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HUMANITARIAN LOGISTICS MODEL DEVELOPMENT FOR RELIEF DISTRIBUTION AND MEDICAL SERVICE IN EMERGENCY RESPONSE OPERATIONS

A Dissertation

Submitted to the Department of Transdisciplinary Science and Engineering

In Partial Fulfillment of the Requirements of the Degree of

Doctor of Engineering

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Department of Transdisciplinary Science and Engineering

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Verily, with every hardship comes ease! - 94:6

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ABSTRACT

Emergencies and disasters flounced through innumerable parts of the world and received much consideration over the past decade. The challenges are not only affected to immediate relief supply, but also have a higher intensity in the healthcare and medical sector, including medical supplies and lack of medical care resource availability. As the decisive purpose of humanitarian operations involvement is to reduce the loss of life, the ability to provide those needs is essential. Effective logistics planning and operations are a critical component of addressing the issues. Healthcare sector focuses to save lives and to maintain the community's health. In parallel, logistics sector supports all other sectors by mobilizing resources (goods, information, vehicle, and people) to maintain smooth response operations.

Emergency and disaster planning require different dimensions to be work together to achieve a better emergency response and should be deliberate together, as the substratum of disasters planning is the local responders. Regardless of how large the emergency and disasters perchance, the base of response operations will be at the local scope. Unfortunately, many disaster plans are focusing on how to deal with a mid-big range of disasters and neglect the role of local resources as the first responder. This study develops models for both tactical and operational level for relief distribution and medical service based on humanitarian logistics principles. Aside from national level, advancing the logistics performance in local and regional level will help to reduce the number of suffering people. Build up local responder capability and improves its logistics and supply chain performance can help to develop routine emergency preparedness and response while also preparing for a response to the disasters.

The first study focuses on developing a model for multi-modal relief distribution with multi-trip consideration as part of disaster response planning. The study investigates the possible network from supply node to affected area using the logistics operational area as hub concept. Several considerations are integrated into the model such as multi-modal modes, multiple trips, time-varying supply and demand, also state of transportation availability. The proposed model is applied to Java Island in Indonesia as a case study, to examine the model feasibility as part of ongoing discussions between Indonesian disaster agency (BNPB) and World Food Program (WFP). As a comparison, several analyses are conducted to explore the possibility of other constraint's consideration.

The second study focuses on developing models for the last mile relief distribution using different types of vehicle with dynamic and stochastic demand consideration. Truck and Trailer, are regarded as different type of vehicle which associated with different types of demand node, illustrate the road accessibility status. The demand uncertainty including its location and the magnitude is solved using a recourse function to achieve the minimum delivery time. The model is examined using the Yogyakarta Earthquake 2006 case with sensitivity analysis based on the level of demand dynamicity. The results show that the additional time needed to satisfy all of the demand is less than the additional demand satisfaction, justify the decision of the related organization for satisfied all demands while still being responsive.

Lastly, the study presents the logistics problem arose in healthcare and emergency medical response operations, focusing on routine emergencies case and disaster case. As emergency and disaster preparedness and planning requires multi-sectoral outlook, aside from delivering relief goods to the affected people, it is essential to maintain a surge capacity at a local and

national level to respond immediately when a health emergency or disaster struck. The study initially explores the logistical problems of medical responders and built a model that is applicable to the decision maker. The routine emergency model focuses on ambulance pre-positioning as part of emergency preparedness to reduce the response time, in the hope of increasing the life expectancy rate. The second part, proposed a mobile clinics concept for conduct medical service during disaster response phase, as part of medical relief support when the primary healthcare system is breakdown or overwhelmed.

The contributions of this study are claimed to be twofold. First, the contribution lays on the proposed model for relief distribution from the supply node to affected area and last mile distribution in the affected area. Prior studies observed that multi-trips distribution and dynamic demand location had not been regarded yet. In upstream level, a multi-modal distribution with multi-trips consideration based on the logistics capacity is presented. Furthermore, a dynamic distribution routing model for downstream or last mile distribution with stochastic demand consideration is formulated. The results of both models allow us to understand the needs for logistics capacity assessment for relief distribution in emergency response operations. Further, how geographical condition and transportation infrastructure might impact the stakeholder strategies and decisions also illustrated in the model, respectively.

Secondly, this study investigates the local capacity in for medical service, focusing on proposing ambulance pre-positioning model for low- and medium-income country without centralized ambulance system for routine emergency cases and pointed out challenges faced by medical service's responders in disaster response operation. The ambulance pre-positioning model tries to shift the current practice in the study area, with hospital-based ambulances, to the time-dependent and static ambulance location for rush hour and non-rush hour. In addition, the emergency medical service roles during disaster are also presented with additional recommendation from logistics perspectives are proposed. The mobile clinics routing, in addition, give an insight on how private organization could contribute and support government during disaster situation by providing medical care for non-emergency patients. This is particularly essential, as disaster pose a threat, and will impact the public health.

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Chapter 1 Introduction

1.1. Background

Emergencies and disasters flounced through innumerable parts of the world and received much consideration over the past decade. The event might disrupt day to day activities and caused a certain level of suffering. When an emergency happened, extra efforts and measures need to be taken to avert a disaster. The efforts, or commonly known as disaster management, can be divided into four phases. The first two phases include pre-disaster activities such as mitigation to reduce the risk and community vulnerability and preparedness which ensures a plan to mobilize victims and resources. The other efforts consist of post-disaster activities; include effective response operations to minimize the loss and fast recovery to support the restoration of the damage system and infrastructure. How response can be made expertly has a high dependency on the contingency and preparedness activities done beforehand.

When emergency or disaster happen and affect a region, several efforts need to be conducted to minimize the economic and human losses. The challenges, however, is not only affected the immediate relief supply such as a tent, food, water, or daily needs but also have a higher intensity in the healthcare sector, including its supplies, resources and service availability (WHO, 2006). To survive, people need food and water to survive, shelter to stay, with the injured and sick need healthcare and medical help. Natural disasters such as earthquakes, tsunami, eruptions, droughts, flood, and soon, nevertheless, can severely affect food and water availability. Disaster's victims can be homeless due to the unsafe situation and infrastructure breakdown, with public health resources are incapable of handling many injured and wounded victims.

As the ultimate purpose of humanitarian operations involvement is to reduce the loss of life, the ability to provide those needs is essential. Humanitarian relief activities are vital that a slight improvement in the planning and implementation might result in a significant impact on reducing people suffering (Ertem et al., 2010). The emergency, unfortunately, also engaged with exceptional demands on the logistical skills of the affected region/country (WFP, 2005). Thus, it requires logistical knowledge to plan the emergency and disaster planning and overcome the complexities of response strategies, with an effective logistics planning as a critical constituent for answering the challenges.

1.1.1. Emergency and Disaster

Based on the United Nation (UN) framework of response and recovery, there is a distinguishing difference between emergency and disaster. A situation is called emergency when an event can be responded using the resources available at hand without external assistance. Disaster, however, has an overwhelmed impact which resulted in incapability of local responders thus requires the involvement of external assistance. Although there is no reliable way to distinguish between emergency, disasters, and catastrophes, adapted from Tierney (2008), Table 1.1 shows the different size of the event and of the response in case of emergency and disaster.

Table 1.1. Emergency and Disaster Clarifications

(Source: Modified from Tierney, 2008)

	Routine		**Disaster**	
Classification	Incident	Major incident	Regional/State	National
Example	Minor traffic accidents, minor train/bus accident, vehicle fires, an accident with injuries with minimum fatalities	Train derailment, major bus/train accidents, major traffic accidents, hazard material spills, an accident with fatalities and injuries	Train/ Airplane crashes, hazard material incidents, major traffic accidents, multiple fatalities, and injuries, building fires or explosion, industrial accidents	A terrorist attack, natural disasters (earthquake, tsunami, tornadoes), transportation infrastructure collapse, riots, mass casualties
Expected duration	0-2 hours	2-24 hours	days	Weeks
Responders	Local responders (Emergency Medical Service (EMS), police, firefighter)	Local and some regional responders (Search and Rescue (S&R), Military, Regional Disaster agency)	Red Cross, Military, Regional, Inter-Regional, and National Disaster Agency	Red Cross, Military, Regional, and National Disaster Agency, International resources

Emergency and disaster planning require several different dimensions and all of them need to work together to achieve a better emergency response. The dimensions include hierarchical divisions, geographical divisions, organizational divisions, and functional division. Figure 1.1 illustrates the different dimensions worked in emergency and disaster planning. Geographical and hierarchical division refer to spatial jurisdictions and government tiers respectively, while organizational indicates different agencies that might involve in the emergency response operation. Lastly, functional divisions involved different sectors such as decision maker (government), health, logistics, and public works (shelter and sanitation). With the healthcare sector objective is to save lives and maintain the community's health, a continuous service flow should be created prior to an emergency to the final treatment. In parallel, the logistics sector will support all other sectors by mobilizing resources (goods, information, vehicle, and people) to maintain smooth response operations.

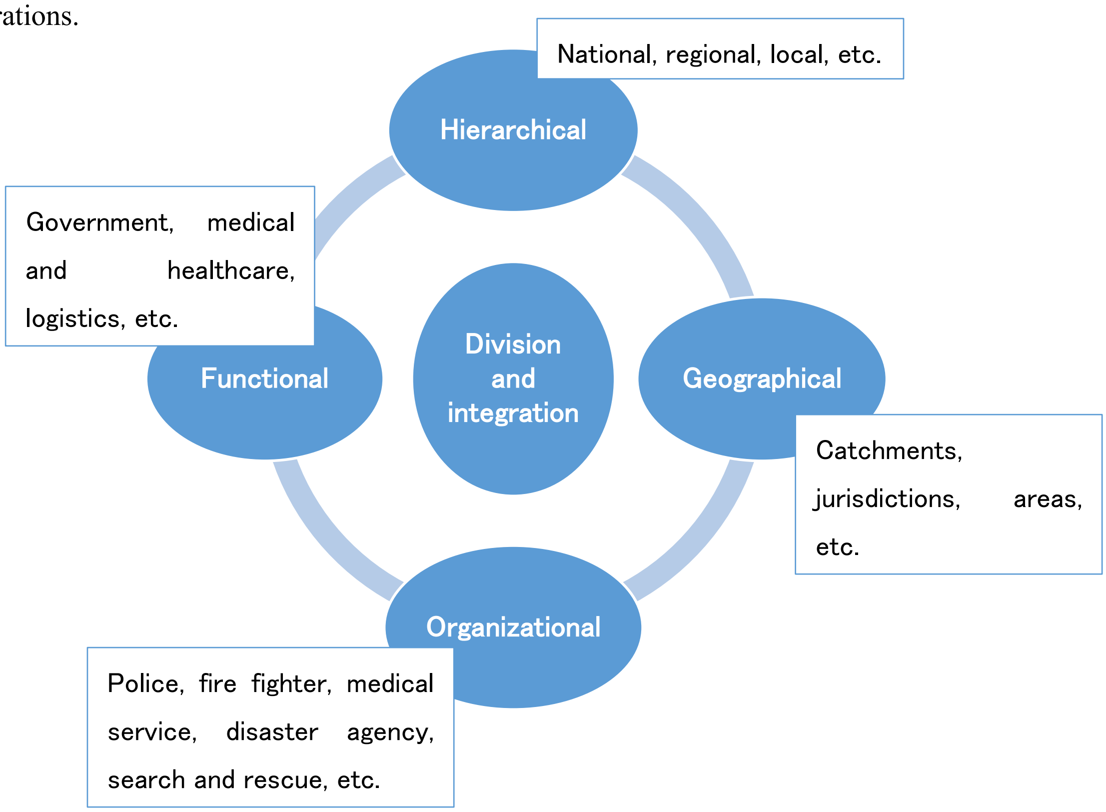


Figure 1.1. The dimensions of division in emergency and disaster planning (Source: Alexander, 2015)

1.1.2. Emergency Response Operation and Humanitarian Logistics

Irrespective of the type of emergencies, its occurrences are often unpredictable in terms of the time, location, magnitude, and a number of affected people. In such events, depending on the scale of the emergency, preparedness alone may not always be adequate which makes response activities one of the most critical components of disaster management. Emergency response operation is defined as the actions performed by organizing, coordinating, and directing available resources to save lives, reduce people suffers, and prevent extra damage due to the event. The objectives of response operation are to provide immediate assistance to maintain life, to improve health condition, to sustain the affected people and to support the morale of the affected population. Emergency response operation consists of activities performed to fulfill the basic needs of the affected population until more permanent and sustainable solutions can be found — the needs including relief goods, health and medical care, shelters, and adequate sanitation.

Owed to its significance, this study aims to enhance response operation by proposing models for response preparedness and response planning to an emergency or disaster situation. In emergency response operation, the right goods, people, and skills/service must be sent to the right place, time, and quantity. Thus, logistics are necessary to the planning and decision-making process in regards with capacity, distribution planning, transportation management, and supply-demand management. The lack of logistical consideration during response operation might lead to a failure such as:

a. Chaos and unmanageable donated relief supply due to lack of warehouse, limited moving equipment and no availability of suitable transport mode (Perry, 2007);
b. Information conflict and lack of need assessment;
c. Relief goods duplication, wastage of resources due to inefficient planning, long waiting time, or unmet demand (Das, 2014).

Nevertheless, logistical knowledge is required to overcome the complexities during response operations.

The logistics operation during emergencies is often called as '*humanitarian logistics*,' serves as a link between disaster preparedness and response, and between the central government and the local responders (Thomas and Mizushima, 2005). Main activities in humanitarian logistics consist of several operations including facility locations, transportation and distribution systems, demand, supply and inventory management, resources allocation and scheduling, etc. According to IRFC (2007), humanitarian logistics needs to ensure that the right *relief goods and service* must be sent to the right place, time and required quantity while ensuring the best value for money. World Food Program (WFP) along with Medicines Sans Frontiers (MSF) agree that humanitarian logistics includes not only the movement for relief good, but also aid services, resources, and also information, for the purpose of meeting the end beneficiary's requirements (Thomas, 2005). Different with commercial logistics, humanitarian logistics face challenges that will affect to its performance with high level of uncertainty (magnitudes, locations, number of demands, availability of resources), lack of resources (supply, people, technology, vehicle), limited information, and the poor state of infrastructure and network (Balcik and Beamon 2008).

Humanitarian logistics accounts for roughly 80% of the relief operation; hence developing a logistics plan is a crucial factor for the success of relief operation (Van Wassenhove, 2006). An adequate humanitarian logistics preparation can smoothen the relief operation, as it is generally possible to predict the type of emergency in a given area. The plan must be able to offer an answer on what kind of operations should be carried out, who will be performing the operations, what kind of resources needed and it's alternative if it is somehow disrupted. Based on the vulnerability level and result of resources (critical infrastructure, strategic infrastructure, local responders' readiness, and soon) assessments, an emergency response plan can be developed. Table

1.2 shows the compilation of humanitarian logistics activities conduct during response preparedness and response operation based on the need's category.

Table 1.2. Humanitarian Logistics Activities during Response Preparedness and Response Operation

(Source: Modified from Thomas, 2008 and Altay et al., 2009)

Needs / **Phase**	**Evacuation and Shelters**	**Relief Goods**	**Health and Medical Service**	**Water and Sanitation**
Response Preparedness	Decision on location for evacuation and shelter. Evacuation planning and evacuation drill	Logistics capacity Relief goods distribution planning Establish logistics center, temporary warehouse, and logistical hubs	Emergency medical service location decision Decision on medical facilities for emergency situation Medical operators training	Ensure availability of proper sanitation in a selected evacuation center
Response	Evacuation process for affected population Opening of shelters and provision of mass care	Acquire vehicles and network Maintain emergency supplies Receiving and Transporting relief goods to affected area Planning last mile distribution for beneficiaries	Emergency rescue and medical care Medical personnel allocation Reestablish the medical center or healthcare center Sustained medical care for displaced people	Emergency infrastructure protection Recovery of sanitation services

1.2. Motivation and Focus of the Study

1.2.1. Motivation of the Study

Emergencies and disasters are coupled with a series of undesirable consequences –displacement of affected population, loss of lives, wounded and injured, water and food shortage, inaccessibility, and break down of services and infrastructure damage/destruction (Hampton, 2000). The Sendai Framework for Disaster Risk Reduction (SFDRR) 2015-2030, which represent the global policy for reducing disaster risk reduction and building resilience, reflects an important shift from managing disaster towards reducing disaster risk (UNISDR, 2015). Four importance priorities for action including (1) Understanding disaster risk; (2) Strengthen disaster risk reduction resilience;

(3) Investing in disaster risk reduction for resilience; and (4) Enhancing disaster preparedness for effective response and to ‘build back better’ in recovery, rehabilitation, and reconstruction. An integration between local, regional, and national coordination is emphasized more, which suggest the importance of local responders’ function for emergency. Furthermore, healthcare sector is also strongly encouraged throughout.

Through 2018, Indonesia`s National Disaster Agency (BNPB) has recorded nearly 2,000 natural disasters with fatality almost hit 4,000 lives and estimated $2.9 billion economic losses due to Lombok earthquake, Sulawesi earthquake and tsunami, and Sunda strait tsunami (Renaldi and Shelton, 2018). Need assessment and immediate assistance, including first aid and medical service, shelter and sanitation, food and water, are being carry out alongside with S&R and some recovery effort to improve smoothen response operations. Although the information about damages can be gathered rather quickly, the lack of disaster awareness and preparedness still resulted in high fatalities and chaos. In Lombok case (July 29-August 18, 2018), as the vital transportation node such as airport can be normally utilized, the relief goods can be carried directly by airplanes from Malang and Jakarta. However, although the conditions of connecting roads between districts have been repaired and access to affected locations is increasingly accessible, some remote locations that requires transportation vehicles with load capacity less than 500kg to 1 ton, faces some accessibility problem (IFRC, 2018). Due to difficult geographical topography, the last mile distribution operation for such locations are hindered. The Sulawesi earthquake and tsunami (September 28, 2018) faces problems that are more serious. The disaster excise much of affected area and vital city nearby from the outside world for several days. The airport was severely damaged and the seaport, which the region relied on for fuel supplies, lost its crane for loading and unloading cargo. This has hindered the scale up of response activities for affected people as well as other more remote areas that remain largely inaccessible (UNDP, 2018). In both disasters, the healthcare sector faces some problems also as the medical facilities are damaged. Health shelters along with mobile emergency medical team are dispatch to extend the outreach of health services (WHO, 2018).

Many studies have been working in the humanitarian logistics field with on natural and man-made disaster cases such as earthquake, tsunami, eruption, flood, civil war, and terrorism. The applications, however, focus more on facility location, evacuation process and relief goods distribution (Dhamala et al., 2017) and rarely give attention to the medical service or healthcare. This study, then, will focus on humanitarian logistics for activities related to relief goods distribution and medical service in different level of emergencies. As relief goods are the most crucial item during response actions (Das, 2014), medical service also equally crucial to minimize the number of fatalities and maintain health status of the affected population.

Another point is that emergency and disaster planning should be deliberate together, as the substratum of disasters planning is the local responders. Regardless of how large the emergency and disasters perchance, the base of response operations will be at the local scope. When local responders feel overwhelmed, then an escalation to external assistance such as regional, national or international will be needed. However, without any prior emergency and disaster planning, local responders might feel overwhelmed and could not the response even the small event effectively without any guidance. The responder's threshold will depend on their capabilities including a number of available personnel, equipment, supplies, and their preparedness level. In that sense, it is essential to develop an emergency and disaster response plans that not only focus on an operational level but also tactical level in every sector. Regrettably, many disaster plans are focusing on how to deal with a mid-big range of disasters and neglect the role of local resources as the first responder, regardless of the scale of the emergency.

1.2.2. Relief Goods Distribution

Managing disasters impact, conducting effective evacuation and delivering relief goods to the victims as quickly and efficiently as possible can help to minimize the suffering. In the aftermath of disaster, the distribution of relief goods is essential for successful response operations. Since response activities extend over several weeks, or months, distribution operations will be repeated over time. Given the exertion of predicting disasters, resulted in difficultly for realizing affected area and number of affected people. The relief demands, which depend on the total number of affected people, become uncertain. As some routes might be total or partially blocked due to disaster impact, some remote locations might not be known in the first initial response. Further, relief supply mostly arises from donations or additional inventories after some period due to information extent to humanitarian organizations/other countries. The new information available will strongly affect the relief distribution system, thus building a flexible distribution system is crucial.

The increase in response capacities was varied across countries as decision maker learns from their past mistake. However, according to Sendai Framework priorities for action (3) and (4), more deed is needed to improve the underlying level of preparedness and continuously strengthened and update based on the risk and changing factors, such as warning system, information technologies, or infrastructure stated. The challenges are more prominent in the developing countries, since the infrastructure and number of resources usually lack to fulfill the demand. Such cases happened during Yogyakarta Earthquake 2006, Haiti Earthquake 2010, and

Nepal Earthquake 2015. Although a country can receive large amount of relief goods, transport it to the affected area is challenging. Airport breakdown, no airport/port available, and road destruction hamper the relief goods to be received. Combinations of modes of transport (such as sea–road, air–rail, and air-road) might advance the performance of humanitarian relief distribution systems.Multi-modal transportation can be a solution when transportation resources are scarce during the immediate aftermath of a disaster.

Nonetheless, distribution of the relief aids in the affected area is equally crucial since last mile distribution is the last effort for delivering relief aid from local distribution centers to the population in the affected area (Balcik et al., 2008). The challenges in last mile distribution stem from the high demand for supplies due to insufficient prepositioned stockpiles, high uncertainty of actual demand, uncertainty of travel time due to infrastructure obstruction, breakdown of communication channels, transportation problems, security issues, and limited resources (Balcik and Beamon, 2008; Oloruntoba, 2010, Penna, et al., 2018). Furthermore, it is common to use heterogeneous vehicles, same transport mode with different characteristics and capacity, and to conduct multiple delivery trips using the same vehicle owing to an inadequate number of vehicles. In particular, the accessibility problem may result in the use of any type of "compatible" transport that is available at the time, including big trucks, vans, cars, or motorcycles. Yet, decision-makers are also encountered a dynamic problem in which reliable information about victims' locations and demands is not available, thereby forcing them to make urgent decisions with limited information and to change distribution routes frequently.

The relief distribution in this study is divided into two parts, upstream level, and downstream level. Upstream level starts from the supply node to the consolidation node in the affected area. Downstream level focuses on relief delivery inside the affected area from the local distribution point to the shelters. Each level has different challenges accordingly. In the upstream level, the challenge lays on how to deliver the existing relief supply to the affected area. The decision will be made based on consideration of a number of reliefs supply available, transport mode available, and infrastructure and accessibility restriction to reach the affected area. In the other hand, downstream level or last mile distribution faces challenges in the restricted number of vehicle available, accessibility issue, the uncertainty of demand magnitude and locations, and also the dynamic information (Sumalee and Kurauchi, 2006; Girard et al., 2014).

1.2.3. Medical Service

According to UNISDR (2013), more than 4.4 billion people were affected by disasters happened from 1992-2012. In addition, 1.35 million people are estimated killed due to traffic accidents each year (WHO, 2018). Emergency and disaster situations affect the health status of individuals and communities, directly and indirectly. Death, injuries, illness, disabilities are some of the direct effects, while indirect effect includes health facilities breakdown, delayed health service, or damage to the health system. The Sendai Framework highlight concerns about health, healthcare and well-being; climate change; and sustainable development (UNISDR, 2015) and is relevant within and beyond the healthcare sector and development from its predecessor, the Hyogo Framework (UNISDR, 2005), which lack of attention to the health issues during emergency and disaster.

In humanitarian logistics, the healthcare sector is also one of the principal entities considering its goal to reduce the number of suffering and/or victims. Needs for healthcare (medical intervention) and health-related operation during emergency depends on the type of emergency or disaster, as each type of emergency associated with different magnitudes and patterns. Emergencies and disasters require healthcare sector responders to carry out tasks such as search and rescue, triage, health facilities evacuation, managing medical inventories, ensure the people well-being, and managing contamination (Heide and Scanion, 2007). Emergency planning in healthcare sector should be done in pre- and post-event including pre-hospital resources, hospital-based care, outpatient-based care which should be able to assist communities to address healthcare service (day-to-day/ routine emergency) and disaster. Furthermore, the availability of local health responders and healthcare facilities will also impact how the operations should be channeled.

The emergency planning in the healthcare sector started from assessing the healthcare service in local, regional, and national level that currently in place. That is including the readiness of emergency medical system (EMS) service, availability of health infrastructures (especially emergency department), and availability of emergency dispatcher system, which expected to be the first responders during an emergency. Well-develop and prepared EMS that is functional on day-to-day basis for routine emergencies, will also has overall long-term effect on disaster response. Whilst resources are continually changing; the decision makers must assess the healthcare services currently in place and develop an agreed-upon comprehensive community disaster response and recovery plan prior to a disaster. Ensure adequate emergency response for routine emergency and disaster requires planning and preparation across multisector. While it is not possible to make an EMS available everywhere all the time, the classical approaches to improving ambulance response time over the last four decades have been geared toward intelligently positioning the ambulances and routing them more efficiently.

Unfortunately, although EMS can handle the emergency problem, solely relying on their capacity can lead to an increment of people agonized, when disaster strikes. According to Guha-

Sapir et al. (2012), 68.2% of mortalities due to disaster globally, concentrated in developing countries. In fact, other healthcare and medically related entities are as critical, and a part of a community's resilience. It plays a prominent role as the backbone of medical response and support system for the local responders, to natural and manmade disasters. Disasters bring negative consequences and related directly with people live and suffering. Prodigious efforts should be prepared and made to guarantee that affected people can receive proper medical care (Swathi et al., 2017).

In most cases, the scale of the disaster can overwhelm the local EMS. Thus national or international organizations support will be needed. Medical care response activities during disasters including acute response such as: mass-casualty triage (Clarkson and Williams, 2018), on-scene treatment (Ramesh and Kumar, 2010), evacuation and mobilization patient to the hospitals (Catlett et al., 2011) and post-acute response such as: continuous medical treatment for the injured, constant care of the affected people, including the mental health of the affected population (Kaji and Waeckerle, 2003). The first five activities can only be done during the first initial response by the local responders, hospitals on-hand and in some cases by DMTs available. The rest of the activities, conducted after the initial response phase passed. The importance of healthcare entities to remain operational to sustain continuous medical services for the community is beyond necessity. An operational strategy for other medical service responders is needed.

1.3. Research Objectives

In response to emergency and disasters, an emergency planning related to relief distribution and medical service is needed. Decision-maker needs to think about integrating and utilizing available resources for delivering relief goods. At the same time, decision-maker also need to understand their capacity and improve their capacity for responding to both emergency and disaster to reduce fatalities. In accordance to challenges, this study defines the research questions as below:

a. How can relief network design be improved considering several challenges pertain?
    1. How to transport the relief goods from supply node to affected area with limited transportation infrastructure and resources?
    2. How to distribute the relief goods to beneficiaries in the affected area when information is changing over time?

b. How to improve the performance of medical service personnel in emergency and disaster situation?
    1. What is the issue related to EMS and how to improve the response time for saving more patients?

2. What types of medical service planning can be adopted during response operation?

To answer the research questions, this study develops a model for both tactical and operational level in two different sectors, namely relief distribution sector and the healthcare sector. Aside from the national level, advancing the logistics performance in local and regional level will help to reduce the number of suffering people. Building up local responders' capability and improving its logistics and supply chain performance can help to develop routine emergency preparedness and response while also preparing for a response to the disasters. In consideration of functional, hierarchical and organizational division of emergency and disaster planning, there are four objectives achieved in this study:

Objective I. To develop a relief distribution model for emergency response operations

I.1. To assess the logistics capacity and develop a multi-modal distribution planning for disaster response with time-varying parameters

I.2. To develop a dynamic model with two different types of vehicle for last mile relief distribution during disaster response phase

Objective II. To minimize the impact of emergency events through effective emergency medical response

II.1. To apprehend the current situation of EMS as local responders and improved its performance by developing a model for EMS ambulance pre-positioning for routine emergency response planning

II.2. To develop a model for mobile health unit / mobile clinics routing for maintaining health status during disaster response

1.4. Scope and Limitations of the Study

This study focuses on the emergency and disaster operation by tackled both tactical and operational decision level for relief goods and medical response. Relief is one of the essential needs of the affected people to sustain their life during the aftermath. At the same time, medical and health-related service is also needed to minimize people suffering and treat the injuries people. Two different levels of emergencies, local and national, are covered in this study. The model development focuses on cases happened in developing countries in the form of the optimization problem. Thus the constraints and findings on the optimization results may differ from other types of humanitarian logistics model. Some limitations regarding data collection, the actual situation of the responders also affect the model development. Furthermore, since the contributions of this study are a focus on model development, this study uses several disaster cases which makes some parameters were not possible to measure based on real data. Limitations and assumptions used are explained in each related chapter.

1.5. Dissertation Framework

This dissertation is grouped into six related chapters with the flow and relationship of the chapter are provided in Figure 1.2. Chapter 1 explains the background of the study, motivations and objectives, scope and limitations, dissertation framework, and contributions to the study. Chapter 2 provides the relevant literature on the humanitarian logistics issue in local, regional, and national level for distribution and healthcare sectors. An extended overview of the model development for humanitarian logistics also being reviewed in Chapter 2.

Chapter 3 develops a model for multi-modal relief distribution network with multi-trip consideration as part of disaster response planning. This chapter investigates the possible network from supply node to affected area using the operational logistics area as the hub concept. The proposed model is applied to Java Island in Indonesia as a case study, to examine the model feasibility as part of ongoing discussions between Indonesian disaster agency (BPBD Yogyakarta) and World Food Program (WFP).

Chapter 4 models the last mile relief distribution using different types of vehicle with dynamic and stochastic demand consideration to show the response distribution activity. Truck and trailer, as different types of vehicle which associated with different types of demand node, illustrate its accessibility status. The demand uncertainty including its location and the magnitude is solved using a recourse function to achieve the minimum delivery time. The model is examined using Yogyakarta Earthquake 2006 case with sensitivity analysis based on the level of demand dynamicity.

Chapter 5 presents the logistics problem arose in emergency medical response operations in the healthcare sector, both in routine emergency cases or in disaster cases. This chapter initially explores the logistical problems of healthcare/medical responders and built a model that is applicable to the decision maker. Two types of emergency medical response, routine emergency, and disaster, are presented. The routine emergency model focuses on ambulance pre-positioning as part of emergency preparedness to reduce the response time, in the hope of increasing the life expectancy rate. The second model developed to illustrate the mobile clinic's service during disaster response phase, as part of medical relief support when the primary healthcare system is a breakdown or overwhelmed. Finally, chapter 6 summarizes the study outcomes with the highlight for the future study needs.

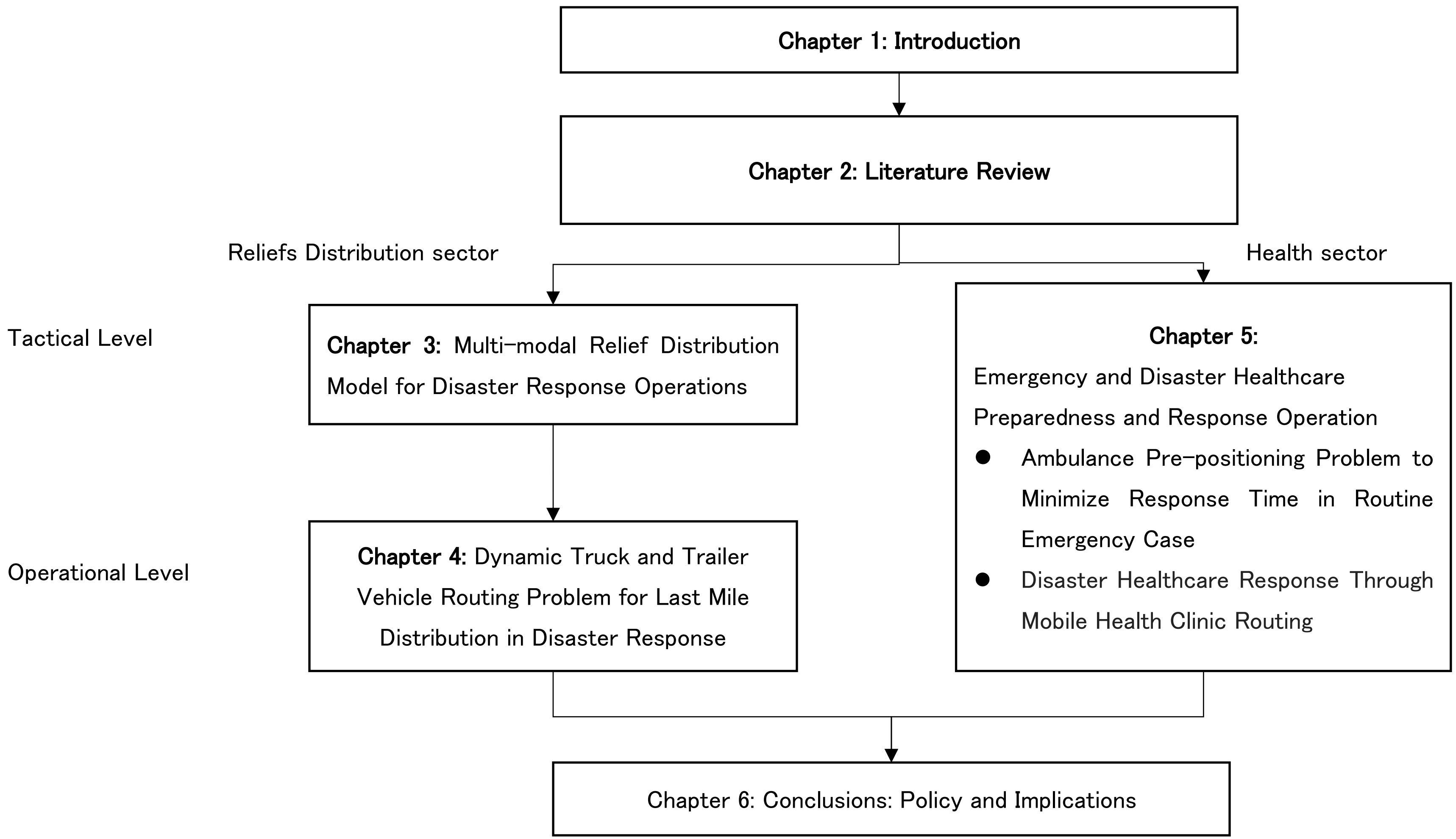


Figure 1.2. Dissertation framework

1.6. Contributions of the Study

The contributions of this study are claimed to be twofold. First, the contribution lays on the proposed model for relief distribution from the supply node to the affected area and last mile distribution in the affected area. Prior studies observed that multi-trips distribution and dynamic demand location had not been regarded yet. In this study, a multi-modal distribution with multi-trips consideration based on the WFP logistics capacity result is presented. Furthermore, a dynamic distribution routing model for last mile distribution with stochastic demand consideration is also formulated. The results of both models allow us to understand the needs for logistics capacity assessment for relief distribution in emergency response operations; and how geographical condition and transportation infrastructure might impact the stakeholder strategies and decisions.

Secondly, this study investigates the local capacity in for medical service in healthcare sector, focusing on proposing ambulance pre-positioning model for low- and medium-income country without centralized ambulance system for routine emergency cases and understanding the medical service position and roles during disaster. The ambulance pre-positioning model tries to shift the current practice in the study area, with hospital-based ambulances, to the time-dependent and static ambulance location for a rush hour and non-rush hour. The analysis of EMS roles, in addition, give an insight on how medical service organization, owned by public and private organization could contribute and support the local government in the healthcare sector during disaster situation by providing medical care for non-emergency patients. The mobile clinics routing model shows advantage when displaced people are evacuated to disperse locations with small capacity. The mobile clinic's function, particularly essential as disaster pose a threat and will impact the public health.

Chapter 2 Literature Review

2.1. Disaster Management and Humanitarian Logistics

Disaster management aims to avoid or to reduce the impact on the communities, environment, and economy due to the occurrence of emergencies or disasters. The processes are implemented before, during, and after the disasters (Nikbakhsh and Farahani, 2011). It consists of four stages: Mitigation, Preparedness, Response, and Recovery, in which different activities and sectors are involved according to the phase. Logistics is recognized as the critical activities in particular during preparedness and response phase. Table 2.1 reviews the activities in the four-phase of disaster management.

Emergency response operations are crucial in disaster reliefs due to the urgency and importance of saving victims' lives. In emergency response operation, the right goods, people, and skills/service must be sent to the right place, time, and quantity. According to International Federation of Red Cross and Red Crescent Societies (IFRC), humanitarian logistics defined as the processes and systems involved in mobilizing people, resources, skills, and knowledge to help vulnerable people affected by emergencies and/or disasters. Humanitarian logistics focuses on the task to smoothen response operation, not only focus on relief goods distribution but also services needed such as medical care, search rescue (S&R), evacuation process, including some recovery activities such as cleaning up debris and rebuilding infrastructure.

As it utilizes the idea of transport modeling, disaster management, and also commercial supply chain and logistics (Das, 2014), humanitarian logistics has been receiving attention in the literature during the last decades. Many researchers focus on tackling the relief distribution problem, starting from facility location, route and modes selection, the decision on routing, and inventory problem. Some other focus on the humanitarian logistics in the healthcare sector, including some activities to pre-position the medical resources (people, vehicle, and medical goods), doctor and nurse scheduling, and also allocating ambulance or mobile clinics during the emergencies or disasters response. The lack of logistical consideration during response operation might lead to a failure such as chaos and unmanageable donated relief supply due to lack of warehouse, limited moving equipment and no availability of suitable transport mode (Perry, 2007); information conflict and lack of need assessment; and relief goods duplication, wastage of resources due to inefficient planning, long waiting time or unmet demand. Thus, humanitarian logistics are necessary to the planning and decision-making process in regards with capacity, distribution planning needs, transportation management, and supply-demand management.

Table 2.1 Typical activities of disaster operations management
(Source: Modified from Altay and Green, 2006)

Mitigation	Response
・Zoning and land use controls ・Barrier construction to deflect disaster forces ・Active preventive measures to control developing situations ・Building codes to improve the disaster resistance of structures ・Controls on rebuilding after events ・Risk analysis to measure the potential for extreme hazards ・Insurance to reduce the financial impact of disasters	・Activating the emergency operations plan and emergency operations center ・**Evacuation of threatened populations** ・**The opening of shelters and provision of mass care** ・**Emergency rescue and medical care** ・**Urban search and rescue** ・**Relief distribution** ・Emergency infrastructure protection and recovery of lifeline services ・Fatality management
Preparedness	**Recovery**
・Emergency planning ・Development of mutual aid agreements and memorandums of understanding ・Disaster drills ・**Develop distribution planning** ・**Budgeting for and acquiring vehicles and equipment** ・**Maintaining emergency supplies** ・**Location selection for shelter, warehouse, and evacuation center** ・Construction of an emergency operations center and communications systems ・Conducting disaster exercises to train personnel and test capabilities	・**Disaster debris cleanup** ・Financial assistance to individuals and governments ・**The rebuilding of roads and bridges and essential facilities** ・**Sustained mass care for displaced human and animal populations** ・Reburial of displaced human remains ・Full restoration of lifeline services ・Mental health and pastoral care

*__the bold mark__ shows the activities that include logistics in its procedure

2.2. Relief Goods Distribution

Relief goods distribution start from the supply point to the hand of the affected people as illustrated in Figure 2.1. The relief goods, is transported, and distributed using the available network and transportation resources. The relief goods distribution system in humanitarian logistics will depend on each characteristic of the affected area and the area surrounding it. The difficulties of the emergency relief goods distribution are rooted in the uncertainty's nature of the disaster self. First, the need assessment will be hard to forecast in the chaotic situation (Moreno et al., 2018), with information changes over time. The transportation infrastructures and links (road, railway) may be destroyed, or partially inaccessible. The challenges are more noticeable in the developing countries, where resources usually lack to fulfill the demand.

Unlike commercial supply chain, where infrastructure is available, and transportation mode and vehicle are abundant and stable, relief distribution often destabilized. Further, the vehicle has to be organized first at the affected area from available resources before the relief distribution can be started (Kovacs and Spens, 2007). In the affected area and its surrounding area, transportation infrastructures are often destroyed, leading to a limited capacity of relief goods that can be transported (Thomas and Kopczak, 2005). The appropriate transport mode should be utilized even with slower speed or small capacity. In some developing countries, it is quite often the motorcycle, non-motorized vehicle, or even animals are used to transport the relief goods due to accessibility issue. The relief goods from the supply side also cannot enter the affected area smoothly due to the infrastructure breakdown. Destruction in the airport, breakdown in road and railway, or unavailability of a seaport in the affected area, forced decision maker to choose the transport mode for delivering relief goods. In the end, a full variety of transport mode choice are needed and should always be considered, including road, air, and even sea. The planning of transportation and the delivery in the preparedness phase is vital in humanitarian aid and disaster relief.

Nevertheless, Özdamar et al. (2004), Beamon (2004), Balcik and Beamon (2008), Balcik et al. (2009), Tomasini and Wassenhove (2009), Afshar and Haghani (2011), Ji and Zhu (2012), Noyan et al. (2015) and Bozorgi-Amiri et al. (2011) pinpoint the dominant characteristics of humanitarian logistics that are the uncertainties linked to the emergency context. High uncertainty has made the task of satisfying relief demand more challenging. Although the goal of relief distribution is to fulfill the population's urgent needs in the shortest possible time and with the fewest resources (Tomasini and Wassenhove, 2009) but flexibility to deal with time-varying or dynamic demand could be even more critical.

