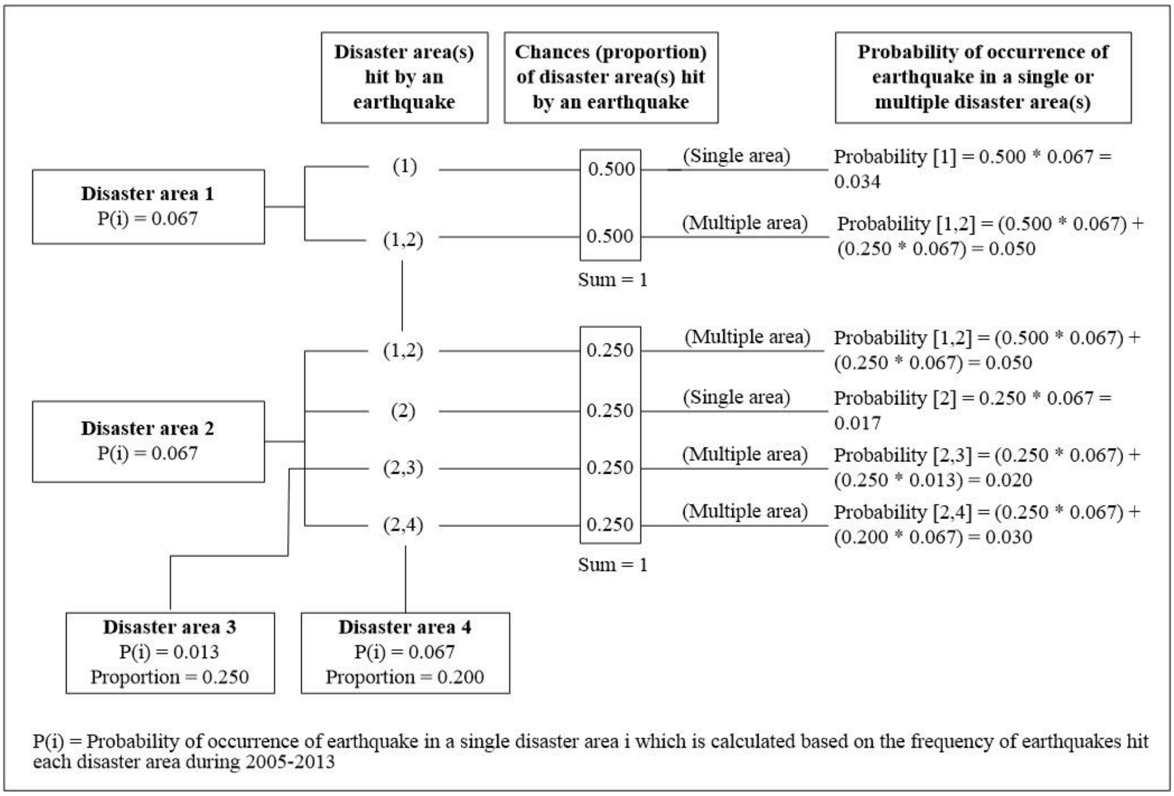

Figure 4.2 Illustration on generating the probability of occurrence of earthquake for each combination of disaster areas 1 and 2

There are two types of vehicles used for transporting items: helicopter (v_1) and truck (v_2). In this model, 5 helicopters and 10 trucks are available in each distribution center. Maximum weight capacity for each helicopter is 4,100 kg, while for truck is 14,000 kg. Maximum response time is expected to be 12 hours. There are 9 critical items: A. Medicine (box), B. Instant food (box), C. Rice (per 50 Kg sack), D. Drinking water (box), E. Blanket (unit), F. Clothes (packet), G. Tent (unit), H. Mat (unit) and I. Lantern lamp (unit). Amount of demand is assumed to be 1% of total population of each province in year 2010.

This model is executed under four normal service periods ($\bar{t} = 4$) and two delayed service periods ($\bar{s} = 6$). Since we assume that 1 period is equal to 12 hours, hence the total of normal and delayed period is equal to 72 hours. The capacity of each distribution center is assumed to be 84,000 m³. Unit cost of operating a single distribution center is \$6,100/5 years. Maximum pre-disaster and post-disaster budgets are \$857,317,919.075 and \$116,589,595.375, which are adapted from the budget allocation of Indonesian government for preparedness and emergency response programs in period 2010-2014 (Republic of Indonesia. Indonesian National Board for Disaster Management, 2010). The expected satisfied relief demand value (denoted by EL_{ik}) is set to be 0.6% to 12%. The details of data estimation can be seen in Chapter 3, Table 3.3.

4.5 Computational Results and Analysis

Based on the mathematical model presented in Section 4.3, we code each formulation on GAMS 24.1.3 and run by CPLEX 12.5.1.0 solver on an intel® Core™ i7-3770 Dual Processor with 24 GB RAM and 3.40 GHz CPU. The computation time of each test problem is less than 5 minutes. The results of stage I, which is the lower bound of proportion of unsatisfied relief demand (for item type A to I) are: 0.352, 0.000, 0.911, 0.464, 0.000, 0.351, 0.542, 0.000 and 0.000, respectively. These results are used as inputs in stage II.

Next, in the second stage formulation, we set the value of degree of importance of each item type (denoted by m_k) is to be 0.85. Thus, the result of total expected relief demand covered by distribution centers is 35,396.761. This result indicates no zero proportion of satisfied relief demand occurs, even for tent (type G) which has high prices and large sizes.

There are 4 disaster areas: 6, 7, 31 and 32 in which each proportion of demand satisfied is equal to 1. This means demands for all items in disaster areas 6, 7, 31 and 32 are fully satisfied for each scenario. On the contrary, Table 4.3 presents three disaster areas, 13, 14 and 16, which are less covered by distribution centers for each scenario. Since we set the value of expected satisfied relief demand (denoted by EL_{ik}) for disaster areas 13, 14 and 16 to be equal to 0.01, which are smaller compared to other disaster areas, the results of the average proportions of satisfied relief demand in disaster areas 13, 14 and 16 are also found to be minimum. This makes EL_{ik} becomes one of the most restrictive constraints in this model. We determine EL_{ik} based on the size of population in each disaster area. To ensure that the solution is feasible, we assume that the larger the population, the smaller the value of EL_{ik}. In this case study, disaster areas 13, 14 and 16 are found to be the most populous areas.