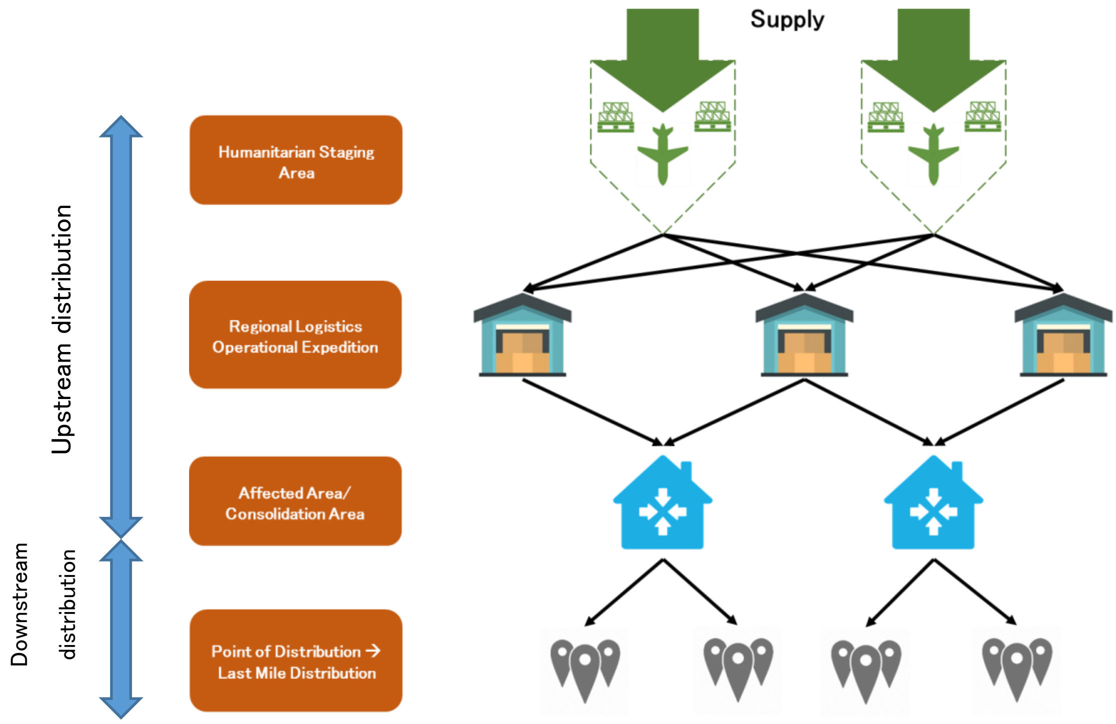


Figure 2.1. Relief Distribution Flow in Humanitarian Logistics

2.2.1. Multi-modal Distribution Network Design

Distribution network design is created based on some factors such as a specific number of supply node, distribution centers, demand node, and its mutual connections (Straka and Malindzak, 2010). It involves some decisions such as where to locate the facilities, finding the optimal distribution flow route from a set of potential routes, choose the appropriate transport modes, with objectives to minimize cost and time while satisfying the demand based on the service level requirements (Klose and Drexl, 2005**)**. Humanitarian relief activities, however, are vital that a slight improvement in the planning and implementation might result in a significant impact on reducing people suffering (Ertem et al., 2017). Relief distribution network developed to date also varies with some characteristics differ according to the type of distribution levels, type of planning horizon, facility location function, number of echelons, transportation mode selection, and infrastructure states. In the disaster context, distribution network needs to be planned and organized at once even though the knowledge of the situation is minimal (Beamon, 2004; Long and Wood, 1995; Tomasini and Wassenhove, 2006).

In disaster response operations, relief goods will arrive from several corridors; international, national, or regional and then send to the logistics operational center/consolidation area located in an affected region or its surrounding. In the disaster context, many routes and modes alternatives are considered when planning the distribution network. Efficient planning should achieve a robust yet flexible relief distribution and fit the character of the disaster in the affected area. Furthermore, the decision-maker must consider not only quantitative factors such as costs and distances but also qualitative factors, such as economies of scale, natural environmental conditions, infrastructure conditions, and geography (Hesse and Rodrigue, 2004) in the planning process.

During disaster, some uncertainties such as demand variations, network, and facility damage and shortages in resources are expected. One to be noted is the transportation network uncertainties. Road accessibility changes, airport and seaport availability, or unexpected events while vehicle on routes is the examples (Long and Wood, 1995). As the effect of disaster cannot be predicted, identifying damaged distribution network such as road, rail, or availability of airport might be difficult. Although it is crucial for humanitarian logistics, network information is not readily available in the aftermath of a disaster. Therefore it takes time to obtain factual route-maps. Diverse disaster types might result in obstructed usage of several transport modes. In earthquake/tsunami case, road and rail transportation might be damaged and unavailable. Thus air transportation becomes the primary mode to rely on. Furthermore, there is the uncertainty arising from inability to predict the victims, the degree of relief urgency, and the time-vary relief demand.

However, studies focusing on relief networks design has always been a focus on last mile distribution as it has the most breakdown among all. One of the studies conducted by Barbarosolu and Arda (2004) proposed multi-commodity and multi-modal network flow model for relief supplies transportation in disaster responses. Their study is closest to our study where they tackled the regional distribution network by considering multi-modal. Their study, however, only focus on utilizing road and helicopter, where the mode shift will only happen if road is not available. Özdamar et al. (2004) modeled emergency logistics as a multi-period multi-commodity network flow problem with different transportation modes. Their model focus on the last mile distribution and vehicle routing problem are optimized. Hu (2007) built an integer-linear-programming model for the container multimodal path selection in the context of emergency relief. Lin et al. (2011) propose a logistics model for the delivery of prioritized items in disaster relief operations by considering multi-items, multi-vehicles, multi-periods, soft time windows, and a split-delivery strategy. Haghani and Oh (1996) formulated the distribution problem in disaster as a multi-commodity, multi-modal network flow model with time windows, and presented two heuristic algorithms to solve the model. Najafi et al. (2013) proposed a multi-mode stochastic model to manage the logistics of both commodities, and injured people, in the earthquake response, and then developed a dynamic model for the same problem. In these studies, multiple transportation modes including air, railway, and road were simultaneously considered, aiming at selecting suitable modes with different transportation efficiencies for kinds of relief supplies in different urgency degrees.

Table 2.2. Study position in the literature of multi-modal relief goods distribution

		Multi-trip				Single trip			
		Deterministic		Stochastic		Deterministic		Stochastic	
		Time-Varying	Time-invariant	Time-Varying	Time-invariant	Time-Varying	Time-invariant	Time-Varying	Time-invariant
International						Aurelie (2010)			
Upstream/ National-Regional	Hub	**[This Study]**			Barbarosolu and Arda (2004)				
	No Hub		Haghani and Oh (1996), Hu (2007)						
Downstream/Last Mile					Lin et al. (2011), Özdamar et al. (2004)				Najafi et al. (2013)

The model developed, focus on regional distribution system or upstream level of supply chain. The consideration of time-varying model is arising due to the limitation of historical data in related study area. The critical point of this study is to fit the relief goods to suitable transport mode based on its infrastructure availability. As each disaster has different impact on infrastructure, stochastic approach as not suitable, as stochastic approach give an optimal result based on several disaster probabilities. In particular, regional distribution network mainly focus on configuring different nodes to improve the distribution process efficiency (Zhang et al., 2017). Thus, this study aims to develop a time-varying, multi-modal model for relief distribution networks with multi-trips by maintaining undisrupted network services in large-scale failure scenarios. To the best of our knowledge, this model is the first to consider multi-modal transportation with multi-trip consideration for upstream relief distribution system with time-varying consideration. Table 2.2 shows the study position in the literature of multi-modal relief goods distribution model.

2.2.2. *Last Mile Relief Distribution*

As last mile distribution has extremely dynamic nature, routes can frequently be changing. In the context of humanitarian logistics, the last mile stage is even critical since it is there that distribution has the most breakdowns and blockages occurred. Many studies have tackled humanitarian distribution network models. Fiedrich et al. (2000) introduced a dynamic operations model for emergency response for earthquakes and suggested an optimal assignment of resources to affected zones. Odzamar et al. (2004) investigated dynamic time-dependent distribution networks for inner-city transportation by modifying the vehicle routing problem (VRP) with pick-up and delivery using multiple vehicles and commodities for minimizing unmet demand. Lin et al. (2011) developed a multi-objective mixed-integer nonlinear programming model to minimize the total unsatisfied demand, total travel time, and the difference in satisfaction rate by considering the uncertainty of demand and supply. Ahmadi et al. (2015) provided a mathematical model for humanitarian logistical operations that considers road destruction possibility and standard relief time as constraints. Zhou et al. (2017) modeled dynamic resource scheduling for relief distribution in consideration of several objectives. Elluru et al. (2018) proposed a proactive and reactive model that considers both facility location and routing.

Balcik et al. (2008) noted that last mile distribution planning consists of decisions on how vehicles will make deliveries and designing the routes, including allocating relief goods to distribution centers or demand points. Yi and Kumar (2007) used an ant colony optimization (ACO) method to minimize the sum of unsatisfied demands for multi-commodity relief aid while minimizing the number of unsaved people in each node. Ozdamar and Demir (2012) formulated a last-mile pickup and delivery problem and proposed a hierarchical optimization model to minimize the total travel time. Noyan et al. (2014) investigated last mile distribution in post-disaster situations and proposed a two-stage stochastic model for deciding distribution locations and goods allocation to maximize the expected accessibility to distribution centers. Ahmadi et al. (2015) applied a multi-depot location routing problem to last mile distribution. Ferrer et al. (2015) used the concept of vehicle routing for last mile distribution and incorporated the failure rate as reliability and security factors. Penna et al. (2018) recently used the concept of rich vehicle routing and considered accessibility constraints that allowed only compatible vehicles to serve particular routes owing to road blockage or geographical conditions.

Although many studies have investigated multi-trip and heterogeneous distribution, distribution planning approaches proposed thus far have been applicable only to static planning problems. Very few studies have focused on last mile distribution with evolving and uncertain information regarding the demand size or demand location. Sheu (2010) discussed dynamic relief demand due to imperfect information and proposed the use of data fusion to forecast demand data over a period of large-scale disasters. Wohlgemuth et al. (2012) modeled the last mile distribution problem as a dynamic vehicle routing problem with pick-up and delivery. Lu et al. (2016) developed a real-time relief distribution model for disaster response that includes a demand and time estimator as well as a module for solving optimal distribution flows. However, most of these studies did not consider accessible or inaccessible demand locations. To the best of our knowledge, therefore, no published paper has considered both heterogeneous vehicles from an accessibility viewpoint and stochastic dynamic demand. Our study aims to address this research gap. Table 2.3 illustrates the position of this study in last mile relief distribution literature.

Table 2.3. Study position in the literature of last mile relief distribution

		Dynamic		Static	
		Stochastic	Deterministic	Stochastic	Deterministic
Heterogeneous vehicle	Accessibility status	**[This study]**	Balcik et al. (2008)	Penna et al. (2018), Noyan et al. (2014)	
	Without accessibility status	Odzamar et al. (2004)	Fiedrich et al. (2000)	Ozdamar and Demir (2012)	Berkoune et al. (2012)
Homogenous vehicle		Lu et al. (2016)	Wohlgemuth et al. (2012), Sheu (2010)	Ferrer et al. (2015)	

2.3. Healthcare and Emergency Medical Service

2.3.1. Emergency Medical System

The first decade of the twenty-first century has seen a major epidemiologic transition as 68% global deaths were attributed to non-communicable diseases—an 8% increase from the statistics in the year 2000. At the same time, there has been a sharp increase—to 9% by 2012—in deaths due to injuries (WHO, 2015). Many of these deaths were caused by time-sensitive illnesses and injuries, which could have been treated with early interventions. At present, time-sensitive illnesses and injuries, such as ischemic heart disease, perinatal conditions, diarrheal disease, traffic accident injuries, and suicide-attempt injuries, account for 14.64% of global deaths and disability-adjusted life years (WHO, 2015), of which 49.40% are from injuries (accidents, falls, and suicide attempts) and 24.55% are from heart disease.

Emergency medical service (EMS) is an important key component for all national healthcare systems and offer many efficiencies and cost effectiveness of care delivery within the broader healthcare system (Holliman et al., 2011). Overall, EMS plays a significant role in healthcare by contributing to sufficient, safe, efficient, and cost-effective patient care. One of the key performance indicators of an emergency medical service (EMS) is the emergency response time, which involves sending an ambulance to fetch the patient. Mayer (1979) defined ambulance response time as the interval between the call to the EMS and ambulance arrival. This definition has been widely followed by numerous researchers (Lee, 2011; Wilde, 2013) in the developed world. Unfortunately, within Asia, the initiation, awareness of the value of EMS, along with its acceptance and subsequent pace of development of emergency medicine vary widely beyond our geographical and cultural differences.

While it is not possible to make an EMS available everywhere all the time, the classical approaches to improving ambulance response time over the last four decades have been geared toward intelligently positioning the ambulances and routing them more efficiently. The overall approach has mainly involved formulating a location-allocation model that simultaneously solves the problem by selecting a set of locations for facilities and assigning sets of demands to these facilities with objectives to optimize the entire system to maximize patient coverage and minimize the response time or the number of vehicles.

2.3.2. Ambulance Pre-positioning

Emergency medical service planning is important to determine the quality and to review the status of the system. Figure 2.2 illustrates the different discipline involved in the EMS planning which includes service design; logistics; and analytics (Reuter-Oppermann et al., 2015). The logistics discipline has been adopted to solve some of problems in health and medical service, which include ambulance location problem, dispatching problem, staff, and paramedic scheduling, including transport scheduling. Finding a base location for dispatching an ambulance and relocate location of ambulance based on the forecast emergency demand are some tactical and operational level decision in EMS. Since ambulance response time is one of the crucial factors in patient survival, the location of the ambulance base will also determine the transport time to reach the patient. In particular, logistics concept and decision are used to develop the EMS planning.

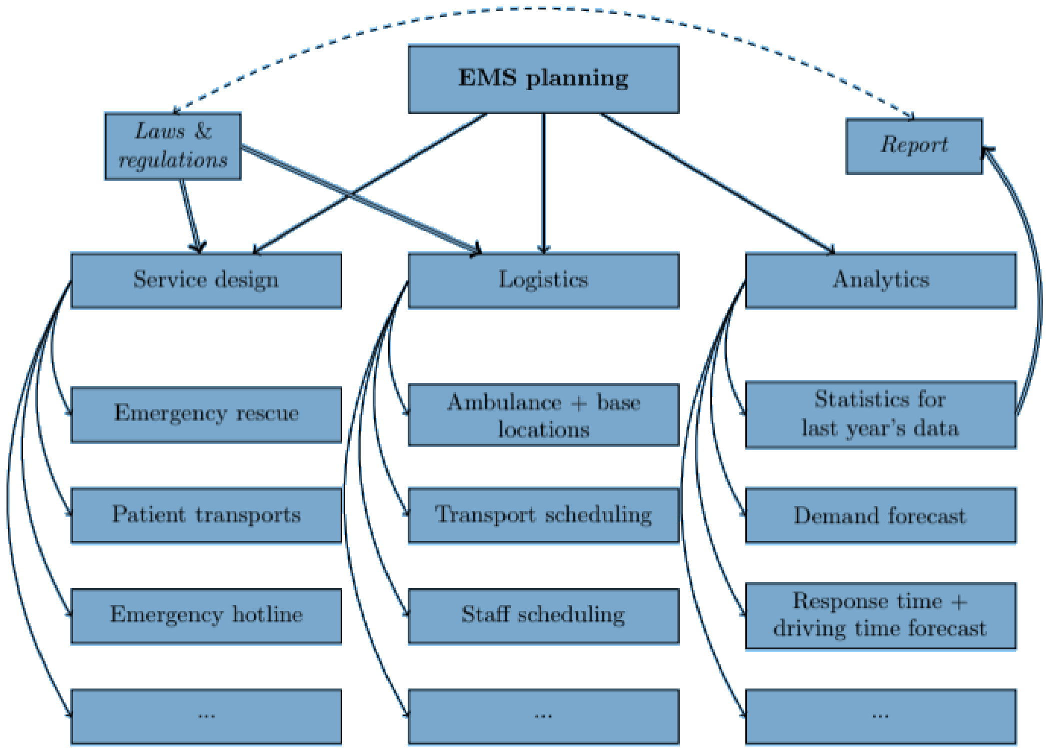


Figure 2.2 EMS planning-related disciplines (Source: Reuter-Oppermann et al., 2015)

Many people in low- and middle-income countries do not receive even primary health care (WHO, 2010). Health facilities are often located only in urban areas, far from rural areas and frequently difficult to access. The medical care that is provided can be costly and substandard as there is no centralized medical service and private organization might have a higher percentage as the ambulance provider. Although many countries have been incorporated advanced technology, low- and middle-income countries do not have the same privilege. Our study focuses on the ambulance location problem which involves the decision where to locate or position the ambulance to reach as much as patient as possible. Furthermore, we solved the case in low- and medium-income country without centralized medical service system. The study aims to give an alternative strategy for Ambulance Company, from their previous hospital-based location to demand-based location. Table 2.4 shows the study positioning in the literature.

Table 2.4. Study position in the literature of ambulance pre-positioning

	Centralized		Non-centralized	
	Static	Dynamic	Static	Dynamic
High quality of EMS preparation	Limpattanasiri and Taniguchi (2011), Schmid and Doerner (2010)	Thirion (2006), Schmid (2012)		
Have adequate EMS preparation	Ingolfsson et al. (2008) Li et al. (2016)		Pacheco et al. (2015)	
Low quality of EMS preparation			**[This study]**	

2.3.3. *Medical Service during Disaster Response*

Disaster often results in the ill-health and deaths either directly or through the disruption of health systems. The latter case happened due to lack of access to healthcare for the affected population. The health impact of disasters, however, can be minimized when local responders such as EMS, firefighter, police, S&R, together with national agencies are well-prepared (WHO, 2006). The disaster, in fact, also affect the local responders, as they are also part of the affected area. Thus, medical service during disaster response is also often done by the communities as the health facilities are disrupted and local responders are stunned by the scale. From experience and studies conducted by Auf der Heide (2006), the situation during disaster is much chaotic. Furthermore, the assumptions used for building the emergency planning often do not correspond to the field evidence. Table 2.5 provides the difference between the assumptions and evidence from the field.

Solely relying on local responders' capacity can lead to an increment of people agonized. According to Guha-Sapir et al. (2012), 68.2% of mortalities due to disaster globally, concentrated in developing countries. The empirical study result is expected as several factors added up to the problems such as population, urbanization, and level of vulnerability in developing countries. In fact, other healthcare and related medical organizations are as critical, and a part of a community's resilience. It plays a prominent role as the backbone of medical response and support system for the local responders, to natural and manmade disasters.

Table 2.5. Commonly Held Misconceptions during Disasters
(Source: Auf der Heide, 2006)

Assumption	Research Observation
Dispatchers will hear of the disaster and send response units to the scene.	Emergency response units, both local and distant, will often self-dispatch.
Trained emergency personnel will carry out field search and rescue.	Most initial search and rescue are carried out by the survivors themselves.
Trained EMS personnel will carry out triage, provide first aid or stabilizing medical care, and decontaminate casualties before patient transport.	Casualties are likely to bypass on-site triage, first-aid, and decontamination stations and go directly to hospitals.
Casualties will be transported to hospitals by ambulance.	Most casualties are not transported by ambulance. They arrive by private car, police vehicle, bus, taxi, on foot, etc.
Casualties will be transported to hospitals appropriate to their needs, and no hospital will receive a disproportionate share.	Most casualties are transported to the closest or most familiar hospitals.
Authorities in the field will ensure that area hospitals are promptly notified of the disaster and the numbers, types, and severities of casualties they will receive.	Hospitals may be notified by the first arriving victims or the news media rather than authorities in the field. Often, information and updates about incoming casualties are insufficient or lacking.
The most severe casualties will be the first to be transported to hospitals.	The least severe casualties often arrive first.

The importance of healthcare organizations, in particular hospitals, to remain operational extends beyond the necessity to sustain continuous medical services for the community, in the aftershock of a disaster. In order to lessen the local responder's burden, some countries are developed special Disaster Medical Teams (DMTs) specific to providing medical treatment in the affected area in the initial phase of a sudden-onset disaster. Arziman (2015) listed some example of DMTs such as from United States (Disaster Medical Assistance Team); Canada (Disaster Assistance Response Team); Japan (Japan Disaster Medical Assistance Team); Israel (under military); and Turkey (national Medical Rescue Team). Apart from DMTs, other medical-related organizations such as WHO, IFRC, or Doctors without Borders are often involved in a big disaster case.

2.4. Modeling Uncertainty

Dealing with emergencies means dealing with uncertainty, both disaster uncertainty and environmental uncertainty. Disaster uncertainty related to when and where emergencies and disaster happen, while environmental uncertainty related to uncertainty arose after the occurrence of the disaster. According to Das (2014), environmental uncertainty includes demand uncertainty, supply uncertainty, and network uncertainty. In that sense, it is important to include the uncertain parameter when developing the model for emergencies related problem. Table 2.6 summarizes uncertain parameters considered in the literature in the context of humanitarian logistics.

Table 2.6. Uncertain parameters considered in humanitarian logistics
(Source: Modified from Das, 2014)

	Type of Uncertainty	**Example**
Demand	Demand Location	New location of movement of location due cascading events
	Affected Population	Evacuees, Injured, affected disease
	Relief Goods	Food and water, medicines, response equipment, first aid supplies, tent, clothes, and miscellaneous
Supply	Provider	Number of providers, the availability of donors
	Relief Goods	Product capacity, quality, good losses, goods availability
Transport Network	Transport mode	Transport mode availability, number of vehicles
	Network infrastructure	Infrastructure availability, links availability, links capacity, links reliability

The methodologies in the literature related to uncertainty for humanitarian logistics and disaster management can be classified based on probabilities and that base on the type of uncertainty characteristics, such as fuzzy logic. Table 2.7 shows some classification of methodology for solving uncertainty and the drawback for each methodology.

Table 2.7. Classification of methodologies for solving the uncertainty
(Source: Liberatore et al., 2013)

Methodology	Explanation	Parameters	Remarks
Stochastics Programming	Optimized expected value of a given function of decisions and random variables	Uncertain, but following a probability distribution	Data should be known or can be estimated
Robust Optimization	Optimized problems with uncertain data but belong to some uncertainty set	Possible set of values	Suitable for modeling in the absence of data
Simulation Models	Mathematical model of a system which tries to replicate the system's behavior	Varied: dynamic, static, deterministic, stochastic	Need large number of data, Output to evaluate strategy and not the best decision
Fuzzy Sets	Concept to address imprecision, uncertainty other than probability concept	Based on fuzzy set theory and degree of membership	Can be used to explain linguistics description

2.5. Taxonomy of the Model

Uncertainties are common in the post-disaster context due to chaos and disruptions in the affected area. In optimization and simulation models, incorporating what is known about the uncertainty into input parameters and variables can support in quantifying the uncertainty in the resulting model estimates – the model output. Under the classification of information quality or input available for users, the model can be classified as deterministic and stochastic. Deterministic models associated with a designed or known external cause, with accurate descriptions. As the input model are known, the output of the model will not be change unless the input variables changed. On the contrary, model considered stochastic when some or all the design variables are expressed probabilistically, due to some randomness. The same set of parameter values and initial conditions will lead to an ensemble of different outputs. Stochastic modelling has long been recognized as a way to represent sufficiently random processes acting on fast time scales and affecting the slow time-scale variables of interest (Hasselmann, 1976).

Aside from the uncertain parameters, uncertainty also can happen due to the changes in the information or additional data. In emergencies case, where information is imprecise and sometimes unreliable, a decision based on additional information or new information are common.

Furthermore, the information is often changing overtime/time-varying (Balci, 2013). Thus, based on the system characteristics, model can also be classified as time-varying and time-invariant. Time-varying model contains collections of parameters or variables that are altered in time, due to parameters or variables updates or sequential change of parameters or variables value. In opposed to time-varying, in time-invariant model, response or output does not depend on the time at which the input is applied, as the value of the variables do not change across time.

Powell et al. (1995) distinguish between dynamism within a problem, a model, and the application of a model. They argue that:

> *"A problem is dynamic if one or more of its parameters are a function of time. This includes models with dynamic data that change constantly as well as problems with time-dependent data which are known in advance.*
> *A model is dynamic if it explicitly incorporates the interaction of activities over time. Here one should distinguish between deterministic dynamic models and stochastic models.*
> *An application is dynamic if the underlying model is solved repeatedly as new information is received. Consequently, solving models within dynamic applications require huge computational resources."*

In corresponded with type of response characteristics model can be divided into static and dynamic. While static condition does not represent time, dynamic condition implies that the situation represents time, with the decision output is based on the previous decision and newly added information.

2.6. Comprehensive Review of Model

2.6.1. *Multi-modal Distribution Network*

Numerous researchers have attempted to address the multi-modal distribution problem in a disaster context. The multi-modal distribution network problem can be modeled as a multi-commodity capacitated network design problem, where the transport mode act as different commodity. Pirkul and Jayaraman (1996) develop a distribution network planning with multi-commodity in the multi-echelon system. The problem is modeled as mixed integer programming to locate the plant and warehouse simultaneously for minimizing total transport cost and opening cost of the facilities. Gendron et al. (1998) solved the multi-modal distribution network problem by modeling it as capacitated multi-commodity distribution network. In their model, an arc-based formulation is developed, and a greedy algorithm is presented to counter the problem.

Several studies focusing on multi-modal distribution problem based on both studies can be easily found in commercial supply chain cases. In the disaster context, the multi-modal distribution network is proposed to shows the model shifted from accessible network to non-accessible network. To date, the study by Haghani and Oh (1996) has been used as a model based for multi-modal relief distribution model. They have developed the multi-modal distribution model as time-space network by illustrating different nodes supply and demand for each transport mode in time horizon. Although considering multi-modal transportation, the mode can only be shifted if the node has a transshipment role. The study also set the time-windows to calculate the penalty cost for the late delivery. The related literature and proposed model have been analyzed in the section 2.2.1 before. The problem on multi-modal distribution network is solved by several approaches, such as Lagrangian relaxation (Pirkul and Jayaraman, 1996, Odzamar et al., 2004), greedy heuristics (Gendron et al. (1998), Haghani and Oh, 1996), and metaheuristics approaches (Hu, 2007; Yi and Kumar, 2007; Lin et al., 2011)

2.6.2. Facility Location Problem

In the case of ambulance pre-position, many kinds of literature refer to the facility location models that adopt the emergency as their criteria of objectives, constraints, solutions, and other attributes. In particular, several facility location models can be used to model the ambulance pre-positioning problem. Some of the models adopted including P-median, maximal covering location problem, double coverage location problem, and lately dynamic ambulance location problem. Church and Revelle (1974) developed the maximal covering location problem with an objective function to maximize the population to be served within a specified distance or time for a given number of emergency facilities. The P-median model developed by Pirkul and Schilling (1988) set out to minimize the total distance covered by the ambulance. One of the major drawbacks of these models has been the assumption that emergency facilities will remain available throughout the day. Later, therefore, Gendreau et al. (1997) introduced a double-standard model in which the patient's location can be covered by more than one ambulance (multiple coverages). This concept is based on the limitation that an individual share of the demand must be attended with a minimum response time while the remaining demand can be served with larger response time.

Similar models were later used as case studies with real data, such as in Austria by Doerner et al. (2005), in Belgium by Thirion (2006), and in Montreal by Gendreau et al. (2001). Some other examples of the EMS pre-positioning problem in the developing countries include ambulance pre-positioning in Kumasi, Ghana (Amponsah et al., 2011), Tijuana, Mexico (Pacheco et al., 2015), and Tianjin, China (Li et al., 2016). The ambulance location and allocation problem in dynamic environments has also been studied, such as time-variant travel times (Repede and Bernardo, 1994), real-time ambulance allocation with several scenarios (Gendreau et al,. 2001), multi-period model (Rajagopalan et al., 2008; Schmid and Doerner 2010), time-delay consideration (Ingolfsson et al., 2008), and time-dependent travel times and dynamic requests (Schmid 2012). The improved model of ambulance pre-positioning is developed with as the data availability and technology for centralized ambulance system is improving in some of the developed countries. The findings of these studies revealed substantial variations in the results when variable travel time was introduced. Along with improving the service by pre-positioning the ambulances, recent studies have also attempted to focus on the equity of the ambulance service (Drezner et al., 2009; Smith et al., 2013; Khodaparista et al., 2016), dynamic positioning (Degel et al., 2015; Schmid, 2012), and dispatching strategy (Lee, 2011; McLay and Mayorga, 2013).

Several methods were used to solve these ambulance location cases, such as metaheuristics (Thirion, 2006; Limpattanasiri and Taniguchi, 2011), simulations (Lim et al., 2011), integer programming (Looije, 2013), dynamic programming (Schmid, 2012), and Markov chain (Alanis et al., 2013). In the developing countries, ambulance pre-positioning in Kumasi, Ghana was addressed using simple Genetic Algorithm (GA) demonstrating that the number of ambulance location to cover demand based on US Federal EMS Act requirement was not sufficiently fulfilled in the study area (Amponsah et al., 2011). Pacheco et al. (2015), with data from Tijuana-Mexico, modeled the problem using Weber Facility Location Problem which ignores dynamic travel time and applied GA to conclude that the objective values (response time) were superior for new ambulance location with a promising result (feasibility of new location). Li et al. (2016) used a simple heuristic based on medoids for ambulance location selection with data-driven travel time. The method proves to be able to find a nearly global optimum with a case study in Tianjin, China.

2.6.3. Vehicle Routing Problem

The capacitated vehicle routing problem is introduced by Dantzig and Ramser (1959). It is known that Capacitated Vehicle Routing Problem (CVRP) is an NP-hard problem (Lenstra and Kan, 1981), in which an instance with a large number of customers might not be possibly solved in a reasonable amount of computing time using exact solution methods. Hence, numerous studies have tried to develop heuristic methods to obtain a near optimal solution even though not necessarily guaranteeing an optimal solution. Toth and Vigo (2001) classified the heuristic into two major categories: classical heuristic and meta-heuristic. Classical heuristics was developed mostly between 1960 and 1990, with early attempts to solve the problem focusing on route construction, route improvement, and two-phase heuristic. These approaches tend to perform a relatively limited investigation of the search space.

Gendreau et al. (2001) suggested that a metaheuristic approach is suitable for main class optimization problems such as the vehicle routing problem (VRP) and its variants. Neighborhood-centered methods generally proceed by iteratively exploring the neighborhoods of a single incumbent solution; examples of such methods include simulated annealing (SA) (Kirkpatrick and Vecchi, 1983), Tabu search (Glover and Laguna, 2013; Taillard, 1993), variable neighborhood search (VNS) (Mladenovic and Hansen, 1997; Kytöjoki et al., 2007), adaptive large neighborhood search (ALNS) (Ropke and Pisinger, 2006), and iterated local search (ILS) (Lourenco et al., 2003). By contrast, population-based methods are inspired by natural mechanisms; examples of such methods include genetic algorithms (GA) and evolutionary algorithms (EA) (Holland, 1975), memetic algorithm (Moscato, 2010), path relinking (PR) and scatter search (SS) (Glover, 1999), particle swarm optimization (PSO) (Eberhart and Kennedy, 1995), and ant colony optimization (ACO) (Dorigo and Stützle, 2003). Numerous types of hybrid metaheuristics have also been proposed for solving VRP variants; these include SA + Tabu (Osman, 1993), GRASP (greedy randomized adaptive search procedure) + ILS (Prins, 2009), ILS + VND (variable neighborhood descent) (Chen et al., 2010), and TABU + ILS (Cordeau and Maischberge, 2012).

Single-solution-based heuristics have been extensively studied because of their proven ability to solve NP-hard problems with robust quality and time efficiency. TTRP, a VRP variant, is one such problem that can be solved effectively using this approach. Some notable methodologies include Tabu search (Chao, 2002; Scheuerer, 2006), SA (Lin et al., 2009), large neighborhood search (Derigs et al., 2013), hybrid GRASP (Villegas et al., 2010; Villegas et al., 2011), and matheuristic (Villegas et al., 2013; Drexl, 2011). Furthermore, some methods such as VNS (Gutjahr, 2007; Sarasola et al., 2016), ALNS (Azi et al., 2011), and hybrid metaheuristics (Ritzinger, and Puchinger, 2013) have been shown to provide robust results for solving both stochastic and dynamic VRP variants. Many researchers have proposed metaheuristics approaches for solving disaster response problems. For example, Yi and Kumar (2007) used ACO, Lin et al. (2011) used GA, Wilson et al. (2013) used VND, and Zhou et al. (2017) used EA. Many studies have successfully applied SA algorithms to various problems, and therefore, this study uses a hybrid SA/VNS approach.

The relief distribution in this study is divided into two parts, upstream level, and downstream level. Upstream level starts from the supply node to the consolidation node in the affected area. Downstream level focuses on relief delivery inside the affected area from the local distribution point to the shelters. Each level has different challenges accordingly. In the upstream level, the challenge lays on how to deliver the existing relief supply to the affected area. The decision will be made based on consideration of a number of reliefs supply available, transport mode available, and infrastructure and accessibility restriction to reach the affected area. In the other hand, downstream level or last mile distribution faces challenges in the restricted number of vehicle available, accessibility issue, the uncertainty of demand magnitude and locations, and also the dynamic information (Sumalee and Kurauchi, 2006; Girard et al., 2014).

2.6.4. Mobile Facility Routing Problem

The concept of mobile facility routing problem (MFRP) is introduced by Halper and Raghavan (2011) to provide service in large region more effectively than fixing the number of facilities. The mobile facility is supposed to relocate to other locations once the demand has been served. The study presented a deterministic with multiple mobile facility routing problems for maximizing the number of demand covered. Different from vehicle routing problem, the mobile facility will serve the demand based on the amount of the service provided. It has many application domains from cellular telephone coverage, postal service (United Kingdom Department of Transportation, 2009; Hong Kong post, 2008), and healthcare related service (Alexy and Elnitsky, 1996). Halper and Raghavan (2011) also showed that as MCLP as a special case of MFRP with constant rate demand and non-relocated facility, MFRP can be regarded as an NP-hard problem. Two types of heuristics are performed to solve both single and multiple mobile facility routing problem.

Although the concept of mobile facility is not new, the most relevant research on the date is limited to Lei et al. (2014) and Lei et al. (2016). In their study, Lei et al. (2014) assumed that demand should not be deterministic and use the probability distribution to include uncertainty in the model. They proposed two-stage stochastic programming model for solving the location problem as the first decision and solving the demand allocation for the second decision. The later study by Lei et al. (2016), extend the problem by adding the fleet size decision in consideration with different number of demands covered for each location. Robust optimization is performed for handling the uncertain demand.

2.7. Summary of the Chapter

Humanitarian logistics focuses on the task to smoothen emergency response operation, not only focus on relief goods distribution but also services needed such as medical care. Previous disasters give information about how vital the multi-sector outlook for responding to emergencies and disasters. The emergencies response planning should ensure the coherence between national, regional, and local responders' roles, capacities, and responsibilities. This study modeled the response planning for tactical and operational decision in relief distribution and medical care service, in different scale of emergencies.

Furthermore, in consideration with the scale of emergency, the uncertain parameters also are different, respectively. The model presented in this study referred to all type of uncertainties, focusing on supply uncertainty in upstream level of distribution, demand uncertainty in downstream level of distribution, and network uncertainty for the medical service operation. Due to limited access to data collection and limited data availability, the type and scale of uncertainty considered are also narrow. In summary, this study focus for each chapter can be found in Table 2.8 below.

Table 2.8. Summary of each study chapter model developed

	Model	**Scale of emergency**	**Scope**	**Uncertainty Type**
Chapter 3	Multi-modal Relief Distribution	Medium-Large Scale Emergency /Disaster	Regional-National	Time-Varying Input for: • Supply • Number of vehicles • Demand
Chapter 4	Last mile relief distribution	Medium-Large Scale Emergency /Disaster	Local	• Dynamic node (demand location) • Stochastic demand values
Chapter 5	Ambulance Pre-positioning	Routine emergency	Local	Time-dependent travel time
	Mobile Health Clinics Routing	Medium-Large Scale Emergency /Disaster	Local	Scale of disaster probability: Number of affected people

Chapter 3 Multi-Modal Relief Distribution Planning for Disaster Response Operations

3.1. Introduction

As one of the aims of this study is to develop a relief distribution planning for disaster response operation, as a starting point, this chapter focuses on providing details on logistics capacity and the importance of multi-modal transportation for relief distribution in upstream level. Upstream level consists of supply node, where the goods and donation from national and international agencies are received, logistics operational area, in which functioned as a hub to stage and to move relief goods to more appropriate mode of transport, and consolidation node or affected area where all of the relief donations are collected before dispatch to the affected people. The output of the chapter helps to build knowledge of the multi-modal transportation advantages for relief distribution.

In the aftermath of disasters, the distribution of emergency supplies and relief goods is essential for successful disaster operations. Fast and efficient distribution systems can minimize the number of fatalities and provide quick relief to people in distress. Combinations of modes of transport (such as sea–road, air–rail, and air-road) might advance the performance of humanitarian relief distribution systems. Multi-modal transportation can be a solution when transportation resources are scarce during the immediate aftermath of a disaster. As an alternative to road transportation in the short term, if available, other modes of transport (such as railways) can move relief supplies in higher amounts on a single trip. Air transportation also becomes significant for disaster response operations – especially for distributing relief goods – as it provides speed and high coverage of affected areas (Hanaoka et al., 2011). Vessel or maritime transportation, on the other hand, provides large capacity that will be useful for transporting large amount of goods/bulk in a cost-efficient manner. In response to disasters, decision-makers often integrate any available transportation tools to deliver relief supplies.

According to Ruan et al. (2014), most extant multi-modal emergency studies belong to transport mode selection problems, aiming at selecting proper transportation tools for different kinds of relief supplies. Different from commercial logistics with fixed inventory cycle, humanitarian distribution operation has a specific lifecycle, starting from early assessment period, building the foundation of the supply chain, then deliver the supply to the affected region. Within a short period of time, the supply chain and distribution operation will change progressively, become more structured compared to the early period, and have a fixed route and strategy before the operation slowly terminates or transfers to local agencies.

However, generating transportation plans for relief goods transportation is challenging, and some issues need to be addressed:

a. Post-disaster environment changing over time. During the initial period, some important transportation resources in affected area such as airport and port as nodes or railway and road as network, are commonly destructed and could not be operated for receiving goods. The restoration attempted to fix such resources will change the availability status of the supposed important nodes.
b. The time-varying values for some variables, such as supply, demand, number of vehicles, capacities due to information evolution. It is quite common on how the first relief goods transported to affected area are the prepared inventories from disaster preparedness stage. At the same time, the available emergency resources, including vehicles and supplies, are always limited. As the information concerning the occurrence of the disaster is dispersal, more relief goods are donated and sent to affected country, affecting the total number of available supplies. From the side of affected area, the demand value also changing over-time as the information gathered evolves.

This chapter purposes to develop a multi-modal model for relief distribution networks with time-varying features and multiple trips by maintaining undisrupted network services in large-scale failure scenarios. The time-varying features, following three phases of disaster response operations: (1) emergency response; (2) continuum response; and (3) initial recovery. The model aims to discover the relationship between time-varying data input that are predictive of any of a number of time-varying outcomes. A strategic distribution plan is developed for the island of Java, Indonesia in general and Yogyakarta Province as a specific example. A case study for distribution networks and multi-modal transportation systems in Java are developed. The comparison is evaluated with scenarios considering the different phase of response depict essential factors such as network condition and demand fluctuation.

3.1.1. Response Phase and Time-Varying Supply

The time-varying features in the disaster context are often used for understanding how the environment and some parameters value do depend on the time. Adapting Sheu and Pan (2014), this study divided the disaster response into three phases as follow:

a. Initial response period

   After a disaster strike, response operation will immediately follow. This period is regarded as the most critical period for searching for and rescuing trapped survivors (Sheu 2007). This period may extend to three or four days.

b. Continuum response period

Following the initial response, this period starts when the search-and-rescue mission is almost complete and is regarded as the appropriate time to meet the basic subsistence needs of survivors, including shelter, water, food, and emergency medical assistance (IDNDR/DHA 1992; UNDP/UNDRO 1992). This period may last from two to three weeks. At the beginning of the period, the number of relief supply will increase and decrease slowly as the urgent needs are all delivered.

c. Initial recovery response period

This period follows the continuum response as the early recovery period when the environment is cleaned up, and damaged infrastructure is repaired in the affected areas.

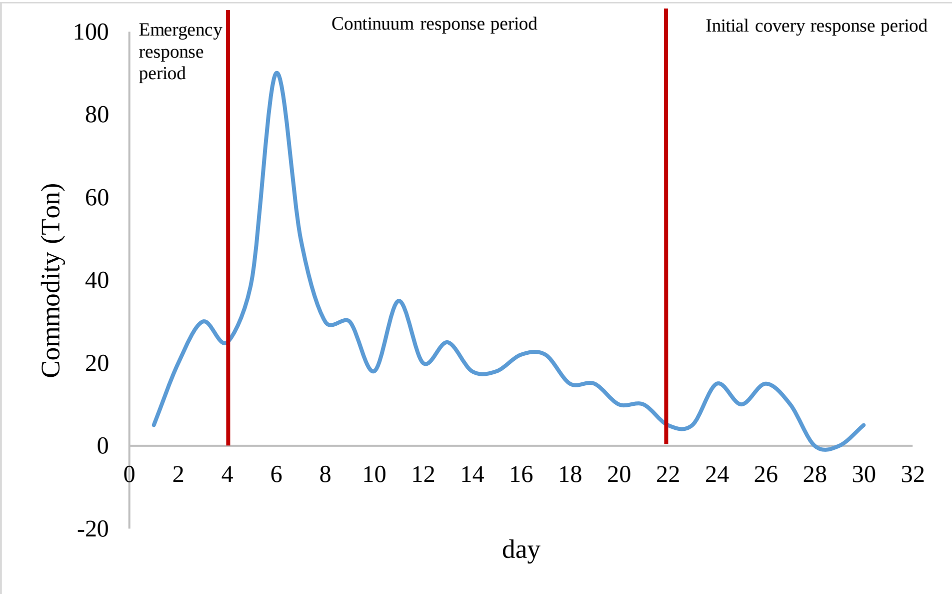


Figure 3.1. Approximate Relief Supply Deliver during Disaster Response Period (Source: Sheu, 2007)

The number of supply available during response phase will follow a time-varying manner based on Figure 3.1. The time-varying values in particular occurs due to update information and additional resources for improving the distribution system. In summary, the amount of relief goods supply tends to vary according to the progress of the relief response. The number of supply and demand will increase within 3 days - 1 week after the occurrence of disasters. As this study suggests considering the three-response phase, each phase is driven by the urgency of the needs. As a time-dependent logistics problem, there are high stakes associated with the accurate delivery time of relief supplies. For example, during the initial response phase, the decision maker will focus on speed of delivery, as the challenge will be to minimize the delay in the arrival of relief goods at the affected area. The supply is reaching maximum number within the first week after the disaster. Thus the focus shifted from delivery time to how to make sure all of supply can be delivered with available resources. During this continuum response period, it is expected that all transportation mode can be utilized. After several weeks of response, the affected area will receive a smaller number of relief goods, which again shift the goal with cost reduction become the distribution process driver. During the initial recovery response phase, the relief supply chain starts to resemble a regular business supply chain (Tomasini and Van Wassenhove, 2009).

3.1.2. Logistics Capacity, National Disaster Management Agency and Logistical Challenges in Indonesia

Logistics capacity calculates qualitatively the readiness in the logistics sector to cope and operate if disaster strike. As part of the preparedness phase, it is necessary for a country to conduct logistics capacity assessment. The assessment, provide information about the related logistics resources, consist of logistics infrastructure and service, transportation infrastructure and service, the related area capacity, and the vital location or node for emergency humanitarian response operations. The results are expected to be shared among the organizations in-charge with emergency response, locally, regionally, nationally, and internationally, in hoped to enhance the coordination during the actual response operations.

Among all factors for developing relief distribution, based on the result of logistics capacity, as in Table 3.1, main consideration for the model developed in this study is transportation infrastructure, transportation mode, multimodality, the capacity of node and vehicle, number of the available vehicles, and time-varying trend of the relief supply. By understanding the logistics capacity, the decision maker should be able to plan the relief distribution network easily and coordinate with several agents prior to the disaster.

Table 3.1. Success factor for humanitarian logistics and information collected from Logistics Capacity

(Source: Modified from Pettit and Beresford, 2009)

	Alternative descriptor	**Key aspect**	**Remarks**
Transportation planning	Transport availability and constraints	Transport infrastructure	Port, airport, railway, road, waterway
		Transport mode	Vessels, ferry, boat, airplane, helicopter, truck, trailer, minitruck, train
		Scheduling and maintenance	
		Intermodality and multimodality	
Capacity planning	Warehouse, service, and transport capacity	Number of warehouses	The available warehouse that owned by the government rent from private or belongs to a relief organization
		The capacity of warehouse/node	
		Number of vehicles	Number of the vehicle in each critical node
		Capacity of vehicle	
		Demand number	The short-long term, Stochastic, Deterministic, Static, Dynamic
Other aspects	Seasonal effect	Season (rainy, dry, summer, winter) Bottleneck due to cultural/religion	

As a priority for Government of Indonesia, disaster management system has been built and improved in the last decades, with Badan Nasional Penanggulangan Bencana (BNPB) as the national disaster management agency. It functions as a coordinator and commander during emergency response operations. At the regional and local level, provincial disaster management agency (BPBD Provinsi) and district disaster management agency (BPBD Kabupaten) in-charged with emergencies in local and provincial level.

During a disaster response, many relief goods are sent directly to affected area, without concern about the availability of storage, handling, and people that are able to sort and distribute the goods. Excessive supply within the same period leads to the bottleneck in relief distribution operation. Further, there is also congestion happened due to the disproportionate vehicle in the network. Cooperation among nearest regional government is essential to achieve an effective emergency response since one critical entity (port, airport, and node) would not be able to cope with its capacity. Learning from previous disasters, decision maker feels the necessity to form a relief distribution network with a hub concept. The hub will act as logistics operational area, in which the relief goods will be moved to other transport mode based on the link and transport infrastructure availability.

3.2. Problem Description and Model Development

The underlying problem in these situations is to assign a limited number of transportation resources (which can include various modes and their availability) to the shipment of goods – whereby demands arise at specific destinations –across to transportation network. In emergency response, the transportation network and important nodes may or may not be damaged due to a natural catastrophe. In that case, the disruptions in the delivery network are presented by removing the impacted nodes and links and shifting the relief goods to different routes and modes. During a transportation decision-making process, the goal is to deliver the required demand by considering objective function for each period. At the same time, the process must stay flexible in light of changes in the transportation network configuration, which may have resulted from the cause of the emergency.

This study developed multi-modal distribution model with three layers of a relief distribution network: (1) a supply node (SN), (2) a logistics operational area (LOA); and (3) a relief distribution operation area/affected area (AA) as presented in Figure 3.2. Since the appropriate transportation of relief supplies plays an essential role in emergency responses and directly affecting the efficiency and effectiveness of disaster relief, decision-makers often integrate different modes of transport to deliver relief supplies as soon and as much as possible. In the context of the problem investigated by this study, nodes in the time-space network represent the physical locations of the supply and demand points for each mode of transports as well as over time, while the links represent the connecting routes for each transport mode between these points.

Multi-modal relief distribution is represented by different types of modes utilized from node to node and modes of transport changes in LOA nodes. In this study, multi-modal transportation considered including truck, train, airplane, helicopter, and vessels. Furthermore, the logistical operations of the three layers are characterized by the status of time-varying logistics operations, represented by a time period. A physical network is converted into a time-space network, and a disaster scenario is generated to represent a different scale and after-disaster situation, such as node availability and link accessibility.

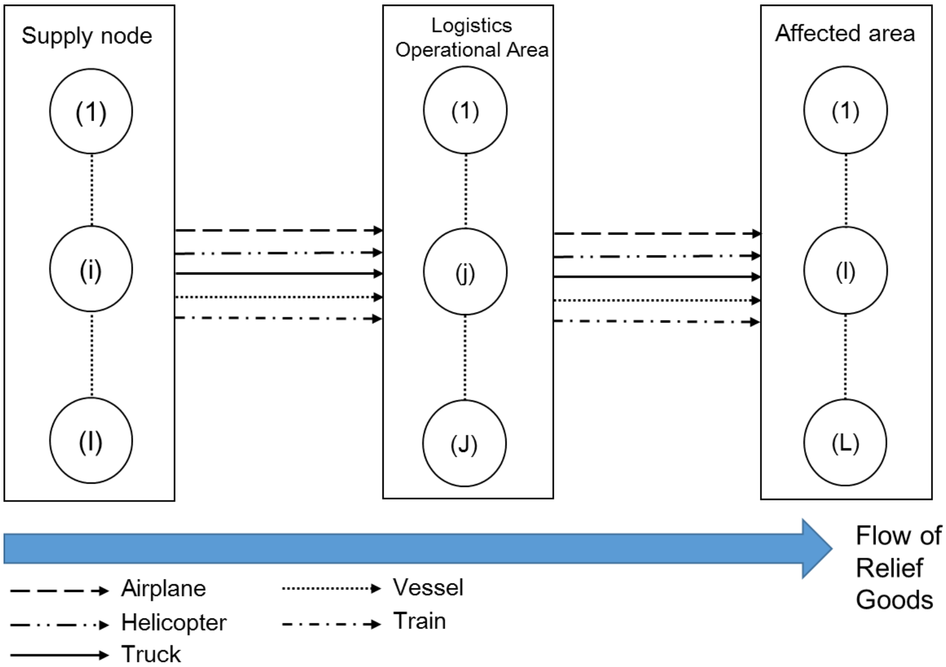


Figure 3.2. Humanitarian Relief Goods Distribution Flow

Humanitarian logistics use three performance measurement as the target for its operation. The efficiency factor usually represented by costs such as transportation cost, inventory cost, or distribution cost (Haghani and Oh, 1996; Barbarosoglu and Arda, 2004). The effectiveness factor is represented by the level of demand satisfaction and time minimization (Ozdamar et al., 2004; Yi and Kumar, 2007) and equity which means fairness during the relief distribution operation (Lin et al., 2011). Many researchers have been doing single objective and multi-objectives to see the trade-off between each type of measurement. This study integrates the cost aspect and time aspect by calculating it as one objective function.

All the transport mode selection and transportation decisions are taken over a finite horizon divided into 3 day-long for each period which further divided into hourly micro-time periods. In the beginning of each period, new information about supplies, demands, number of resources (vehicles), and availability of vital nodes will be updated. In disaster situation, the number of vehicles available to transport large quantities of relief goods is limited. In some cases, the capacity is smaller compared to the actual quantities of relief goods. Thus, a vehicle can be reuse, which allowed them to perform multi-trip distribution throughout the period. When multi-trip is not permitted, the vehicle can only perform one round trip delivery during the same period. In that case, the required number of vehicle to meet the demand needed should be assumed unlimited, which is not practical. Thus, if multi-trip delivery is allowed, vehicles are able to perform other delivery, which implied to the actual need of the transport mode. The illustration for the multi-trips transportation is show in figure 3.3.

3.2.1. Model Development

3.2.1.1. Assumptions and Limitation

a. A number of the affected area (AA), logistics operational area (LOA), and supply node (SN) are known.
b. The links and their availability statuses for initial response can be obtained during the first period after disaster strike
c. The update links and nodes availability information for each period is update after the end of previous period
d. Mode of transportation used are truck, train, vessel, airplane, and helicopter
e. For each mode of transportation only one type of vehicle (homogeneous), with same capacity and configuration, is considered
f. The total supply available in each supply node is different
g. The demand needed at each affected area depends on the number of affected people
h. Each vehicle is allowed to have multi-trips within one working period
i. Logistics operational area and affected area nodes can only be served using the resources status in each period (no availability of port/airport will affect the decision)
j. The maximum number of the available vehicle is determined per node
k. The cost for mode changes is not considered, and transfer goods from one transport mode to others is assume to be independent.

3.2.1.2. Decision Variables and Notations

Notations

i = set of node in the Supply layer (I) $(i=1,2,\ldots I)$

j = set of node in the Logistics Operational layer (J) $(j=1,2,\ldots J)$

l = set of node in the Demand layer (L) $(l=1,2,\ldots L)$

k = set of transportation mode *(k*=1,2,…*K)*

h = set of period *(h*=1,2,…*H)*

τ = set of micro-time period (τ=1,2,3,…,T)

Parameters

t_{ij}^{k} = travel time (hours) needed to transport goods from node *i* to *j* using mode *k*

Vc_k = fixed cost for using mode *k*

c^k = unit cost (USD/ton.hr) for using transportation mode *k*

$M_i^{k\tau}(h)$ = maximum number of vehicle available for *k* mode in node *i* during in micro-time period τ during period *h*

$S_i(h)$ = relief supply (ton) in supply node *i* during period *h*

Cap_i = capacity available of facility in node

Q_k = vehicle capacity (ton) of transportation mode *k*

$\delta_l(h)$ = demand needed (ton) in node *l* during period *h*

Decision Variables

$X_{ij}^{k\tau}(h)$ = equal 1 if there is a relief delivery from supply node *i* to logistics operational area *j* using transportation mode *k* in micro-time period τ during period *h*, equal 0 if otherwise.

$X_{jl}^{k\tau}(h)$ = equal 1 if there is a relief delivery from logistics operational area *j* to affected area *l* using transportation mode *k* in micro-time period τ during period *h*, equal 0 if otherwise.

$Y_{ij}^{k\tau}(h)$ = amount of relief delivered (ton) from supply node *i* to logistics operational area *j* using transportation mode *k* in micro-time period τ during period *h*

$Y_{jl}^{k\tau}(h)$ = amount of relief delivered (ton) from logistics operational area *j* to affected area *l* using transportation mode *k* in micro-time period τ during period *h*

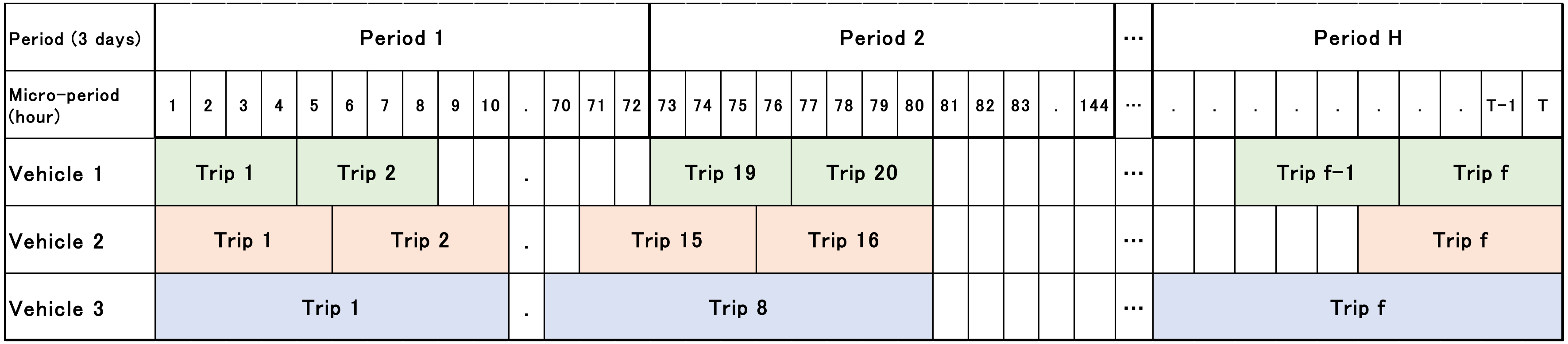


Figure 3.3. Illustration of Multi-Trips Relief Distribution System

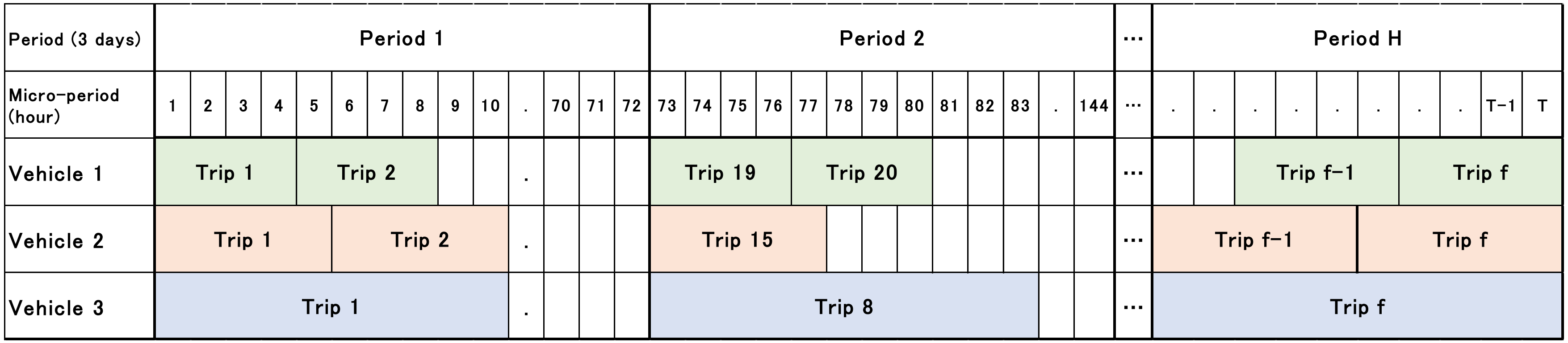


Figure 3.4. Illustration of Partially Multi-Trips Relief Distribution System (within one period)

3.2.1.3. Objective function

The objective function consists of two parts. The first part focus on minimizing delivery time which will be the focus of decision maker during the initial response phase from period 1 to period $h_{initial}$.

Time-period $h_1 \sim h_{initial}$

$$min \sum_{h=1}^{h_{initial}} \left[\sum_{i}^{I} \sum_{j}^{J} \sum_{k}^{K} \sum_{\tau}^{T} Y_{ij}^{k\tau}(h)\, t_{ij}^{k} + \sum_{j}^{J} \sum_{l}^{L} \sum_{k}^{K} \sum_{\tau}^{T} Y_{jl}^{k\tau}(h)\, t_{jl}^{k} \right] \tag{3.1}$$

The second part, representing the continuum response period, from period $h_{initial+1}$ to $h_{continuum}$ with focus on minimizing total cost for transporting the goods from SNs to AAs including vehicle cost, cost of transporting goods from SNs to LOAs and cost for transporting goods from LOAs to AAs demand area.

Time-period $h_{initial+1} \sim h_{continuum}$

$$\begin{aligned} \min \sum_{h_{initial}+1}^{h_{continuum}} \Bigg[& \sum_{i}^{I} \sum_{j}^{J} \sum_{k}^{K} \sum_{\tau}^{T} X_{ij}^{k\tau}(h)\, Vc_k + \sum_{i}^{I} \sum_{j}^{J} \sum_{k}^{K} \sum_{\tau}^{T} Y_{ij}^{k\tau}(h)\, c_k t_{ij}^{k} \\ & + \sum_{j}^{J} \sum_{l}^{L} \sum_{k}^{K} \sum_{\tau}^{T} X_{jl}^{k\tau}(h)\, Vc_k + \sum_{j}^{J} \sum_{l}^{L} \sum_{k}^{K} \sum_{\tau}^{T} Y_{ij}^{k\tau}(h)\, c_k t_{jl}^{k} \Bigg] \end{aligned} \tag{3.2}$$

3.2.1.4. Constraints

$$S_i^{\tau}(h) = \sum_{j}^{J} \sum_{k}^{K} \sum_{\tau}^{T} Y_{ij}^{k\tau}(h) \qquad \forall i, h \tag{3.3}$$

$$\sum_{l}^{L} \sum_{k}^{K} \sum_{\tau}^{T} Y_{jl}^{k(\tau - t_{ij}^{k})}(h) = \sum_{i}^{I} \sum_{k}^{K} \sum_{\tau}^{T} Y_{ij}^{k\tau}(h) \quad \forall j, h \tag{3.4}$$

$$\sum_{j}^{J} Y_{ij}^{k\tau}(h) \le Cap_i^k(h) \quad \forall i, k \tag{3.5}$$

$$\sum_{i}^{I} Y_{ij}^{k\tau}(h) \le Cap_j^k(h) \quad \forall j, k \tag{3.6}$$

$$Y_{ij}^{k\tau}(h) \le \; Q_k \;\; \forall i, j, k, \tau, h \tag{3.7}$$

$$Y_{jl}^{k\tau}(h) \le \; Q_k \;\; \forall j, l, k, \tau, h \tag{3.8}$$

$$\sum_{i}^{I} X_{ij}^{k\tau}(h) \le I \qquad \forall j, k, \tau, h \tag{3.9}$$

$$\sum_{j}^{J} X_{jl}^{k\tau}(h) \leq J \qquad \forall l,\ k, \tau, h \tag{3.10}$$

$$\textstyle\sum_{i}^{I} \sum_{\tau' = \tau-(2t_{ij}^{k}-1)}^{T} X_{ij}^{k\tau} \leq M_{i}^{k\tau}(h) \quad \forall i, k, \tau, h \tag{3.11}$$

$$\textstyle\sum_{j}^{J} \sum_{\tau' = \tau-(2t_{jl}^{k}-1)}^{T} X_{jl}^{k\tau} \leq M_{j}^{k\tau}(h) \quad \forall l, k, \tau, h \tag{3.12}$$

$$\sum_{j}^{J} \sum_{k}^{K} \sum_{\tau}^{T} Y_{jl}^{k\tau}(h) \geq \delta_{l}(h) \quad \forall l, h \tag{3.13}$$

$$Y_{ij}^{k\tau}(h) = 0, \exists j \in \{j: K_j \leq 0\} \tag{3.14}$$

$$Y_{jl}^{k\tau}(h) = 0, \exists l \in \{l: K_l \leq 0\} \tag{3.15}$$

$$Y_{ij}^{k\tau}(h), Y_{jl}^{k\tau}(h) \geq 0 \qquad \forall i, j, k, \tau, h \tag{3.16}$$

$$X_{ij}^{k\tau}(h), X_{jl}^{k\tau}(h) \in \{0,1\} \qquad \forall i, j, k, \tau, h \tag{3.17}$$

Constraint (3.3) and (3.4) conserve the relief goods flow from SN to LOA and from LOA to AA, respectively. Constraint (3.3) postulates that a number of total relief goods deliver to all LOAs should not exceed the total relief supply available for each period while constraint (3.4) make sure that a number of total relief goods deliver to AAs should be the same with the total available good in the LOAs for each period. The same constraint also keeps the relief goods availability, in which the relief goods in LOA are available during micro-time period τ when it sends from SN during micro-time period $\tau - t_{ij}^{k}$. Constraint (3.5) and (3.6) entails the maximum capacity for the SN node per transport mode and a maximum capacity for each node (LOA) per transport mode, respectively. Vehicle capacity constraint that ensured relief delivered at micro-time period τ should not exceed the transport mode capacity k is depicted by constraint (3.7) and (3.8). Constraint (3.9) indicates that each LOA can be served by multi SNs and constraint (3.10) ensures each AA demand node can be served by multiple LOAs. Constraint (3.11) and (3.12) ensure that only vehicles that were available at a respected node may be used to deliver relief goods. Constraint (3.11) - (3.12) indicates maximum vehicles available for each mode of transportation in each node during micro time period τ, with constraint (3.13) ensure all demand to be satisfied in each AA. Constraint (3.14) and (3.15) preventing to allocate or send relief goods to nodes that is not available during micro time period τ. Constraint (3.16) and (3.17) indicates the decision variables for this problem.

3.2.2. Solution Methodology

The problem formulation proposed requires a large amount of time to be solved by commercial solvers such CPLEX. Further, rather than taking a dynamic approach for dealing with information evolution, we divided the post-disaster stage into several periods (h), and assume that within each period the environment and information is static. In that case, for each period h, different decision in regards with input value can be evaluate clearly. The problem then solves independently for each period *h* to give a better understanding on how the time-varying values should be considerate in different disaster response period. Thus, a simplified model is proposed and solved instead.

3.2.2.1. Model simplification

Although constraints (3.11) and (3.12) are quite general, allowing multi-trips inter-period resulted in a bigger solution space. Thus, partial multi-trips then considered in this study. Consequently, additional parameters are introduced, by calculating the maximum frequency (*f*) of each round trip in one period for each transport mode from origin to destinations node, based on capacity of the vehicle, respectively. The simplification of the model also ensures that by the beginning of each period, all number of vehicle will be available. The illustration of the system is presented in figure 3.4.

Decision Variables

$X_{ij}^{k}(h)$ = equal 1 if there is a relief delivery from supply node *i* to logistics operational area *j* using transportation mode *k* in period *h*, equal 0 if otherwise.

$X_{jl}^{k}(h)$ = equal 1 if there is a relief delivery from logistics operational area *j* to affected area *l* using transportation mode *k* in period *h*, equal 0 if otherwise.

$Y_{ij}^{k}(h)$ = amount of relief delivered (ton) from from supply node *i* to logistics operational area *j* using transportation mode *k* in period *h*

$Y_{jl}^{k}(h)$ = amount of relief delivered (ton) from logistics operational area *j* to affected area *l* using transportation mode *k* in period *h*

$f_{ij}^{k}(h)$ = delivery frequency from corridor *i* to logistics operational area *j* using transportation mode *k* in time *h*

$f_{jl}^{k}(h)$ = delivery frequency from logistics operational area *j* to affected area *l* using transportation mode *k* in period *h*

Constraint (3.11) and (3.12) are then modified as follows:

$$f_{ij}^{k}(h) \leq \frac{72}{2t_{ij}^{k}(h)} \qquad \forall i,j,k,h \tag{3.18}$$

$$f_{jl}^{k}(h) \leq \frac{72}{2t_{jl}^{k}(h)} \qquad \forall i,j,k,h \tag{3.19}$$

Each period in this study is equal to 3 days = 72 hours micro-periods. The number of multi-trips for transport mode k from SN to LOA is stated as constraint (3.18) and from LOA to AA stated in constraint (3.19). Thus, a modification and simplification of other constraints (3.1) - (3.17) are needed by relaxing micro-time period constraint.

Objective:

The first part focus on minimizing delivery time which will be the focus of decision maker during the initial response phase.

For Time-period= $h_0 \sim h_{initial}$

$$min \sum_{i}^{I}\sum_{j}^{J}\sum_{k}^{K} Y_{ij}^{k}(h)\, t_{ij}^{k} + \sum_{j}^{J}\sum_{l}^{L}\sum_{k}^{K} Y_{jl}^{k}(h)\, t_{jl}^{k} \tag{3.20}$$

The second part, representing the continuum response period, from period $h_{initial+1}$ to $h_{continuum}$ with focus on minimizing total cost for transporting the goods from SNs to AAs including vehicle cost, cost of transporting goods from SNs to LOAs and cost for transporting goods from LOAs to AAs demand area.

For Time-period= $h_{initial+1} \sim h_{continuum}$

$$\begin{aligned} \min \sum_{i}^{I}\sum_{j}^{J}\sum_{k}^{K} X_{ij}^{k}(h)\, Vc_k + \sum_{i}^{I}\sum_{j}^{J}\sum_{k}^{K} Y_{ij}^{k}(h)\, c_k t_{ij}^{k} + \sum_{j}^{J}\sum_{l}^{L}\sum_{k}^{K} X_{jl}^{k}(h)\, Vc_k \\ + \sum_{j}^{J}\sum_{l}^{L}\sum_{k}^{K} Y_{ij}^{k}(h)\, c_k t_{jl}^{k} \end{aligned} \tag{3.21}$$

Constraints:

$$\sum_{j}^{J}\sum_{k}^{K} Y_{ij}^{k}(h) \leq S_i(h) \quad \forall i,h \tag{3.22}$$

$$\sum_{l}^{L}\sum_{k}^{K} Y_{jl}^{k}(h) = \sum_{i}^{I}\sum_{k}^{K} Y_{ij}^{k}(h) \quad \forall j,h \tag{3.23}$$

$$\sum_{j}^{J} Y_{ij}^{k}(h) \leq Cap_i\ (h) \quad \forall i \tag{3.24}$$

$$\sum_{i}^{I} Y_{ij}^{k}(h) \leq Cap_j\ (h) \quad \forall j \tag{3.25}$$

$$Y_{ij}^{k}(h)/f_{ij}^{k} \leq Q_k \ \ \forall i,j,k,h \tag{3.26}$$

$$Y_{jl}^{k}(h)/f_{jl}^{k} \leq Q_k \ \ \forall j,l,k,h \tag{3.27}$$

$$\sum_{j}^{J} X_{ij}^{k}(h) \leq M_i^{k}(h) \qquad \forall i,k,h \tag{3.28}$$

$$\sum_{l}^{L} X_{jl}^{k}(h) \leq M_j^{k}(h) \qquad \forall j,k,h \tag{3.29}$$

$$\sum_{i}^{I} X_{ij}^{k}(h) \leq I \qquad \forall j,k,h \tag{3.30}$$

$$\sum_{j}^{J} X_{jl}^{k}(h) \leq J \qquad \forall l,\ k,h \tag{3.31}$$

$$\sum_{j}^{J}\sum_{k}^{K} Y_{jl}^{k}(h) \geq \delta_l(h) \quad \forall l,h \tag{3.32}$$

$$Y_{ij}^{k}(h) = 0, \exists j \in \{j: K_j \leq 0\} \tag{3.33}$$

$$Y_{jl}^{k}(h) = 0, \exists l \in \{l: K_l \leq 0\} \tag{3.34}$$

$$Y_{ij}^{k}(h), Y_{jl}^{k}(h) \geq 0 \qquad\qquad \forall i,j,k,h \tag{3.35}$$

$$X_{ij}^{k}(h), X_{jl}^{k}(h) \in \{0,1\} \qquad \forall i,j,k,h \tag{3.36}$$

Constraint (3.22) postulates that a number of total relief goods deliver to all LOAs should not exceed the total relief supply available for each period while constraint (3.23) make sure that a number of total relief goods deliver to AAs should be the same with the total available good in the LOAs for each time period. Constraint (3.24) and (3.25) entails the maximum capacity for the SN node per transport mode and a maximum capacity for each node (LOA) per transport mode, respectively. Vehicle capacity constraint that ensured relief delivered should not exceed the vehicle capacity is depicted by constraint (3.26) and (3.27). Constraint (3.28) and (3.29) indicates maximum vehicles available for each mode of transportation in each node. Constraint (3.30) indicates that each LOA can be served by multi SNs and constraint (3.31) ensures each AA demand node can be served by multiple LOAs. Constraint (3.32) ensure all demand to be satisfied in each AA for each period and constraint (3.33) preventing to allocate or send relief goods to nodes that is not available during period h. Constraint (3.34) and (3.35) indicates the decision variables for this problem.

The model developed is a mixed integer linear programming problem and is coded in C++ and solved using Branch and Cut with optimization software CPLEX 12.8 and executed on a computer with an Intel i5 2.66 GHz CPU and 16 GB RAM running the Windows 7 64-bit operating system. First, for feasible solution, the decision variable on whether the relief goods are sent using transport mode k through link $i \rightarrow j$ and $j \rightarrow l$ must be binary, with the number of relief goods sent must be an integer. The decision founded on which LOA is chosen by calculating the relief goods flow through each LOA in the current linear programming (LP) solution. Consider a sub problem at the node, and let Z_0^j, Z_1^j, Z_2^j as the set of used, unused, and free LOA, respectively. Using LP, let CM_l denote the smallest time needed to satisfy demand at demand node l among used LOA using transport mode k.

$$CM_l = \min_{i \in Z_1^I, j \in Z_1^J} t_{ij}^k + t_{jl}^k \qquad (3.37)$$

For the LOA with the highest CM_l value, we fixed the corresponding value to 0, suggesting the path going to and from particular LOA is not used.

3.3. Logistics Capacity in Java Island

As a country located at the meeting of three large plates of the earth (Eurasian plate, Indo-Australian plate, and Pacific plate), Indonesia encounter movement of three plates which makes it prone to a disaster such as an earthquake, tsunami, and volcano eruption. Among all island, Sumatra and Java Islands are two areas often affected by the earthquake. Based on data from United States Geological Survey (Jones et al., 2014) for the period from January 1973 to April 2017, Java Island was stroked by 488 earthquakes with magnitude ≥ 5 and depth ≤ 70 km. As an effort to reducing the risk and improve their response if a disaster happens, the logistics capacity calculation is indeed obligatory.

3.3.1. Overview of Major Node in Java and Bali Island

It is prominent that as wealth and economic activity center, the infrastructures development focus on Java Island. Transportation infrastructure state in Java Island vary from port, airport, railway, and toll/highway road with road infrastructure dominates the mobility of people and goods (Leung, 2016). Adopting the centrality concept, this study evaluated 13 critical nodes in Java and Bali Island and ranked it based on its degree of centrality as shown in Table 3.2. The centrality concept is used as a way to evaluate whether the node is critical and linked with another node by different types of transportation mode (Bloch et al., 2017). Figure 3.5 shows the important nodes (cities) available on Java Island.

Table 3.2. Node centrality ranking in Java and Bali Island

Node	Degree of Centrality	Ranking
Jakarta	1	1
Surabaya	0.8235	2
Semarang	0.5882	3
Surakarta	0.5882	3
Yogyakarta	0.5882	3
Bandung	0.5294	4

Node	Degree of Centrality	Ranking
Malang	0.4705	5
Cilacap	0.4706	5
Bali	0.4117	6
Tasikmalaya	0.2941	7
Magetan	0.2941	7
Cirebon	0.1765	8
Pangandaran	0.1176	9

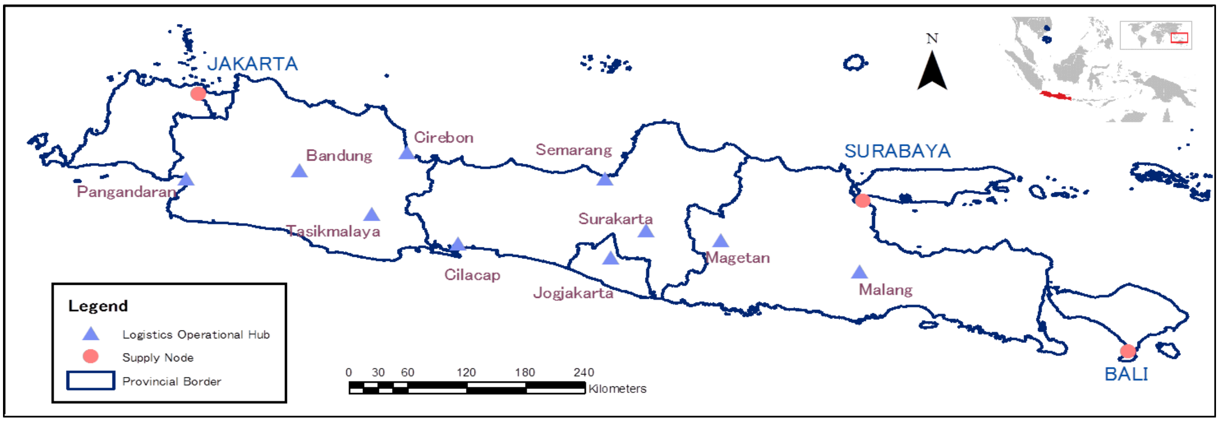


Figure 3.5. Major Nodes based on degree of centrality in Java Island

3.3.2. Overview Rail/Road Transportation and Major Airport and Port in Java Island

3.3.2.1. <u>Valuation of Port and Airport in Java Island</u>

From the existing major port and airport, the overall strategy for Java Island relief distribution plan can be summarized and divided based on its functions. The choice options of logistics operational expedition location will depend on the affected area and the availability of transportation resource during the particular period. As international airport in Java, Soekarno-Hatta Airport in Jakarta and Juanda Airport in Surabaya, are chosen as relief international corridor/entry point in airlift side. Further, two major ports also located in Jakarta and Surabaya will be served as an international corridor in sealift side.

The operation plan must be made and adjusted based on the operational advancement and new route opening access to the affected area. Thus, support transportation network valuation is needed to understand the logistics capability in Java Island. Aside from international corridor nodes, the information about the military airport, cargo airport, support port, and fishery port could support the distribution of relief goods in the early response case. Thus, valuation of the alternative airport and port is essential for constructing the distribution plan framework.

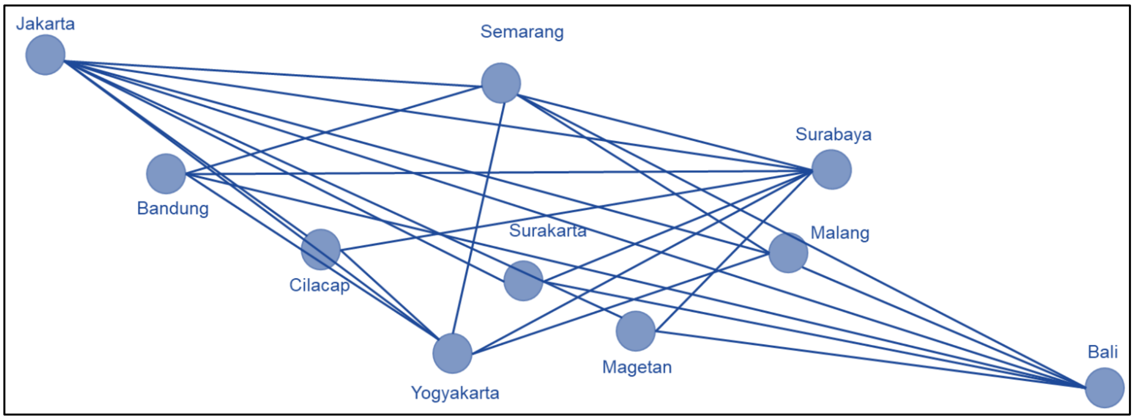


Figure 3.6. Airlift Network for Disaster Relief Operation in Java Island (Indonesia Ministry of Transportation. 2010)

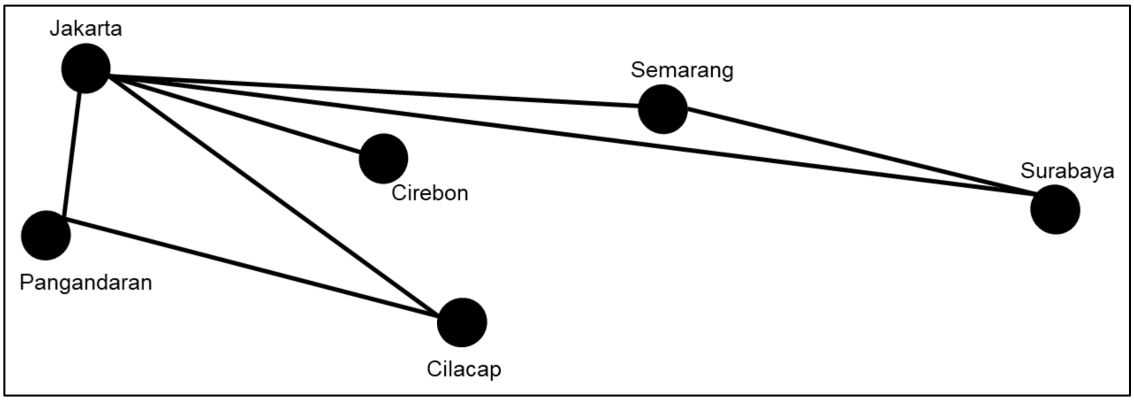


Figure 3.7. Sealift Network for Disaster Relief Operation in Java Island (Indonesia Ministry of Transportation. 2016)

The airplane/airlift network in Java Island can be seen in Figure 3.6, while the vessels network/maritime network is shown in Figure 3.7. While many fishery ports are available in the south part of Java Island, the capacity of it to be utilized as an operational logistics expedition is less likely adequate. However, in the case of the earthquake in the south coast of Java happened, these fishery port might be utilized as entry corridor of consolidation area. The situation will need to be assessed based on the seasonal condition. The details summary and detailed information about existing transport infrastructure in Java Island and its function for the distribution network plan can be found in Table 3.3.

Table 3.3. Summary of Java Island Distribution Network Plan

Function	Main location		Alternative location	
	Airport	**Port**	**Airport**	**Port**
Point of Entry	Soekarno-Hatta International Airport	Tanjung Priok Port, Jakarta	N/A	Lamong Bay Port, Surabaya
	Juanda International Airport, Surabaya	Tanjung Perak Port, Surabaya	-	Banten Port, Tangerang
	Halim Perdana Kusuma Airport, Jakarta	-	-	-
Logistics Operational Expedition	Achmad Yani Airport, Semarang	Tanjung Emas, Semarang		Lamong Bay Port, Surabaya
	Tunggul Wulung Airport, Cilacap	Tanjung Intan Port, Cilacap	Wiriadinata Airport, Tasikmalaya	Ciwandan Port, Banten
	Adi Soemarno Airport, Surakarta	-	Nusawiru Airport, Pangandaran	-
	Adi Sutjipto Airport, Yogyakarta	-	Gading Military Airport, Yogyakarta	-
	Raden Saleh Airport, Malang	-	Iswahyudi Airport, Magetan	-
Consolidation Area	The nearest airport of the affected region			

3.3.2.2. Valuation of Road Network

As the vital road connecting west and east side of Java Island, the 1,430 km Jalur Pantai Utara (North Coast Line) passed through Jakarta, Cirebon, Semarang, Surabaya, and Banyuwangi with roughly passed by 20,000~70,000 vehicles (Leung, 2016). Aside from that, the road is branched from Cikampek to Bandung, Purwokerto, Yogyakarta and go to the east via Surakarta and Madiun. The new toll from Semarang to Surakarta 76 km in the Central part of Java Island. North Coast Line is categorized as a national road with heavy load up to ~43 tons. The province-level road would be able to have maximum heavy load ~20 tons (Indonesia Ministry of Public Works, 2012). The road network in Java Island is illustrated in figure 3.8. Rail transportation might increase the effectiveness of the relief distribution network if the infrastructure is available.

With limited air transportation and road capacity, rail transportation offers alternative transportation mode with relatively moderate speed and low cost. Although Java Island has two central railway connecting West Java and East Java, rail transportation, however, is not considered in this study. The reasons including rail reliability problem and lack of maintenance (JICA, 2009; Leung, 2016), the possibility of extended reconstruction period (Anand, 2005; Palliyaguru et al., 2007), and low rail cargo capacity (ADB, 2012), with mainly focusing on passenger's movement. As it runs service with terminal to terminal concept with large consignment, rail transportation, nevertheless, can be utilized for transporting specific product such as fuel or gasoline to the affected area. Cilacap and Cepu as the major oil refineries in Central Java (IEA, 2014), could be involved as the supply node for fuel and gasoline, and focusing the distribution by using rail transportation.

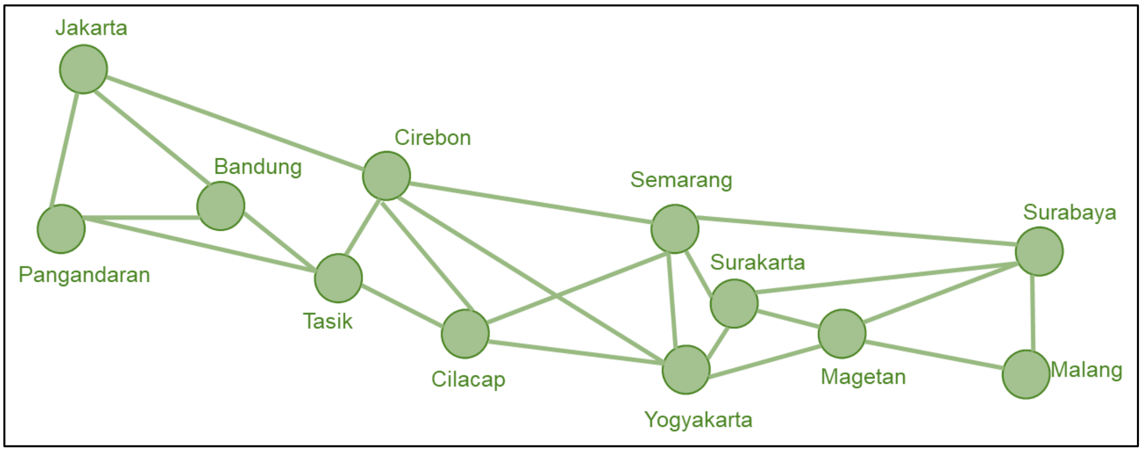


Figure 3.8. Road Network for Disaster Relief Operation in Java Island (Indonesia Ministry of Transportation. 2010)

3.4. Numerical Example

3.4.1. Scenario and Input Parameters

The numerical example was performed using a disaster data from Yogjakarta earthquake 2006. An earthquake with a magnitude of 6.3 on the Richter scale struck nearby the city of Yogyakarta destroying the city and its surrounding. The destruction including the railway connecting to Purwokerto and Surakarta; national road and province road connecting to another city, with some villages in more remote areas south of Yogyakarta as well as in and around Bantul the most severely affected (Elnashai, et al., 2007). Tremors were felt through the region as far away as Semarang and Surabaya on the opposite coast of Java. The airport runway cannot be used by commercial airplane but can be accessed by helicopter. The runway needs time to be able to operate, but road can still be partially accessed with restoration underway. Based on the disaster location, the operational logistics nodes are selected as shown in Figure 3.9.