Due to its large number of population, although demand in disaster areas 13, 14 and 16 are less covered by the distribution centers, the amount of items delivered within normal and delayed period to these areas are bigger compared to the amount of items delivered to other disaster areas as shown in Table 4.4 and 4.5. Meanwhile, disaster areas 17, 24, 25 and 33 with relatively small numbers of population received the minimum amount of items. The value of the average proportion of satisfied relief demand for these four disaster areas however, are much higher compared to disaster areas 13, 14 and 16.

Table 4.3 Disaster area with minimum average proportion of satisfied relief demand

Disaster area	Item type								
	(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)	(I)
13	0.217	1.000	0.013	0.080	1.000	0.162	0.069	0.150	1.000
14	0.415	1.000	0.013	0.080	1.000	0.272	0.069	0.150	1.000
16	0.283	0.978	0.013	0.080	1.000	0.236	0.069	0.150	1.000

Table 4.4 Disaster area with maximum and minimum amount of each item delivered within normal service period (thousand unit)

Disas-ter area	Item type								
	(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)	(I)
Maximum amount of item delivered within normal service period									
13	56.783	41.958	8.660	9.827	280.254	35.238	4.885	4.809	7.416
14	88.483	46.258	6.199	7.226	160.708	46.312	3.017	5.070	7.876
16	61.361	38.106	7.307	8.409	162.655	62.516	4.082	4.427	9.238
Minimum amount of item delivered within normal service period									
17	1.467	0.293	6.496	0.489	5.759	1.467	0.912	0.142	1.019
24	2.733	1.043	6.540	1.738	0.516	1.964	0.147	0.467	0.112
33	0.912	0.851	6.674	0.721	4.068	4.735	0.831	0.301	0.339

Table 4.5 Disaster area with maximum and minimum amount of each item delivered within delayed service period (thousand unit)

Disas-ter area	Item type								
	(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)	(I)
Maximum amount of item delivered within delayed service period									
13	36.564	44.149	0.609	1.711	150.282	34.408	0.046	5.954	28.461
14	45.899	18.506	0.772	1.452	163.118	41.620	0.692	3.025	19.109
16	44.805	35.210	0.761	1.634	212.112	25.888	0.210	4.942	21.992
Minimum amount of item delivered within delayed service period									
24	4.647	0.433	4.674	0.721	6.864	5.417	0.360	0.762	0.502
25	6.534	0.815	4.195	1.366	7.617	6.419	0.622	1.503	0.897
33	6.691	0.669	5.644	1.813	3.535	2.868	0.377	0.965	0.294

Another constraint that has been proven to be very restrictive is the maximum number of vehicles available in each distribution center (denoted by $\bar{n}_{sjv}$), particularly $\bar{n}_{sj1}$ (maximum number of helicopter available). As if we reduce the number of helicopters available in distribution centers, the proportions of satisfied relief demand in disaster areas for each scenario will be decreased. In some cases, reducing the number of helicopters available will lead to an infeasible solution. In order to improve the proportion of satisfied relief demand, especially in disaster areas with large populations, it is better to add the number of helicopters available in some of distribution centers that located near to these densely populated areas.

4.6 Conclusion

This study proposes a stock pre-positioning model of disaster relief supplies that integrates the decisions of the maximum proportion of relief demand covered in distribution centers, the maximum amount of relief supplies delivered to a single disaster area and the number of optimum vehicle available in distribution centers. This model also considers multi-items, multi-vehicles, and multi-periods. In contrast to the previous models presented in Chapters 2 and 3, in this new model, the earthquake can occur at the same time in multiple disaster areas.

First, all potential disruptions scenarios of distribution center(s) that located in one or more disaster areas are generated. Afterward, the probability of occurrence of earthquake for each scenario is calculated. The next step, mathematical model, is formulated as a mixed-integer programming model. Stage I of the mathematical model formulation is developed to minimize the lower bound of the proportion of unsatisfied relief demand. Stage II of the mathematical model formulation is developed to maximize the proportion of relief demand satisfied by each distribution center for all potential disruption scenarios. Similar to the previous models that have been discussed in Chapters 3 and 4, stage II is executed by inputting the optimum results of stage I.

By using Indonesia as a case study, this new model generates 118 potential disruption scenarios. The results show that the proportions of satisfied relief demand in some disaster areas can be fully satisfied for each scenario, while in other areas these proportions are much smaller, especially in the areas with large number of populations. According to these results, the maximum number of vehicles available in each distribution center is proven to be one of the most restrictive constraints. Hence, to improve the proportions of satisfied relief demand, the government needs to consider adding the number of helicopter in some of distribution centers that located near to the densely populated areas. It is not recommended however, to add the number of helicopters in a distribution center that located inside the densely populated areas since the distribution center itself may be collapsed as an earthquake hit.

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Chapter 5

Distribution Model of Disaster Relief Supplies by Considering Route Availability

5.1 Introduction

In this chapter, we study a distribution model of emergency relief supplies that integrates the transportation plans and demand satisfaction decisions by considering route availability at a specific period of time. This chapter is organized as follows: First, we define the literatures related to this study and explain the objective of our study. Afterward, we describe the problem and concept of this study. Then, we build the algorithm and formulate the mathematical model. Finally, we perform the sensitivity analysis based on probability of path availability and budget availability.

5.2 Literature and Objective

Transportation or distribution planning of emergency relief supplies has constantly been a great challenge for years. Various uncertainty factors such as road conditions following a disaster and the amount of emergency supplies required to be sent to the affected area are always difficult to predict. The previous work of Opit et al. (2013) who develops a stock pre-positioning model to obtain the maximum expected relief demand covered by existing distribution centers (by preventing the result of zero proportion of relief demand satisfied) under budget constraints, has also motivated us to expand our research and develop a new model that focuses on distribution planning for emergency relief supplies.

In this new model, we consider transportation and vehicle purchase budgets as constraints. Our intention is that this model can be applied not only to developed countries, but also to developing countries. Therefore, we propose a distribution model that considers a single distribution center, multiple disaster areas, a homogenous fleet of vehicles, multi-items and multi-periods. The objective of this study is to simultaneously determine the maximum amount of relief supplies that can be sent to disaster areas and the optimum number of vehicles required for the distribution center by considering route availability.

In recent years, few papers have focused their studies on the transportation and distribution of disaster relief supplies. Some of these papers are reviewed in a study conducted by Manopiniwes and Irohara (2014). Lin et al. (2011) propose a multi-objective distribution model of prioritized items for disaster relief operations. They create a real-world earthquake scenario using a GA-based approach and decomposition and assignment heuristics.