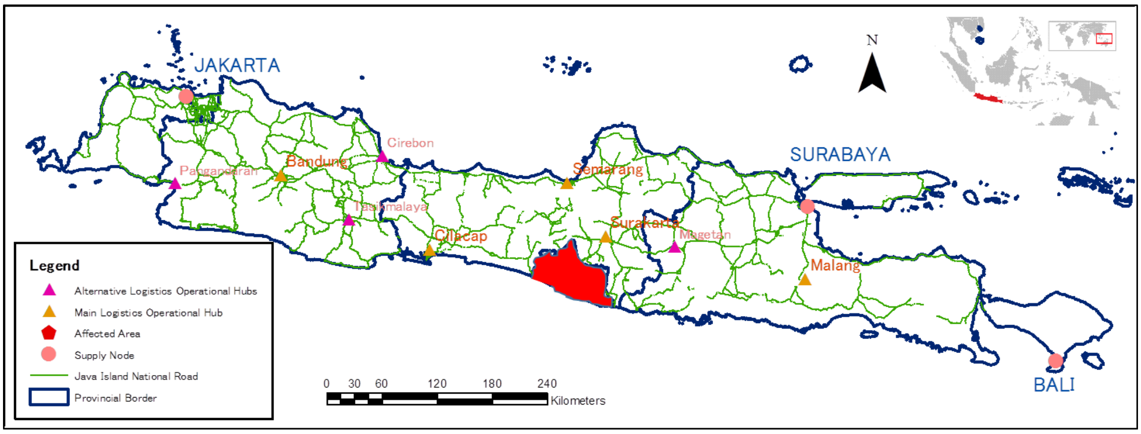


Figure 3.9. Major Node and its Function during Disaster Relief Operation in Java Island

A quick assessment concluded that in total 12 cities, represented by nodes, selected as the SN area, LOA, and central distribution center in AA. In this study, the SN will act as a point of entry from the national and international donor and supply point for relief delivery. The selection of Jakarta, Surabaya, and Bali as a supply corridor is due to its capacity to handle sudden upsurge relief goods from an international donor, respectively. The LOA nodes are chosen based on its degree of centrality as discussed before. The AA represents the location of aggregate demand, which includes Westside, Eastside, and the Southside of Yogyakarta Province. The number of supply available is assumed time-varying, increasing rapidly during the first period, and the decreasing a bit and stagnating after a while before decreasing until supply is not needed. Each operational horizon in this study is assumed three days, and each 0.8 kg of relief emergency can sustain an individual for one day. The summary of the distribution configuration and nature of the model parameters can be seen in Table 3.4 and 3.5. The detail of each node location and data input can be found in Appendix 1.

Table 3.4. Summary of Relief Delivery Configuration

Function	Details
Supply Corridor	3 cities: Jakarta, Surabaya, Bali
Logistics Operational Area	9 cities: 5 main location with 4 alternatives
Affected Area	3 demand nodes in Yogyakarta

Table 3.5. Input parameter for the model

Parameters	Nature of data input	Remarks
Operational Horizon	Finite	10 periods
Transportation cost	Static	Deterministic
Supply availability	Time-varying	
Relief Demand	Time-varying	
Number of vehicles	Time-varying	
The capacity of Node and Vehicle	Static	

3.4.2. Result and Discussion

As the model is simplified, the number of variables and constraints in reduced MIP has 3082 rows, 5323 columns, and 14662 nonzeros, and solved within 0.6 second using CPLEX 12.8 solver. In this study, the focus will be to deliver all relief available on hand to be sent to the affected area with two factors included; cost and time. The study expectation is to find the transportation network from each SN to AA via LOA with the lowest cost using the only available vehicle. The vehicle availability in each node is limited, which will affect the goods movement shift to other LOA or another transportation mode in consideration of cost. Table 3.6-3.9 shows the results of the optimization for multi-modal relief distribution on Yogyakarta earthquake case.

Table 3.6 depicts the detail results of logistics operational node selected including transportation mode needed from Jakarta corridor. Five LOAs are selected, with truck dominating the delivery, followed by airplane to Cilacap, Surakarta, and Semarang having a large number of goods sent. Table 3.7 presents the delivery flow from Surabaya, and Table 3.8 entails the detailed flow from Bali. Delivery flow from Surabaya centered in Surakarta as LOA, with Magetan and Semarang as additional LOAs for exceed goods. Truck again is the main transportation used for delivering relief followed by airplane. Similar with relief flow from Jakarta, vessels only utilized in a small percentage. In relief flow from Bali, airplane is the only allowable transportation available thus dominating the network.

Further, Table 3.9 shows the results for relief distribution of each operational logistics area to affected area, Yogyakarta. Due to the high accessibility of road transportation from LOAs to two AAs, the truck is dominating the relief flow. However, one AA is located in the mountainous area, which only countenances air transportation (helicopter) to send the relief goods. The mode of transportation is a change from period 1 to period two due to change of airport accessibility status (from non-accessible to accessible).

Based on the optimization result, the peak of relief flow is in period 2, right after the initial response phase due to the drastically increment of relief goods available in SN. It forced the utilization of most of the transportation mode, including vessels in Semarang and Cirebon to accommodate a large number of goods that need to be delivered to the affected area. The port in the south part of Java islands, such as Pangandaran and Cilacap, is regarded as too far, which resulted in high total cost due to lengthy transportation time. Surakarta and Cilacap become the critical node and act as LOA covering west part of Java for Cilacap, and east side for Surakarta. Also, Magetan support the relief goods flow comes from Bali with Semarang support rest of the goods needs to be delivered from both west and east side. By multiplying cost/unit-time with the time needed for each ton to be delivered, the results suggest that the air transportation still have high utilization compared to the vessel as it requires less time to reach the target node. Accordingly, road transportation checks all the marks on both cost and time, and suitable for relief delivery in the case where road infrastructure is accessible.

In a disaster situation, it is expected that the required number of the vehicle will not be sufficient during the beginning of the response period. In the developed model, we restrict the vehicle availability at each node, and indexing by h (3 days) allows parameter input to specify the number of vehicles available over the time. This study believes that as disaster response started, the decision maker will be able to secure more vehicles for the relief goods distribution. The additional vehicles might be donated by the military, NGOs, or private sectors. The model initially chooses trucks or airplane based on cost and time consideration. However, as a number of each transportation mode is limited, it leads to the model choose vessels to ensure the remaining relief goods to be delivered, fulfilling constraint (3.32). Limited trucks at each node cause a large number of airplane utilization, regardless of the relatively high cost. Although the model uses the multi-trips concept, it is only allowed the vehicle to deliver the goods within one layer (SN to LOA, or LOA to AA). In this way, the distribution system might be easier to be managed rather than using a pooling system which allowed vehicle movement to a node with the high demand for vehicle.

Table 3.6. Relief Distribution Flow from Jakarta to LOAs

Period	Jakarta											Total Cost
	Semarang			Cilacap			Tasik		Surakarta	Cirebon		
	Vessels	Truck	Airplane	Vessels	Truck	Airplane	Truck	Airplane	Airplane	Vessels	Truck	
1	4,200	2,772	3,216	0	3,168	2,412	3,564	1,675	4,824	4,200	3,168	$85,417.20
2	10,500	5,572	9,648	0	6,400	14,472	5,400	6,700	12,060	21,000	3,168	$243,518.00
3	0	8,400	9,648	0	6,400	14,472	375	6,700	12,060	3,245	6,400	$212,199.50
4	0	8,400	4,824	0	8,000	9,648	5,400	0	6,030	0	3,200	$136,307.20
5	0	8,400	3,216	0	8,000	4,824	4,320	0	4,824	0	3,200	$106,110.40
6	0	8,400	3,216	0	8,000	2,412	3,564	0	4,824	0	1,600	$91,537.20
7	0	8,400	1,608	0	8,000	0	0	0	3,618	0	0	$59,813.60
8	0	8,400	0	0	8,000	0	0	0	0	0	0	$41,000.00
9	0	0	0	0	8,000	0	0	0	0	0	0	$20,000.00
10	0	0	0	0	5,000	0	0	0	0	0	0	$12,500.00

Table 3.7. Relief Distribution Flow from Surabaya to LOAs

Period	Surabaya							Total Cost
	Semarang			Surakarta		Magetan		
	Vessels	Truck	Airplane	Truck	Airplane	Truck	Airplane	
1	0	0	3,216	2,772	4,824	2,772	3,216	$54,381.60
2	0	2,772	9,468	8,400	12,060	5,600	8,940	$151,614.80
3	0	0	2,772	8,400	12,060	1,484	8,940	$110,289.20
4	0	0	0	8,400	7,236	5,600	2,412	$69,732.80
5	0	0	0	8,400	7,236	2,772	0	$53,979.60
6	0	0	0	8,400	6,030	2,772	0	$49,638.00
7	0	0	0	8,400	2,412	0	0	$29,683.20
8	0	0	0	7,672	0	0	0	$19,180.00
9	0	0	0	3,360	0	0	0	$8,400.00
10	0	0	0	0	0	0	0	$0

Table 3.8. Relief Distribution Flow from Bali to LOAs

Period	Bali			Total Cost
	Malang	Magetan	Surakarta	
	Airplane	Airplane	Airplane	
1	4,800	1,000	0	$20,880.00
2	12,060	4,020	0	$57,888.00
3	9,648	0	0	$34,732.80
4	7,236	0	0	$26,049.60
5	6,513	0	0	$23,446.80
6	5,547	0	0	$19,969.20
7	3,618	0	0	$13,024.80
8	2,412	0	0	$8,683.20
9	1,206	0	0	$4,341.60
10	0	0	0	$0

Table 3.9. Relief Distribution Flow from LOAs to Affected Area

Period	Semarang			Cilacap			Cirebon	Tasik	Surakarta		Malang	Magetan		Total Cost
	Yogyakarta													
	Truck	Airplane	Helicopter	Truck	Airplane	Helicopter	Truck	Truck	Truck	Helicopter	Truck	Truck	Airplane	
1	10,800	0	1,520	5,580	0	0	7,169	5,239	3,870	8,550	4,800	6,988	0	$202,959.00
2	18,600	16,080	1,228	14,400	5,712	760	24,168	12,100	19,695	12,825	12,060	10,424	11,256	$561,271.70
3	4,560	16,080	0	14,400	5,712	760	9,645	7,075	19,695	12,825	9,648	0	10,424	$372,505.70
4	15,938	0	0	14,400	3,248	0	3,200	5,400	21,666	0	7,236	8,012	0	$315,100.80
5	11,616	0	0	12,824	0	0	3,200	4,320	20,460	0	6,513	2,772	0	$246,820.00
6	11,616	0	0	10,412	0	0	1,600	3,564	19,254	0	5,547	2,772	0	$219,060.00
7	10,008	0	0	8,000	0	0	0	0	14,430	0	3,618	0	0	$144,224.00
8	8,400	0	0	8,000	0	0	0	0	7,672	0	2,412	0	0	$105,936.00
9	0	0	0	8,000	0	0	0	0	3,360	0	1,206	0	0	$50,264.00
10	0	0	0	5,000	0	0	0	0	0	0	0	0	0	$20,000.00

3.4.3. Analysis of multi-modal transportation

This study focus on how the multi-modal transportation can improve the relief distribution system with transshipment system. In this case, the different objectives from the initial response phase and the continuum response phase resulted in a different transportation mode configuration. During the initial response phase (Period 0-3), the focus is to deliver all the supply to affected area using the fastest transportation mode such as airplane and helicopter. In the continuum response phase, however, focus on delivering supply using the transportation mode with two considerations: time and cost. In regards to vehicle capacity and number of available vehicles per mode, the multi-modal options give an alternative on how to deliver the relief goods but still maintaining the objectives and constraints at the same time. Table 3.10 shows the percentage of transportation mode transferred in the relief distribution. The multi-modal transportation is counted to be 45.67% (31.98% for airplane-truck, 7.95% for vessels-truck, and 5.74% for airplane-helicopter) from all goods delivered within 10 periods. The highest percentage is the airplane-truck combination, followed by vessels-truck, and airplane-helicopter.

Table 3.10. Percentage of transportation mode transferred

From \ To	Truck	Airplane	Helicopter	Vessels
Truck	45.97%	0.00%	0.00%	0.00%
Airplane	31.98%	8.36%	5.74%	0.00%
Helicopter	0.00%	0.00%	0.00%	0.00%
Vessels	7.95%	0.00%	0.00%	0.00%

3.4.4. Sensitivity Analysis

3.4.4.1. Effect on Limited Type of Transport Mode

Our model focus on how multi-modal transportation help to smoothen the relief distribution operation while still maintaining the efficiency and effectiveness of the system. From the results in section 3.4.2, in period 2 and 3, which have highest number of relief supply, vessels are utilized to deliver the rest of the relief good, when other transport modes is fully occupied. This sub-section analyzes if limited type of transport modes is used during relief distributions, and compared it in term of cost, average delivery time, and unmet demand. The number of available vehicles per each transport mode is the same as the calculation in section 3.4.2. We ignore constraint (3.32) in this calculation, to let unmet demand transpired without giving a penalty cost.

Table 3.11 shows the results of the analysis, using an only airplane, combination of airplane and truck, and all type of transport mode, respectively. Within the same period, it can be seen how big the function of vessels as one of transport mode choice. In particular, during the initial response phase where available transport number is not adequate, the unmet demand for not utilizing vessels accounted for ~ 40%. In addition, only having airplane as the transport mode choice, lead to having constant unmet demand through the operations. This study, however, limits the number of available vehicles that can be used, even after additional vehicle retrieved. This consideration for sure, are not suitable for developing countries with abundant resources and active cooperation with private sectors.

Table 3.11. The results of transport mode limitation

Period	Airplane			Airplane + Truck			Airplane + Truck + Vessels		
	Total Cost (USD)	Unmet demand (%)	Total delivery time (hour)	Total Cost (USD)	Unmet demand (%)	Total delivery time (hour)	Total Cost (USD)	Unmet demand (%)	Total delivery time (hour)
1	$216,679.40	41.43%	265.0	$321,779.40	39.02%	423.4	$363,637.80	0%	753.4
2	$676,556.10	39.10%	561.0	$835,941.30	33.19%	1139.1	$1,014,292.50	0%	1,968.2
3	$598,496.60	29.59%	445.7	$757,898.90	4.79%	1061.1	$729,727.20	0%	1,133.2
4	$480,216.80	8.97%	387.4	$538,429.76	0.00%	845.7	$547,190.40	0%	845.7
5	$406,086.24	7.17%	315.2	$430,352.24	0.00%	755.0	$430,356.80	0%	755.0
6	$371,120.16	4.33%	314.2	$380,208.96	0.00%	726.9	$380,204.40	0%	726.9
7	$264,230.40	1.00%	183.1	$246,745.60	0.00%	437.2	$246,745.60	0%	437.2
8	$194,718.40	0.00%	125.0	$174,799.20	0.00%	353.3	$174,799.20	0%	353.3
9	$92,301.60	0.00%	175.0	$83,005.60	0.00%	476.8	$83,005.60	0%	476.8
10	$36,000.00	0.00%	12.5	$32,500.00	0.00%	53.4	$32,500.00	0%	53.4

3.4.4.2. Effect on Logistics Operational Area

The idea of having Logistics Operational Area (LOA) in this chapter arising from the field interview conducted with Provincial Disaster Management Agency (BPBD Yogyakarta), in which locations with hub function are needed to help relief distribution system to operate seamlessly. During the past disaster, as the goods were transported directly to affected area, overwhelmed the local logistician to sort, consolidate, and manage it. It resulted in chaos and bottleneck of the operation. It is also to ensure the coordination and sharing of infrastructure inter-regional could happen if disaster happened. On the contrary, the hub function might also hinder the relief distribution operation if coordination is not working or no available logisticians' ready to manage the LOA, if the proposed idea is implemented. In addition, once the continuum response period started, affected area is assumed ready for receiving the relief goods directly from supply nodes.

In that regards, the sensitivity analysis is conducted to understand the effect of direct distribution from supply node to affected area.

The modification of the model is needed to transform the hub network model into mixed network problem that allows the distribution to have direct delivery from SN to AA with U_{il}^{k} as its decision variable, while still consider the possibility for using LOA. The objective function that can be rewritten as follow:

Time-period h_0 ~ $h_{initial}$

$$min \sum_{i}^{I}\sum_{j}^{J}\sum_{k}^{K} Y_{ij}^{k}(h)\, t_{ij}^{k} + \sum_{j}^{J}\sum_{l}^{L}\sum_{k}^{K} Y_{jl}^{k}(h)\, t_{jl}^{k} + \sum_{i}^{I}\sum_{l}^{L}\sum_{k}^{K} Y_{il}^{k}\,(h) t_{il}^{k} \tag{3.37}$$

Time-period $h_{initial+1}$ ~ $h_{continuum}$

$$\begin{aligned} \min \sum_{i}^{I}\sum_{j}^{J}\sum_{k}^{K} X_{ij}^{k}(h)\, Vc_k + \sum_{i}^{I}\sum_{j}^{J}\sum_{k}^{K} Y_{ij}^{k}(h)\, c_k t_{ij}^{k} + \sum_{j}^{L}\sum_{l}^{L}\sum_{k}^{K} X_{jl}^{k}(h)\, Vc_k \\ + \sum_{j}^{J}\sum_{l}^{L}\sum_{k}^{K} Y_{jl}^{k}\,(h) c_k t_{jl}^{k} + \sum_{i}^{I}\sum_{l}^{L}\sum_{k}^{K} U_{il}^{k}\,(h) Vc_k \\ + \sum_{i}^{I}\sum_{l}^{L}\sum_{k}^{K} Y_{il}^{k}\,(h) c_k t_{il}^{k} \end{aligned} \tag{3.38}$$

Additionally, since direct distribution is allowed, all of the available vehicles can be pooled to the SN or LOA based on the decision variable. That way, the limitation of a maximum number of available for each node SN and LOA will be:

$$\sum_{l}^{L} U_{il}^{k}(h) \leq M_{i}^{k}(h) \ + \ M_{j}^{k}(h) \quad \forall i,k,h \tag{3.39}$$

The result of the model modification and its comparison with the proposed model is presented in table 3.12. Although the modification is able to minimize the total cost needed to transport the supply from SN to AA, we can also notice that for the first 3 periods, the mixed network model resulted in slower average delivery time. The results, however, shows how using mixed network can be reduced both average delivery time and total cost starting from period 4 onward. The hub network, although is beneficial for the initial response phase, leads to higher cost as the relief goods need to be transported first to LOA before being transport to AA. However, by not pooling the vehicle in the SN, resulted in faster delivery time when the limited vehicle or large amount of relief goods are presents in Period 1, 2, and 3. Once the number of relief goods stabilized, accompanied by an adequate number of vehicles, the mixed network with direct delivery might be more suitable for this problem.

Table 3.12. Comparison of hub network and mixed network for relief goods delivery system

Period	Hub network		Mixed network	
	Total delivery time (hours)	Cost (USD)	Total delivery time (hours)	Cost (USD)
1	753.4	$363,637.80	774.46	$297,168.90
2	1,968.20	$1,014,292.50	2118.66	$770,439.60
3	1,133.20	$729,727.20	1305.68	$483,757.10
4	845.7	$547,190.40	673.54	$332,257.60
5	755	$430,356.80	615.3	$271,814.96
6	726.9	$380,204.40	613.42	$241,800.24
7	437.2	$246,745.60	408.89	$162,634.00
8	353.3	$174,799.20	373.48	$125,712.80
9	476.8	$83,005.60	525.95	$59,952.40
10	53.4	$32,500.00	92.59	$25,000.00

3.4.5. *Logistics Capacity Assessment*

Based on the optimization results in sub-section 3.4.2, some nodes are confirmed to have a vital job as the LOA in the relief distribution system. These nodes including Surakarta, Semarang, and Cilacap.

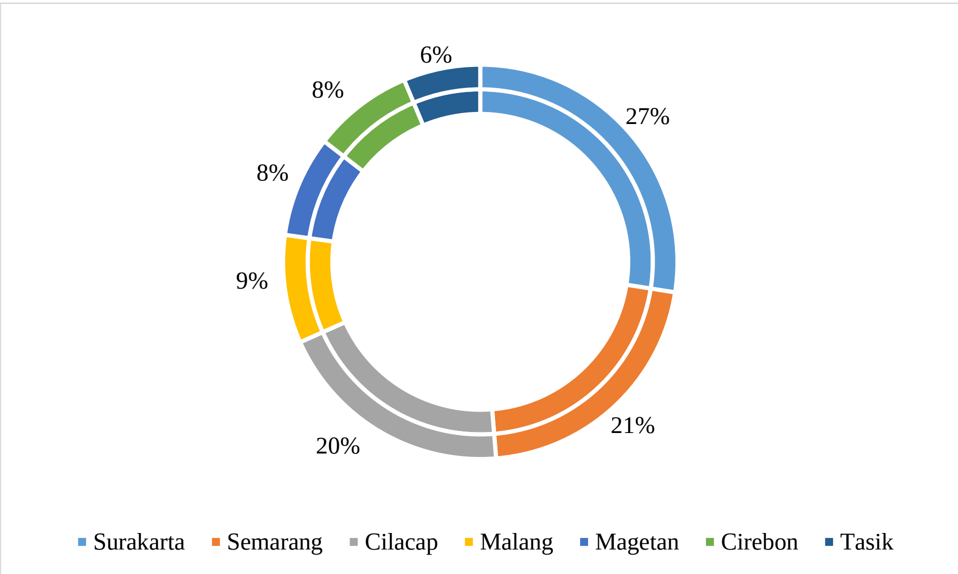


Figure 3.10. Percentage Relief Goods in each Selected LOA

Figure 3.10 shows the percentage proportion of the relief goods throughout all of the LOA before sending it to AA. LOA Surakarta, specially, handled 27% of the total relief goods delivered from SN to AA, with 60.9% transported via airlift and another 39.1% transported using truck. In addition, Semarang also counted vital with 21% relief goods delivered from SN to AA. In Semarang case, 40.0% goods are transported via airlift, 48.4% via truck, and small percentage 11.6% transported using sealift/vessels. Cilacap rank number 3, with 58.8% relief goods transported via truck and 41.2% transported via airlift.

Table 3.13. Results comparison of vital nodes rank

Node	Ranking based on Degree of Centrality	Ranking based on Optimization results
Jakarta	1	1
Surabaya	2	1
Semarang	3	3
Surakarta	3	2
Bandung	4	not use
Malang	5	5

Node	Ranking based on Degree of Centrality	Ranking based on Optimization results
Cilacap	5	4
Bali	6	1
Tasikmalaya	7	8
Magetan	7	6
Cirebon	8	7
Pangandaran	9	not use

The optimization results show that some alternative/candidate nodes such as Tasik, Cirebon, and Magetan are utilized several times, in specific, during initial period, as the capacity of other node and number of available vehicles for each transport mode are limited. However, two nodes, Bandung and Pangandaran, are not used for transporting relief goods to AA, Yogyakarta. Although optimization results did not contradict with degree of centrality results, it is shown how some nodes are more vital for the Yogyakarta case, and should be prepared more in advanced. Thus, rather than focusing on having proactive capability and measurement for all nodes based on the degree of centrality level, some more vital nodes could be considered.

Table 3.14. Additional Capacity Needed with Selected LOA Nodes

LOA Nodes	Additional Capacity for all transport mode (%)
Surakarta	35.337%
Cilacap	52.139%
Semarang	55.32%

This assessment is conducted by calculate the additional node capacity that should be added for selected vital nodes that should be owned to accommodate the disaster scenario. This approach is hoped to be able to give deeper analysis for decision maker as preparedness response. Hence, we limit the nodes selected and focusing on three most vital nodes: Surakarta, Semarang, and Cilacap. The results are presented in Table 3.14.

3.4.6. Evaluation for Strategies

In case of disaster, the effectiveness factor has the highest weight considering that the supply from outside the affected area starts to take place. The effectiveness factor consists of sending the relief goods as soon as possible and as much as possible. However, based on the complexity of the situation in affected area and availability of transportation resources, the option to send the goods to the affected area cannot be done directly; thus the LOAs are needed as a staging area of relief goods before sending it to the affected area. Such strategy, in particular, will benefit the relief distribution operation when number of vehicles is limited and/or amount of relief goods to be transported is enormous. By doing so, the relief goods can be transferred to another mode of transportation such as road network, airplane, or helicopter. Apart from that, the other transportation mode such as sealift/vessel is also utilized as the capacity of the road network, and airport capacity from each SN to the LOAs is limited. That being said, airlift is utilized to transport the relief goods as soon as possible effectively, with road transportation as the main mode, and vessels as an alternative to sending a large number of goods.

Depending on the number of the demand, the use of the vessel is most likely immobile. The helicopter airlifts are utilized due to the road accessibility problem and allowing relief goods to be sent directly to AA from the nearest LOA. When the access road to the AA is improving, countenancing relief goods to be transferred via road in a higher amount and more frequency. In parallel with helicopter airlift, the road transportation is utilized considering the accessibility level increasing. After the third period, as the relief supply is decreasing and road accessibility is increasing, relief goods can be sent in higher volume to the affected area directly. In this phase, once the procedure has been arranging with better visibility about the process to assist beneficiaries, the distribution system shifted from humanitarian relief chain to chain that is more commercial. The airlift usage percentage is moved, and road transportation becomes the primary transportation mode. In summary, the decision maker might select the transportation mode based on some points as shown in Table 3.15.

Although multi-modal transportation does give advantages for relief distribution planning, several factors need to be considered when choosing the transportation mode. Decision maker needs to explore the possibility of multi-modal transportation considering factors such as capacity of transportation mode; availability of transport mode; cost related to each transport mode; distance to be covered and time needed to deliver good based on transport mode; quantities of relief movement for each period; are deliberated when building the model. All factors mentioned above are considered quantitative factors and can be calculated in a particular model. However, other qualitative factors such as: geographical condition, human resources readiness, type of disaster, and how flexible multi-modal transportation is executed are also important to be included in the model.

Table 3.15. Criteria of mode choice selection in disaster response

Criteria	Road	Sea	Air
Delivery time	Moderate	Slow	High
Cost per unit	Medium	Low	High
Flexibility	High, Extensive network	Low, Restricted network	Medium, Limited network
Advantages	Relatively fast, no transshipment, direct delivery, flexible	Economical, large loading capacity	Fast, reliable, direct, easy tracking
Disadvantages	Roads may be blocked	Slow, transshipments at the port, not flexible	Expensive, limited loading capacity
When to use	During whole disaster response operation from supply node to affected node if possible If the pending establishment of road transportation occurs in affected area only (partially disrupted)	If no limited time frame to deliver a high number of goods During the initial response, suitable for non-urgent goods in a situation where air and road transport are overwhelmed with capacity	Urgently needed in a location with limited timeframe, road/rail access, or landlocked countries High level of insecurity
Type of relief goods	Food Tent, blanket	Additional clothes, canned food	Medicament, Priority goods for baby and elderly Food

3.5. Conclusions of the Chapter and Practical Implications

Relief goods distribution is a critical process of disaster management with logistics support is one of the significant activities in disaster response. Relief goods such as food, shelter, and medication must be sent from the supply nodes to the affected area rapidly to support disaster operation. In a disaster preparedness planning, decision maker needs to build a robust but flexible distribution network to increase efficiency in the relief distribution process. Even though every disaster may be divergent, the process of reacting to it remains relatively similar. The difference lies in the type of disaster that occurs, the number of people affected, the resources needed in national, regional and local levels, and the easiness to work on site. From a supply node, a large number of commodities must be transported to the extent that multi-modal transport is utilized.

The unavailable transport resources might hinder the optimal usage of all transportation modes. This study develops a model for relief distribution network considering multi-modal transportation and multi-trips distribution system. A strategic distribution plan is developed for Java Island, Indonesia in general and Yogyakarta Province as a specific example. During the first phase of the response, time become the driver. Thus transportation modal such as helicopter and airlift are mostly utilized. In the second phase, the transport modal changed from the air transportation to road transportation until demand number reach a relatively low amount. During the last phase, the distribution system more alike to commercial distribution with cost as its driver. Thus, utilization of road transportation is maximized. Although the model uses the multi-trips concept, it is only allowed the vehicle to deliver the goods within one layer (SN to LOA, or LOA to AA). In this way, the distribution system might be more managable rather than using a pooling system which allowed vehicle movement to a node with the high demand for vehicle.

The chapter contributes knowledge on the transport mode choice basis for relief distribution in upstream level. Accordingly, government, as a decision maker, should first understand their logistics capacity before developing their distribution network. The proactive move, during disaster preparedness, includes assess multiple alternatives for important nodes and links, multiple allocation strategies and fortification of hub nodes, and conduct on a survey of transport service providers, government entities and private organizations with fleets available that can assist in case of humanitarian operations. Furthermore, after the disaster strike, the decision maker should jump to reactive capability by resume the links after the disaster (limitation on time and budget) or even change the plan by selecting alternative nodes (port, airport) and transportation modes based on links availability.

Chapter 4 Dynamic Truck and Trailer Routing Problem for Last Mile Distribution in Disaster Response

4.1. Introduction

In chapter 3, the relief distribution model for delivering the relief goods from the supply node to the affected area, are developed. However, relief distribution inside affected area or called the last mile relief distribution has yet to be tackled. In this regard, last mile distribution refers to the final stage of delivering relief aid from local distribution centers to populations in affected areas (Balcik et al., 2008), and it represents an inherent risk in the relief chain. The challenges in last mile distribution stem from the high demand for supplies due to insufficient prepositioned stockpiles, high uncertainty of actual demand, uncertainty of travel time due to infrastructure obstruction, breakdown of communication channels, transportation problems, security issues, and limited resources (Balcik and Beamon, 2008; Oloruntoba, 2010, Penna et al., 2018). Although the approximate demand assessment is conducted, miscalculation of actual demand and high possibility of new information are uncommon. Furthermore, it is common to use heterogeneous vehicles, same transport mode with different characteristics and capacity, and to conduct multiple delivery trips using the same vehicle owing to an inadequate number of vehicles. In particular, the accessibility problem may result in the use of any type of "compatible" transport that is available at the time, including big trucks, vans, cars, or motorcycles.

Distribution relief goods to beneficiaries is critical responses during disaster. Unfortunately, uncertainty factors make it hard for generating optimal plans. In this chapter, three important issues-dynamic, uncertainty and evolution, are addressed:

a. *Dynamic*, means that environment after disaster occurrences changes over period. In the affected area, specifically in last mile area, might exhibit more locations to be served conferring to the progress of relief efforts.
b. *Uncertainties* due to information gap between actual conditions and data available. The high degree of uncertainty during last mile relief distribution happened owing to people movement from one municipal region to another or unsettling to incorrect calculations performed using outdated data.
c. *Information evolvement* based on update information gathered by decision maker. As more data and information such as demand number, demand location, commodities needed, distribution plan should be adjusted, respectively.

This chapter is motivated by the need for distributing relief goods in a time-efficient manner during disaster response. If last mile operations are executed correctly, the response time could be significantly minimized. Incorporating different types of vehicles can be beneficial to tackle issues such as accessibility or vehicle capability to reach remote and disrupted areas. However, decision-makers are faced with a dynamic problem in which reliable information about victims' locations and demands is not available, thereby forcing them to make urgent decisions with limited information and to change distribution routes frequently. This chapter investigates the application of the dynamic vehicle routing problem for last mile distribution during disaster response to deal with this uncertainty and unpredictability. We explore a model that involves limited number of different type vehicles, multiple trips, locations with different accessibilities, uncertain demands, and anticipating new locations that are expected to build responsive last mile distribution systems.

4.2. Last Mile Distribution in Disaster Response

Last mile distribution in disaster response involves the distribution/movement of goods from Local Distribution Center (LDC) to beneficiaries (final delivery destinations). Last mile distribution operations are characterized by complex network designs, and therefore, several factors must be considered. From the viewpoint of the response team, one goal is that all beneficiaries should have the necessary immediate support to meet their basic needs for food and nonfood items and shelter until their permanent, long-term needs are met. However, information gaps might make it difficult to achieve this goal. Such gaps may occur when assessments leave out affected areas or groups, miscalculate actual needs due to aggregation, deal with different geographic and administrative categories resulting in data mixture, or encounter obsolete and outdated data. Each factor can be related to increased possibilities of distribution strategies, as shown in Table 4.1.

4.2.1. Dynamic systems and degree of dynamism

The concept of degree of dynamism (*dod*) is used to handle the dynamic nature of and uncertainty level during the routing process. Larsen et al. (2002) defined *dod* as the expected percentage of uncertain requests, explicitly, as the ratio between the expected number of customers at the start of the routing process and the new demand requests. The *dod* indicates the dynamicity of the logistics process, and the *dod* value decreases over time. This study uses demand-based *dod*, where the dynamicity is calculated by the ratio between the total immediate demand and the expected aggregate demand at the start and the expected demand deviation.

$$dod = \frac{E|D_{imm}|}{E|D_0| + E|D_+|} = \frac{E\left|\sum_{i=1}^{I_{imm}} d_i\right|}{E\left|\sum_{i=1}^{I} d_i\right| + \Delta \sum_{i=1}^{I} d_{i+}} \tag{4.1}$$

Notation

dod	Degree of dynamism
$E\lvert D_0\rvert$	Expected initial demand
$E\lvert D_+\rvert$	Expected additional demand
$E\lvert D_{imm}\rvert$	Expected immediate demand
d_i	Demand at node i

Table 4.1. Factors affecting last mile distribution in humanitarian logistics

Factors	Descriptions
System description	Relief supplies from LDC to demand nodes in affected area, dynamic and stochastic environment
Demand location	Uncertain: a. Accessible b. Partially accessible or Remote, can only be accessed by certain type of vehicle
Demand characterization	Uncertain, lumpy, high risk, unpredictable Multiple types: critical items at the beginning, regularly consumed item, periodically occurs
Vehicles	heterogenous, limited, different compatibility with various routes
Route and Network availability	Infrastructure limitations, damages road, non-existed route, congestion
Information and Decision Support	Multi-agents, high information gap during the beginning of operations, unreliable
Planning horizon	Length is variable and unknown a priori
Goal(s)	Varied, depending on agent/organizations, such as: - maximize satisfied demand - minimize response time - minimize cost, etc.

4.2.2. Vehicle routing plan

This section describes last mile distribution routing plans in the context of humanitarian logistics. Relief goods must be delivered from the supply side to the demand points by using available resources and infrastructure. The primary task is to generate last mile distribution plans from the consolidation points or LDCs to meet the affected population within a limited amount of time. This problem is complicated by the dynamic nature of disasters and information gaps that result in dynamic distribution plans. It is also essential to measure how the response to disasters must be designed to fit the characteristics of the disaster and the affected areas. In other words, humanitarian logistics should be adjustable and adaptive to respond to dynamic situations.

Given the starting point of LDCs and demand nodes, the goal of this model is to find a combination of heterogeneous vehicles to minimize the total travel time. Two types of demand nodes, which the vehicles are assigned to serve, will also comply, accordingly. This model modifies the Truck and Trailer Routing Problem (TTRP) concept to allow different type of vehicle, namely trucks and mini trucks, to serve demand sites or LDCs called the root of the sub tour. Furthermore, mini trucks serve demands on sub tours, following which they return to the root of the sub tour, while trucks continue to serve remaining demands on the same route. Both vehicle types can serve independently without being limited by the same nodes. The solution routes can be classified as follows: (1) pure accessible routes are served by a truck (without any sub tours performed by mini trucks); (2) remote/inaccessible routes are served by mini trucks; and (3) partially accessible routes consisting of the main tour are traveled by trucks and at least one sub tour is traveled by a mini truck. Mini trucks are used to serve demand nodes that cannot be accessed by trucks. A sub tour begins and ends at the same distribution point on the main tour.

After disaster occurred, dynamic environment, in which the information and condition will be changes over time, is mostly happened during initial response. The need assessment conducted to calculate the approximate number of affected people might missed some locations, that cannot be access, or miss calculate the demand. In this situation, demand profiles (demand location, actual demand, or commodities need) may not be known at the time of the distribution begin. In consideration of its unpredictable and unanticipated demand nodes, the route might be modified to serve new demand nodes. This modification will change the solution routes developed prior to new demand realization. Psaraftis (1995) uses the following classification of the static routing problem:

> *"If the output of a certain formulation is a set of preplanned routes that are not re-optimized and are computed from inputs that do not evolve in real-time".*

While a problem is categorized as dynamic routing problem:

> *"If the output is not a set of routes, but rather a policy that prescribes how the routes should evolve as a function of those inputs that evolve in real-time".*

Figure 4.1 shows dynamic routing problems for last mile distribution systems in disaster response. When dealing with the dynamic nature of disaster response for last mile delivery, the problem can clearly be divided into two phases based on the information quality and process evolution. First, an initial distribution plan is formulated using the limited information available for demand locations, demand volume, and infrastructure availability. Then, each vehicle is dispatched to serve the assigned route. Information gaps will inevitably result from the continuous process of modifying tours and serving demands. During emergencies, many events can impact the information available, such as infrastructure breakdowns, unsatisfied beneficiaries, additional beneficiaries from other areas, and route unavailability.

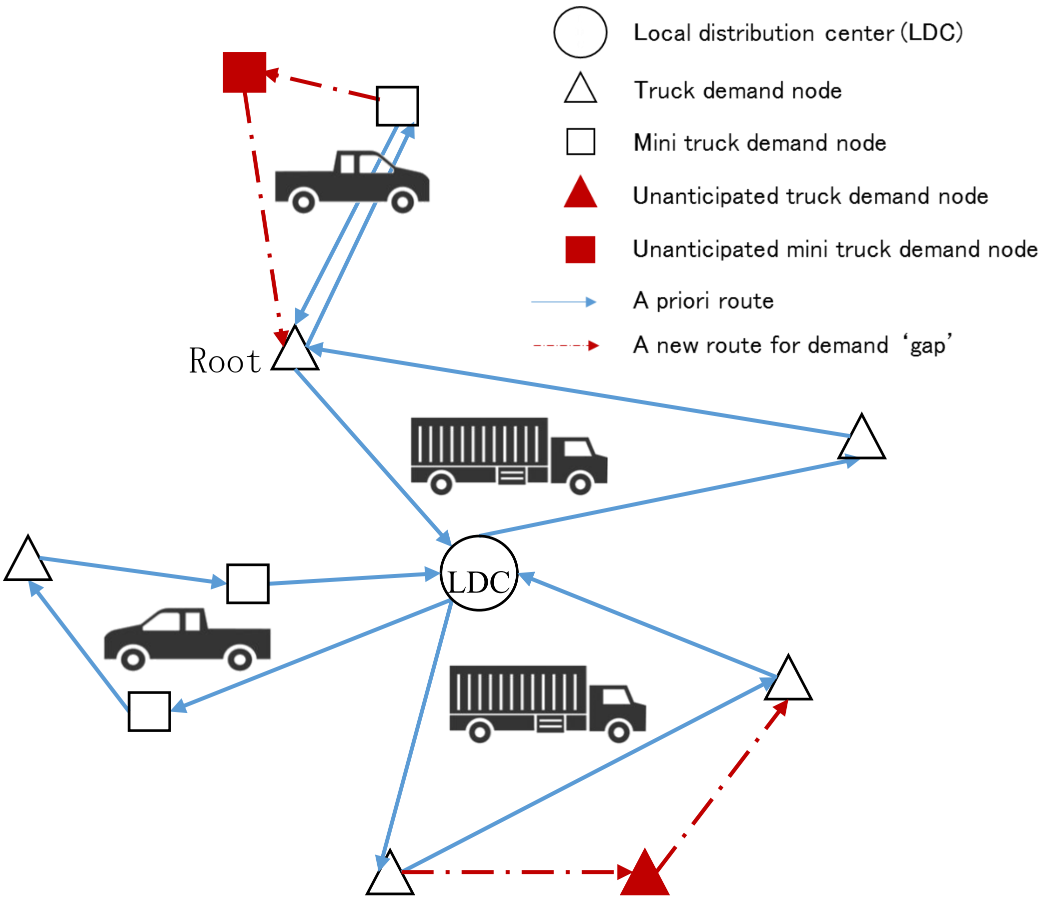


Figure 4.1. Illustration of dynamic truck and trailer routing problems

Thus, these plans have to be modified as disaster agencies deal with such situations. By using the additional information received during the implementation of routing, the distribution plan can be modified based on the dynamics of the environment. Unlike static cases in which all customers are defined at the start of the operation, dynamic routing allows newly arriving demands to be added during routing. When a new demand is identified, operators need to decide whether to accept or reject a request. Ideally, they should be able to add unanticipated demand locations and continue with routing as per the plan. Unfortunately, this is difficult to achieve because of time constraints and vehicles' limited capacities. Nevertheless, the most recent information is observed, and unattended demands are served by adding more vehicle.

Aside from dynamic demand location realization, unpredictable demand patterns, and density increase the complexity of relief distribution plans (Balcik et al., 2008). Demand uncertainty is a serious problem appearing in the VRP which leads to unmet demands (Sungur et al., 2008). Many researchers have been dealing with this uncertain demand by modelling it as stochastics value, following a certain probability distribution. Plump for a particular distribution probability accuracy is not the main goal of this chapter modelling. Normal distribution is one of the most used probability distributions to model demand uncertainty in both commercial logistics and humanitarian logistics (Dror et al., 1989; Laporte et al., 2002; Jabali and Rei, 2014; Lu et al., 2016; Qin et al., 2017). Normal distribution parameters are said to be independent from each other. As the result, if any error occurs in measuring the population mean, it will not affect the standard deviation measure (Taylor, 1997). Demand density is usually modelled by normal distribution, which at most, will resulted in skewed or fat tailed probability distribution. To deal with stochastic demand, a recourses policy is considered by calculating the probability of failure due to limited vehicle capacity and returning to the LDC for supply replenishment. In the first stage, a planned or a-priori route is designed and then a recourse is used in the second stage to accommodate problems like for instance exceeded capacity.

4.3. Dynamic Truck and Trailer Routing Problem for Last Mile Distribution

4.3.1. Assumptions and limitations

This study postulates several assumptions and limitations to facilitate mathematical formulation.

4.3.1.1. <u>Assumptions</u>

a. The set of demand nodes is divided into accessible demand nodes that can be served by both types of vehicles and non-accessible demand nodes that can only be served by small vehicles.
b. Each type of vehicle has different capacities.
c. A set of routes is a feasible solution if the routes start and end at the LDCs. However, a sub tour can start either from demand nodes (e.g., evacuation shelters, affected areas) or from other designated nodes. However, the total demand for any vehicle route cannot exceed the total capacity of the allocated vehicles used on that route.
d. Two types of vehicles are used, and the number of vehicles required is less than the number of vehicles available in the fleet.
e. The present study focuses on the delivery of consumer goods prioritized based on urgency.

4.3.1.2. Limitations

a. The distribution plan focuses on last-mile distribution, starting from LDCs to demand nodes.
b. Information for a priori distribution planning is obtained based on result of need assessment, and new information will be realized during the distribution process.
c. Traffic congestion and road capacity constraints are not considered due to limitation of data
d. This study focuses on daily-requirement demand-response goods such as water and food, and the demand volume is calculated using volume metrics.
e. The distribution plan is created only until all demand locations are known.
f. We exclude air transport and focus on road transportation.

4.3.2. Mathematical formulation

4.3.2.1. Indices, parameters, and decision variables

Let the undirected graph $G=(N,A)$, where $N=\{0,1,2,\ldots,n\}$ is the set of nodes and $A=\{(i,j):i,j\in N\}$ is the set of links. Node 0 represents the point of distribution, and the remaining nodes in V=$N\setminus\{0\}$ are demand nodes. The node in which the sub tour starts is called the root (c) of the main tour. A node type β_i indicates whether node i can be served by a truck or a mini truck. $\beta_i = 0$ indicates that node i can be served by both trucks and mini trucks, and $\beta_i = 1$ indicates that node i can only be served by mini trucks. The travel time t_{ij} between nodes is calculated by dividing actual distance from node i to j with assumed speed of 30km/hr.

The nonnegative actual demand at each node i can only be known once the vehicle arrives at the demand node. The uncertain demand is a stochastic value, following a truncated normal distribution $\sim N(\mu_i, \sigma_i)$, with minimum value of 0. K heterogeneous vehicles are available. The distribution process is only performed during working hours [0, T] for security reasons, such that each node i has available time $\tau_i \in [0, T]$. The available time indicates when both demand locations and demand amounts become known: for static demands, $\tau_i = 0$, and for dynamic demands, $\tau_i \in (0, T]$.

<u>Sets, indices, and parameters</u>

T	Total working hours allocated in one day
V	A set of nodes, $V = \{1, 2,\ldots,\lvert V\rvert\}$
S	A set of mini trucks available $S = \{1,2,\ldots, m_s\}$
R	A set of trucks available $R = \{1,2,\ldots, m_r\}$
i, j	Demand node $i, j \in V$

s	Mini truck indices $s \in S$
r	Truck indices $r \in R$
Q_s	Mini truck capacity
Q_r	Truck capacity
t_{ij}	Travel time from node i to j
η_j	Service time at node j
ξ_i	Nonnegative stochastic (random variable) demand at node i following a normal distribution $\xi_i \sim N(\mu_i, \sigma_i)$
$E[\zeta_i]$	Expected demand value at node i
γ	Demand satisfaction fraction
$E[FC(p_r)]$, $E[FC(p_s)]$	Expected additional travel time/recourse for route p by truck r and mini truck s due to capacity shortage

Decision variables

x_{ij}^r	Binary variable for truck r that travels from i to j
y_{ij}^s	Binary variable for mini truck s that travels from i to j
W_i^r	Binary variable regarding whether node i can be serviced by truck r
W_i^s	Binary variable regarding whether node i can be serviced by mini truck s
z_{ij}^s	Continuous variables represent the capacity flow in mini truck s after serving demand node i
z_{ij}^r	Continuous variables represent the capacity flow in truck r after serving demand node i

4.3.2.2. Objective function

The objective function is to minimize the travel time, including the time needed to return to the depot or main tour route to refill the vehicle to capacity and the expected time to fulfill all demands (both priori and new demands) due to vehicle shortages.

$$\min \sum_{i=1}^{V}\sum_{j=1}^{V}\sum_{r=1}^{R} t_{ij}x_{ij}^r + \sum_{i=1}^{V}\sum_{j=1}^{V}\sum_{s=1}^{S} t_{ij}y_{ij}^s + \sum_{r=1}^{R} E[FC(p_r)] + \sum_{s=1}^{S} E[FC(p_s)] \quad (4.2)$$

This model is developed based on the outcome of an interview with the logistics operation manager of Badan Penanggulangan Bencana Daerah (Regional Disaster Management Agency), Yogyakarta, Indonesia, that revealed that the concern during relief distribution is that each demand point is served (i.e., demand satisfaction). In this model, any demand gap occurrence is considered, and vehicle recourse is performed given adequate working time and vehicle availability. As the model tries to satisfy all demands, the responsiveness level of the disaster response operation is optimized.

4.3.2.3. Constraints

$$\sum_{j\in V}\left(\sum_{r\in R} x_{ij}^{r} + \sum_{s\in S} y_{ij}^{s} = 1\right), \qquad \forall i,j \in V \tag{4.3}$$

$$\sum_{j\in V}(x_{0j}^{r} + y_{0j}^{s}) = 1, \qquad \forall r = 1,\dots,R, \forall s = 1,\dots,S \tag{4.4}$$

$$\sum_{i\in V}(x_{i0}^{r} + y_{i0}^{s}) = 1, \qquad \forall r = 1,\dots,R, \forall s = 1,\dots,S \tag{4.5}$$

$$\sum_{i\in V} x_{ij}^{r} - \sum_{i\in V} x_{ji}^{r} = 0, \qquad \forall j \in V;\ \forall r = 1,\dots,R \tag{4.6}$$

$$\sum_{i\in V} y_{ij}^{s} - \sum_{i\in V} y_{ji}^{s} = 0, \qquad \forall j \in V;\ \forall s = 1,\dots,S \tag{4.7}$$

$$\sum_{j\in N}\sum_{s\in S} y_{ij}^{s} \le m_s, \qquad \forall i \in N;\ \forall s = 1,\dots,S \tag{4.8}$$

$$\sum_{j\in N}\sum_{r\in R} x_{ij}^{r} \le m_r, \qquad \forall i \in N;\ \forall r = 1,\dots,R \tag{4.9}$$

$$W_i^r \le \sum_{j\in N} x_{ij}^{r} \qquad \forall i \in V;\ \forall r = 1,\dots,R \tag{4.10}$$

$$W_i^s \le \sum_{j\in N} y_{ij}^{s} \qquad \forall i \in V;\ \forall s = 1,\dots,S \tag{4.11}$$

$$\sum_{r\in R}\left[\sum_{j\in N} z_{ji}^{r} - \sum_{j\in N} z_{ij}^{r}\right] - \xi_i \ge 0, \qquad \forall i \in V \tag{4.12}$$

$$\sum_{s\in S}\left[\sum_{j\in N} z_{ji}^{s} - \sum_{j\in N} z_{ij}^{s}\right] - \xi_i \ge 0, \qquad \forall i \in V \tag{4.13}$$

$$x_{ij}^{r}\, Q_r \ge z_{ji}^{r}, \qquad \forall i \in V, \forall j \in V, \forall r \in R \tag{4.14}$$

$$y_{ij}^{s}\, Q_s \ge z_{ji}^{s}, \qquad \forall i \in V, \forall j \in V, \forall s \in S \tag{4.15}$$

$$\sum_{i\in V}\sum_{j\in V} x_{ij}^{r} t_{ij} + \sum_{i\in V}\sum_{j\in V} x_{ij}^{r}.\ \eta_j + E[FC(p_r)] \le T, \qquad \forall r = 1,\dots,R \tag{4.16}$$

$$\sum_{i\in V}\sum_{j\in V} y_{ij}^{s} t_{ij} + \sum_{i\in V}\sum_{j\in V} y_{ij}^{s}.\ \eta_j + E[FC(p_s)] \leq T, \qquad \forall s = 1, \dots, S \tag{4.17}$$

$$x_{ij}^{r}, y_{ij}^{s} \in \{0,1\}, W_i^{s}, W_i^{r} \in \{0,1\} \qquad \forall i \in V, \forall j \in V, \forall r \in R, \forall s \in S \tag{4.18}$$

$$z_{ij}^{s}, z_{ij}^{r} \geq 0 \qquad \forall i \in V, \forall j \in V, \forall r \in R, \forall s \in S \tag{4.19}$$

Constraint (4.3) indicates that each demand node has to be serviced by a single mini truck or truck. Constraints (4.4) and (4.5) respectively indicate that the mini truck and truck leave from and return to the depot and go to exactly one node. Constraints (4.6) and (4.7) respectively express vehicle constraint flows on the routes for complete trucks and mini trucks. In the case of a disaster, limited resource availability needs to be considered. Constraints (4.8) and (4.9) ensure that at most m_s mini trucks and m_r trucks are used for serving nodes, respectively. Constraints (4.10) and (4.11) express node service constraints that indicate the relationship between the binary flow variable and the binary service variable for accessible and inaccessible nodes, respectively. These constraints imply that the service variable can only be true when a vehicle physically passes a node.

Constraints (4.12) and (4.13) enforce a balanced material flow requirement for demand nodes for trucks and mini trucks, respectively. However, because there is a parameter ξ_i that represents the uncertain demand parameter, stochastic programming is needed to handle the problem of performing vehicle recourse. Real demands are unknown; however, this study assume that all demands have a normal distribution with mean μ_i and standard deviation σ_i due to the deviation of demand calculation at node *i*. Demand deviation might occur owing to people moving from one municipal region to another or owing to incorrect calculations performed using outdated data. Constraints (4.14) and (4.15) express the construction of demand flows as long as sufficient capacity is available. It should be noted that travel times vary depending on road conditions, traffic conditions, or vehicle speed, especially during disaster response. Hence, this study limits this chapter to considering only deterministic time. As it is realized how distributing goods during nighttime will not be feasible owing to security reasons. Thus, additional constraints regarding time are added. Constraints (4.16) and (4.17) indicate that the total service time for each vehicle type cannot exceed the available distribution time. Finally, constraints (4.18) and (4.19) impose domain conditions on the variables.

4.3.3. *Routing policies: Recourse function and dynamic demand allocation*

4.3.3.1. <u>Initial solution for vehicle route</u>

This section illustrates the effects of different demand node types, demand amounts, and network characteristics on vehicle allocation and route planning. The model assumes that one demand node can only be visited one time during one working period, with a limited number of available vehicles. Assuming vehicle capacity Q_r = 300 and Q_s = 150, Figure 4.2 shows the routing and vehicle allocation decision for five demand nodes, one LDC node, and four available vehicles (m_s = 2, m_r = 2) in the initial distribution planning phase.

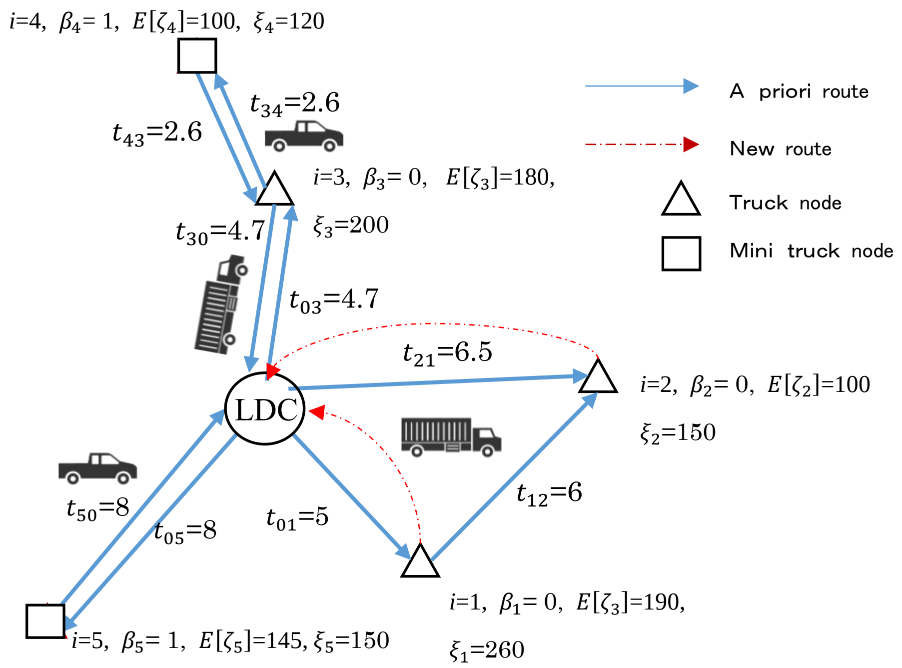


Figure 4.2. Example of allocation of four available vehicles for one LDC and five demand nodes

The distribution should be planned based on vehicle availability, vehicle capacity, and allowable time constraints. Thus, the initial solution ensures route feasibility based on equations (4.20) and (4.21).

$$\sum_{i\in V}\sum_{j\in V} y_{ij}^{s} E[\zeta_i] \le Q_s, \qquad \forall s \in S \tag{4.20}$$

$$\sum_{i\in V}\sum_{j\in V} x_{ij}^{r} E[\zeta_i] \le Q_r, \qquad \forall r \in R \tag{4.21}$$

Both equations guarantee that the expected total demand does not exceed the respective vehicle capacities. All constructed routes satisfy the conditions specified by the constraints, and the total times for all routes are minimized using $\sum t$ = 48.1. In addition, when the route needs to be modified owing to the probability of shortage, a recourse can be factored in to serve the next customer. Therefore, the first route is modified by considering the possibility of a shortage, in addition to other constraints such as vehicle capacity and availability of working time. This results in additional recourse time $\triangle$t = 5.5 compared to no recourse. As a tradeoff, all demands can be satisfied.

4.3.3.2. Vehicle recourse function in shortage situations

Route failure occurs when a vehicle is running out of capacity and is therefore not able to adequately service current customer *i* or when the distribution process exceeds its working time *T*. The first case occurs because there is a probability that the remaining vehicle capacity will not be enough to satisfy the demand for the next node; as a result, the current route is terminated. The second case occurs if there is road blockage or traffic congestion during the distribution process. This subsection focuses on the first case where a failure occurs owing to a shortage of supplies.

After a vehicle is dispatched, at each node it services, the probability of shortage for the next node is calculated. If the probability is higher than the level of confidence, recourse will need to be taken. The probability of the total demand up to customer *i* is calculated by following the recursive concept proposed by Gendreau et al. (1996). Following the recourse action, which consists of sending the vehicle back to the depot, notifying the depot to send another vehicle (if available), or replenishing the same vehicle to serve again, the vehicle continues to serve customer *i*, and resumes the route as originally planned. If recourse is performed, additional travel time must be added to account for the vehicle's return to the LDC for replenishing supplies. However, this policy requires a feasibility check of the maximum working hours, because recourse implies additional time. However, in light of two types of vehicles and sub tour formations, recourse might occur from a node in the sub tour to the root of the main tour. Thus, five types of recourse functions are considered.

Given a route p $(i_1, i_2, \dots, i_h)$, where $i_l \in V$ for $h \in \{1, 2, \dots, h\}$, the cumulative expected demand at i_h will be $\sum_{l=1}^{h} E[\zeta_{i_l}] = \Lambda_{i_h}$ with expected cumulative variance equal to $\sum_{l=1}^{h} V[\zeta_{i_l}] = \Phi_{i_h}$. The expected failure cost/recourse function at demand node i_h for p is $EFC(\Lambda_{i_h}, \Phi_{i_h}, i_h)$. Notation *u* denotes when failure occurs at i_h given that it has not occurred on any previously visited customer along the route. Notation *u*, can be replace by a really large number for practical computations (Christiansen and Lysgaards, 2007). The detailed calculation for each recourse type is as follows:

a. Failure occurs in inaccessible route served by mini truck

This failure occurs if the cumulative demand up to the customer i_h is larger than the mini truck capacity ($\sum_{l=1}^{h} \xi_{i_l} > Q_s$). In non-accessible routes, the vehicle will return to depot (the 0) to refill supplies and continue to service the demand from i_h according to equation (4.22).

$$EFC\left(\Lambda_{i_h}, \Phi_{i_h,} i_h\right) = 2t_{0i_h} \sum_{u=1}^{\infty} \left(P \left[\sum_{l=1}^{h-1} \xi_{i_l} \leq uQ_s < \sum_{l=1}^{h} \xi_{i_l} \right] \right) \tag{4.22}$$

b. Failure occurs in sub tour of partially accessible route served by mini truck

If $\sum_{l=1}^{h} \xi_{i_l} > Q_s$ occurs in the sub tour of a partially accessible route, then the vehicle will return to the root (*r*) of the main tour, refill supplies, and continue to service the demand from i_h according to equation (4.23).

$$EFC\left(\Lambda_{i_h}, \Phi_{i_h,} i_h\right) = 2t_{ri_h} \sum_{u=1}^{\infty} \left(P \left[\sum_{l=1}^{h-1} \xi_{i_l} \leq uQ_s < \sum_{l=1}^{h} \xi_{i_l} \right] \right) \tag{4.23}$$

c. Failure occurs in pure accessible route served by truck

This failure occurs if the cumulative demand up to the customer i_h is larger than the truck capacity ($\sum_{l=1}^{h} \xi_{i_l} > Q_r$).

$$EFC\left(\Lambda_{i_h}, \Phi_{i_h,} i_h\right) = 2t_{0i_h} \sum_{u=1}^{\infty} \left(P \left[\sum_{l=1}^{h-1} \xi_{i_l} \leq u(Q_r) < \sum_{l=1}^{h} \xi_{i_l} \right] \right) \tag{4.24}$$

d. Failure occurs in partially accessible route served by a truck after servicing the sub tour

In this case, the truck capacity is $Q_r - Q_s$ as the sub tour has been serviced. Thus, failure will occur if the cumulative demand up to custthe omer i_h is larger than the available truck capacity($\sum_{l=1}^{h} \xi_{i_l} > (Q_r - Q_s)$).

$$EFC\left(\Lambda_{i_h}, \Phi_{i_h,} i_h\right) = 2t_{0i_h} \sum_{u=1}^{\infty} \left(P \left[\sum_{l=1}^{h-1} \xi_{i_l} \leq u(Q_r - Q_s) < \sum_{l=1}^{h} \xi_{i_l} \right] \right) \tag{4.25}$$

e. Failure occurs in any tour with cumulative demand up to the customer i_h equal to vehicle capacity

If $\sum_{l=1}^{h} \xi_{i_l}$ is equal to vehicle capacity, then after the vehicle refills supplies (either at depot (0) or root (*c*) of main the tour), it will continue the service from i_{h+1} according to equations (4.26) and (4.27) for mini trucks and trucks, respectively.

$$EFC\left(\Lambda_{i_h}, \Phi_{i_h,} i_h\right)$$
$$= \left(t_{i_h c} + t_{c i_{h+1}} - t_{i_h i_{h+1}}\right) \sum_{u=1}^{\infty} \left(P \left[\sum_{l=1}^{h-1} \xi_{i_l} \leq uQ_s < \sum_{l=1}^{h} \xi_{i_l} \right] \right) \tag{4.26}$$

$$EFC\left(\Lambda_{i_h}, \Phi_{i_h,} i_h\right) = \left(t_{i_h 0} + t_{c i_{h+1}} - t_{i_h i_{h+1}}\right) \sum_{u=1}^{\infty} \left(P\left[\sum_{l=1}^{h-1} \xi_{i_l} \leq uQ_r < \sum_{l=1}^{h} \xi_{i_l} \right] \right) \tag{4.27}$$

4.3.3.3. Dynamic demand allocation

Unlike in static cases where all customers are defined at the start of operations, dynamic routing involves newly arriving demands n^+ during routing hours. Thus, assuming that n^+ demand nodes are added, let the new customer set $V^+ = \{n+1, n+2, \ldots, n+n^+\}$. The set of all demand nodes will be $V' = V \cup V^+$ for all locations $N' = V' \cup \{0\}$, with the travel times between i and j for all $i, j \in N'$ denoted as t_{ij}.

For meeting the requirements of dynamic demand, we model the problem as a sequence of static subproblems. The distribution horizon T is split into s parts, such that the time interval for each part is v = T/s. When a new demand is identified, the vehicle needs to decide whether to accept or reject the request based on the availability of relief goods and time. When the dynamic demand is known in $\tau_i \in (0, T]$, the vehicle needs to check the availability of supplies, probability of shortage, and vacant time. If all conditions are satisfied, then the new demand can be added to the route; otherwise, it shifts to the next working slot. All these dynamics nodes are treated as static customers for the next distribution period.

4.4. Solution method

4.4.1. Simulated annealing/variable neighborhood search (SA/VNS)

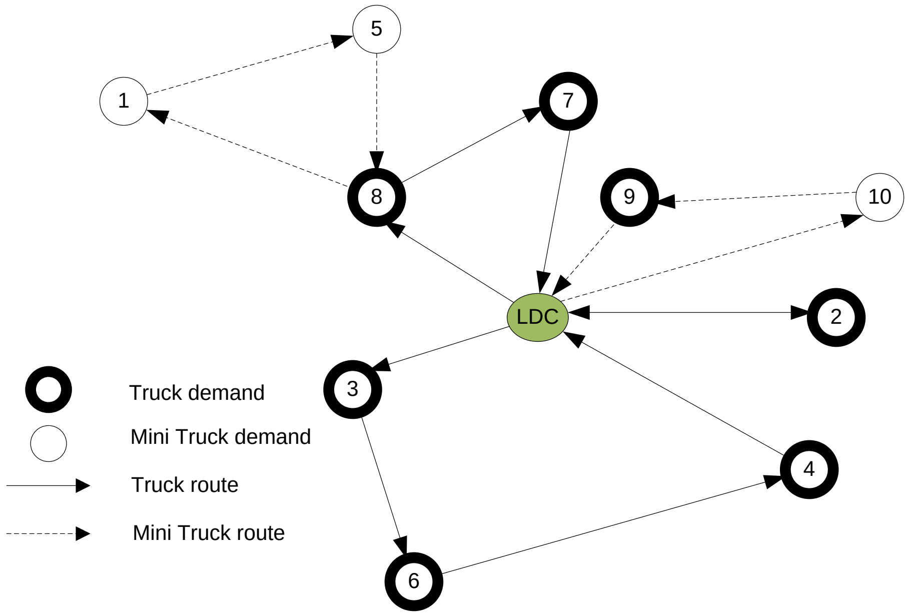
This chapter incorporates a hybrid SA algorithm that can use a hill-climbing approach to escape from local optima (Gendreau and Potvin, 2010). We modified the basic SA algorithm to solve dynamic stochastic problems. The SA algorithm itself comprises two stochastic processes, one of which is the solution acceptance criterion; therefore, it does not require any modifications for solving stochastic problems. An event scheduler architecture developed by Montemanni et al. (2005) is used to deal with dynamic demand requests with the time stamp. However, it is also important to note that the initial solution and intensification phase of the algorithm affect the quality of the ultimate solution. Furthermore, as we add VNS to the diversification and intensification strategy, we include the stochastic framework by adding the sample average estimator (SAE) that is performed if a comparison is required during the *MoveorNotMove* part.

The proposed SA algorithm has been successfully applied to a combinatorial optimization problem such as VRP and its variants, such as TTRP. Its probabilistic mechanism, which is based on the Monte-Carlo simulation, can capture the uncertainty and randomness of disaster response operations. Furthermore, it can be combined with other methods and can be modified and hybridized easily, thus strengthening its ability to deal with complex real-world disaster response problems. Many studies have successfully applied SA algorithms to various problems, and therefore, this study uses a hybrid SA/VNS approach.

4.4.2. Initial solution

The solution is represented by a permutation of n customers denoted by a set of string numbers {1, 2, 3,…, *n*}. Additional zeros are added to represent LDCs and points for sub tours. Each demand number has additional information regarding the types of demands/services that indicate that the node is served by a particular vehicle on a different route. The service type determines the type of vehicle used to service the demand, thus resulted in exactly one solution representation. The *i*th non-zero number in the first *n*+0 position denotes the *i*th customer to be serviced. The solution representative as in illustrate in figure 4.3 is further explained as follows. The first number in the solution indicates the first customer to be served in the first route. Thus, explained the decision variable x_{ij}^r if the node is served by truck or y_{ij}^r if served by minitruck, in consideration with the node type. Other node will be added to the route one by from left to right to represent the sequence in which they are served, provided that either constraints (4.16) and (4.17) or constraints (4.20) and (4.21) is not violated.

However, as constraint (4.8) and (4.9), limit the maximum number of vehicles that can be used for the distribution process, a route combination procedure is needed to reduce the number of vehicles for both truck and mini truck. The route combination procedure simply checks if it is possible to combine two existing routes without violating vehicle's capacity and working time constraints. If so, the routes are merged without any modification. The procedure continues until the number of vehicles used is less or equal than the number of available vehicle or there are no routes can be combined without violating the capacity and working time constraint of the vehicle in use. The solution illustration in figure 4.3 will comply with the decision variables x_{ij}^r and y_{ij}^s, respectively.



Solution	0	3	6	4	0	2	0	8	1	5	7	0	10	9	0
Location type		1	1	1		1		1	0	0	1		0	1	
Route	Route 1					Route 2		Route 3				Route 4			

Figure 4.3. Solution representation illustration for TTRP

We use two types of initial solutions, namely. IS_G and IS_N:

a. Heuristic initial solution (IS_G)

It is important to allocate demand nodes to the routes associated with their types of demand. Thus, this study adopted and incorporated the generalized assignment problem (GAP) to solve the node allocation problem (refer to Chao (2002) for the detailed algorithm). After all demand nodes are allocated to a particular route, the demand node sequence problem for each route is constructed using the insertion heuristic.

b. Nearest neighbor (IS_N)

By using the GAP concept for node allocation, path construction is performed using information relay based on nearest neighborhood heuristics. We try to find the closest candidate node with respect to travel time t. As we deal with multimodal routing and sub tours are allowed, it is necessary to modify the basic nearest neighbor. First, we consider a number of unimodal graphs $\{G_1, G_2, G_3\}$ that represent each vehicle associated with different types of routes. Each graph consists of nodes, arcs, and demand label sets $G_i = (V_i, A_i, L_i)$. The arc set is the union of all input graphs' arcs and a set of transfer arcs $A_{transfer}$; therefore, the total arc set is $A_{mm} = A_1 \cup A_2 \cup A3 \cup A_{transfer}$. Transfer arcs are used to connect the unimodal graphs, and they make it possible to transfer from one unimodal graph to another.

4.4.3. Detailed algorithm

Because the problem is a mix of stochastic and dynamic routing problems, it is important to treat it as a multi-time interval static problem. Then, a plan must be formulated at the start of each time interval for how to service the currently known demand nodes. Recourse will be considered at the same time if the constraints are satisfied. Otherwise, the plan will be changed at the start of the next time interval. In dynamic problems, it is essential to embed the simulator that will receive new demand requests and manage the simulation time T_{sim} such that when the dynamic demand is known in $\tau_i \in (0, T]$, the vehicle will try to service the demand as soon as possible or process it at the end of the time period. The distribution horizon T is split into s parts with v time intervals. First, the event scheduler sets the simulation time, and then, the initial solution is constructed based on static demand node information. Optimization is performed until the current T/s is over and the vehicle is sent to new demand nodes in the next T/s time units. In the following periods, this process is repeated using the solution from the previous period and by including new demand nodes using the Clarke-Wright algorithm (Clarke and Wright, 1964).

The SA/VNS optimization for each timestamp v will improve the results of the initial solution by randomly choosing different improvement moves, such as swap, insertion, 2-opt, and reverse. We also allow a change in service vehicle type for obtaining solutions that are more diverse by exchanging the vehicles used in particular nodes as long as the solution is feasible. The algorithm starts by setting current temperature $Temp_0$ and generating an initial solution X. The current best solution X_{best} and the best objective function of X F_{best} are set to X and $obj(X)$, respectively. Figure 4.4 shows a flowchart of the SA/VNS algorithm.

For diversification and intensification, we use the stochastic variable neighborhood search (S-VNS) algorithm. This local search is performed after every three temperature *Temp* decrements. The SAE procedure is performed in VNS to use the stochastic information to compare solutions. The procedure draws a sample of scenarios of unserved customer demands to obtain the average value of objectives function in each scenario. However, we select different types of neighborhoods in the VNS algorithm. First, we adopt sub tour removal heuristics that relocates sub tours and transfers them to other potential roots. The other neighborhoods are *2-opt* and *2opt**.

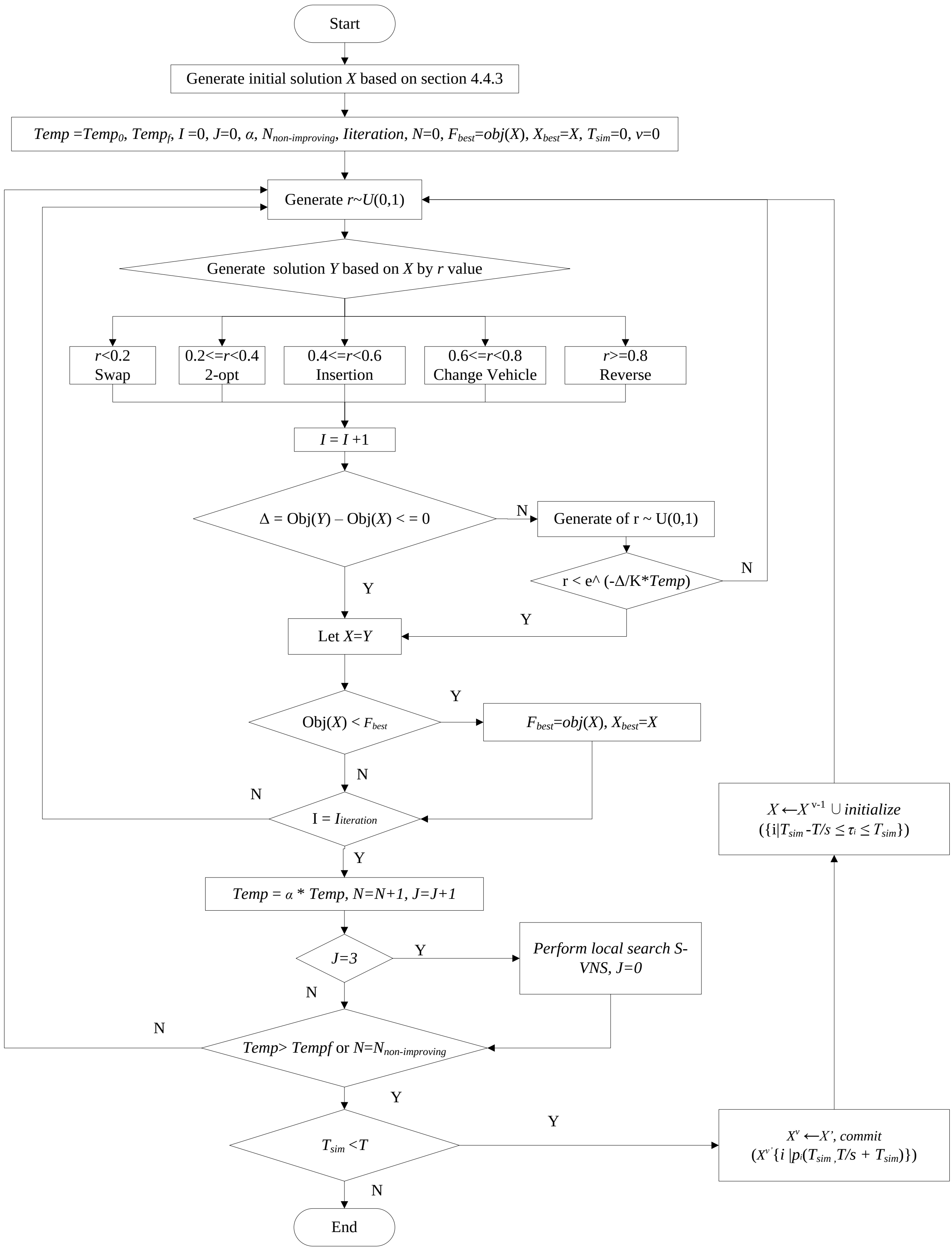


Figure 4.4. Flowchart of SA/VNS algorithm for dynamic and stochastic routing problem

4.5. Results and Discussions

The proposed SA/VNS was coded in Microsoft Visual C++ 2012, and executed on a computer with an Intel i5 2.66 GHz CPU with 16 GB RAM running the Windows 7 64-bit operating system. The proposed method was first tested on Chao's (2002) TTRP benchmark that consisted of 21 instances of 50–199 demand nodes to understand its performance. Then, the proposed algorithm was used to solve the problem derived from a real case study in Yogyakarta, Indonesia. The experiment compared the performance of the SA/VNS implementation using basic SA, SA/VNS-IS_G, and SA/VNS-IS_N.

This study uses Taguchi's method with a two-level factorial design to set parameters. The result of this design experiment indicates that the best parameter combination for SA is $N_{non\text{-}improving} = 2N$, the initial temperature $T_0 = 1$, final temperature $T_f = 0.01$, number of iterations $I_{iteration} = 500*N$, Boltzmann constant $K = 1/3$, and cooling coefficient $\alpha = 0.9$, where N is the total number of demand nodes. We also performed an analysis to determine the maximum number of neighborhoods (k_{max}) in the VNS algorithm, and we set $k_{max} = 3$ to reduce the computational time.

4.5.1. Algorithm verification

To benchmark the performance of the proposed SA/VNS algorithm, we compared it with other methods. We used 21 instances from Chao's (2002) datasets and compared it with Best Known Solution (BKS). The dataset comprised seven sizes with 50–199 demand nodes and three different proportions of node types, namely, 25%, 50%, and 75%. All three modifications of the proposed algorithm were run ten times, and the best solution was recorded. The algorithm's performance was measured in terms of the percentage gap between the algorithm's solution values and the BKS values by considering the average performance of the algorithm. As the datasets were deterministic with static demand, we did not use the demand simulator to run the instances; instead, we focused on minimizing the distances traveled by vehicles.

Table 4.2. Deterministic TTRP from Chao (2002): Comparison results

Data Set	Node	Best Known Solution (BKS)	SA/VNS	Gap (%)	SA/VNS-IS_N	Gap (%)	SA/VNS-IS_G	Gap (%)
1	50	564.68[a]	**564.68**	**0.00%**	**564.68**	**0.00%**	**564.68**	**0.00%**
2		611.53[b]	**611.53**	**0.00%**	**611.53**	**0.00%**	**611.53**	**0.00%**
3		618.04[a]	**618.04**	**0.00%**	**618.04**	**0.00%**	**618.04**	**0.00%**
4	75	798.53[a]	808.84	1.29%	**798.53**	**0.00%**	**798.53**	**0.00%**
5		839.62[a]	**839.62**	**0.00%**	**839.62**	**0.00%**	**839.62**	**0.00%**
6		930.64[b]	**930.64**	**0.00%**	**930.64**	**0.00%**	**930.64**	**0.00%**
7	100	830.48[a]	**830.48**	**0.00%**	**830.48**	**0.00%**	**830.48**	**0.00%**
8		870.94[c]	875.76	0.55%	872.56	0.19%	872.56	0.19%
9		912.02[b]	912.64	0.07%	**912.02**	**0.00%**	**912.02**	**0.00%**
10	150	1036.20[e]	1053.90	1.71%	1039.07	0.28%	1039.07	0.28%
11		1091.90[c]	1093.57	0.15%	1093.57	0.15%	**1091.90**	**0.00%**
12		1149.40[c]	1155.44	0.52%	1154.70	0.46%	1154.70	0.46%
13	199	1284.70[c]	1320.21	2.76%	1287.10	0.19%	1287.10	0.19%
14		1333.70[c]	1351.54	1.34%	1347.40	1.03%	**1333.7**	**0.00%**
15		1416.50[c]	1436.78	1.43%	1425.80	0.66%	1425.8	0.66%
16	120	1000.80[e]	1004.47	0.36%	1002.40	0.16%	1004.47	0.36%
17		1026.20[d]	1026.88	0.07%	**1026.20**	**0.00%**	**1026.2**	**0.00%**
18		1098.20[d]	1099.09	0.09%	**1098.20**	**0.00%**	**1098.2**	**0.00%**
19	100	812.69[d]	814.07	0.17%	813.30	0.08%	813.30	0.08%
20		848.12[e]	855.14	0.83%	848.93	0.10%	848.93	0.10%
21		909.06[a]	**909.06**	**0.00%**	**909.06**	**0.00%**	**909.06**	**0.00%**
Average Gap (%)				**0.54%**		**0.16%**		**0.11%**
Number of BKS			**7**		**11**		**13**	

Bold values indicate that the BKS has been found ([a]Scheuerer (2006), [b]Lin et al. (2009), [c]Villegas et al. (2011), [d]Derigs et al. (2013), [e]Villegas et al. (2013))

As shown in Table 4.2, the basic SA/VNS algorithm with random initial solutions performed well in medium-sized instances with 50–75 demand nodes. However, we failed to achieve optimal results for instances with more than 75 nodes. In contrast, the modified SA/VNS with IS_N and IS_G could solve instances with up to 120 demand nodes. However, it still failed to reach the best-known solutions for instances with more demand nodes. The modified SA/VNS with IS_N and IS_G obtained 11 and 13 BKSs out of 21 datasets and registered average deviations from the BKS of 0.16% and 0.11%, respectively. The results for both modified SA/VNS algorithms deviate at most within 1.03% and 0.66% from the BKS. Although SA/VNS-IS_G seems to show a better result than SA/VNS-IS_N, the difference is not significant considering that the p-value of the statistical test is 0.35304008, which is greater than the α value, indicating no significant difference between the results obtained by SA/VNS-IS_G and SA/VNS-IS_N.

Both of our SA/VNS heuristics can solve the TTRP in terms of solution quality. Therefore, the analysis indicates that to obtain quality solutions for the TTRP, the proposed SA/VNS heuristic is as effective as other heuristics and seems to be as efficient. However, it failed to outperform the solution quality of matheuristics. In particular, the proposed algorithms achieved the best results in small and medium instances with up to 75 demand nodes.

4.5.2. Case study and datasets

4.5.2.1. Case study description

In 2006, Mw 5.9 earthquake struck Yogyakarta, Indonesia, causing more than 5000 deaths, destroying 370,776 private houses, and public structures (BAPPENAS, 2006). A field study and data collection drive conducted in 2016 in Yogyakarta, Indonesia, revealed that although the Badan Penanggulangan Bencana Daerah (Regional Disaster Management Agency), Yogyakarta, is currently very actively coordinating with local and international nongovernmental organizations related with disaster risk reduction projects; there unfortunately remains a great lack of awareness about the importance of relief supply chains and their preparedness.

Owing to inadequate information about evacuation processes, including where to evacuate temporarily, earthquake victims scattered over a large area in relatively small groups and frequently moved to look for safer places or relief aids. These problems hampered the disaster response teams, as the exact information kept changing and became unreliable, resulting in deviations in the actual demand volume and location accuracy.

This section discusses the applicability of the proposed dynamic model for last mile distribution by considering different types of demand nodes and limited vehicle availability. In commercial logistics, demand data can be forecasted, and demand error can be corrected quickly.

However, logistics management in disaster situations relies entirely on administrative data held by the government, which leads to the need for flexible relief distribution. Accordingly, this study uses past data in the numerical analysis to show the model's performance over a set of more realistic data.

4.5.2.2. Datasets

All 17 wards in Bantul District, Yogyakarta, Indonesia, were chosen to test the model and calculations. Each ward has a different topography and has different proportions of low- and high-accessibility demand nodes as illustrate in figure 4.5. The number of initial demand points is based on the number of villages/hutments in each ward, and the locations are scattered. The LDC is located within the ward boundary.