Another research conducted by Berkoune et al. (2012) define and formulate a practical transportation problem often encountered by crisis managers in emergency situations, while Özdamar and Demir (2012) describe a hierarchical cluster and route procedure (HOGCR) for coordinating vehicle routing in large-scale post-disaster distribution and evacuation activities. Taniguchi and Thompson (2013) propose a multi-objective vehicle routing and scheduling problem. The model is applied to the case of Ishinomaki City following the Tohoku disaster in 2011.

Other papers, such as the one written by Mete and Zabinsky (2010), develop a two-stage stochastic programming approach for disaster preparedness, which consists of warehouse selection and inventory decisions, and transportation plans and demand satisfaction decisions. Abounacer et al. (2014) propose a multi-objective emergency location-transportation problem for disaster response. A plan for strengthening structures of vulnerable areas, retrofitting transportation link to ease access to the affected areas, and locating and equipping emergency response centers has been presented by Edrissi et al. (2013). Nakanishi et al. (2013) propose a methodology to analyze transportation demand in a post-disaster regional community. Huang et al. (2013) focus on the assessment routing problem, which routes teams to different communities to assess damage and relief needs following a disaster. Rawls and Turnquist (2011) discuss pre-positioning and delivery planning in the event of a natural disaster. Their model includes requirements for reliability that ensures all demands to be satisfied in scenarios comprising at least 100α% of all outcomes.

Although the above papers are important for our research, as they provide several different concepts on how to develop a distribution model in order to support emergency response, the above papers do not consider route or link probability in their transportation plans. Route probability, which relates to road conditions, represents one of the uncertainty factors that occur after a disaster strikes. Therefore, it is very important to consider route probability into the model.

As have been discussed in Chapter 1, section 1.5.2, Hamedi et al. (2012) address humanitarian response planning for a fleet of vehicles with reliability considerations. The authors focus on minimizing total time in a network with and without considering the probability of route failure. We find that the method they developed is interesting. But rather than just focus on route probability, in this study we also focus on route availability for all possible scenarios. Ukkusuri and Yushimito (2008) develop an approach to disaster pre-positioning problems that account for the routing of vehicles and possible disruptions in the transportation network. While the authors focus on finding the best location to pre-position inventories, our research which considers a single existing distribution center, focuses on maximizing the amount of each item to be delivered to the affected areas using a certain number of vehicles in a specific period of time. In addition, not only considering a single routing problem period as discussed in the pre-positioning model of Ukkusuri and Yushimito (2008), we propose a multi-period distribution model. The situation of route recovery can be considered in this multi-period distribution model. Hence, our model is more realistic to be applied to the real system.

Since we are interested in routing problems and determining the optimum number of vehicles required for the distribution center, several papers related to the topic are also studied. Choi et al. (2003) present a genetic algorithm to solve the asymmetric traveling salesman problem. Kim (2012) builds a dual stochastic programming model with chance constraints that concern the number for an optimal dispatch policy. Zhang and Li (2012) analyze multi-periodic vehicle fleet size and routing problems. Repoussis and Tarantilis (2010) design an adaptive memory programming solution approach for the fleet size and mixed vehicle routing problem with time windows. In this study, rather than just focus on routing problem and determining the optimum number of vehicles, we also focus on determining the maximum amount of supplies to be sent to each disaster area in a specific period of time. Therefore, our proposed model integrates the transportation plans and demand satisfaction decisions by considering route availability.

5.3 Problem Description

In this study, we consider a single distribution center as the starting point for each vehicle to deliver supplies (items) to a specific disaster area. However, to deliver items to their destination, each vehicle should travel via a certain route. In terms of disaster relief transportation, after a disaster strikes, this route may or may not be available at some point in time.

To understand our proposed model better, we provide a case study as shown in Fig. 5.1. Figure 5.1 illustrates all areas affected by a disaster. Let N = $\{1,2,\ldots,\bar{n}\}$ be the set of paths. As given in Fig. 5.1, we assume $\bar{n}$ = 6. Based on Fig. 5.1, we also assume that the probability of each path available at period 1 $(P_n^1) = 0.5,$ $n \in N$, while the probability of each path available at period 2 $(P_n^2) = 0.7,$ $n \in N$. According to Hamedi et al. (2012), for real-world scenarios, one can determine the probability of path availability using historical data and topographical GIS.

We use binary code (0,1) to represent each path availability at one point in time, where 0 means the path is unavailable and 1 means the path is available. It is important to note that, in this model, we use a homogenous fleet of ground vehicles such as trucks to deliver items to disaster areas. Hence, for example, if vehicle *v* is assigned to deliver items to disaster area D, then vehicle *v* will have two options: travel via path 3, or travel via path 2 and path 5. Let's say that the decision-maker has assigned vehicle *v* to travel via path 3, yet in the field, path 3 is actually unavailable, while paths 2 and 5 are both available during period 1. This means, if vehicle *v* eventually travels via path 3 during period 1, it would not be able to reach its destination.

The above example simply describes one possibility that could happen in the system. In a real system with various uncertainties of events, it is recommended to observe not only one possibility, but all of the possibilities that might occur in the system. Therefore, we need to generate all possible scenarios based on route availability for each period of time. Table 5.1 shows detailed information for each route and its destination as illustrated in Fig. 5.1.

As shown in Fig. 5.1 and Table 5.1, we have six paths, seven routes, four disaster areas, and one distribution center. For the sake of simplicity, we assume that the distribution of emergency relief supplies is supposed to be completed in two periods (1 period = 24 hr). This also means that each vehicle is assumed to be able to complete its round-trip travel in one period of time (including loading and unloading time). Given the number of paths ($\bar{n}$ = 6), the possible scenario for period 1 is formulated as the combination of paths available. Thus, the number of scenarios $= \{2^{\bar{n}} = 64\}$.