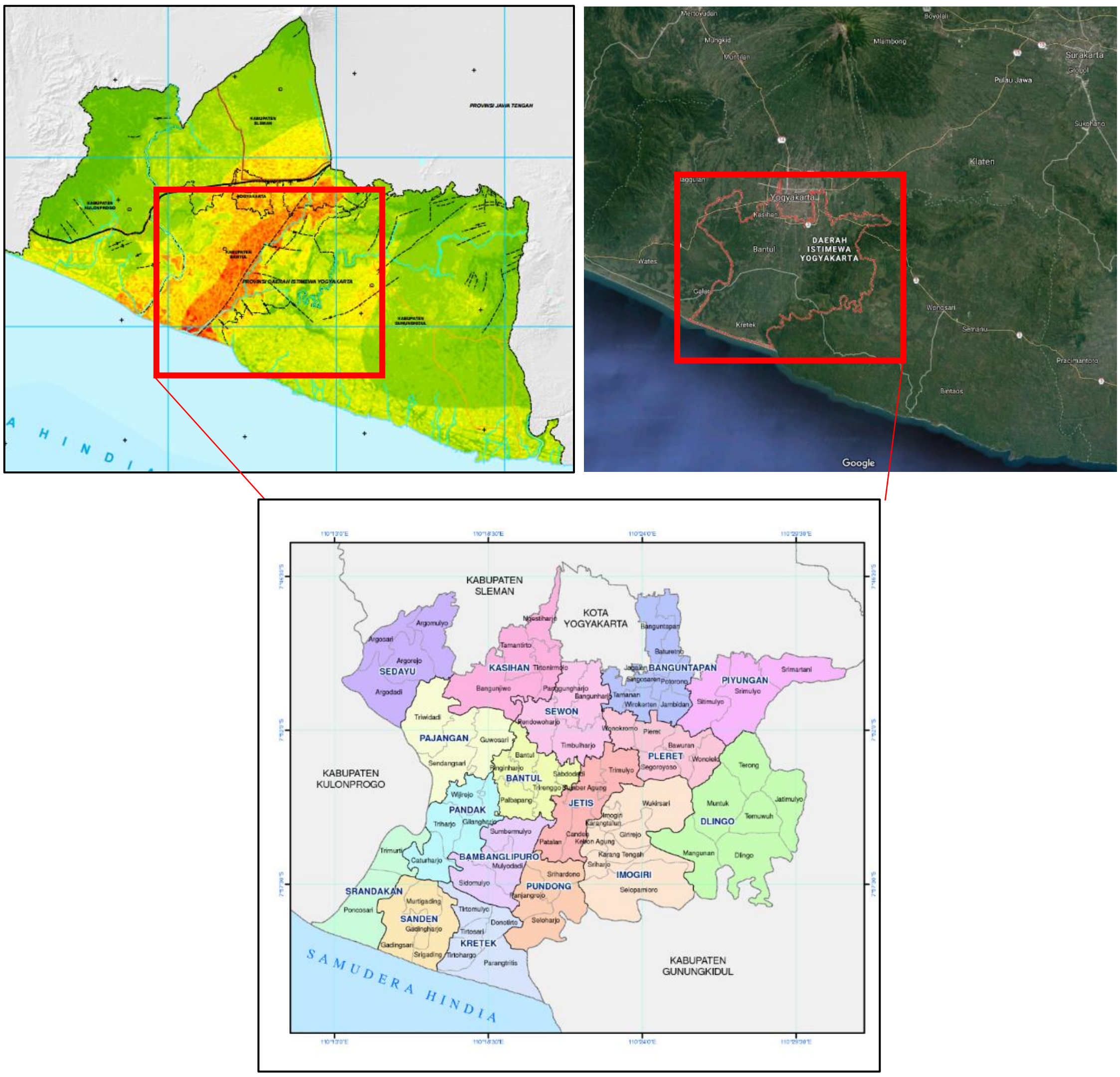


Figure 4.5. Study Area: 17 wards in Bantul, Yogyakarta

Table 4.3 shows the demand data for the ward. The requirement for relief goods was calculated based on the standard requirements established by the disaster agency in Indonesia (BNPB, 2009). According to the disaster agency, the basic consumable goods needed by one person per week are as follows:

Rice	2.8	kg/week
Drinking water	15–20	L/week
Supplementary foods	1.2	kg/week
Others	0.5	kg/week

Table 4.3. Details of the demand dataset

Data Set	Ward Name	Initial Number of Demand Points	Total Population in Need of Relief	Demand Node Proportion (Low Accessibility: High Accessibility)
B_01	Bantul	50	58,462	10:90
B_02	Dlingo	58	34,263	60:40
B_03	Imogiri	72	56,446	50:50
B_04	Jetis	64	50,974	20:80
B_05	Pundong	49	31,447	30:70
B_06	Banguntapan	57	98,557	15:85
B_07	Bambang Lipuro	45	38,223	30:70
B_08	Kasihan	53	92,099	25:75
B_09	Kretek	52	28,648	40:60
B_10	Pajangan	55	28,942	40:60
B_11	Pandak	49	45,924	50:50
B_12	Piyungan	60	44,811	20:80
B_13	Pleret	47	41,902	25:75
B_14	Sanden	62	29,449	25:75
B_15	Sedayu	54	40,948	30:70
B_16	Sewon	63	87,786	25:75
B_17	Srandakan	43	28,367	75:25

Accordingly, the number of relief goods needed was calculated by multiplying the basic needs for one person/week and the population count in each demand node. Considering that water occupies more space based on its demand, we divided the vehicles into those that would transport water and those that would transport foods. However, the distribution followed the same route with the assumption that both goods would be transported at the same time. The travel time was calculated based on the travel distance divided by the worst-case speed during the distribution process (e.g., 30 km/h). The summary of the distribution configuration and nature of the model parameters can be seen in Table 4.4 and 4.5. The example of node location and data input can be found in Appendix 2.

Table 4.4. Summary of Last Mile Relief Distribution Configuration

Function	Details
Local Distribution Center	1 depot per Ward
Demand Node	43~72 node (Refer to table 4.3)

Table 4.5. Input parameter for the model

Parameters	Nature of data input	Remarks
Operational Horizon	Finite	8 periods
Transportation time	Deterministic	Static
Supply availability	Deterministic	Static
Relief Demand	Stochastics	Dynamic
Demand Location	Deterministic	Dynamic
Number of vehicles	Deterministic	Static
The capacity of vehicle	Deterministic	Static

4.5.3. Computational results and discussion

Solutions were provided for 17 case studies, one for each ward in Bantul, Yogyakarta, using four different algorithms, namely, SA, VNS, ACO, and our proposed hybrid SA/VNS. We compared the results from the computational experiments to determine the performance of our proposed algorithm. In this section, we compare basic SA and VNS to understand the robustness of our hybrid algorithm compared to the basic algorithm. We also compare it with ACO, a population-based algorithm that can solve VRP variants; the results are competitive, although the computational time is slightly longer (Yu et al., 2009).

As there are two types of initial solutions, the best result from between the two-hybrid methods, namely, SA/VNS-IS_N and SA/VNS-IS_G, is selected. For all cases, we first ran the deterministic problem as an initial distribution plan. Then, we ran the dynamic stochastic problem with default settings that included 10% *dod* and 10% demand standard deviation from the initial data stated in Table 4.6. In this computational experiment, we set the number for each vehicle type as 20 with the following specifications: mini trucks have 20-ton capacity and trucks have the 30-ton capacity. It shows the computational results in terms of distance travel and computational time for stochastic dynamic routing.

Table 4.6. Dynamic stochastic result for 17 wards in Bantul district

Data Set	SA		VNS		ACO		SA/VNS	
	Travel distance	Computational Time (second)	Travel distance	Computational Time (second)	Travel distance	Computational Time (second)	Travel distance	Computational Time (second)
B_01	**2072.63**	173.84	2148.27	165.37	**2072.63**	261.94	**2072.63**	170.71
B_02	1783.16	141.67	1754.78	101.40	1717.07	200.01	**1682.30**	178.32
B_03	3914.25	163.40	3831.12	144.99	3739.80	370.41	**3609.62**	223.71
B_04	2616.33	175.89	2583.98	179.00	**2501.28**	354.53	2513.26	235.48
B_05	1818.63	136.12	**1782.92**	127.23	**1782.92**	145.02	**1782.92**	138.23
B_06	3619.78	160.99	3619.78	123.77	3336.65	253.26	**2957.47**	179.20
B_07	1515.08	128.58	1591.65	98.23	**1477.72**	117.07	1515.08	130.97
B_08	2964.94	175.89	2973.20	129.00	**2843.14**	233.39	**2843.14**	181.33
B_09	1910.06	129.63	**1809.57**	111.09	1822.27	232.08	**1809.57**	138.05
B_10	1683.74	156.38	1683.74	171.44	1612.16	288.13	**1531.46**	168.61
B_11	2002.66	127.30	2002.66	108.72	1987.71	197.83	**1982.31**	124.30
B_12	2155.08	153.67	2196.40	129.48	**1894.01**	280.69	**1894.01**	185.95
B_13	**1580.29**	110.81	1705.39	99.31	**1580.29**	160.99	**1580.29**	132.87
B_14	1809.71	152.63	1856.82	149.49	1809.71	349.04	**1762.05**	162.10
B_15	1864.89	153.67	1864.89	113.95	**1807.87**	277.98	1810.20	150.15
B_16	2757.19	177.72	2834.49	110.81	2757.19	302.33	**2693.96**	195.49
B_17	1504.79	100.56	**1452.76**	94.08	1487.36	142.17	**1452.76**	125.78
Average	2210.19	148.16	2217.20	126.90	2131.16	245.11	2087.83	165.96
Number of Best solutions found	2		3		8		14	

Bold values indicate a higher quality solution

Table 4.6 shows that the proposed SA/VNS provides better results in terms of solution quality compared to the other algorithms. Bold numbers indicate that the objective function value is equal to the best solution found during the computational experiment. The result also shows that the solution quality of the ACO result is better than that of the basic SA or VNS results.

However, SA/VNS shows a slightly better result compared to ACO. SA/VNS can achieve 14 better solutions compared to other algorithms, and ACO can provide better solutions compared to SA or VNS. Explicitly, for data B_04, B_07, and B_15, ACO outperforms our proposed algorithm with a slightly better result. ACO performs well when the number of remote nodes is less than 40% regardless of the total number of demand locations that need to be served. This may be because ants (on whom ACO is based) choose a route based on either its attractiveness (i.e., travel distance) or pheromone level (that indicates past movement). The additional information relay for each time interval might help to improve the ACO performance.

In terms of computational time, VNS is slightly faster compared to SA and hybrid SA/VNS. By contrast, ACO is slower compared to SA, VNS, and SA/VNS, as has been mentioned previously (Yu et al., 2009). Although SA and VNS have low computational time, their solution quality gap with SA/VNS is 5.86% and 6.19%, respectively. SA/VNS combines the complexity of the local search implementation by using VNS, which requires slightly longer computational time. Nevertheless, SA/VNS has a reasonable computational time and provides a robust result.

As the proposed algorithm can solve the problem with better results, its results are discussed in detail. Table 4.7 shows the results of the proposed methods for solving deterministic and stochastic dynamic distribution plan problems. For the 17 datasets solved, SA/VNS-IS_G seems to perform slightly better in terms of an average gap for initial and dynamic routing phases. However, both proposed algorithms show varied performance in terms of solution quality for each dataset. In the initial solution phase, SA/VNS-IS_N tends to show better results for smaller population datasets, which also have mostly accessible demand nodes available. By contrast, SA/VNS-IS_G performs better for a relatively higher number of less-accessible demand nodes.

However, after stochastic data and dynamic requests were obtained, the performance of both algorithms changed slightly. SA/VNS-IS_G showed better solution quality for datasets that had a higher proportion of accessible demand nodes, whereas SA/VNS-IS_N showed the opposite tendency. We performed a t-test with $\alpha = 0.05$ for both solutions (initial and dynamic phase) and found that the difference is not significant for both cases, with p-values of 0.293 and 0.271 for the initial and dynamic phase, respectively. We suggest that although the nearest neighbor seems to be less robust in deterministic cases, it fits with stochastic and dynamic cases as it offers a higher possibility to include or modify the route during the modification process in cases when the demand proportion of less-accessible demand nodes is higher.

Table 4.7. Dynamic stochastic result for 17 wards in Bantul district

Data Set	SA/VNS-IS_N (1)				SA/VNS-IS_G (2)				Travel Time Gap ((1)-(2)/(1))	
	Initial Solution		Dynamic Routing		Initial Solution		Dynamic Routing			
	Travel Distance (km)	Travel Time (hours)	Travel Distance (km)	Travel Time (hours)	Travel Distance (km)	Travel Time (hours)	Travel Distance (km)	Travel Time (hours)	Initial Solution	Dynamic Routing
B_01	**1632.52**	**54.42**	2155.65	71.86	**1632.52**	**54.42**	**2072.63**	**69.09**	0.00%	3.85%
B_02	1375.22	45.84	**1682.30**	**56.08**	**1370.73**	**45.69**	1783.16	59.44	0.33%	-6.00%
B_03	2642.75	88.09	**3609.62**	**120.32**	**2617.42**	**87.25**	3739.80	124.66	0.96%	-3.61%
B_04	1701.03	56.70	**2513.26**	**83.78**	**1700.89**	**56.70**	2532.74	84.42	0.01%	-0.78%
B_05	**1369.28**	**45.64**	**1782.92**	**59.43**	**1369.28**	**45.64**	1916.71	63.89	0.00%	-7.50%
B_06	**2250.72**	**75.02**	**2957.47**	**98.58**	**2250.72**	**75.02**	2970.28	99.01	0.00%	-0.43%
B_07	**1242.51**	**41.42**	1838.51	61.28	1243.09	41.44	**1515.08**	**50.50**	-0.05%	17.59%
B_08	**2370.57**	**79.02**	3205.64	106.85	**2370.57**	**79.02**	**2843.14**	**98.83**	0.00%	7.51%
B_09	1319.35	43.98	**1809.57**	**60.32**	**1319.22**	**43.97**	1817.11	60.57	0.01%	-0.42%
B_10	**1226.67**	**40.89**	**1531.46**	**51.05**	1228.25	40.94	1682.42	58.08	-0.13%	-9.68%
B_11	1528.17	50.94	**1982.31**	**66.08**	**1528.03**	**50.93**	2021.84	67.39	0.01%	-1.99%
B_12	1527.65	50.92	2529.92	84.33	**1526.66**	**50.89**	**1894.01**	**63.13**	0.06%	25.14%
B_13	**1342.89**	**44.76**	1865.40	62.18	**1342.89**	**44.76**	**1580.29**	**52.68**	0.00%	15.28%
B_14	**1310.64**	**43.69**	1951.85	65.06	1315.59	43.85	**1762.05**	**58.74**	-0.38%	9.72%
B_15	1416.91	47.23	1947.41	64.91	**1416.86**	**47.23**	**1810.20**	**60.34**	0.00%	7.05%
B_16	2218.37	73.95	3128.24	104.27	**2214.09**	**73.80**	**2693.96**	**89.80**	0.19%	13.88%
B_17	1183.15	39.44	**1452.76**	**48.43**	**1182.81**	**39.43**	1605.82	53.53	0.03%	-10.54%
Average									0.06%	3.47%

Bold values indicate a higher quality solution

Table 4.8 shows the required number of vehicles for distribution planning and additional travel time as result of route modification. The total number of vehicles is linearly in proportion to the relief goods needed, with data sets B_06, B_08, and B_16 requiring the most vehicles. As the vehicles have limited capacities, additional demand forces the use of additional vehicles for completing the distribution. On average, the number of mini trucks and trucks increased by 11% (~1 vehicle) and 16% (~1 vehicle), respectively. Our statistical test shows the increase in the number of mini trucks with p-value < α, as shown in Table 4.9. However, the number of trucks used does not significantly increase after the dynamic phase with p-value > α, as also shown in Table 4.9. As many datasets have a significant proportion of less-accessible nodes, the number of mini trucks used in distribution routing is higher than the number of trucks. Although mini trucks have a smaller capacity, using mini trucks from the start provides advantages during distribution, such as not requiring a change in vehicle type and the ability to be used for all types of demand nodes.

Table 4.8. Number of vehicles used

Data Set	SA/VNS-IS_N (1)					SA/VNS-IS_G (2)				
	Initial Solution		Dynamic Routing		Additional Travel Time (hours)	Initial Solution		Dynamic Routing		Additional Travel Time (hours)
	Mini Truck	Truck	Mini Truck	Truck		Mini Truck	Truck	Mini Truck	Truck	
B_01	9	8	10	9	17.44	9	8	10	9	14.67
B_02	7	1	7	2	10.24	7	1	7	2	13.75
B_03	9	6	10	7	32.23	9	7	10	7	37.41
B_04	9	8	10	10	27.07	9	8	10	9	27.73
B_05	6	3	7	3	13.79	6	3	7	3	18.25
B_06	15	15	17	15	23.56	15	15	18	15	23.99
B_07	6	5	8	4	19.87	6	5	7	6	9.07
B_08	14	13	15	15	27.84	14	13	15	15	19.81
B_09	5	3	5	4	16.34	5	3	6	2	16.60
B_10	5	5	6	5	10.16	5	5	7	2	15.14
B_11	8	5	9	5	15.14	8	5	8	6	16.46
B_12	7	7	9	7	33.41	7	7	8	6	12.25
B_13	7	6	8	5	17.42	7	6	8	4	7.91
B_14	5	3	6	4	21.37	5	3	6	4	14.88
B_15	6	6	8	4	17.68	6	6	7	5	13.11
B_16	13	13	16	14	57.98	14	13	15	15	16.00
B_17	6	1	6	2	8.99	6	0	7	1	14.10
Average					20	Average				17

Table 4.9. Paired t-test result (α = 0.05) for a number of vehicles used for distribution

	Initial Mini Truck Used	Dynamic Routing Mini Truck Used	Initial Truck Used	Dynamic Routing Truck Used
Mean	8.059	9.241	6.353	6.765
Observations	17	17	17	17
t value	5.996*		1.595	
P value	0.000018*		0.130	

* Significant at 5%

4.5.4. *Sensitivity analysis*

A sensitivity analysis was conducted to analyze the model behavior under two different variables: demand satisfaction level and *dod*. For the sensitivity analysis, we used the SA/VNS-IS_G algorithm as it showed slightly better performance in terms of average travel time and vehicle utilization compared to SA/VNS-IS_N.

4.5.4.1. Reducing demand satisfaction level

In the above computational experiment, we focused on serving all demand nodes with demand satisfaction level γ = 100%. Therefore, the distribution strategy was to satisfy the entire demand and to consider new demand node(s) directly for service when information was received. This can be called an ideal situation, as demand can be fully satisfied. However, drivers often need to ignore additional information owing to several limitations such as the inability to get approval directly from decision-makers, limited supplies, a limited number of vehicles or drivers, and unavailability of additional time for distribution. This means we need to consider whether the new information (stochastic and dynamic) is neglected and sent forward to the next period for consideration.

Unmet demands will occur if the expected demand value is less than the actual demand at node *i*. Thus, by using equation (4.28), we can calculate unmet demands at each node *i*:

$$\varphi_i = \begin{cases} \xi_i - E[\zeta_i] & if\ E[\zeta_i] < \xi_i \\ 0, & otherwise \end{cases} \tag{4.28}$$

Table 4.10 shows the results of reducing the demand satisfaction level (γ). As the decision-making process is sometimes difficult to achieve quickly during emergencies, some demands might not be satisfied. Nevertheless, Table 4.10 shows that even though vehicles did not have to satisfy 100% of the demand, the travel distance reduces in relation to the gap in demand satisfaction levels. In the first case, for γ = 90%, the travel distance only reduces by 6.09% compared to γ = 100%. For γ = 80%, the travel distance reduces by 5.77% and 11.50% compared to γ = 90% and γ = 100%, respectively. These results clearly show that even if decision-makers prefer to satisfy the entire demand within the respective time, the additional travel distance for performing recourse will not exceed the additional levels of demand satisfaction. However, such decisions might not be possible if we consider the limited number of vehicles or workers during the distribution process.

Table 4.10. Dynamic stochastic routing results for different levels of demand satisfaction

	Demand Satisfaction		
	100%	90%	80%
Average travel distance (km)	2,139	2,008	1,892
Travel distance increment (%)	5.84%		6.02%

In actual disaster response, several other factors such as security level, state of infrastructure, cultural and political conditions, neutrality, humanitarian organizations' independence, and community empowerment level cannot be quantified easily. The ideal situation is to distribute goods based on their needs and priority levels as gathered during need assessment. Accurate assessments should be performed continuously to ensure that relief goods reach the beneficiaries. This is only possible if all humanitarian organizations work together with the government and have a robust sharing information system. In practice, this is not easy as some organizations might be affiliated to political parties or might be tightly connected with specific affected areas. This model also does not consider the probability of self-empowered relief distribution by nearby communities. Cultural aspects should also be considered to achieve an efficient distribution system.

4.5.4.2. Degree of dynamism

The dynamicity of a problem can be measured by the *dod*. In this case, *dod* is calculated as a fraction of the immediate demand divided by the expected total demand within one working period. Thus, the more dynamic the request, as indicated by the high *dod* value, the more complex is the problem. This sensitivity analysis was performed to understand the expected increase in travel times required to serve as many demand nodes as possible. Table 4.11 shows the results for different *dod* values. High *dod* values indicate that distribution requires a longer time to finish fulfilling all demands. Higher *dod* values also represent how many new requests arrived during the distribution process. The average travel distance increases quite significantly from *dod* = 10% to *dod* = 20%; however, it increases only slightly from *dod* = 20% and *dod* = 30%.

Table 4.11. Dynamic stochastic routing result for different degrees of dynamism

Data Set	Initial Demand Node	*dod*=30%		*dod*=20%		*dod*=10%	
		Travel Distance	Travel Time (hours)	Travel Distance	Travel Time (hours)	Travel Distance	Travel Time (hours)
B_01	50	2587.43	86.25	2563.03	85.43	2072.63	69.09
B_02	58	2237.57	74.59	2211.40	73.71	1783.16	59.44
B_03	72	4561.96	152.07	4565.97	152.20	3739.80	124.66
B_04	64	3487.30	116.24	3311.02	110.37	2532.74	84.42
B_05	49	2063.88	68.80	2189.32	72.98	1916.71	63.89
B_06	57	3336.65	111.22	3468.81	115.63	2970.28	99.01
B_07	45	1717.22	57.24	1777.76	59.26	1515.08	50.50
B_08	53	6155.68	205.19	5016.34	167.21	2964.94	98.83
B_09	52	1949.19	64.97	2071.46	69.05	1817.11	60.57
B_10	55	2193.31	73.11	2131.65	71.06	1682.42	56.08
B_11	49	2125.78	70.86	2281.19	76.04	2021.84	67.39
B_12	60	2543.64	84.79	2440.71	81.36	1894.01	63.13
B_13	47	2060.88	68.70	2002.64	66.75	1580.29	52.68
B_14	62	2306.60	76.89	2237.76	74.59	1762.05	58.74
B_15	54	2388.86	79.63	2309.48	76.98	1810.20	60.34
B_16	63	6419.80	213.99	5012.57	167.09	2693.96	89.80
B_17	43	1697.24	56.57	1816.68	60.56	1605.82	53.53
Max		6419.80	213.99	5016.34	167.21	3739.80	124.66
Min		1697.24	56.57	1777.76	59.26	1515.08	50.50
Average		2931.35	97.71	2788.69	92.96	2139.00	71.30

In particular, datasets B_03, B_08, and B_16 showed a significant increase in travel distance with the increase in *dod* for datasets with characteristics such as highly populated areas (>50,000 people) combined with medium to high complexity (less-accessible demand proportion >25%). On the other hand, regardless of the problem complexity, datasets with less populated areas (<30,000 people) show less increase in travel distance. This pattern is revealed in several datasets such as B_05, B_09, and B_11. However, as expected, as new demand nodes appeared within the working period, the initial distribution plan formulated at the start of the response phase was also modified easily. In disaster cases where information systems are not available, disaster agencies are expected to modify the route during the distribution process.

4.6. Conclusions of the Chapter and Practical Implications

This chapter focuses on modeling the last mile relief distribution which incorporates flexible routing for disaster response. This chapter explores the practical complexities faced in last mile distribution for disaster response, and it discusses how stochastic and dynamic vehicle routing models can be combined to represent the problem. After discussing the proposed model, this chapter proposes a metaheuristics approach for obtaining solutions and presents an analysis of how to allocate vehicles based on demand needs and case complexities. The main contributions of this chapter are as follows. (1) It introduces the concept of the truck and trailer model in last mile distribution for disaster response. A main tour and sub tours were constructed, and both were used to serve as many demands as required for different types of vehicles. (2) It introduces the concept of information gaps during last mile distribution for disaster response and discusses the use of flexible routing for tackling this problem. (3) This chapter proposes a method for incorporating the dynamic routing concept for each distribution loop by considering the effects of location and demand uncertainty after a disaster.

The proposed model defines a more realistic last mile distribution problem by considering problems such as accessibility issues, limited and heterogeneous vehicles, and information gaps. This model provides operational insights for government disaster agencies by highlighting the dynamic model concept for supporting relief distribution decisions. The single objective problem focuses on minimizing the travel time as the qualitative form of “responsiveness” while allowing vehicle recourse for satisfying all demands, which is considered the ultimate goal of relief distribution operations. As last mile distribution is the most vulnerable link in the humanitarian supply chain, uncertainty and information gaps are inevitable. Several numerical analyses suggest that different characteristics and complexities of affected areas might require different distribution strategies. In particular, high-population areas will require higher additional resources to anticipate gaps. In contrast, less-populated areas did not show high dynamicity.

It is also important to recognize that the proposed model has some limitations. This model is limited only to day-to-day relief goods, and thus, it might not be implemented for logistics operations with different characteristics, such as medicaments or nonfood relief goods. The distribution of day-to-day relief goods is a very complex problem that includes challenges such as demand uncertainty in the first week of disaster response, cost-effective routing, limited transport resources, mixed location types, e.g., inaccessible demand locations, and the goal of satisfying all demand. Furthermore, in real conditions, the decision of whether new demand nodes should be served or not served might not be an easy one. Thus, the model should use the shape that best reflects the decision maker's objectives. Furthermore, this chapter focuses on road/land transportation for distribution planning; additional transportation modes need to be incorporated by considering uncertain travel times. Although this chapter explicitly shows the model's limitations for disaster response, an operations research approach might be beneficial for decision support, which in some cases relies entirely on one party (e.g., the government). Adjusting and incorporating this approach may provide improvements in distribution system operations and fleet use during disaster response.

Chapter 5 Emergency and Disaster Healthcare Response through Ambulance Pre-positioning and Mobile Health Clinics Routing

5.1. Introduction

Notwithstanding from relief distribution activities, healthcare and medical service are also important for the emergency response operation, with reducing number of fatalities, treatment for the injuries, and minimizing the after effect, as its main responsibilities. With Chapter 3 and 4 focus on modeling relief distribution system in the disaster context, Chapter 5, focus on how preparedness and planning for healthcare sector, specifically for medical service, can be improved from the logistics perspective. The emergency planning for healthcare sector started from assessing the healthcare service in local, regional, and national level that currently in place. That is including the readiness of emergency medical system (EMS) service, availability of health infrastructures (especially emergency department), and availability of emergency dispatcher system, which expected to be the first responders during an emergency. Whilst resources are continually changing; the decision makers must assess the healthcare services currently in place and develop an agreed-upon comprehensive community disaster response and recovery plan prior to a disaster. Ensure adequate emergency response for routine emergency and disaster requires planning and preparation across multisector. This chapter proposed logistics model to improve the performance of medical service responders in emergency and disaster situation.

An EMS plays a critical role in health service management as it is responsible for pre-hospital activities that can determine whether a patient survives. At the same time, EMS will be the first responder in the case of emergencies regardless of its scale. One of the key performance indicators of an EMS is the response time that is, the time required to send an ambulance and fetch the patient. Mayer (1979) defined the ambulance response time as the interval between the call to the EMS and the arrival of the ambulance. This definition has been widely followed by numerous researchers (Wilde 2013; Lee 2011) in the developed world. In developing countries, unfortunately, poor management and a lack of knowledge about the ambulance service are few of the main issues that need to be solved regarding the service of the EMS. No availability for the emergency dispatcher, a limited number of hospitals owned ambulances, and third-party private ambulance companies that charge high to provide ambulance services can be easily found in such countries.

With uncoordinated and inefficient service resulted in long response time due to the long route in most emergency cases, this chapter set out to understand the current situation and problems arise in the EMS management in developing countries. Furthermore, a case study analysis is conducted to understand the particular problems and seek a way to improve the EMS in a particular city by reducing the response time of its ambulance service. In local level, a study conducted to investigate the chronology and state of the art in EMS response improvement, suggests that substantial effort has been put into this field in the developed countries, although there have been very few related studies in the developing countries. Hence, rather than taking a complex approach, this chapter set out to investigate the efficacy with which the EMS service could be improved through response time improvement and location optimization by applying facility location model.

Further, to ensure availability and continuity of access to medical care services, especially during disaster, this chapter proposed a model for serving the affected area, aside from the victims transported to hospitals/medical facilities. A disaster, not only disrupted daily activities but also will affect the health status in the affected area. At the same time, it is also caused some medical disabilities, as hospitals need to treat many victims at the same time while some other victims need to wait in their shelter to received medical intervention. Herein, providing medical and healthcare during a disaster is a difficult task for healthcare providers. The difficulties are varying from the limitation of resources and medical kits, various illnesses and undefined period. With hospitals and clinics focusing on emergency patient's treatment, some victims might not be able to receive treatment due to non-availability of such service. Some major issue in healthcare logistics needs to be tackled wisely during such event. Several recommendations from logistical perspectives are presented in this chapter. A proper logistics strategy, such as mobile health clinics routing can improve the success of medical service in disaster event aside from availability of trained personnel and well-prepared staff.

5.2. The Current EMS State in Asian Countries

This chapter seeks out to do a comprehensive review of EMS practices in developing countries around Asia. In order to do that, a literature review from practices that are disclosed and necessarily cover practice in all developing countries, are gathered and analyzed. Information regarding EMS current practice in several countries are gathered from various secondary sources, such as country reports, articles, and journals. The results from literature study will be analyzed, and root cause analysis is done to identify underlying factors of the EMS problem, especially in developing countries in Asia. The literature search included 15 cities in 14 countries in Asia, with 5 countries categorized as middle-low income, 3 countries upper-middle income, and 6 countries categorized as high income. The analysis focused on system characteristics of pre-hospital care and ambulance/EMS service in the selected study area. Table 5.1 clarified the comparison between each city in Asia countries based on the EMS system.

From Table 5.1, high-income countries used the fire-department based ambulance operation with fire department acted as a dispatch center, except for UAE and Saudi Arabia. On the contrary, upper-middle income and low-middle income countries adapted hospital-based EMS without any coordination between hospital and EMS as pre-hospital care due to unavailability of the dispatch center. Among 14 countries, Japan and Korea have the fastest response time (time needed to arrive at patient location) with under 10 minutes. Hong Kong, Singapore, Iran, and Thailand has an average response time of 10.2-12.8 minutes, while India, Pakistan, and Bangladesh have the highest response time with more than 1 hour. Based on the US Federal EMS Act, an out-of-hospital cardiac arrest patient might not gain much benefit as the response time still exceeds the standard laid down in (i.e., response time < 10 min). Unfortunately, the response time recorded for Bangladesh, India, and Pakistan shows that the role of EMS in these countries is not functioned as it should be.

A further comprehensive literature analysis is conducted to understand the cause of lack of EMS performance in the low-middle income countries (developing countries). According to Asian Disaster Preparedness Center, the main problem of EMS system in developing countries lays on the absence of emergency dispatch service. Without any dispatch center to accommodate coordination between pre-hospital activities and in-hospital activities, the patient being transported to either one hospital as per patient choice or to nearest hospital without any confirmation whether the selected hospital can handle the patient or not. The other problem is the limited number of ambulance and no ambulance standardization. In develop countries, the ambulance available consist of two types, basic life support (BLS) and advance cardiovascular life support (ACLS), with each ambulance, will be dispatch accordingly based on the case. However, in developing countries with low-middle income, the health expenditure per capita are low, resulting in a lack of medical resources, with mostly only BLS is available. Further, as the emphasis of emergency in most of these countries relies profoundly on in-hospital activities, low attention is given on pre-hospital care other than rapid transport. The quality acts to be related to the country’s economic status along with government and health authority’s efforts on supporting the development of pre-hospital services (Rahman et al., 2015).

The same problems also hindered the EMS system in Jakarta, Indonesia. Having multi-organization provide ambulance service did not guarantee the performance of EMS. Although the government has developed emergency dispatch system, from total 55 ambulances only five ambulances equipped with advanced life support, while rest only have basic support (Zumbach, 2011). Besides, community does not have enough information and awareness regarding emergency service. Thus walk-in to the emergency department is preferable. The private ambulance companies also set a high service price, without much of public sector involvement, also become problem is not only in Indonesia but also in Pakistan. Along with extensive traffic jam, the ambulance service also is not given a priority in the road, resulting in slow response time. While India has been improving their EMS system by having cooperation with American and European countries and fast improvement in healthcare infrastructure and service (Das and Desai, 2017), it faced challenges on lack of paramedics training, or training facilities and lousy traffic jam in big cities, become the source of slow response time. In Pakistan, many organizations provide EMS, however, establishing coordination with receiving hospitals was often challenging, due to no initial arrangement (Sriram et al., 2016). In summary, the low EMS performance in developing countries is illustrated as fishbone diagram in Figure 5.1.

Table 5.1. Comparison of EMS Structure in Asia Countries

	Income group	Operation of ambulance	Dispatched Center	Ambulance personnel	Ambulance station	Electronic Patient Record	Transport method (except walk-in)	Mean response time
Hong Kong[a]	High-income	Fire Department	Fire Department	Paramedic	Fire Station	Yes	Ambulance, rapid vehicle, helicopter	12 min
Osaka, Japan[b]	High-income	Fire Department	Fire Department	EMT, first aider	Fire Station	Yes	Ambulance, helicopter	7.8 min
Tokyo, Japan[b]	High-income	Fire Department	Fire Department	EMT, first aider	Fire Station	Yes	Ambulance, helicopter	6 min
Singapore[c]	High-income	Fire Department	Fire Department	EMT intermediate	Fire Station	Yes	Ambulance	10.2 min
Seoul, Korea[d]	High-income	Fire Department	Fire Department	EMT	Fire Station	Yes	Ambulance, helicopter	6.8 min
Dubai, UAE[e]	High-income	Hospital	Fire Department	Paramedic	Hospital	No	Ambulance	N/A
Saudi Arabia[f]	High-income	NPO	N/A	EMT	Hospital	No	Ambulance, Police vehicle, helicopter	N/A
Iran[g]	Upper-middle income	N/A	N/A	EMT Basic	Hospital	No	Public-private ambulance	12.8 min

Table 5.1. Comparison of EMS Structure in Asia Countries

	Income group	Operation of ambulance	Dispatched Center	Ambulance personnel	Ambulance station	Electronic Patient Record	Transport method (except walk-in)	Mean response time
Bangkok, Thailand[h]	Upper-middle income	Hospital	Fire Department	Nurse, EMT Intermediate	Hospital	No	Public-private ambulance, hospital ambulance, volunteer	12.16 min
Kuala Lumpur, Malaysia[i]	Upper-middle income	Hospital, NGO	Hospital, NGO	Medical assistant, EMT Basic	Hospital	No	Ambulance	22.5 min
Jakarta, Indonesia[j]	Lower-middle income	Hospital, NGO	Hospital, NGO	Physician, EMT Intermediate	Hospital	No	Public-private ambulance, hospital ambulance, volunteer	N/A
Pakistan[k]	Lower-middle income	NGO, Hospital	Hospital, NGO	Doctor, Paramedic	Hospital	No	Private ambulance, hospital ambulance	98 min
India[l]	Lower-middle income	NGO, Hospital	Hospital, NGO	Paramedic	Hospital	No	Private ambulance, hospital ambulance	<1 hour
Dhaka City, Bangladesh[m]	**Lower-middle income**	**Hospital, Private company**	**Hospital, Private company**	**EMT Basic**	**Hospital**	**No**	**Private ambulance, hospital ambulance**	**85.3 min**

[a]Graham et al. (2009), [b]Tanigawa and Tanaka (2006), [c]Ong et al. (2008), [d]Ahn et al. (2010), [e]Partridge et al. (2009), [f]Alanazi (2012), [g]Bahadori et al. (2016), [h]Mnuaypattanapon and Udomsubpayakul (2010), [i]Hisamuddin et al. (2007), [j]Pitt and Pusponegoro (2005), [k]Razzak et al. (2013), [l]Das and Desai (2017), [m]Maghfiroh et al. (2018)

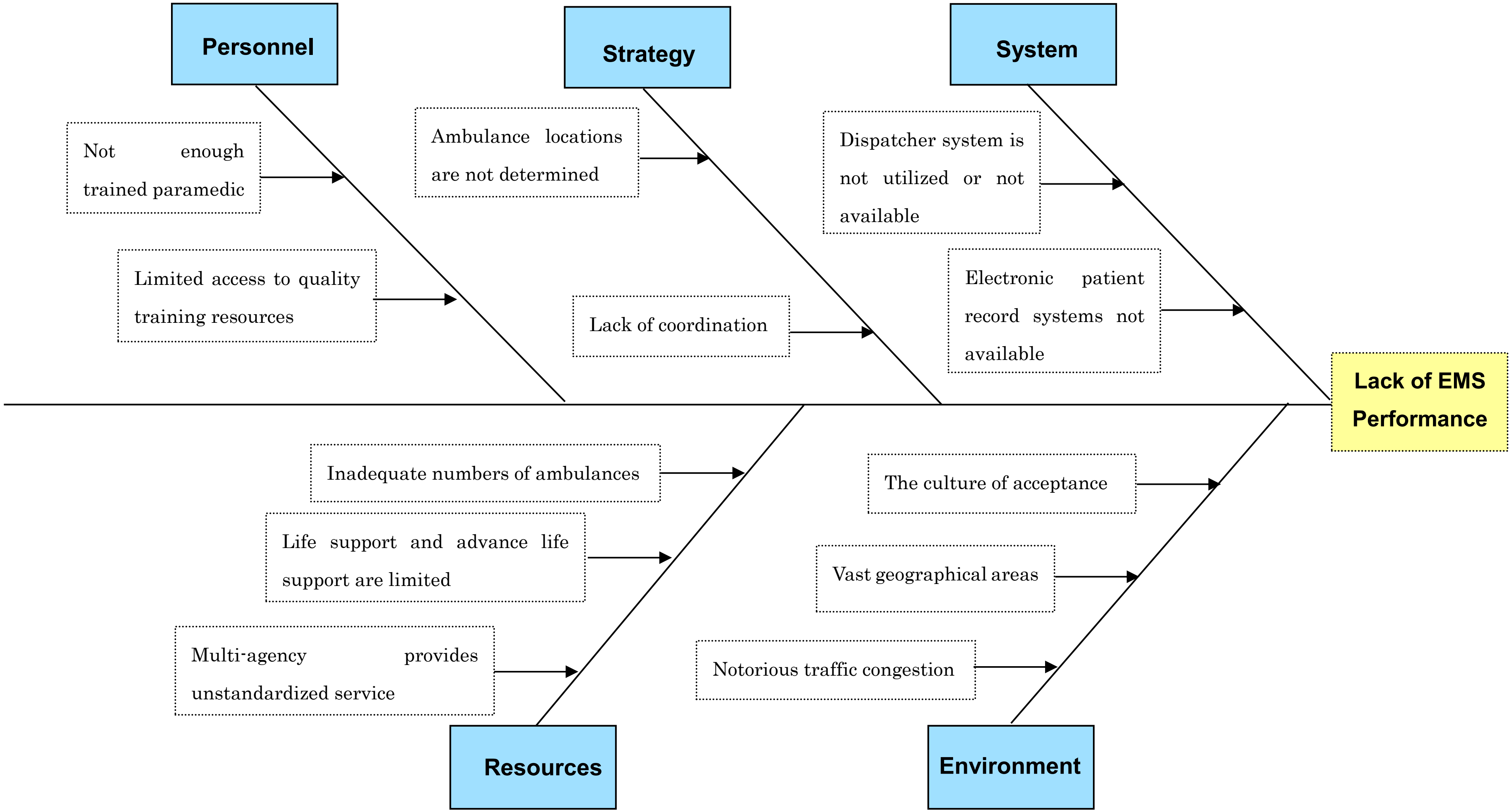


Figure 5.1. Fish bone diagram for Lack of EMS Performance in Developing Countries

5.3. Field Study: EMS in Dhaka City, Bangladesh

Based on the literature study presented in section 5.2 regarding the performance of EMS in Asia countries, it is prominent how there is a major drawback in the EMS system in low-and-middle-income countries, with one of them in Bangladesh. In this chapter, we will focus on understanding the problems and current situation of EMS in Dhaka city, Bangladesh. Further, an attempt to improve the performance of EMS system by proposing a logistical perspective on how to pre-position the ambulance is offered. Observation study was applied in 10 major hospitals, and the premises of 2 ambulance service providers in Dhaka city, Bangladesh with detailed can be found in Table 5.2.

Table 5.2. A survey conducted for observation study in Dhaka city

	1st survey	2nd survey
Respondents	Drivers, owners, and operators of ambulance companies	Patients of 13 major hospitals in Dhaka city
Data collected	A log file consisting of: - vehicle ID; - date of trips; - details of each trip with time stamps, patient`s location, destination location, trip expenses, and medical complexity.	Basic information consisting of: - hospital name; - details of each trip with time stamps, the medical complexity of the patient, the transportation mode, and the reason for choosing the hospital.
Amount of data collected	189 trip samples (from 29 drivers, two companies)	2890 mergency patients' data

5.3.1. *Survey of Ambulance Companies*

The unobtrusive and participant observation studies provided an overview and revealed several problems associated with the existing EMSs in Dhaka city, where no centralized and integrated call-center-based EMSs exist at present. Some observations were made after investigating the ambulance operation. Most large hospitals own some ambulances (2–3), but there are privately owned ambulances parked within the vicinity of those hospitals, which in most cases are owned by one person or a group of people, and they may operate independently or join to form an informal business organization. Most of these ambulances do not have in-vehicle basic treatment facilities, such as: first-aid boxes or oxygen cylinders, and even in cases where they have these basic facilities, the paramedic support is missing. Only one large ambulance company was found to be operating in Dhaka city (Ngongo 2012), with a fleet that was monitored through tracking devices and whose service could be obtained through a call center.

The results extracted from the ambulance log data suggest that for one of the ambulance operators, only 13% of the trips were for emergency cases, with another 38% being to the patients' homes, and 49% being for transferring patients to other hospitals and diagnostic centers. In the case of another ambulance operator, the shares were 15.15%, 69.7%, and 15.15%, respectively. The average response time (T1-3) and cost of these ambulances were 33 min and 5054 BDT (equivalent to US$68.31), respectively. The average total time (T1-5) needed for the ambulances to pick up and drop patients at the selected hospital was 75.95 min, with 6.67 min dispatch time (T1-2), 26.67 min travel time 1 (T2-3), 9.24 min service time (T3-4), and 33.37 min travel time 2 (T4-5). The results of this observation study clearly indicate the need for pre-positioning to reduce the emergency response time.

People can request an ambulance by either calling the hospital or directly fetching it by going to the hospital. However, without references from the hospitals or some prior acquaintance, ambulances may refrain from providing services to unknown persons owing to security issues, such as vehicle hijacking. The connection between supply and demand is unclear, and ambulances remain unused for a large part of the day. Hence, whenever an ambulance is called, the price per kilometer is considerably higher than that of a regular taxi as there is no fare structure and the supplier want to recover the loss incurred while the ambulance stands idle.

In many cases, ambulances also operate as general taxi services to offset their losses or to maximize profits. This generally happens with the privately-operated ambulances, but not with those owned and operated by the hospitals. In the latter case, sometimes the ambulances may be used for transporting hospital personnel. In addition, it is common for ambulances to be used for public transport during political unrest, as they are less likely to be the target of violence. The starting point and destination of a trip are decided by the patient's representative/acquaintance/attendant, and the route is generally determined by the ambulance driver. Moreover, there is no culture of yielding to ambulances or making way for them; however, ambulances using a siren and carrying a patient can take the liberty of operating on the wrong side of the road if the driver finds that side of the road less congested.

5.3.2. A survey in Hospital Emergency Rooms

This chapter confirmed many of the findings of the survey of the ambulance operators and provided new insights into the problem domain. People tend to choose a hospital based on their experience. That is, if the patient was having treatment at a given hospital for a given condition, then she/he is likely to be brought to the same hospital. Moreover, some large government hospitals in Dhaka specialize in dealing with patients with specific medical conditions. For example, patients having an emergency related to a heart condition are likely to be taken to Shaheed Suhrawardy Medical College Hospital while road accident victims or victims of violence are generally taken to Dhaka Medical College Hospital.

It was observed that the patients or their attendants had very little or no knowledge of smaller medical facilities nearer to the origin of their emergency where they could have received treatment. In general, a hospital is not contacted before a patient is brought in. Hence, the persons accompanying the patients do not have any prior knowledge about the current load of the emergency rooms. The observation study revealed that the emergency rooms of the reputed government hospitals sometimes become overcrowded with patients who consequently must wait for their treatment to start. People generally have a negative attitude toward ambulances as they are difficult to access, are costly, and slower than alternative transportation options. However, people would like to see the service improve and would prefer using ambulances if they were available, reasonably priced, and fast. Cell phones play an important role in communication during an emergency.

An analysis of the emergency room data reveals that 29.7% of hospital selections are based on the distance of the hospital from the patient, 25.6% were chosen based on recommendations (drivers, neighbors, police, etc.), 20.9% were selected based on patients' preferences, and 0.7% were based on sudden decisions. Of the 2952 persons interviewed, only 18.68% of patients were transported to a hospital by ambulance, with the other 81.32% using either private cars or public transportation. Around 40% of the respondents explained that they did not need ambulance service, 32% found the ambulance service to be unreachable, slow to respond, or unavailable, while 16% chose to transport the patient by themselves as they were close to the hospital. Moreover, 11% chose to use their private car/motorcycle for convenience, and they felt that ambulances were too expensive. The average cost of an emergency trip was found to be 2000 BDT (equivalent to US$27) from the emergency room data, suggesting a much lower value compared with the ambulance log files. The influence of traffic congestion was quite significant for different times of the day and night; the average trip time of ambulances was around 20 min, and during peak traffic hours, it was more than 2 h.

Figure 5.2 presents the descriptive statistics of the response time for different modes of transport used for bringing patients to the emergency rooms. The difference in response time for each transportation mode used in Dhaka city can be observed. The emergency room data and ambulance company data were compared, and a breakdown of each transportation mode was obtained. The time shown in the figure consists of six components, notably T1-2, T2-3, T3-4, T4-5, T1-3 (response time), and T1-5 (total time). In an emergency, the response time (T1-3) is very critical because it is the time needed until the ambulance reaches the patient location. The number within the brackets is the sample size used for the calculation.

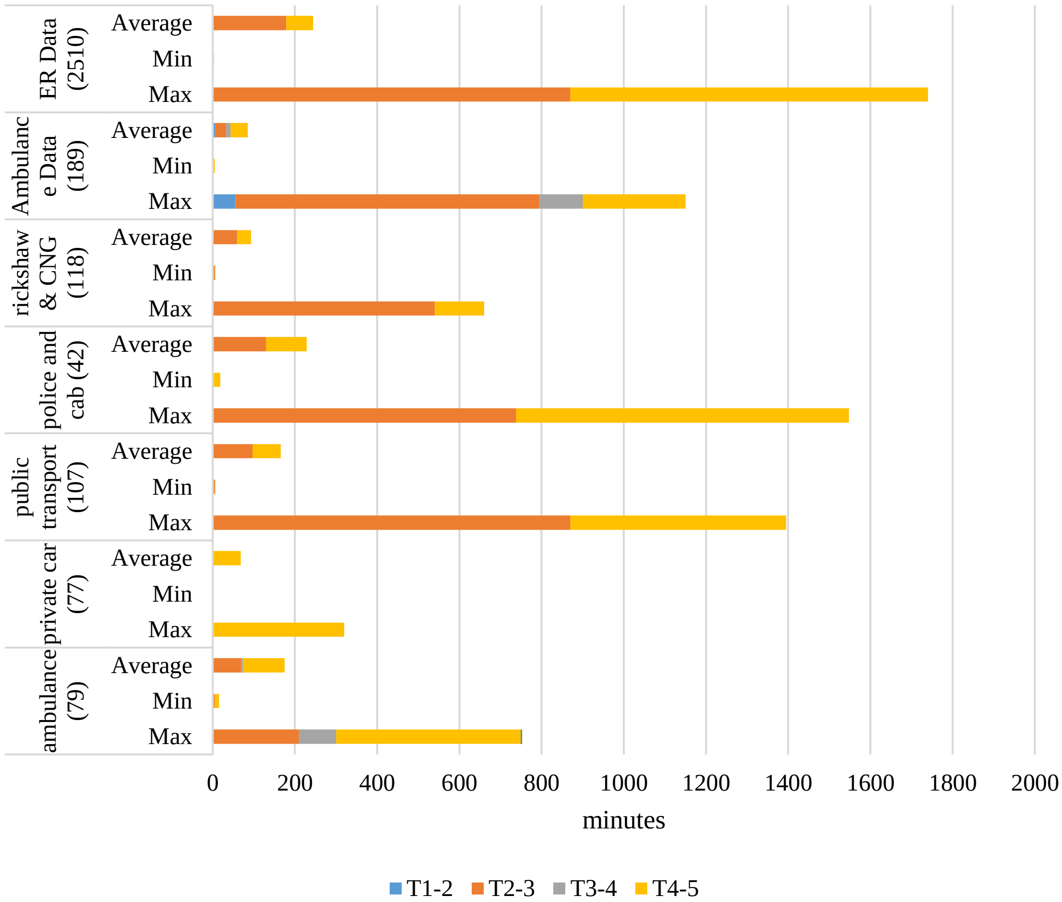


Figure 5.2. EMS data based on ambulance and survey data

Based on the survey log, 81.3% of all the patients chose to come to the hospital using a mode of transport other than an ambulance. The use of private vehicles is high owing to the fast response time, as the patient can be sent directly to a hospital without having to wait for a vehicle to come and pick them up. Furthermore, rickshaws and compressed natural gas–operated three-wheeled scooters (CNG) are used for shorter trips. As public transportation is also the main transportation mode, the average time needed for the entire trip is quite low.

In summary, if the ambulance logs and emergency room survey logs are compared, on average, the ambulances need less time to make the trip regardless of the need for dispatching and traveling from their location to the patient's location as compared to most other modes. Although private cars have the lowest average response time, it should be noted that the demography of a developing country like Bangladesh suggests very low car ownership. Hence, it cannot be expected that a higher proportion of the patients needing emergency medical attention will have access to private cars. In addition, the relatively short response time of ambulances is still very high, suggesting the need for improvement.

Finally, based on the results of the surveys conducted both in the emergency rooms and at the ambulance companies, the current EMS operation in Dhaka city can be summarized as shown in Figure 5.3. Less than 20% of patients use ambulances as their transportation mode, while the remaining patients choose other modes, with most of them using public transportation owing to the cost issue. The remaining patients are transported using private cars as they were found to be available and more efficient upon the occurrence of an emergency.

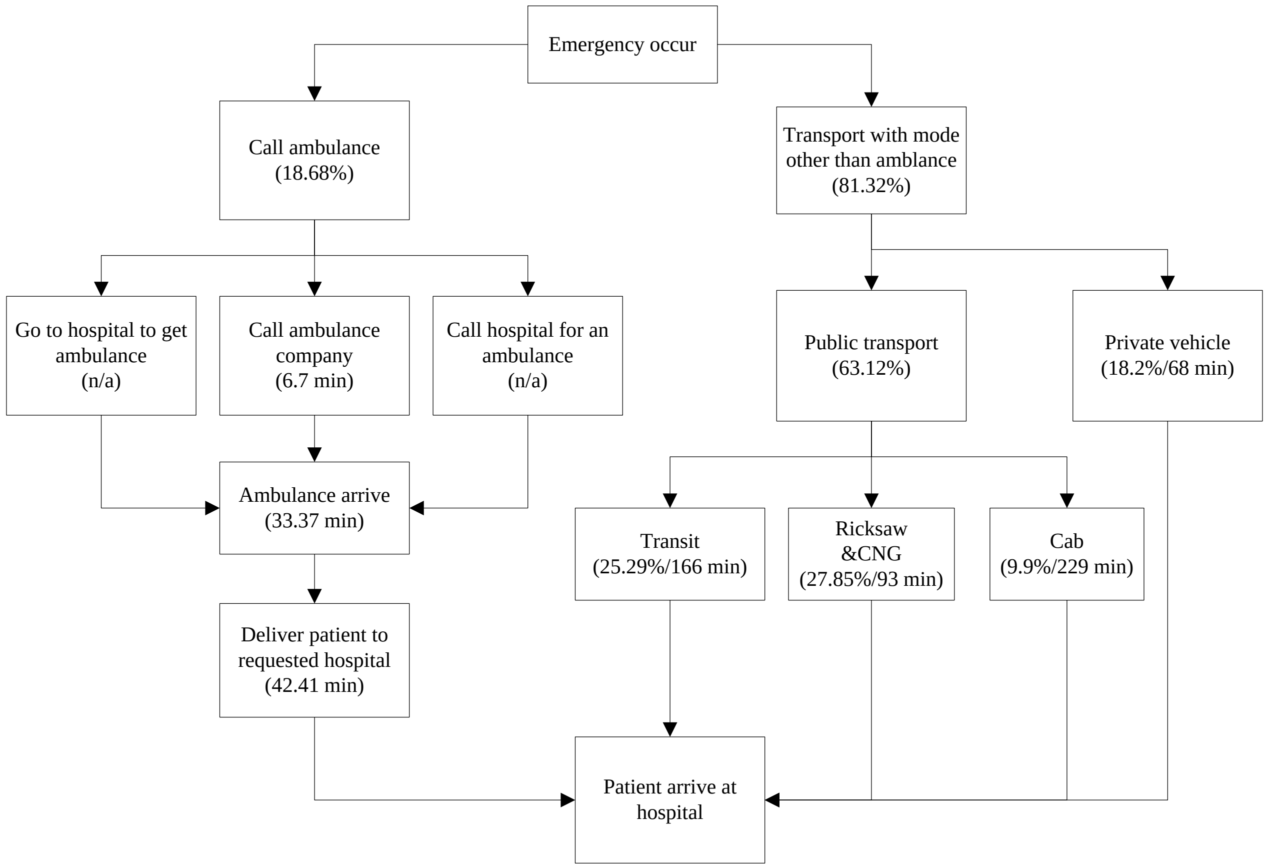


Figure 5.3. Current EMS flow in Dhaka city

5.4. Ambulance Pre-positioning Problem for Routine Emergency

The performance of EMS can be measured based on how long the response time and service time for EMS to pick up and deliver its patient to the selected hospital. Closely related, is how big the EMS can cover a demand area within predetermine response time allowed. Thus, by planning how to pre-positioned an ambulance, will give an impact on how fast the EMS can reach out to the patient and deliver them to the hospital. Further, a model is developed to improve the EMS performance as the case study of this chapter. The time-dependency for the second model accounts for variations in travel speed caused by congestion.

5.4.1. Mathematical Formulation for Ambulance Pre-positioning

Ambulance location problems deal with selecting a location for ambulances to cover the demand in an area. Operation research has been used to assist such problem, and this chapter set out to use model for facility location problem in consideration with traffic condition for both cases. This study has several assumptions and limitations to facilitate mathematical formulation.

a. The set of demand nodes can be served by the all available ambulance.
b. Only two types of traffic conditions are applied in the model, namely peak traffic, and off-peak traffic to simulate the different results on both situations.
c. The number of ambulances used is assumed adequate to serve the demand.
d. The present study focuses on the location problem. Thus patient consideration and hospital selected in the model are not included
e. The candidate locations can be hospitals, public facilities, or open area in Dhaka city region

5.4.1.1. Pre-positioning based on Maximal Covering Location Problem

Based on the available data, the proposed model seeks to maximize the total covered demand within an impedance cutoff by locating the candidate facilities near the population density. The impedance cutoff is calculated by assuming that the vehicle speed is 25 km/h, which is at the higher end of the average speed during peak hours in Dhaka city (Anwar 2010). Based on the US Federal EMS Act requirement, which states that an ambulance should be able to cover a 10-min buffer zone, the cutoff of the service distance from a selected hospital was found to be within 5 km. As per this method, a facility that is located near high-density demand has the advantage of being selected first.

Now, let the graph $G = (V \cup W, A)$ have a set of V patient location nodes and a set of W potential ambulance location nodes, where d_i is the demand number at nodes i. N_i is denoted as the set of all candidate sites that can cover demand nodes i. P is the number of facilities to be located, while dis_{ij} is the distance between the hospital and the patient nodes. The optimization problem can be formulated as follows:

Max

$$\sum_{i \in V} d_i x_i \tag{5.1}$$

Subject to

$$x_i \leq \sum_{j \in N_i} y_i , i \in V \tag{5.2}$$

$$\sum_{j \in W} y_j = P \tag{5.3}$$

$$\sum_{i \in V} \sum_{j \in W} dis_{ij} x_i \leq 5000 \tag{5.4}$$

$$x_i \in \{0,1\},\ i \in V \tag{5.5}$$

$$y_j \in \{0,1\},\ j \in W \tag{5.6}$$

Equation (5.1) denotes the objective function for maximizing the demand coverage. In Equation (5.2), if $x_i \geq 0$, then at least one set of facilities *j* must be selected. Equation (5.3) gives the total number of facilities that can be located. Equation (5.4) postulates that all the demands located outside the facility's impedance cutoff will be regarded as being uncovered. Equations (5.5) and (5.6) are binary variables for demands and facilities, respectively.

5.4.1.2. Pre-positioning based on P-median Model

Given the road network data, peak and off-peak data, and projected demand data, the model seeks to find the location for ambulance pre-position. This model aims to determine the optimal locations for ambulance pre-positioning to minimize the travel time. Thus, the objective function will be:

Min

$$\sum_{j=1}^{W} \sum_{i=1}^{V} \varphi_{ji} . TT(j \rightarrow i, t_i) \tag{5.7}$$

Subject to

$$\sum_{j \in W} y_j = p, (j = 1, \dots, W) \tag{5.8}$$

$$\sum_{i \in V} d_i . \varphi_{ji} \geq \alpha \sum_{i \in V} d_i \tag{5.9}$$

$$\varphi_{ji} \leq y_i, j \in J, \forall i \in J, \tag{5.10}$$

$$\varphi_{ji} \in \{0,1\} \tag{5.11}$$

$$y_j \in \{0,1\} \tag{5.12}$$

In an area, let graph $G = (V \cup W, A)$, where V is the set of patient location nodes, W is the set of potential ambulance location nodes, and A is the set of edges/links $\{(i,j): j \in W; i \in V\}$. The demand at each node $i \in V$ is denoted as d_i. Furthermore, t is a time variable in the time domain T and r/s is stated as the origin and destination nodes, respectively $\{r = 1,2, \dots\dots, q = s\}$ with q being the maximum number of nodes. With edge $a(i, i+1) \in A, i = 1,2, \dots, q-1,$ a link ($r \rightarrow s$) with departure time from source t_r, the travel time will be $TT(r \rightarrow s, t_r)$. For example, if the ambulance is called at 7 AM from node 0 to node 5, the travel time $TT(0 \rightarrow 5, t_7)$ will be equal to distance 0→5/vehicle velocity on the road at 7 AM.

In this proposed model, the number of ambulances available to be located at candidate location is equal to p, as denoted by Equation (5.8). Equation (5.9) ensures that at least α% of the total demand can be covered. Equation (5.10) guarantees that each demand node can be assigned to an open facility only. Equations (5.11) and (5.12) are binary variables, with φ_{ji} being the binary variable, which will be equal to 1 if the demand at node i is covered by facility j and decision variable y_j, indicating the open facility located at candidate site j.

5.4.1.3. Estimating Existing Response Time

The emergency response time is defined as the interval between receiving an emergency call and the patient reaching the emergency room or the interval between realizing that the patient needs to be taken to a hospital and starting treatment in the emergency room, depending on the availability of the data. The emergency response time was further divided into five components, as follows, along with the calculation steps:

a. Dispatch time for EMS personnel to be notified and depart from the station ($T_{1\text{-}2}$) [Calculated from the time at which a request for an ambulance was placed until the ambulance is dispatched].
b. Travel time to the patient location by the EMS ($T_{2\text{-}3}$) [The average travel time from the ambulance location to the patient location].
c. On-site EMS rescue time (service time) ($T_{3\text{-}4}$) [The average time an ambulance spends at a demand site].
d. Travel time to a hospital ($T_{4\text{-}5}$) [Calculated from the time taken to leave the patient location and reach the selected hospital].
e. First treatment received ($T_{5\text{-}6}$) [Calculated from emergency room data].

5.4.1.4. Emergency Demand Estimation

Based on the survey results, the average demand d was calculated to be 30.53 patients/ward/hour with W = 92 wards and the total demand D was calculated to be 2,806 patients/hour for Dhaka city. The demand percentage for each ward (*%d*) was calculated by dividing the actual population in Dhaka city (D) by the population in each ward (pop); thus $\%d = d/pop$. The demand percentage ($\%d$) for each ward varied from negligible to 1.45% of the entire population. With D = 2,806 emergency patient demands/hour and a total H = 300 hospitals available in Dhaka city, each hospital might receive, on average, $\bar{d} = 9 \pm 1$ emergency cases/h, assuming that the basic medical facilities required to treat patients are available in all hospitals and that the patients are evenly distributed throughout the hospitals. In this study, emergency "demand" points were assigned at intersections, and the ambulance stations were referred to as the "supply" points. In total, it is involving 18,688 demand points and a total of 300 hospitals and public facilities as potential locations for ambulance stations.

5.4.1.5. Solving Procedure

This chapter incorporated the ArcGIS Network Analyst location-allocation tool and modified K-means clustering to select optimal ambulance stations from among candidate stations. The modified K-means clustering is essentially a constrained K-means method that indirectly optimizes the location-allocation quality, since the allocation strategy adopted from the K-means algorithm can ensure a near-optimal allocation result on the basis of its distance metrics (Park and Jun 2009; Thakare and Bagal 2015). Further, the clustering algorithm has the capability to adapt to the demand distribution. In the K-means clustering algorithm, the coordinates of each centroid are the means of the coordinates of the objects in the cluster, with every object being assigned to the nearest centroid. As K-means clustering might be sensitive to the outliers, medoids were used instead of centroids. Medoids have similar in concept to means or centroids but are always members of the dataset. In this case, the selected location is also a member of the set of patient demand points and existing hospital locations. The ArcGIS 10.2 network analysis option calculates the distances and travel times between locations or points on networks such as roads, which can be used to develop location-allocation models to solve different types of objectives and constraints. The ArcGIS also used for visualizing the result of the ambulance pre-positioning.

In addition, two traffic scenarios will be an analyst to understand the difference strategy should be used for different traffic condition:

a. Off-peak scenario

Using the proposed K-means clustering, the potential location was selected. In this scenario, after selecting the candidate locations, the existing hospital locations were added, and the optimal locations for the pre-positioning problem were selected.

b. Peak scenario

In the second scenario, the same method was used with the peak traffic data. The steps followed were identical to those for the off-peak scenario.

5.4.2. *Result and Analysis of Case Study*

5.4.2.1. Pre-Positioning Ambulances with MCLP Model

The MCLP model seeks to find the best location for maximizing the demand coverage considering the distance or time threshold and maximum number of facilities opened. The aims of this model approach are to find number of facilities that should be open for maintaining the demand coverage. Based on the optimization result, with 60 hospitals selected as ambulance-based locations, the EMS can cover up to 89% of the total demand around Dhaka city with an expected travel time of 80.32 min. These outcomes suggest that the selected 60 locations are sufficient to cover the demand in most areas.

Sensitivity analysis was then performed to determine the total number of ambulance locations where ambulances should be positioned to maximize the coverage demand while minimizing the total travel time. A sensitivity analysis was conducted by selecting different numbers of pre-positioning locations from 300 hospitals available around Dhaka city. In summary, 60, 80, and 100 locations were selected. The sensitivity analysis results are illustrated in Figure 5.4. Figure 5.4 shows the increasing demand coverage along with the decreasing emergency response time as the demand coverage increases by 25% and the response time decreases by 7 min with an additional 20 locations (from 60 to 80 locations). On the other hand, adding another 20 ambulance locations (up to 100 locations) did not significantly boost the results in terms of demand coverage, although it reduced the response time by a further 4 min. This is because the additional 20 locations added are closer compared with the other 80 locations used in the model, and around 5% of the city cannot be reached from any of the 100 hospital locations considered in the model because they are located more than 5 km from all 100 of these locations.

In this study, locating ambulances at all hospitals with a proper EMS did not significantly affect the demand coverage, but reduced the estimated average total travel times by up to 60%—from 175 min (based on survey logs) to 80 min 32 s. Allocating ambulances to an area with a high demand for EMSs can reduce the possibility of long response time and the total travel time for the ambulance that is deployed. In this analysis, the potential ambulance locations were identified by minimizing the patient distance to the ambulance station.

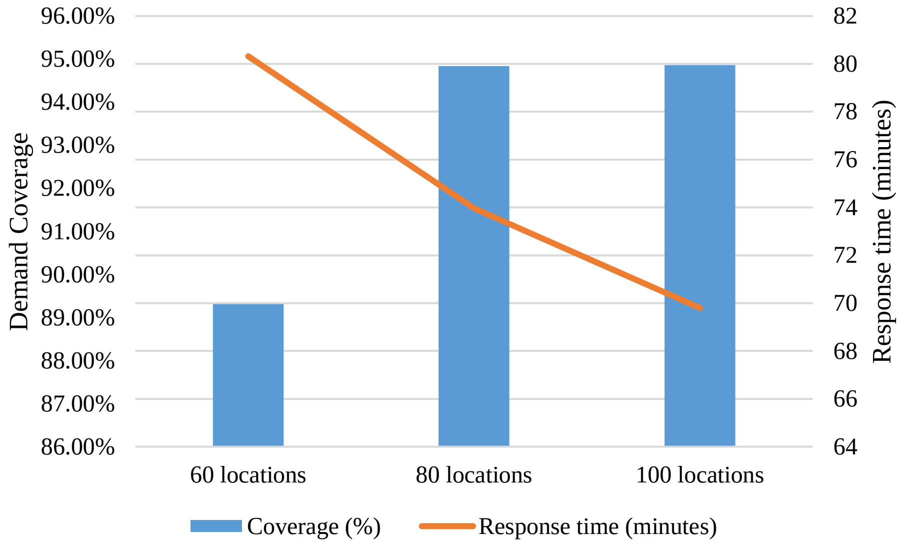


Figure 5.4. Comparison of sensitivity analysis results

5.4.2.2. Pre-Positioning Ambulances with P-medians Model

The main goal of this approach is to minimize the response time to patient requests while not depending on the placement of ambulances on the map. Since the generation of demand for future emergency cases is a random phenomenon, the objective was to cover all nodes, i.e., junctions on the road network. Furthermore, two scenarios were run for both peak and off-peaks, and the results are illustrated in Figures 5.5 and 5.6.

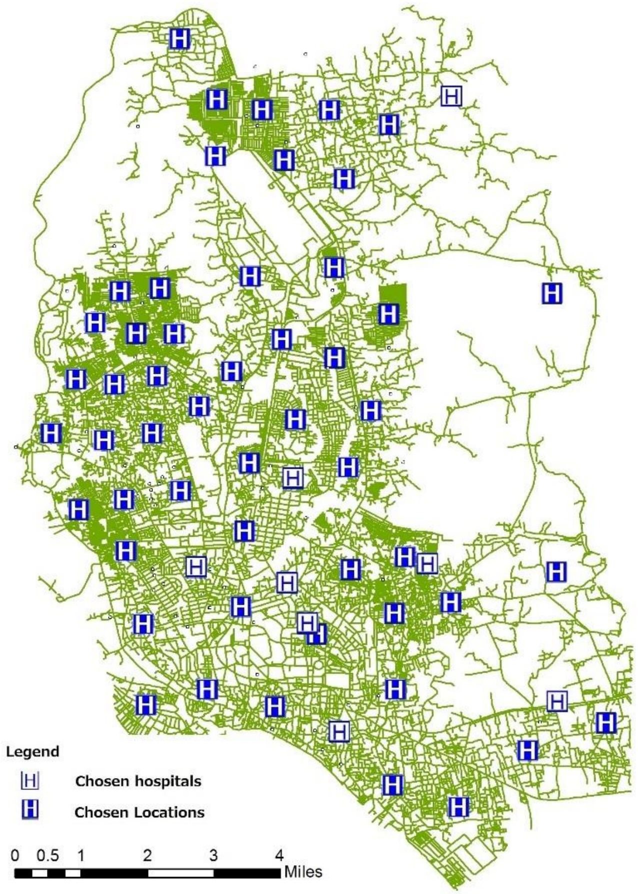
As drivers have preferences regarding the location in which to park their ambulances, different conditions were applied. The results are shown in Figure 5.5 (a) are the results of density-based location-allocation using modified K-means clustering. The modification was made so that during the iteration process, both medoids and centroids are considered as candidates. These medoids included hospitals with a proper EMS and centroid for each ward. In summary, the positions selected might consist of hospitals, ward centers, and new locations that can minimize the overall total time for the emergency response. Figure 5.5 (b) shows the hospital-based location-allocation, which are addressed on the drivers' experience. In this case, as the driver chooses to park near a hospital to cater for non-emergency patients, that hospital will be afforded a higher selection priority. Nevertheless, a new location can also have a high chance of being selected in order to optimize the system. The optimizations include reducing the total time and maximizing the demand coverage.

Figure 5.5 shows the differences between conditions (a) and (b). As can be seen, density-based K-medoids clustering (Figure 5.5(a)) produces more scattered locations with only eight selected hospitals. In contrast, the hospital-based result (Figure 5.5(b)) shows those hospitals chosen in specific areas where there are already several hospitals present and some new locations to cover the outskirts where there are fewer hospitals. The result of the peak scenario was slightly different. Figure 5.6(a) postulates that during peaks, rather than stationing the ambulances in hospitals, selecting locations near high-density populations and junctions can reduce the response time. Compared with the off-peak scenario, the locations are more scattered. The selected locations included hospitals, public facilities (mosque, school, and university), police stations and firefighter stations, and residential areas. In Figure 5.6(b), a new location is selected to cover a specific area without any available hospitals. The detailed results are presented in Table 5.3.

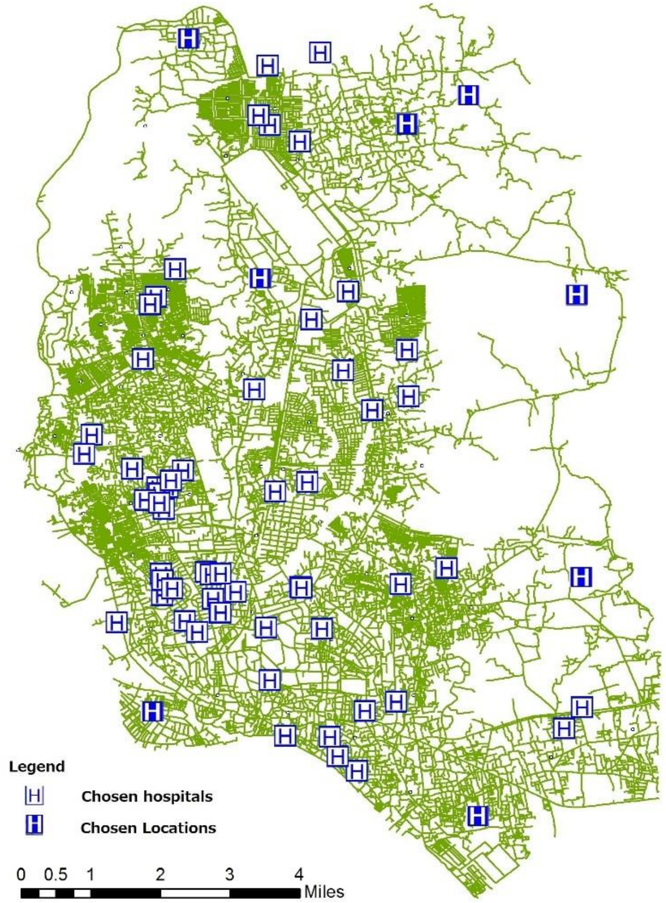
Table 5.3. Location-allocation results using K-medoids clustering

Scenario	Location choice	Location number	Total time (min)	Demand coverage (%)
Off-peak	Hospital-based location result	60	40.98	96.10
	Density-based result		35.98	96.10
Peak	Hospital-based location result	70	58.24	95.99
	Density-based result		52.12	95.99

It can be seen that the results for the off-peak and peak times in Dhaka city are different. Nevertheless, for the density-based results, the total travel times are slightly lower, i.e., 52 min, compared with the existing standard (75.98 min). The K-medoids algorithm, however, is not designed to optimize any particular performance measure, with this analysis focuses on finding the vulnerable area of the EMS to determine the location of new facilities. Although the current 5-km service area can cover 96% of the study area, it can also detect vulnerable areas. These findings suggest that having additional EMS facilities in the potentially vulnerable neighborhoods and investing more in basic emergency facilities in hospitals would improve the quality of the EMS by substantially reducing the response time. A solution to this can be systematically optimizing the ambulance positioning in small clusters rather than stationing them in large clusters and responding quickly to ambulance requests by dispatching the nearest ambulance through the fastest route at that time.



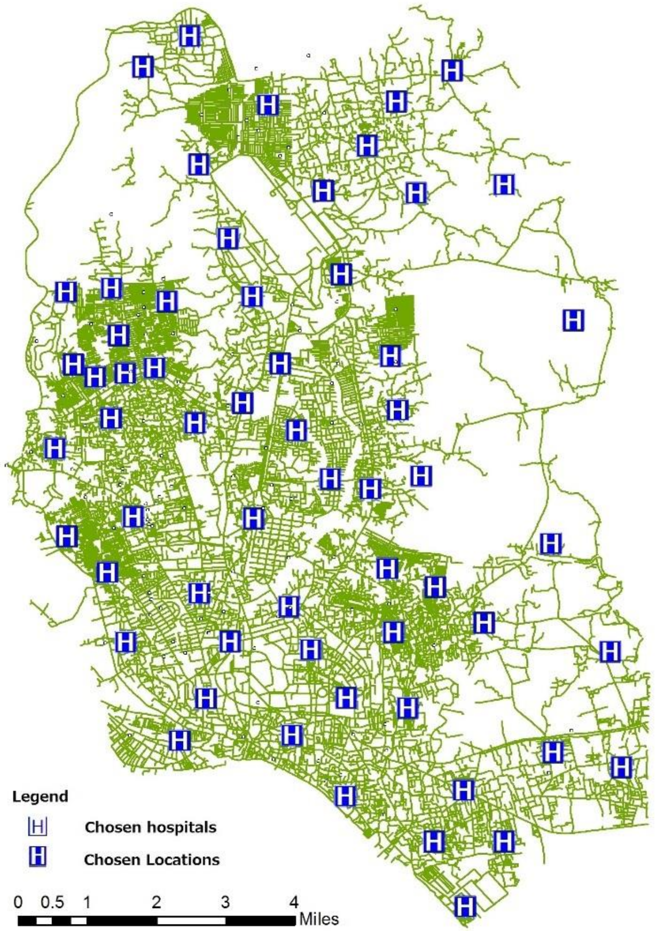
(a)



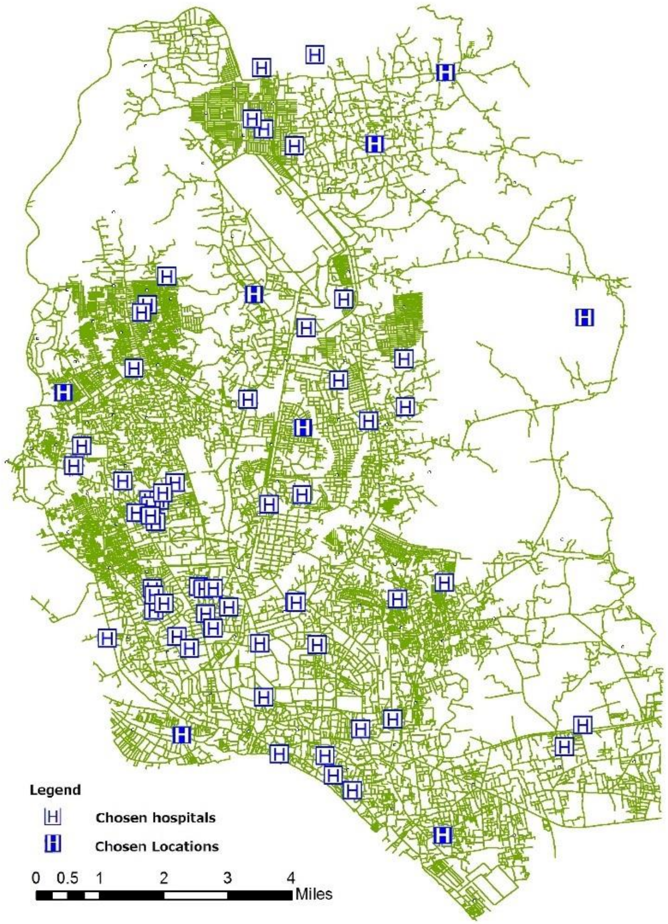
(b)

Figure 5.5. Off-peak pre-positioning results

a.) Density -based result b.) Hospital-based result



(a)



(b)

Figure 5.6. Peak pre-positioning results

(a) Density-based result (b) Hospital-based result

5.4.2.3. <u>Comparison with Actual Data</u>

Table 5.4 compares the response times and the corresponding demand coverage for all scenarios along with the actual response times obtained from the ambulance and survey logs. It was not possible to compare how the coverage will change relative to the current situation, as no information was available regarding the proportion of the emergency demands that are being covered by ambulances at present.

Table 5.4. Response time and demand coverage results

	Selected location	Total time (min)	Coverage (%)
Actual data	Ambulance log	85.3	N/A
	Emergency room survey	175.0	N/A
Pre-positioning result	Hospital-based location result	58.2	96.1
	Density-based location result	52.1	96.1

From Table 5.4, it can be seen that repositioning ambulances close to the demand points (K-medoids clustering) and near strategically important hospitals for maximum coverage, substantially improves the response time. K-medoids clustering yielded better results, suggesting that pre-positioning ambulances near demand points will be more effective for reducing the emergency response time (52.1 to 58.2 min), compared with the response time with no strategy. Apart from these positive points, clearly, based on the results of ambulance pre-positioning, above, an out-of-hospital cardiac arrest patient might not gain much benefit as the response time still exceeds the standard laid down in the US Federal EMS Act (i.e., response time < 10 min).

A cohort study about the effects of reducing response times on cardiac arrest patient's survival rate was conducted by Pell et al. (2001). Using data obtained from the Scottish Ambulance Service, covering almost 7 years, the study found that reducing the 90th percentile of the response time to 8 min increased the predicted survival rate to 8%, and while reducing it to 5 min increased the survival rate up to 10–11%. Nevertheless, some incidents such as traffic accidents, disease, or traumatic wounds that demand appropriate handling and care during the patient transportation phase can still benefit from such improvements as demonstrated in this study. Lastly, while some patients might also require better handling and care during the initial treatment, many concerns related to ambulance safety were also raised in the literature owing to the high speed at which ambulances are expected to operate while they are responding to an emergency (Al-Shaqsi 2010).

5.4.3. Evaluation for Strategies and Practical Implementation

Owing to the lack of centralized control and security, ambulance operators prefer parking their ambulances near hospitals and offset the losses incurred by the ambulances' sitting idly by charging more per trip. This increases the response time and often makes the service unavailable, as well as unaffordable, to most of the population. The findings also suggest that the population lacks knowledge about the medical facilities that they could access more quickly in the event of an emergency. Utilization of a Decision Support System (DSS) with GIS- and Global Positioning System (GPS)-equipped ambulances could improve the efficiency of an EMS. By establishing DSS, detailed EMS data can be collected for analyzing the system's performance. In addition, station planning (location number, station location) based on the optimization result can be implemented by ambulance companies.

Apart from the encouraging findings, the study has some limitations which can be predominantly ascribed to the lack of an established electronic emergency patient care record system as well as real-time traffic data for Dhaka city. In this chapter, ambulances are always assumed sufficient for each demand call. At the same time, all the ambulances were assumed similarly equipped (that is, they are homogenous). As for the future scope, several enhancements to the model can be introduced. Such as, a sophisticated emergency demand forecasting can be introduced including socio-economic variables rather than estimating the demand using population data only. Response time reduction through real-time traffic routing can be appraised. Opportunity to equip a fraction of the ambulances with paramedic service can be estimated. Finally, the data analysis suggests that a substantial number of emergency trips currently use public transport. This instigates the necessity to explore the possibility of integrating public transport with the emergency response systems of developing countries.

5.5. Medical Service Planning for Disaster Response Operation

Disasters bring negative consequences to the communities, including economic and political impacts, costs impact, social and psychological impacts, disruption of the system, and destruction of infrastructure (Pourhosseini et al., 2015). Among all this, the health consequences are related directly with people live and suffering. Prodigious efforts should be prepared and made to guarantee that affected people can receive proper medical care (Swathi et al., 2017). It is expected that EMS will come forward as the first responders after the occurrence of disaster. However, in most cases, the scale of the disaster can overwhelm the local EMS. Thus national or international organizations support will be needed. Medical care response activities during disasters including acute response such as: mass-casualty triage (Clarkson and Williams, 2018), on-scene treatment

(Ramesh and Kumar, 2010), evacuation and mobilization patient to the hospitals (Catlett et al., 2011) and post-acute response such as: continuous medical treatment for the injured, constant care of the affected people, including the mental health of the affected population (Kaji and Waeckerle, 2003). The first five activities can only be done during the first initial response by the local responders, hospitals on-hand and in some cases by DMTs available. The rest of the activities, conducted after the initial response phase passed. With local responders focusing on injured and wounded people, there are percentages of displaced people that required constant medical care. Besides, continuous medical service is still essential to maintain the health condition of the affected population.

5.5.1. *Challenges for Medical Service Provider during Disaster*

This section focuses on analyzing some challenges faced by medical service provider during disaster response. According to disaster medicine's literature study, some challenges faced by medical service providers including:

a. Lack of effective health response and lack of health facilities for dealing with disasters (Zhong et al., 2014; Smith et al., 2010)
b. Health disparities might happen due to overstretched public healthcare services after disasters (Davis et al., 2010). The disrupted healthcare facilities often result in limited service forcing the affected community with no health service available.
c. The study by Watson et al. (2007) explained the possibility of epidemic disease after the disaster when a huge number of populations are evacuated to shelters. The study also includes example epidemic diseases occurred associated with specific type of disasters and risks pertain in the evacuation centers.
d. Lack of medical service for people with constant care needs including vulnerable people such as the elderly, children, and a pregnant woman (Attawel, 1999)
e. The needs for maintaining immunization as counterproductive for the affected population.
f. Psychological problems have become common especially during natural disasters, and treatment is as importance (Udomratn, 2008)

According to Arziman (2015), the shortage of medical service can be mitigated by creating mobile health clinics (MHC) or unit that consist of trained medical team to provide medical treatment. Thus, this section tries to propose strategies for medical assistance group, apart from local responders and healthcare facilities, to support medical service activities during disaster response. The availability of mobile health clinics also supports the healthcare system as the first tier of health center, for the displaced and affected population. Although providing sustainable healthcare is quite challenging, MHC has been implemented in several disaster cases to ease the local health authority. The MHC can be performed by government, international organization such as WHO, or health-related NGO such as Merlin or Plan International.

5.5.2. Mobile Health Clinics as Medical Service Support System

The idea of mobile clinics or mobile health clinics (MHC) is to provide healthcare service to reach population groups and expected to improve the accessibility of healthcare service. Affected communities might rely on mobile clinics team during disaster which road accessibility is low, or health facilities are being reestablished. Mobile health clinics targets are rather for non-emergency patients, but do have a medical care need. In that sense, MHC provides the medical service for people with constant medical care needs, provide immunization, and ensure the health status of the displaced people. Table 5.5 shows the example of some MHC implementations for disaster response phase.

Based on IFRC, there are two types of mobile clinics functions: temporary mobile clinics as health center (alternative for disrupted/non-existed permanent health facility) and the mobile clinics specific for isolated populations and specific functions. The mobile clinics for isolated populations or specific function including mobile surgical teams (case of Somalia in 1992, Sudan in 2000); mobile dental clinics in Sri Lanka; and mobile vaccination units (case of Mali in 1996, Myanmar, Sierra Leone in 2001, and Colombia). The availability of mobile clinics also supports the healthcare system in Colombia and Sri Lanka as the first tier of health center. In case of disaster, mobile clinics performed by NGO improved the healthcare performance in Yogyakarta earthquake 2006, Malaysia flood in 2007, and Sichuan Earthquake 2008. The contribution of this team in such mission may not be that much. However, it can reduce the burden of the local health authority.

Although the MHC concept is to eliminate barrier of healthcare provider and patient such as distance, geographical difficulties, extensive waiting time, and accessibility problem, the utilization of MHC can also be limited by several logistical challenges such as:

a. Finding a suitable location for MHC to park and operate. The location for MHC to operate should be easily accessed by the patients, such as yard/field, school, or community centers near the evacuation area. A geographical condition in the affected area might hinder some operations.
b. Allocating the limited number of MHC to serve the patients. Due to limited number of MHC available and high number of disaster victims, allocating the MHC to serve several locations can be challenging.