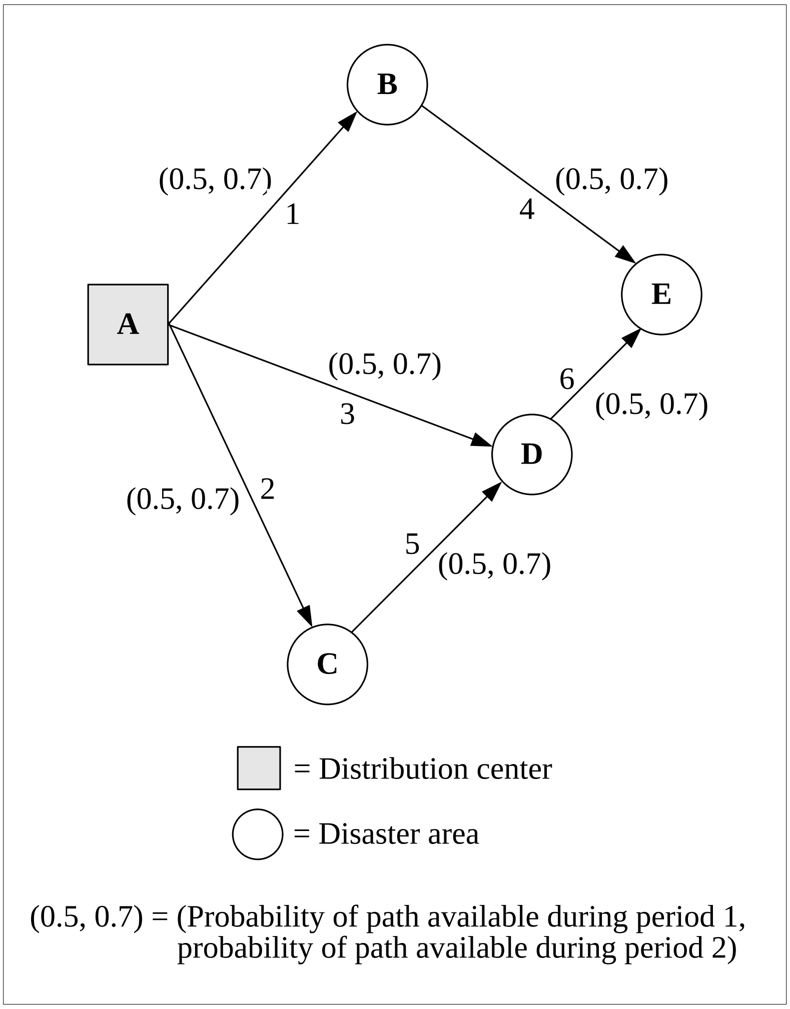

Figure 5.1 Illustration of disaster areas affected by a disaster

Table 5.1 Paths and routes used to reach each destination

Path	Route						
	1	2	3	4	5	6	7
1	*			*			
2		*				*	*
3			*		*		
4				*			
5						*	*
6					*		*
Destination	B	C	D	E	E	D	E

We assume that every available path during period 1 remains available during period 2. This specific condition means the disaster occurs prior to the first delivery. There is no secondary disaster that will follow. For example, in the event of an earthquake, there are no major aftershocks occurring after the first delivery. Given *k* combinations from set *l* of *n* elements, the possible scenario during period 2 = $\sum_{k=0}^{\bar{n}} \sum_{l=0}^{k} \binom{\bar{n}}{k} \times \binom{k}{l} = \sum_{k=0}^{\bar{n}} \binom{\bar{n}}{k} 2^{k} = 3^{\bar{n}} = 3^{6} = 729.$

To understand the concept better, Let S_1 = {1,2,3,…,$\bar{s}_1$} be the set of scenarios during period 1, and S = {1,2,3,…,$\bar{s}$} be the set of scenarios during period 2. Additionally, let $f(s)$ be the scenario of routes available during period 1 linked to scenario s, $s \in S$. Table 5.2 explains this concept of generating the number of possible scenarios for each period with the given number of paths ($\bar{n}$ = 6), as shown in Fig. 5.1. Based on the above assumption, paths available during period 1 would remain available during period 2. Therefore, S_1 = {1,2,3,…,64}, while S = {1,2,3,…,729}.

For example, scenario 2 during period 1 would be the combination of path availability = (0,0,0,0,0,1), while scenario 66 during period 2 would be the combination of path availability = {(0,0,0,0,0,1), (0,0,0,0,1,1)}. Additionally, $f(s) = 1$ for each scenario S = {1,2,3,…,64} during period 2 would be the combination of path availability of scenario 1 during period 1 = (0,0,0,0,0,0) that linked to the combination of path availability of each scenario 1 to 64 during period 2.

Table 5.2 Possible scenarios with a given number of paths ($\bar{n}$ = 6)

S_1 (scenarios during period 1)	Path combination availability during period 1	Path combination availability during period 2	S (scenarios during period 2)
1	0,0,0,0,0,0	0,0,0,0,0,0	1
		0,0,0,0,0,1	2
		0,0,0,0,1,0	3
		0,0,0,0,1,1	4
		…	...
		1,1,1,1,1,1	64
2	0,0,0,0,0,1	0,0,0,0,0,1	65
		0,0,0,0,1,1	66
		…	…
		1,1,1,1,1,1	96
…	…	…	…
64	1,1,1,1,1,1	1,1,1,1,1,1	729

The probability of route availability for each scenario *s* during period 1 is denoted by $Prob_s^1, s \in S_1$, while the probability of route availability during period 2 based on the previous scenario in period 1 is denoted by $Prob_s^2, s \in S$. The calculation of probability of routes being available for each scenario *s* (denoted by $Prob_s$) is as follows: $Prob_s = Prob_{f(s)}^1 \times Prob_s^2, for\ s \in S$. Table 5.3 describes an example to calculate the probability of route availability based on the probability of path availability given in Fig. 5.1.

Since the available paths during period 1 remain available during period 2, it is not necessary to include the probability of path 5 in the calculation of the probability of route availability during period 2 for the above scenario. Meanwhile, paths 1, 2, 3 and 4 are not available during period 1, and again during period 2, thus, it is necessary to consider the probability of paths 1, 2, 3 and 4 in the above calculation.

Now that we have the concepts to generate all possible scenarios and the probability of route availability for each scenario, the next step is to determine the maximum amount of items to be delivered to each disaster area.

Table 5.3 Calculation of the probability of route availability

Path combination availability during period 1 $f(s) = 2$	Path combination availability during period 2 s = 66
(0,0,0,0,0,1)	(0,0,0,0,1,1)
$Prob^1_{f(s)} = (1- P^1_1) \times (1-P^1_2) \times (1-P^1_3) \times (1-P^1_4) \times (1-P^1_5) \times (P^1_6) = 0.5 \times 0.5 \times 0.5 \times 0.5 \times 0.5 \times 0.5 = 0.015625$	$Prob^2_s = (1- P^2_1) \times (1-P^2_2) \times (1-P^2_3) \times (1-P^2_4) \times (P^2_5) = 0.3 \times 0.3 \times 0.3 \times 0.3 \times 0.7 = 0.00567$
$Prob_{66} = Prob^1_{f(66)} \times Prob^2_{66} = 0.00008859$	

5.4 Problem Modeling

5.4.1 Generating All Possible Scenarios Based on Path Availability during a Period of Time *t*

We set the single distribution center as the starting node. For each trip, vehicle *v* must depart from the starting node and travel straight to destination node *j* before heading back to the starting node. In addition, each vehicle *v* can serve only one disaster area *j* along the route *r*. The algorithm to generate all possible scenarios and to determine the probability of route availability for each scenario are illustrated as follows:

1: Generate all possible path combinations during period 1.

2: Index each combination as a separate scenario respectively.

3: Initialize the starting node for each scenario. Assign a path between two nodes (check the predecessor requirements based on the illustration shown in Fig. 5.1). If the binary value of the path between two nodes is equal to 0, then set the path as unavailable (damaged by a disaster). Otherwise, the path is available (equal to 1).

4: Generate all possible routes between start and end node for each scenario. If there is at least one unavailable path along route *r*, then set route *r* = 0 (unavailable), otherwise 1 (available).

5: Generate all possible path combinations during period 2 based on scenarios during period 1. Repeat steps 2 to 4.

6: Calculate the probability of route availability for each scenario s (denoted by $Prob_s$), where $Prob_s = Prob^1_{f(s)} \times Prob^2_s, for\ s \in S$.

As a result, we generate all possible scenarios during periods 1 and 2. We also get the results of route availability *r* during period *t* for scenario *s* (denoted as $\boldsymbol{R_{srt}}$, where $\boldsymbol{R_{srt} = 1}$ if route *r* during period *t* in scenario *s* is available, 0 otherwise) and the probability of route availability for each scenario s (denoted as $\boldsymbol{Prob_s}$). These two results, $\boldsymbol{R_{srt}}$ and $\boldsymbol{Prob_s}$ will be used as two important inputs in the mathematical model presented in section 5.4.2.

5.4.2 Determining the Maximum Amount of Items *i* to be Delivered to Disaster Area *j*

Given R_{srt} and $Prob_s$ from the previous stage, in this section we develop a model for determining the expected value of the maximum amount of each item to be delivered to disaster areas. This proposed model is formulated as mixed-integer programming with the assumption that the capacity of the distribution center is unlimited, which means the amount of items stocked in the distribution center can always satisfy the demand. This model simultaneously generates the optimum number of vehicles required for each period of time.

Let I = $(1,2,3,\ldots,\bar{\imath})$ be the set of item types, T = $(1,2,3,\ldots,\bar{t})$ be the set of planning periods, and J = $(1,2,3,\ldots,\bar{\jmath})$ be the set of disaster nodes (disaster areas). Let R = $(1,2,3,\ldots,\bar{r})$ be the set of routes, and $R(j)$ be the destinations (disaster areas) *j* of each route $r \in R$.

Parameters:

R_{sr1} route availability r during period 1 in scenario S_1, $r \in R$, $s \in S_1$. $R_{sr1} = 1$ if route r during period 1 in scenario S_1 is available, 0 otherwise,

R_{sr2} route availability r during period 2 in scenario s, $r \in R$, $s \in S$. $R_{sr2} = 1$ if route r during period 2 in scenario S is available, 0 otherwise,

d_{ij} demand of item type i at disaster node j, $i \in I$, $j \in J$,

C_{ir} transportation cost per unit of item i via route r, $i \in I$, $r \in R$,

Cp purchasing cost of a single vehicle,

$Prob_s$ probability of route availability for each scenario s, $s \in S$,

U maximum load capacity of a vehicle,

W_i unit weight of item i, $i \in I$,

α_i criticality weight of item type i, $\sum_i \propto_i = 1$ and $\propto_i \geq 0$, $i \in I$,

TC available budget for transportation cost,

TP available budget for purchasing new vehicles,

M large positive number, where maximum value of $\mathrm{M} = \frac{\mathrm{TP}}{\mathrm{CP}}$,

Decision variables:

A_{sirt} amount of item i delivered via route r during period t in scenario s,

N_{srt} integer number of vehicles required at distribution center to travel via route r during period t in scenario s,

Objective function:

$$Maximize \ \sum_{s \in S} Prob_s \ \sum_{i \in I} \alpha_i \left(\sum_r \ A_{f(s)^1 ir1} + A_{sir2}\right), \qquad (5.1)$$

Constraints:

$$N_{sr1} \leq M \, R_{sr1} \qquad \forall \, r \in R, \ s \in S_1, \qquad (5.2)$$

$$N_{sr2} \leq M \, R_{sr2} \qquad \forall \, r \in R, \ s \in S, \qquad (5.3)$$

$$Cp \ \sum_r N_{sr1} \leq TP \qquad \forall \, s \in S_1, \qquad (5.4)$$

$$Cp \ \sum_r N_{sr2} \leq TP \qquad \forall \, s \in S, \qquad (5.5)$$

$$\sum_j \sum_r C_{ir} \left(A_{f(s)ir1} + A_{sir2}\right) \leq TC \qquad \forall \, s \in S, \qquad (5.6)$$

$$\sum_{r\in R(j)}\left(A_{f(s)ir1} + A_{sir2}\right) \leq d_{ij} \quad \forall\, i \in I, j \in J, s \in S, \tag{5.7}$$

$$\frac{\sum_i W_i\, A_{sir1}}{U} \leq N_{sr1} \qquad \forall\, r \in R,\ s \in S_1, \tag{5.8}$$

$$\frac{\sum_i W_i\, A_{sir2}}{U} \leq N_{sr2} \qquad \forall\, r \in R,\ s \in S, \tag{5.9}$$

$$A_{sir1} \geq 0 \qquad \forall i \in I,\ r \in R,\ s \in S_1, \tag{5.10}$$

$$A_{sir2} \geq 0 \qquad \forall i \in I,\ r \in R,\ s \in S. \tag{5.11}$$

Objective function (5.1) maximizes the expected value of the amount of relief supplies delivered to each disaster area. Constraint sets (5.2) and (5.3) ensure that the vehicles can only travel to certain disaster areas via available routes during a specific period of time. Constraint sets (5.4) and (5.5) guarantee that the expenditure for purchasing the required vehicles prior to the disaster is less than the available budget. Constraint set (5.6) assures that the transportation cost is less than the expected budget. Constraint set (5.7) means the amount of relief supplies distributed to each disaster area does not exceed the demand. Constraint sets (5.8) and (5.9) guarantee that the maximum load of each vehicle does not exceed its weight capacity. Constraint sets (5.10) and (5.11) describe the non-negativity constraints.

5.5 Computational Experiments

Based on the illustration shown in Fig. 5.1, we conduct computational experiments that focus on large-scale observation, and analyze the best option to obtain the optimum result. We code each step explained in section 5.4.1 on Python 2.7.6. The solving time is less than 5 min. The mathematical model presented in section 5.4.2 is coded on GAMS 24.1.3 and run by CPLEX 12.5.1.0 solver on an Intel® Core™ i7-3770 Dual Processor with 24 GB RAM and 3.40 GHz CPU. The computation time of each test problem is less than 3 min.

In this study however, we use assumptions to determine the values of the data used in the mathematical model presented in section 5.4.2. We assume that there are two types of relief items to be delivered immediately: type 1 is medicine (unit) and type 2 is water (bottle). Demand for type 1 in disaster areas B, C, D and E is 50,000, 50,000, 70,000 and 85,000, respectively, while demand for type 2 in disaster areas B, C, D and

E is 10,000, 10,000, 20,000 and 25,000, respectively. The transportation costs per unit of type 1 delivered via routes 1 to 7 are \$5.00, \$5.20, \$5.20, \$6.00, \$7.00, \$6.80 and \$7.20, respectively, while transportation costs per unit of type 2 delivered via routes 1 to 7 are \$5.20, \$5.50, \$5.50, \$6.20, \$7.20, \$7.00 and \$7.50, respectively. Unit weights of Type 1 and Type 2 are 1 kg and 18 kg, respectively, while the maximum load capacity of each vehicle is 14,000 kg. Criticality weights for Type 1 and Type 2 are set at 0.55 and 0.45, respectively. The price of a single vehicle is estimated to be \$15,000.

For real-world scenarios, the types of relief items needed to be stocked in distribution centers are varies. We can determine the type of relief items that should be prioritized by carefully examine the necessity of each item according to the past experiences. The number of demand can be determined based on the population of the area affected by a disaster. The transportation cost can be calculated by considering the cost of gas/fuel needed by each vehicle to delivered items to the affected area. The maximum load capacity and the price of each vehicle are determined based on the type of vehicle used. Criticality weight for each item can be set by classifying all items into primary and secondary items. Primary items are set to have bigger priorities compared to secondary items. The criticality weight of each item can be calculated by dividing the criticality score of each item by the total of criticality weight of all items. As described in the previous section 5.3, we assume that the probability of each path available at period 1 is equal to 0.5, while the probability of each path available at period 2 is equal to 0.7. In a real-world, we can determine these probabilities by using historical data and topographical GIS.

Table 5.4 presents a sensitivity analysis of the computational experiments, while Table 5.5 shows the maximum value of the objective function for each computational experiment. We calculate the results shown in Table 5.4 by multiplying the proportion of relief demand satisfied (during periods 1 and 2) with the probability of route availability for each scenario. To demonstrate the importance of the probability of path availability denoted by $\boldsymbol{P_n^1}$ and $\boldsymbol{P_n^2}$, we changed the probability of path availability from 0.5 (period 1) and 0.5 (period 2) to 0.5 (period 1) and 0.7 (period 2).

Table 5.4 Sensitivity analysis of the average proportion of relief demand satisfied

Exp.	Prob. of path Availability		Expected budget (thousand dollar)		Average proportion of relief demand satisfied							
					Dis. Area B		Dis. Area C		Dis. Area D		Dis. Area E	
	t=1	t=2	Transp.	Vehicle purchase	Type 1	Type 2	Type 1	Type 2	Type 1	Type 2	Type 1	Type 2
1	0.5	0.5	1,000	2,500	0.746	0.225	0.752	0.303	0.806	0.262	0.367	0.036
2	0.5	0.7	1,000	2,500	0.957	0.276	0.790	0.274	0.914	0.914	0.914	0.914
3	0.5	0.5	2,000	2,500	0.746	0.149	0.752	0.150	0.889	0.889	0.852	0.849
4	0.5	0.7	2,000	2,500	0.957	0.191	0.790	0.158	1.000	1.000	1.000	1.000
5	0.5	0.5	2,500	1,000	0.746	0.692	0.752	0.714	0.891	0.839	0.854	0.845
6	0.5	0.7	2,500	1,000	0.957	0.869	0.790	0.729	1.000	0.930	1.000	0.979
7	0.5	0.5	2,500	2,000	0.746	0.746	0.752	0.752	0.889	0.889	0.852	0.852
8	0.5	0.7	2,500	2,000	0.957	0.957	0.790	0.790	0.995	0.995	1.000	1.000

Table 5.5 Maximum value of the objective functions

Exp.	Objective function value
1	95,048.49
2	110,600.05
3	139,543.96
4	161,715.80
5	138,615.16
6	160,277.12
7	139,582.24
8	161,746.71

The expected budgets consist of transportation budget (denoted by *TC*) and vehicle purchase budget (denoted by *TP*). These two budgets restrict the amount of relief supplies delivered to disaster areas. To discover the most restricted budget, first, we set the transportation budget to be smaller than the purchase budget (refer to Table 5.4, see experiments No. 1 and 2; and No. 3 and 4). Then we set the purchase budget to be smaller than the transportation budget (see experiments No. 5 and 6; and No. 7 and 8).

If we compare the computational experiments based on the difference of the probability of path availability—for example, experiments No. 3 and 4 (refer to Table 5.4)—the experiment No. 4, with the probabilities of 0.5 and 0.7, resulted in a higher objective function value (refer to Table 5.5) compared to experiment No. 3 with the probabilities of 0.5 and 0.5. This result generally follows by higher average proportions of relief demand satisfied. Since we set the criticality weight for Type 1 items (denoted by $\boldsymbol{\alpha_i}$) to be higher than Type 2 items, the results of the average proportion of relief demand satisfied for Type 1 items in each disaster area is greater than or equal to Type 2 items.

Regarding the budgets, investing more money for the transportation budget would improve the average proportion of relief demand satisfied. This also means that, in this illustration, the transportation budget could be considered one of the most restricted constraints. However, the two budgets are considered as important constraints and influence each other. Additionally, it should be noted that in some scenarios, although many routes are available, only a few routes would be traversed by the vehicles. This condition is due to the budget limitation. The bigger the budgets, the more vehicles will available at the distribution center, and the more vehicles will deliver items to disaster areas.

As for the experiments No. 7 and 8, by applying as much as $2.5 million for transportation budget and $2 million for vehicle purchase budget, we could satisfy a large proportion of demand for each scenario. In this case, by increasing the transportation budget to more than $2.5 million, the results as can be seen in Tables 5.4 and 5.5 will reach a steady-state condition. The same case applies by increasing the vehicle purchase budget to more than $2.2 million. At this state, the model has reached its optimum solution. Meanwhile, the maximum number of vehicles required at the distribution center for each experiment varied between 66 to 133 units. These numbers are massive and require a large parking area. An option available to avoid this situation is to add more time. This option can be considered in the future since this proposed model uses a single distribution center.

5.6 Conclusion

We propose a distribution model for emergency response that simultaneously determines the maximum amount of relief supplies delivered to disaster areas and the optimum number of vehicles required for distribution center by considering route availability. This model considers a single distribution center, multiple disaster areas, homogenous fleet of vehicles, multi-items and multi-periods. To solve the problem, first we build an algorithm to generate all possible path combinations using binary code. This algorithm generates the number of all possible scenarios and the available routes for each scenario at each planning period. This algorithm also calculates the probability of route available for each scenario. Route availability and probability of route available for each scenario would become the two important inputs for the next stage, mathematical model formulation.

Next, the mathematical model is formulated as a mixed-integer programming model. The objective of this mathematical model is to maximize the amount of relief supplies sent to disaster areas for each scenario. The optimum numbers of vehicles required in distribution centers at each planning period are determined simultaneously. This proposed model generates an extensive number of possible scenarios based on path combinations. Route availability, probability of route availability for each scenario, and budget availability are considered as important parameters in the mathematical model.

Therefore, sensitivity analysis is performed by changing the probability of path availability and the expected budgets (transportation and vehicle purchase budgets). By increasing the value of probability of path availability, the result of the average proportion of relief demand satisfied for each item can be improved. The improvement of the result of the average proportion of relief demand satisfied can also be achieved by increasing the transportation budget more than the vehicle purchase budget.

This proposed model can be used for various events in response to natural disasters such as earthquakes. Moreover, this model is developed to support the government and/or decision-maker to prepare an alternative transportation or distribution plan prior to the disaster. Based on the illustration given in this study, we solve the algorithm presented in section 5.4.1 with a computation time of less than 5 min. This computation time would be much longer if the algorithm is applied to a larger-scale network. In this case, we need to upgrade the algorithm or consider a new approach to obtain the near-optimal solution.

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Chapter 6

Conclusions

This thesis offers the modeling of stock pre-positioning and distribution planning to support emergency relief response. Three new models of stock pre-positioning and one new model of distribution planning are performed and solved using the optimization methods. The results are summarized as follows:

In chapter 2, we focus on how to prevent the result of zero proportion of a single item stored in distribution centers, which is the proportion of relief demand satisfied of disaster areas. A two-stage stock pre-positioning model is proposed by adding a new variable of proportion of unsatisfied relief demand. This model is built with assumptions that the earthquake will not occur at the same time in multiple disaster areas and the demand is deterministic. Fist, Stage I of model formulation is developed to improve the previous model built by Lee et.al. (2011). Stage I aims to prevent the zero proportions of some items covered by distribution centers. Next, by inputting the optimum results of the lower bound of proportion of unsatisfied relief demand for each item generated in stage I, stage II is formulated. Stage II determines the maximum amount of items stocked in distribution centers. This proposed model is applied to a real system with 33 disaster areas and 16 existing temporary distribution centers in Indonesia. The sensitivity analysis is performed to show the effect of different upper bound of the proportion of unsatisfied relief demand. The results show a significant improvement compared to the previous results of single-stage model presented by Lee et al. (2011). By using this model, the amount of each item type stocked in distribution centers, including item type G (tent) which has higher price and larger size per unit compared to another items, is no longer zero. This result is acceptable, based on the government policy that requires the availability of each critical item type in distribution centers. For a long-term planning in an effort to perform emergency response efficiently, the government is encouraged to make a better preparation and invest more budgets.

In chapter 3, the previous model presented in chapter 2 is extended. In this chapter, a stock pre-positioning model that integrates the decisions of the maximum proportion of relief demand covered in distribution centers and the maximum amount of relief supplies delivered to a single disaster area within a certain period of time is developed. This model considers multi-items, multi-vehicles and multi-periods, and is intended to support the government in planning for emergency preparedness. In this model we assume that the earthquake will not occur at the same time in multiple disaster areas. Firstly, the service area for each distribution center is assigned. This service area is determined by considering the given maximum response time limit for a vehicle available in a distribution center to deliver item to disaster area(s). Afterward, stage I of model formulation is developed by adding the new transportation constraints into the model. Stage I is built to generate the minimum value of the lower bound of proportion of unsatisfied relief demand by using the result of the assigned service area of each distribution center as an input. Next, in stage II, the outputs of stage I are used as inputs to determine the maximum amount of critical relief supplies to be stocked in distribution centers. This new model is applied to Indonesia with 34 disaster areas (instead of 33 disaster areas as presented in Chapter 2) and 16 existing temporary distribution centers. To improve the results, some of the data used in this model has been updated. Different scenarios by changing the number of helicopters available in a distribution center, or by adding more periods to the set are provided. The results show by adding one helicopter to a certain distribution center slightly improves some of the proportions of relief demand satisfied. The proportions of relief demand satisfied also improve by adding more periods to the set. This decision however, can slow down the delivery of emergency relief supplies to the affected areas. Therefore, for the better results, we suggest the central or local government to increase the number of vehicles (in this case, helicopter) available at each distribution center.

In chapter 4, a stock pre-positioning model under facility disruptions that considers multi-items, multi-vehicles, and multi-periods is presented. This new model integrates the decisions of the maximum proportion of relief demand covered in distribution centers, the maximum amount of relief supplies delivered to a single disaster area and the number of optimum vehicle available in distribution centers. This model is an extension from the previous model developed in Chapter 3. In this new model, we assume that the earthquake can occur at the same time in multiple disaster areas. All potential disruptions scenarios of distribution center(s) that located in one or more disaster areas and the probability of occurrence of earthquake for each scenario are considered in this model. Similar to the previous models discussed in Chapters 2 and 3, this new model is solved using two stages: stage I is to minimize the lower bound of the proportion of unsatisfied relief demand and stage II is to maximize the proportion of relief demand satisfied by each distribution center for all potential disruption scenarios. Stage II is determined by inputting the optimum results of stage I. The mathematical model is formulated as a mixed-integer programming model. This proposed model is also applied to Indonesia, an earthquake-prone country with 34 disaster areas and 16 existing temporary distribution centers. This new model generates 118 potential disruption scenarios. The results show that the proportions of relief demand satisfied in some disaster areas can be fully satisfied for each scenario, while in other areas these proportions are much smaller, especially in the areas with large number of populations. According to these results, the maximum number of vehicles available in each distribution center is proven to be one of the most restrictive constraints. Hence, to improve the proportions of satisfied relief demand, the government needs to consider adding the number of helicopter in some of distribution centers that located near to the densely populated areas. It is not recommended to add the number of helicopters in a distribution center that located inside the densely populated areas since the distribution center itself may be collapsed as an earthquake hit.

In chapter 5, we build a distribution model of emergency relief supplies that integrates the transportation plans and demand satisfaction decisions by considering route availability at a specific period of time. This model considers a single distribution center, multiple disaster areas, homogenous fleet of vehicles, multi-items and multi-periods. First, an algorithm to generate all possible path combinations using binary code that would lead to the determination of the number of all possible scenarios is developed. Afterward the algorithm would generate the available routes for each scenario at each planning period and then calculate the probability of route available for each scenario. These two outputs, route availability and probability of route available for each scenario would become the two important inputs for the next stage, mathematical model formulation. Second, the mathematical model is formulated as a mixed-integer programming model whose objective is to maximize the amount of relief supplies sent to disaster areas for each scenario. The optimum numbers of vehicles required in distribution centers at each planning period are determined simultaneously. This proposed model generates an extensive number of possible scenarios based on path combinations. Route availability, probability of route availability for each scenario, and budget availability are considered as important parameters in the mathematical model. One could determine the best results for overall scenarios by performing the sensitivity analysis. Hence, probability of path availability and budget availability are used in performing the sensitivity analysis. By increasing the value of probability of path availability, the result of the average proportion of relief demand satisfied for each item can be improved. The improvement of the result can also be achieved by increasing the transportation budget more than the vehicle purchase budget. This proposed model can be used for various events in response to natural disasters such as earthquake, flood, typhoon, etc. Moreover, this model is developed to support the government and/or decision-maker to prepare an alternative transportation or distribution plan prior to the disaster.

From the three studies of stock pre-positioning problems presented in chapters 2, 3 and 4, the last model presented in chapter 4 is considered to be more realistic compared to the previous two models discussed in chapters 2 and 3. This last model integrates the decisions of the maximum proportion of relief demand covered in distribution centers, the maximum amount of relief supplies delivered to a single disaster area and the number of optimum vehicle available in distribution centers. The extended model presented in chapter 4 also considers facility disruption scenarios which makes this model is more preferable to be applied to the real system. The distribution model presents in chapter 5 shows the importance of route availability. In the real system with various uncertainties of events, including roads condition following a disaster, it is more realistic to build a model that considers these uncertainty factors.

By applying the stock pre-positioning model developed in chapter 4, the government can receive information of all possible scenarios that considers the possibility of distribution center(s) to be damaged by a disaster. The government can prepare and decide better the amount of items to be stocked in each distribution center, the amount of items to be deployed to disaster area(s) and even the number of vehicles that needs to be placed at each distribution center prior to a disaster. By applying the distribution planning model presented in chapter 5, the government is able to perform a large-scale observation to all possible scenarios of emergency deployment that concerns the road conditions following a disaster. The government can prepare the optimum amount of items to be transported to each demand point prior to a disaster.

Models developed in this thesis are based on current condition, which means the models can be applied when certain conditions are met. For future research, a new-independent-model can be proposed to the government. For example, a joined model between stock pre-positioning, distribution planning and also facility location, with risk of facility disruptions and by considering route availability. To solve these three problems simultaneously, a new mathematical model and algorithm are needed to be constructed. This joined model can help the government to simultaneously determine the best locations to build new distribution centers, the maximum amount of items to be stocked in distribution centers, the optimum number of vehicles available at each distribution center and the optimum amount of items to be delivered to each demand point by considering certain uncertainty factors such as facility disruptions and road conditions following a disaster. This complex model can offer a better and more realistic result.

In these four studies conducted in chapter 2 to chapter 5, for the sake of simplicity, we assume that the demand is deterministic. In a real system however, the number of demand for humanitarian supplies is always difficult and is a big challenge to be determined. Hence, the next step of this research can also focus on the forecast of demand. In the field, while performing an emergency response, many uncertainty factors may suddenly occur at the same time, for example the unavailability of vehicles (broken, no driver, or no fuel). In the future research, these uncertainty factors can be added as additional parameters into the model. To predict better result for each model, sensitivity analysis can be provided by changing more parameters values such as budgets and capacity of distribution centers. Also, the results of models presented in chapter 2 to chapter 5, show that the value of the average proportion of relief demand satisfied is vary for each item. Although the parameter of criticality weight of each item type has been considered into the model, the values of the average proportion of relief demand satisfied for items with higher price and/or larger size are much smaller compared to items with lower price and/or smaller size. For future work, this issue can be addressed and solved by improving the models.

In many cases, Disaster Operations Management (DOM) claims the involvement of many parties to support an extensive emergency response. These parties include the Non-Governmental Organizations (NGOs), the governments from neighbouring countries, and even the governments from all over the world. In this thesis however, we do not discuss this issue and focus on one government as a single actor. In future research, to connect all of these parties and to perform an organized emergency relief response, an interface of incoming relief supplies from NGOs and other governments is needed to be developed. This interface will also help the decision maker to control the amount of relief supplies available in distribution centers more accurately.

Overall, this thesis states that stock pre-positioning and distribution planning problems are important to be carefully planned prior to a disaster in order to minimize the human suffering and loss of human life. Models related to stock pre-positioning and distribution planning can be used to support the governments and/or decision makers to prepare and respond quickly as the disaster strikes.

PUBLICATIONS

1. Chapter 2: Opit, P. F., Lee, W-S., Kim, B. S. & Nakade, K. (2013) Stock pre-positioning model with unsatisfied relief demand constraint to support emergency response. *Operations and Supply Chain Management: an International Journal.* 6 (2). pp.103-110.

2. Chapter 3: Opit, P. F. & Nakade, K. (2015) *Pre-positioning of emergency relief supplies under facility disruptions.* Proceedings of the IEEE International Conference on Industrial Engineering and Engineering Management (IEEM 2015). Singapore, 6–9 December 2015.

3. Chapter 4: Opit, P. F. & Nakade, K. (2015) *Emergency response model of stock pre-positioning with transportation constraints.* Proceedings of the 2nd East Asia Workshop on Industrial Engineering (EAWIE 2015). pp. 164-169. Seoul, Korea, 6–7 November 2015.

4. Chapter 5: Opit, P. F. & Nakade, K. (2015) Distribution model of disaster relief supplies by considering route availability. *Journal of Japan Industrial Management Association*. 66 (2E). pp.154-160.