Table 5.5. Mobile Health Clinic Implementations during Disaster Response

Author	Location	Type of Disaster	Type of service
Weiss et al. (1999)	Northridge US	Earthquake	respiratory and ear infection, minor injuries, vaccination
Rassekh et al. (2014)	Aceh, Indonesia	Earthquake and Tsunami	emergency surgery, head trauma, diarrhea, respiratory disease, minor injuries, vaccination, medical care for chronic conditions such as hypertension, diabetes, and asthma
Chan and Kim (2010)	Kashmir, Pakistan	Earthquake	earthquake-related trauma, wound, and gastrointestinal infections
Krol et al. (2007)	Mississippi US	Hurricane	common respiratory disease, skin disease, minor injuries, vaccination, medical care for chronic conditions such as hypertension, diabetes, and asthma
Ahmad et al. (2008)	Johor, Malaysia	Flood	Upper respiratory tract infections, musculoskeletal problems, medical care for chronic conditions such as hypertension, diabetes, and asthma
Levine and Shetty (2012)	Libya	Civil war	Blast and burn injuries, gunshot injuries, medical care for medical illnesses
WHO (2013)	Jakarta, Indonesia	Flood	Diarrhea, respiratory disease, medical care for medical illnesses
Cheng, et al. (2015)	Sichuan, China	Earthquake	Emergency surgery, head trauma

c. Routing and scheduling the MHC to maximize the utilization of the vehicle. With limited working hours for the medical operator such as paramedic, nurse, and doctors, the routing sequence and schedule for MHC to stay in a particular location should be optimized to maximize the number of patients treated.

d. Resources availability and limited working hours. The medical operators might be scarce during disaster response as many might be pulled to bigger hospitals for the profoundly injured patients.

e. An uncertain number of patients and type of diseases. Although number of victims can be estimated after the quick assessment, the actual number might be difficult to predict. Disaster environment might worsen the condition of the displaced people and disease might occur after some period of time. Further, as medical treatment is independent for one to each patient, the estimated time for the treatment also uncertain.

5.5.3. *Mobile Clinics Routing Problem*

This study adapts mobile facility routing problem to model the mobile health clinic routing case in disaster response operation. Mobile health clinic can be treated as mobile facility, which can only perform the service only if it stationary in a location. The model is developed as a response planning/ preparedness to provide strategies for medical service providers during disaster response operation, with consideration of demand uncertainties. When preparing for a disaster, it is very difficult to predict the number of evacuated people accurately. It is expected that there will be uncertainty in term of number of patients which in this study is presented as stochastic mobile facility routing problem. Though the stochastic demand can be characterized by a set of probability distribution functions, it is often difficult to do so for each customer in practice. This study uses some pre-specified scenarios to capture different demand patterns, and each scenario is associated with a probability of occurrence.

The objective of the model is to create the route of the MHC to cover as many patients in pre-specified time horizon. Three important features of need to be considered according to Lei et al. (2013) for the mobile facility problem including:

① the medical equipment and healthcare related goods are mounted on vehicles;

② the traveling time of MHC needs to be explicitly accounted in the model;

③ the number of patients to be served at a location is proportional to the duration of the stay at the location.

In this study, the concern is to determine the service sequences of MHCs over a planning horizon to cover the demands of some pre-specified regions at a minimum cost. There is a fixed operating cost associated with each MHC used in the system, includes:

① the cost of allocating MHC and assigning the patients to certain location;

② the routing cost for the MHC to move from one location to another location;

③ the expected cost of the unmet demand due to some patients back out or time limitation.

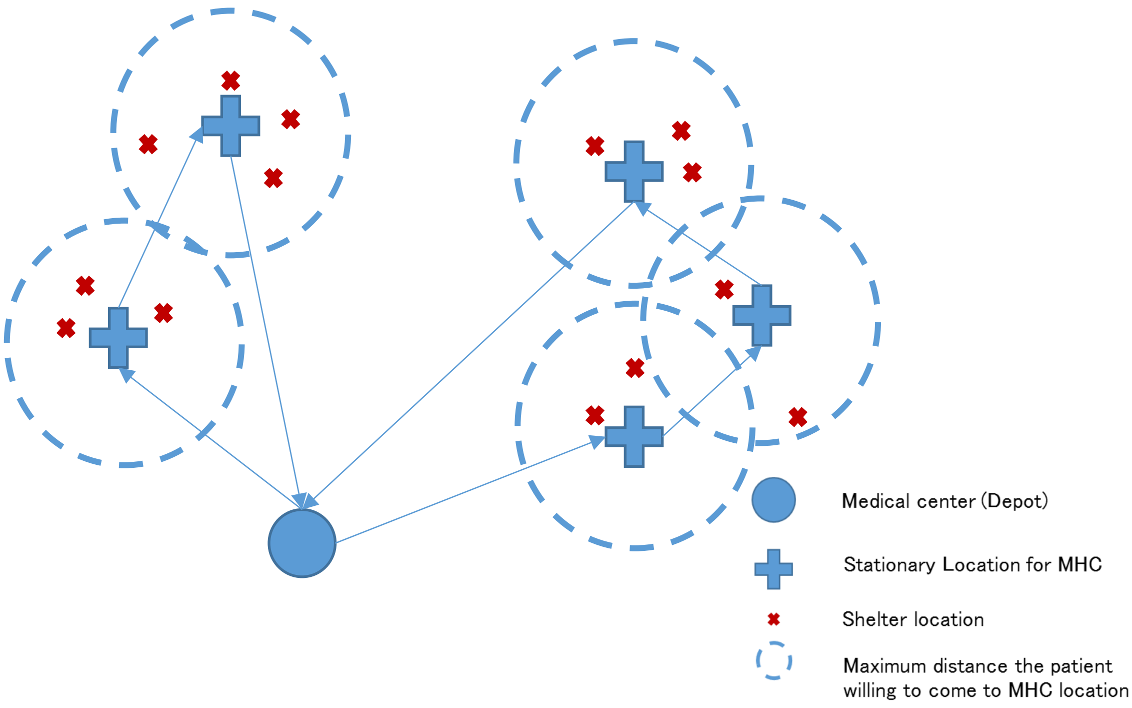


Figure 5.7. Illustration of mobile health routing problem

As illustrated in Figure 5.7, in this study, we consider the single-depot mobile clinics routing problem. The consideration on single-depot is due to the fact that although mobile clinics operate from more than one health facility and sometimes operates by different organizations, the coordination system will be reflected better with the single-depot assumption. Although the coordination for building the routing strategy is important, this study will not focus on how the coordination ensues.

5.5.3.1. <u>Assumptions and limitations</u>

This study postulates several assumptions and limitations to facilitate mathematical formulation.

a. The planning horizon is pre-specified a discrete number with identical length (one working day)
b. The demands are independent, non-stationary and stochastic, with respect to time periods
c. There is a limit to the service capacity for each MHC in the form of maximum service rate
d. The service level of MHC depends on the distance between the customer and the parking location of the MHC
e. A substantial penalty cost would be imposed for untreated patients.

5.5.3.2. Mathematical Formulations

Let the undirected graph $G=(N,A)$, where $N=\{0,1,2,\ldots,n\}$ is the set of nodes and $A=\{(i,j):i,j\in N\}$ is the set of links. The subset $P\subseteq N$ is the set of patient nodes with the subset $L\subseteq N$ is the set of nodes where the mobile clinics can be located.

Sets, indices, and parameters

H	The length of the time horizon
N	A set of nodes, $N=\{0,1,2,\ldots,n\}$
P	The set of all patient demand nodes, $(i\in P)\subseteq N$
J	The set of nodes where the mobile clinics can be located $(j\in J)\subseteq N$
K	A set of mobile clinic available $k=\{1,2,\ldots,K\}$
Z	Set of scenarios $\zeta\in Z$
$t_{jj'}$	Travel time from node j to j'
d_{ij}	Distance (km) between the patient location to where the mobile clinic stationary
α	Assigning patient cost (USD) per unit distance per unit
β	Penalty cost (USD) per unit of untreated patients
γ	Transportation cost (USD) for each mobile clinic
$w_i(\zeta)$	Patient needs to be treated at location i for scenario ζ
$Prob(\zeta)$	Probability for scenario ζ occurrence
Cap	Capacity of the mobile clinics

Decision variables

x_{jkh}	Binary variable for mobile clinic k that stay at location j in time h
y_k	Binary variable for mobile clinic k that is permitted to use
$m_h(\zeta)$	Unmet demand (number of patients not getting treated) in time h for scenario ζ
$z_{ijkh}(\zeta)$	Patient served from location i at location j in time h for scenario ζ

As the objective function consists of two parts: minimizing operational cost (cost for fetching the mobile clinics) and minimizing the cost due to unmet demand, two-stage stochastic programming is employed. Respectively, the mathematical model for the two-stage stochastic programming can be written as:

First stage:

The first stage consists of decision to operate mobile clinics and decision on where to station it. The decision is made before the scenario is being realized. The variable decisions for first stage are:

$$y_k = \begin{cases} 1 & \text{if MHC } k \text{ is allowed to be used} \\ 0 & \text{otherwise} \end{cases} \quad (5.13)$$

$$x_{jkh} = \begin{cases} 1 & \text{if MHC } k \text{ is located at location } j \text{ at period } h \\ 0 & \text{otherwise} \end{cases} \quad (5.14)$$

Second stage:

The second stage decisions involve the recourse actions based on the first stage decision for different scenarios. The decision variables for second stage are: $z_{ijk}^{h}(\zeta)$ defined as the amount of patient in shelter i being served by MHC k, and $m_h(\zeta)$ defined the total amount of patient unserved at period h. The objective of the second stage is to minimize the cost associated with demand satisfaction, including the cost of assigning demands and the penalty cost for unmet demands. The problem can be written as:

$$Q(x,\zeta) = \min \sum_{i}^{P}\sum_{j}^{J}\sum_{k}^{K}\sum_{h}^{H} \alpha d_{ij} z_{ijk}^{h}(\zeta) + \beta \sum_{h}^{H} m_h(\zeta) \quad (5.15)$$

Subject to:

$$\sum_{i}^{P}\sum_{j}^{J} z_{ijk}^{h}(\zeta) \le w_i^h(\zeta), \forall i, h \quad (5.16)$$

$$\sum_{i}^{P}\sum_{j}^{J} z_{ijk}^{h}(\zeta) \le Capy_{jkh} \quad , \forall j, k, h \quad (5.17)$$

$$\sum_{i}^{P}\sum_{j}^{J}\sum_{k}^{K} z_{ijk}^{h}(\zeta) + \ m_h(\zeta) \ge w_i^h(\zeta) \quad , \forall h \quad (5.18)$$

$$x_{jkh} + x_{j\prime kh} \le y_k, \forall h, k, j, j', j \neq j', h' \in \left\{h, .. min\left\{h + t_{jj\prime}, |H|\right\}\right\} \quad (5.19)$$

$$z_{ijk}^{h}(\zeta) \ge 0, \qquad \forall i, j, k, h, \quad (5.20)$$

$$m_h(\zeta) \ge 0, \qquad \forall h \quad (5.21)$$

Constraints (5.16) ensure that the patients served in a time period do not exceed the total patients need medical treatment from MHC in that time period. Constraints (5.17) state the capacity restriction of MHC. Constraints (5.18) ensure that all of the demands have to be met or be subject to a penalty cost. As MHC can only provide medical service when it is stationed, constraint (5.19) ensures that MHC can only perform the service in location *j* and will only be able to serve the next location after it travels to *j'* before the time horizon finished. Constraints (5.20) and (5.21) are nonnegative requirements for decision variables for number of patients served and unmet demand.

The two-stage stochastic programming formulation is expressed as:

$$\min \sum_{k}^{K} \gamma y_k + \phi(x) \tag{5.22}$$

Subject to:

Constraints (5.13), (5.14), (5.19).

Where:

$\phi(x) = \min E_{\zeta}[Q(x,\zeta)]$, which defined as the expected recourse function of second stage decision given that the x is the decision made in first stage.

5.5.4. *Solution Methodology*

This study adopted the scenario based stochastic demand, in which the stochastic demand is pre-specified to capture different patterns. This approach is chosen because the data for probability distribution function is not available during an emergency. Furthermore, considering all type of probability distribution directly will result in high number of solution space. To overcome this challenge, a set of scenarios for different demand with each scenario associated with a pre-specified probability of occurrence, are proposed. Given the limited number of scenarios and the associated probability of occurrence, the above mathematical formulation can be transformed into a mixed-integer programming problem which is often referred to as the Deterministic Equivalent Problem (DEP).

Objective

$$\min \sum_{k}^{K} \gamma y_k + \sum_{\zeta}^{Z} Prob(\zeta) \left(\sum_{i}^{P} \sum_{j}^{J} \sum_{k}^{K} \sum_{h}^{H} \alpha d_{ij} z_{ijk}^{h}(\zeta) + \beta \sum_{h}^{H} m_h(\zeta) \right) \tag{5.23}$$

Constraints

$$\sum_{i}^{P} \sum_{j}^{J} z_{ijk}^{h}(\zeta) \leq w_i^h(\zeta), \forall i, h, \zeta \tag{5.24}$$

$$\sum_{i}^{P} \sum_{j}^{J} z_{ijk}^{h}(\zeta) \leq Capy_{jkh} \quad , \forall j, k, h, \zeta \tag{5.25}$$

$$\sum_{i}^{P} \sum_{j}^{J} \sum_{k}^{K} z_{ijk}^{h}(\zeta) + m_h(\zeta) \geq w_i^h(\zeta) \quad , \forall h, \zeta \tag{5.26}$$

$$x_{jkh} + x_{j'kh'} \leq y_k, \forall h, k, j, j', j \neq j', h' \in \left\{h, .. min\left\{h + t_{jj'}, |H|\right\}\right\} \tag{5.27}$$

$$\sum_k^K y_k(\zeta) \leq M_k \quad \forall i, j, \zeta \tag{5.28}$$

$$\sum_j^J \sum_{j', j \neq j'}^J \sum_k^K t_{jj'} x_{jkh} + \sum_i^P \sum_j^J \sum_k^K z_{ijk}^h(\zeta) \pi w_i(\zeta) \leq H \quad \forall \zeta \tag{5.29}$$

$$y_k, x_{jkh} \in \{0,1\} \tag{5.30}$$

$$z_{ijk}^h(\zeta) \geq 0, \quad \forall i, j, k, h, \zeta \tag{5.31}$$

$$m_h(\zeta) \geq 0, \quad \forall h, \zeta \tag{5.32}$$

The objective function (5.23) aims to minimize the total cost of using MHCs and assigning patients to MHCs during the planning horizon and penalty for not able to treat patients. Constraints (5.24) ensure that the patients served in a time period do not exceed the total patients need medical treatment from MHC in that time period. Constraints (5.25) state the capacity restriction of MHC and constraint (5.26) state that the patient cannot be treated by MHC unless the mobile is stationary at location in period. Constraints (5.27) ensure that all of the demands have to be met or be subject to a penalty cost. As MHC can only provide medical service when it is stationed, constraint (5.27) ensures that MHC can only perform the service in location *j* and will only be able to serve the next location after it travels to *j'* before the time horizon finished. Constraint (5.28) make sure that the maximum number of MHC used are less than available number of MHC provided.

In addition, as to make sure that the MHC will only perform the service in intended time horizon, we constraint working hour (horizon *H*) to be 10 hours, with fixed service time π for all patients (Constraint 5.29). Constraint (5.30) is decision variable regarding the number of MHCs to be used and when and where to locate them. Constraints (5.31) and (5.32) are nonnegative requirements for decision variables for number of patients served and unmet demand. Noticed that we also added more consideration that is practical by adding Constraint (5.28) and (5.29) due to limited number of resources and working hours. The mathematical formulation was coded in Microsoft Visual Studio C++ 2015. It is then solved using Bender decomposition with CPLEX 12.8 solver.

5.5.5. Scenario Generation

These uncertainties are assumed to be well approximated by a finite set of realizations or scenarios *Z*, which represent the probability distribution of the historical data of disaster occurrence and the impacts. Each scenario ζ has a probability of occurrence $\pi(\zeta)$, such that $\pi(\zeta)>0$ and $\sum \zeta \in Z\pi(\zeta)=1$ hold. The scenario derived from monthly Flood Emergency in Jakarta from 2013-2016. The number of mobile clinics operated is set fixed with number of displaced people increased in consideration with bigger flood scenario. The scenario generation method is adopted from Moreno et al. (2016), which estimates the probability of disaster occurrence using historical data and categorize it based on the scale and impact, then calculate the probability by using Bootstrap method (Efron, 1979). Demand associated with each scenario are also calculated.

Candidate locations for mobile clinics are assumed same with the location of the patients/shelters. First, this study assumes that $J \in I$ and the relationship between mobile clinics candidate locations and the shelters locations to be $|J| = \lambda\, |I|$, $\lambda \in (0,1]$, with λ is set to be 1. As the data that available are only the number of displaced people and number of shelters, number of patients for each location i will be equal to:

$$r_i = \mu * ref_i \tag{5.24}$$

r_i denoted the number of people with medical service needs in shelter i, ref_i denoted the number of displaced people located in shelter i, and lastly, μ denoted the proportion of people with medical and healthcare needs. For this numerical example, we set $\mu = 0.1$, with ref_i is set according to avan erage number of displaced people in study location based on historical data. Capacity for each running MHC is set to be 50. The assigning cost per unit distance and per person is set to be equal to 15$ while penalty cost for untreated patient is set to be 100$ per person and vehicle cost is set to be 1500$. The medical care duration is set equally fix, 10 minutes, for all patients. This study imposes a high value of penalty for untreated patient and in the case where number of patients is exceeding the mobile clinics' capacity; additional mobile clinic will be dispatched to the same location to cover the demand. Table 5.6 shows the occurrence probability for each scenario.

Table 5.6. Occurrence probability of each scenario

Scenario	scenario 1	scenario 2	scenario 3	scenario 4	scenario 5
Probability	0.368	0.315	0.157	0.086	0.074
Shelters	Number of displaced people				
KM1	378	1,134	1,750	2,059	2,367
KM2	78	231	328	492	492
KM3	30	89	138	175	176
KM4	23	69	108	136	137
KM5	29	85	132	167	168
KM6	125	375	398	497	497
KM7	151	453	709	898	905
KM8	9	26	40	51	51
KM9	21	63	98	124	125
KM10	23	68	106	134	135

5.5.6. Numerical Example and Analysis

Each scenario at first is solved before the DEP model is implemented. The result comparison between each scenario and DEP can be seen from Table 5.7. From the results, both from independently run scenario and stochastics scenario, the location selected do have a relatively high number of people in a shelter. In particular, location KM1, KM2, and KM7 are selected in all scenarios. Although constraint (5.30) only allowed one vehicle maximum for one location, we realized that after scenario 1, the number of displaced people in shelter KM1 and KM7, increase significantly and dispatching only 1 vehicle will resulted in high number of unmet patients. In that case, modified the input data set, and duplicate the shelter location into different node and equally divide the displaced people. According to additional constraint (5.29), maximum service hour should not be more than 10 hours, which resulted in need of additional mobile clinics when number of patients are reaching 60 people. Thus, duplication of location will be done if number of displaced people are exceeded 600 people. As we tried allowed several vehicles to be dispatched to same location, mobile clinics dispatched for KM1 and KM7 are counted to be more than 1 vehicle, respectively. As can be seen from table 5.7, there is a difference between number of locations selected and number of vehicles dispatched.

Table 5.7. Computational Results for Jakarta Flood Data Sets

Scenario	Parameters		Total Cost (USD)	Number of Mobile clinics dispatched	Expected Number of unmet patients	Location selected
	| I |	Number of Patients Range				
1	10	9~378	3,535.5	2	0	KM1, KM2
2	10	26~1134	9,253.5	6	0	KM1, KM2, KM5, KM6, KM7
3	10	40~1750	11,007.0	7	0	KM1, KM2, KM5, KM6, KM7
4	10	51~2059	15,225.0	10	0	KM1, KM2, KM3, KM5, KM6, KM7
5	10	51~2367	18,225.0	10	30	KM1, KM2, KM3, KM5, KM6, KM7
DEP	10	9~2367	17,335.5	7	66	KM1, KM2, KM5, KM6, KM7

The results also suggest how pre-disaster decision on the locations can affect the number of the affected population treated during the response phase. In regards to the available locations for mobile clinics to stationery, positioning the mobile clinics to serve several shelters resulted in cost minimization and reducing the number of untreated people rather than routing it to all shelters. Further, number of mobile clinics operated is counted to be seven vehicles to minimize the total operational cost, including the penalty cost. Thus, experimental results by limiting the number of mobile clinics to operate are conducted. This analysis is done as in practical situation, not many organizations have and ready to dispatch mobile clinics due to high investment cost or budget limitation. The result of the analysis can be seen in Figure 5.8. It can be observed that while the number of mobile clinics is limited, the number of untreated patients is also enormous which occasioned in the higher total cost. However, when the number of mobile clinics is more than seven, the cost associated with vehicle operational cost is also resulted in higher overall total cost, although the number of untreated patients is smaller.

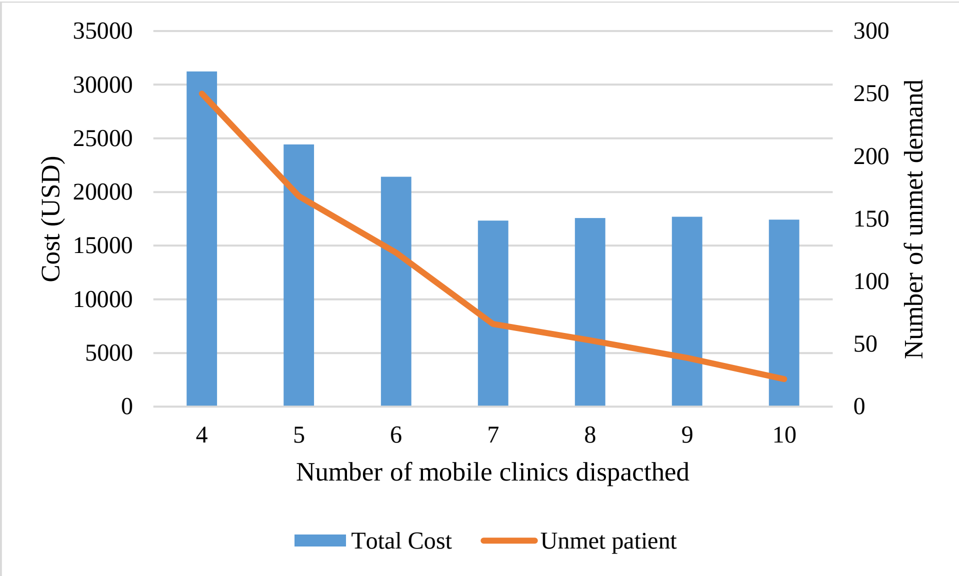


Figure 5.8. Relationship between number of mobile clinics dispatched to cost and unmet patients

5.5.7. *Model Analysis and Evaluation for Strategies*

In this section, we provide some observations and its results to highlight the significance of the proposed mobile health clinics routing under the hybrid policy. In this hybrid policy, we investigate the implications of having medical care center in the shelter with more than 600 people. We realize that having several mobile clinics going to same locations might be costly and operationally inefficient. Looking into practical consideration, a medical shelter is often set up following a mass evacuation. Thus, an investigation of the medical shelter effect in location with high number of displaced people and routing mobile clinics for several shelter locations with small number of people are conducted. The cost for setting up a medical shelter is set to be equal with three unit of MHC, thus 4500$. The result of analysis is presented in Table 5.8. From the numerical results in previous section, it is prominent how MHC do give advantages when there are many shelters with small number of displaced people. Mobile health clinics can serve many locations within appropriate walking distance and routing it to reach other location when the time constraint allowed. In this case, the number of patients per each location should be considerably small. Moreover, from the numerical data used for this study, the location is clustered thus allowing concept of mobile facility routing to be performed. When location of each shelter is dispersed without cluster, the problem is closer to vehicle routing problem. Furthermore, in a location with expected large number of displaced people, this strategy unfortunately is not an appropriate option. With high number of people located in a shelter, building a medical shelter could give a better service, respectively. If the location for all shelters are centered and within walking distance, having health shelter to cover many shelters is possible, although might resulted in higher cost for the initialization of it.

Table 5.8. Result comparison of base policy and hybrid policy

	Total Cost	Expected Unmet patients	Number of medical shelters	Location of medical shelter	Number of mobile clinics	Location selected
Base Policy (Mobile health clinics)	17,335.5	66	0	-	7	KM1, KM2, KM5, KM6, KM7
Hybrid Policy (Medical shelter and mobile health clinics)	12,917.0	20	1	KM1	4	KM2, KM5, KM6, KM7
Shelter Policy (Medical shelter)	20,187.5	20	4	KM1, KM3, KM6, KM7	0	-

Although the result presented in Table 5.8 is optimal for the five selected scenarios, as the probability of the scenario occurrence might be changes, the result might also vary. Disasters are often convoyed by number of extortions to the physical health of people living in affected population and by disruptions of the health care infrastructure. Injury related with the disaster; contact to environmental contaminants; and clinical conditions due to stress, lack of access to medical service, and disruption of continuity of care, are affect the population health status. When medical service is urgently needed, its capacity is often diminished, forced external responders to provide the service. Mobile health clinics have been implemented during disaster response in several countries to help reach the population with deficiency of medical service. The MHC service, however, has several logistical problems to handle before, to optimize not only number of coverages, but also the vehicle utilization.

5.6. Conclusion of the Chapter and Practical Implications

This chapter tackled two types of emergency responders in health and medical service sectors. The first study focusses on the local responders' performance in health sector, especially EMS, for the routine emergency case in developing countries. The challenges in providing a better EMS service lies in several aspects such as coordination between pre-hospital care and in-hospital care, dispatcher system, cultural acceptance and understanding in the community, and traffic problem. Considering how EMS is critical part of community health system, continuous improvement in its practice must become an important aspect of boots the performance of EMS system.

Further, this chapter selected Dhaka city as a developing representative city and conducted an in-depth investigation to understand the current practices in its EMS system. Then, the chapter investigated the possibility of improving both the emergency response time and coverage of such services by formulating it as a location-allocation problem. The response time and service coverage were optimized using K-medoids clustering, which uses both centroids and medoids for the alternative centers and visualizing it using ArcGIS. The results of our study are expected to initiate more research into this area, focusing on the developing countries where most of the medical service improvement investments are directed, either targeting specific diseases or focusing more on the consequences of trauma and injury, or expanding the basic health care infrastructure in which an EMS has often been neglected. Furthermore, the EMS readiness during day-to-day emergencies should be extended for in the disaster or crisis.

The further analysis discussed problems in medical service that often occurred in the disaster case. As large-scale disasters are often unpredicted, limited on-site medical services have never met to fulfill the demand of the sick and wounded. As many highly injured patients will be transferred to available hospitals, some minor injury patients might not get priority to receive medical treatment. Evacuation area and bad sanitation even worsen some people health condition without getting proper treatment. To minimize accidental casualties and reduce the degree of disability, moving the health clinics' platform forward to disaster scene has been a new focus in the modern philosophy of medical care and trauma care.

This study modeled the mobile health clinics problem into mobile facility routing problem with stochastic scenario with objective is to create the route of the MHC to cover as many patients in pre-specified time horizon. Mobile health clinics or mobile clinics can provide medical care to people who are unable to access the health facilities (hospitals, clinics) during disaster response phase. The results also suggest how pre-disaster decision on the locations can affect the number of the affected population treated during the response phase. In regards to the available locations for mobile clinics to stationery, positioning the mobile clinics to serve several shelters resulted in cost minimization and reducing the number of untreated people rather than routing it to all shelters. A mobile health clinic should be operated at the nearest accessible open area by road, where the injured or medical care patient can get centralized treatment.

Not only does the mobile health clinics play an active role of emergency rescue, but it holds the capability to be a substitute for a local hospital destroyed in the disaster. Aside from EMS, healthcare related organizations; both government and non-government agencies that provide medical care/services should work together and have a communication and information system sharing for the benefit of the affected population. In that case, the problem regarding resources allocation can be minimized. Although the mobile clinic contributions to the whole disaster operation may not be that much in comparison, the additional availability of it can reduce the burden of local health authority and lessen the suffering of the affected population.

Chapter 6 Conclusions

Although emergencies and disasters possess different scale of negative concerns, it still caused certain suffering to the affected people. Extra efforts need to be taken to response such events. Further, not only did the affected people need relief goods such as food, tent, clothes, to sustain their life, but also an adequate medical service is vital to reduce the number of fatalities. The challenges arose during relief distribution, and medical service activities on different respond level are presented in this dissertation. This chapter summarizes the findings in this study, including some recommendation for future studies.

6.1. Summary of Findings

This study has addressed some issues related with emergency response operation in local and national scale, focusing on relief distribution and medical service sectors. The general objective is to incorporate the concept of humanitarian logistics for improving emergency response operation and planning, in specified study area, based on interview results of related decision maker. Several literature studies are conducted in Chapter 2 for exploring and building understanding on the humanitarian logistics model, for activities related with relief distribution and medical service, and several uncertainties factors that can be incorporated for the model development.

In Chapter 3, a multi-modal regional distribution network model is presented to tackle the problem related with time-varying supply, limited resources, and time-varying states of infrastructure, during disaster response. The model intended to be used as a base for disaster response planning in the study area. The results suggest the importance of multi-modal consideration for achieving decision-maker objective, in particular during the initial response phase. The sensitivity analysis conducted to understand the effectiveness of having a LOA outside the affected area. It is concluded that LOA should only be used during the initial response, and direct delivery to affected area should be imposed once the state of infrastructure and resources are adequate and ready.

In Chapter 4, still focusing on relief distribution activities, the problems arose in the last mile relief distribution are explored. A vehicle routing problem is modified, and dynamic distribution model are proposed. The idea focuses on differentiating demand node types based on its accessibility status and dispatched different types of ‘compatible’ vehicle, respectively. Further, dynamic, and stochastic parameters are introduced to reflect uncertainty pertaining in disaster response situation. In accordance to decision-maker priority to satisfy all the demand, dispatching new vehicle or having vehicle recourse is necessary. Results show the dynamicity, and stochastic parameters ensued in additional travel time, although in a smaller percentage compared with unmet demand percentage if the new demands are ignored.

In addition, activities related with medical service are also discussed in Chapter 5 of this study. Motivated by Sendai Framework, the preparedness level for medical service responders are primary relied on its local responders, such as EMS. In the higher level, Red Cross and related medical agencies should also be involved when big scale of emergency or disaster occurred. A literature study shows concern on EMS performance for low-middle income countries in Asia. A field study conducted in Dhaka City, Bangladesh shows problems that need to be solved, in order to improve the preparedness level of the medical service. The facility location concept is adopted to solve the pre-positioning strategy for the ambulances in Dhaka City. The model adopted is generalized and basic, as the objective lays onto illustrate if such tactical level is implemented. Numerical analysis shows that pre-positioning ambulance in disperses locations can reduce the response time for the ambulance, rather than centralized ambulances in limited hospitals. The proposed strategy is to divide the role between local responders and other medical service organizations during disaster. In order to minimize casualties and reduce the degree of disability, moving the health clinics' platform forward to disaster scene has been a new focus in the modern philosophy of medical care and trauma care. Not only does the mobile health clinics play an active role of emergency rescue, but also it holds the capability to be a substitute for a local hospital destroyed in the disaster. Such strategy has been implemented to response the medical needs during disaster.

Emergency and disaster planning require different dimensions to be work together to achieve a better emergency response and should be deliberate together, as the substratum of disasters planning is the local responders. Regardless of how large the emergency and disasters, the base of response operations will be at the local scope. Unfortunately, many disaster plans are focusing on how to deal with a mid-big range of disasters and neglect the role of local resources as the first responder. This study develops models for both tactical and operational level for relief distribution and medical service. Aside from national level, advancing the logistics performance in local and regional level will help to reduce the number of suffering people. Build up local responder capability and improves its logistics and supply chain performance can help to develop routine emergency preparedness and response while also preparing for a response to the disasters.

6.2. Practical Implication and Applicability

Based on the insights gained in the development of this dissertation, this section discusses what implications the research findings have for the decision maker for improving emergency response operations.

Chapter 3 – The results of the model can be used as a base for developing national and regional coordination, strengthen the response preparedness, and estimate the additional capacity needs when dealing with the disaster. Although, the numerical illustration has been performed for earthquake-related disaster, the model still applicable to another type of disaster. The input parameters such as number of supplies, number of demands, available infrastructures, and state of networks should be modified, respectively.

Chapter 4 – The dynamic and stochastic nature in the model can illustrate the information changes or information evolution due to chaos. Often during the initial response period, the distribution operation is performed based on the results of need assessment. The decision maker, however, may not have all the information regarding the exact amount and location of the demand. The dynamic model allows the decision maker to modify their distribution operation as the new information is realized. In this case, the driver should also perform as an assessor and keep updating the data while performing the distribution.

Chapter 5 – Medical service is vital for maintaining lives, regardless of the emergency scale. In both routine emergency and disaster cases, preparedness and planning of EMS can help to save more live by responding to the event faster. The improvement can be made by implementing a logistics concept such as facility location, location- allocation, vehicle routing, scheduling, and soon. The strategy, however, should be coordinated with other medical organizations as not to result in service redundancy and oversupply of medical resources.

Concisely interpreting the findings of this study to practical world and policy implications, the following points were found relevant to consider:

a. Multisector outlook is needed when dealing with emergency and disaster. As proposed in Sendai Framework, all level of responders should be included when planning the strategy for emergency response. In this case, the function of logistician is critical to make sure that the mobilization of all components can be efficiently done.
b. Emergency and disaster planning should be prepared as local as possible and as global as necessary. Escalation of the problem to the higher responder’s level is needed when local capacity is overwhelmed.

c. Local responders are the first and fastest to the disaster victims, in regards to any sector. Thus, preparing local responders for worst-case scenario is vital. Adequate training and disaster drill should be performed regularly, for both relief distribution and medical service activities.

6.3. Future Research Direction

The scope of the future research direction is geared towards addressing the limitation encountered in the comportment of this study. Although the findings of this dissertation contribute to the body of the literature, several limitations are inevitable when developing the model and solution methodology. There are also remaining areas to be answered in the future.

a. Decision-makers

The model built in this study focus on operation with single decision maker. Although such case is the actual condition in the study area, Indonesia and Bangladesh, multi-decision-makers situation are also common in disaster case.

b. Dealing with uncertainty

Although this study also incorporates uncertainty in several levels, Chapter 3- time-varying parameter; Chapter 4-dynamic and stochastic demand; and Chapter 5-time-dependent travel time and stochastic demand, more complex uncertainty can be incorporated when the accountability of data input can be achieved. A fuzzy approach or robust optimization could also be solution when data is not available.

Furthermore, the parameters setting for some assumed distribution for explaining the uncertainty might be adjusted with real disaster response data to capture the scale of the uncertainty itself for more practical use of the model.

c. Improving model with better data collection

The challenging factor in this study also lays on the limited data as an input for the model. The stochastic programming model, for example, can be developed if distribution probability is known from a historical data. During disaster response, however, it is not possible to record all activities and issues due to the complexities of disasters. In emergency case, such as EMS, additional technology and the centralized emergency medical system might be able to improve such data collection.

d. Extension of model and solution methodology

Chapter 3--Development a model incorporating several difficulties/considerations such as crew rest time, airport and road congestion, vehicle refueling, vehicle breakdown, and private sectors involvement. If the historical data is present, development a stochastic model in consideration of disaster type and magnitude could be done.

Chapter 4--Model extension from current model with additional concern of vehicle refueling and integrate it with facility location problem to select the local distribution points. For smaller scale of problem, a robust methodology such as bender decomposition and dynamic programming can be performed for solving the model.

Chapter 5--Determine a method for demand estimation for emergency transport demand (EMS) considering limited or no historical data. Robust optimization approach also can be a solution to solve the limitation of data available. Further, a model for illustrating mobile health clinics can be proposed and improved, such as Ambulance Routing Problem and Mobile Facility Routing Problem. For bigger scale of cases, a metaheuristics approaches can be developed for computing time efficiency.

List of Publications

1. Meilinda F.N. Maghfiroh, Shinya Hanaoka, (2018). *Dynamic truck and trailer routing problem for last mile distribution in disaster response*. Journal of Humanitarian Logistics and Supply Chain Management, 8 (2): 252-278. (Chapter 4)
2. Meilinda F.N. Maghfiroh, Moinul Hossain, and Shinya Hanaoka, (2018). *Minimizing emergency response time of ambulances through pre-positioning in Dhaka city, Bangladesh*. International Journal of Logistics Research and Applications, 21(1): 53-71. (Chapter 5)
3. Meilinda F. N. Maghfiroh and Shinya Hanaoka (2017). *Last mile distribution in humanitarian logistics under stochastic and dynamic consideration*. IEEE International Conference on Industrial Engineering and Engineering Management (IEEM), Singapore, 2017, pp. 1411-1415. doi: 10.1109/IEEM.2017.8290125. (Chapter 4)

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Appendix I. Input Data for Chapter 3

Table I.1. Transport mode features

Type	Capacity (TON)	Speed (km/h)	cost/unit ton (USD)	Vehicle cost/vehicle (USD)
Airplane	6,7	829	3.6	3500
Vessels	5100	30	0.5	3000
Truck	4	60	0.8	500
Helicopter	2,9	180	4.6	3000

Table I.2. Relief supplies available in each SN per period

Period	Total Supply (TON)	Jakarta	Surabaya	Bali
1	55000	33000	16500	5500
2	155000	93000	46500	15500
3	110000	66000	33000	11000
4	73000	43800	21900	7300
5	61000	36600	18300	6100
6	59000	35400	17700	5900
7	35000	21000	10500	3500
8	25000	15000	7500	2500
9	35000	21000	10500	3500
10	5000	3000	1500	500

Table I.3. Number of transport mode available in each SN per period

Period	Jakarta			Surabaya		Bali
	Truck	Airplane	Vessel	Truck	Airplane	Airplane
1	400	40	2	300	40	30
2	650	130	6	600	130	80
3	850	130	1	600	80	70
4	800	60		500	40	30
5	770	40		400	30	30
6	700	35		400	25	20
7	550	20		300	10	15
8	550			300		10
9	250			250		5
10	150			120		

Table I.4. Distance Matrix for all Nodes

	Jakarta	Surabaya	Bali	Bandung	Pangandaran	Cirebon	Cilacap	Semarang	Malang	Solo	Tasikmalaya	Jogja 1	Jogja 2	Jogja 3
Jakarta	0	0	0	150	129	217	419	460	817	556	257	0	0	0
Surabaya	0	0	0	786	895	581	510	311	94	271	625	0	0	0
Bali	0	0	0	1180	1290	976	898	738	403	655	1020	0	0	0
Bandung	150	786	1180	0	189	215	243	458	810	554	157	372	370	436
Pangandaran	129	895	1290	189	0	320	485	568	920	664	263	604	630	670
Cirebon	217	581	976	215	320	0	170	252	604	348	110	289	313	353
Cilacap	419	510	898	243	485	170	0	237	513	241	141	150	185	212
Semarang	460	311	738	458	568	252	237	0	397	110	348	131	124	153
Malang	817	94	403	810	920	604	513	397	0	327	0	424	391	390
Solo	556	271	655	554	664	348	241	110	327	0	0	105	70	78
Tasikmalaya	257	625	1020	157	263	110	141	348	0	0	0	270	294	334
Jogja 1	0	0	0	372	604	289	150	131	424	105	270	0	0	0
Jogja 2	0	0	0	370	630	313	185	124	391	70	294	0	0	0
Jogja 3	0	0	0	436	670	353	212	153	390	78	334	0	0	0

Appendix 2. Input Data for Chapter 4

Truck capacity	20 TON
Mini truck capacity	9 TON
Maximum number of trucks	50
Maximum number of mini trucks	50
Vehicle speed	30km/hr

Example of Distance matrix for dataset 1.

	0.0	89.8	74.8	42.4	38.1	37.5	66.8	61.6	47.1	65.9	60.0	55.9	64.8	71.4	16.5	70.2	62.9	84.5	48.6	84.6	56.9	50.9	35.6	55.5	56.9	21.2	26.3	44.6	43.6	69.6	84.7	51.1	74.7	64.8	53.3	40.5	73.9	59.4	62.5	50.0	40.1	9.0	40.5	63.6	58.3	66.1	82.7	52.3	71.3	58.8	45.7
	89.8	0.0	125.4	124.6	72.2	108.8	32.5	28.6	130.5	95.9	54.9	108.8	33.6	88.1	105.6	66.5	150.8	100.7	45.9	174.4	105.0	118.9	80.8	127.6	123.7	101.1	81.0	121.5	133.4	126.6	109.8	43.9	139.4	77.6	136.3	109.3	163.7	143.5	152.4	139.8	63.1	84.4	81.2	92.6	124.7	118.3	142.6	48.8	70.8	105.7	44.2
	74.8	125.4	0.0	104.2	56.7	38.9	92.8	106.4	105.7	31.2	70.8	19.8	118.3	42.5	68.6	63.3	105.6	158.6	82.9	101.3	21.4	28.1	109.3	122.7	126.7	92.9	100.1	111.0	82.8	8.7	30.5	83.9	21.8	50.0	110.4	35.4	94.4	57.0	89.9	84.7	107.5	69.1	114.2	33.9	128.2	8.8	18.9	113.3	140.9	20.3	93.2
	42.4	124.6	104.2	0.0	80.2	66.0	106.7	96.2	6.0	104.2	102.2	88.6	94.0	111.6	37.3	112.4	29.3	78.8	88.9	61.9	91.3	76.3	47.3	19.5	25.7	23.9	44.1	9.4	28.5	96.8	121.5	91.4	95.7	106.2	11.7	69.5	52.8	63.1	42.0	32.6	63.3	51.3	49.6	102.4	27.0	96.6	105.4	78.6	81.3	93.3	82.3
	38.1	72.2	56.7	80.2	0.0	37.5	41.1	50.1	84.6	34.3	25.0	38.0	61.6	35.6	46.4	32.3	97.2	109.3	27.0	111.5	35.3	46.7	62.2	93.4	94.1	59.1	54.2	82.7	74.8	55.9	53.5	28.6	67.7	27.3	90.7	37.5	101.4	74.1	91.5	80.2	54.7	29.1	66.6	31.1	95.5	48.5	71.9	57.6	87.3	36.5	36.6
	37.5	108.8	38.9	66.0	37.5	0.0	78.5	84.1	68.1	42.0	61.3	22.8	92.5	52.4	29.7	63.0	72.1	121.9	62.9	77.9	26.2	13.5	73.0	84.1	87.9	54.2	63.7	72.3	48.3	32.6	56.8	64.9	37.5	51.7	73.2	3.5	68.6	37.1	60.6	51.9	74.6	33.9	77.9	41.4	89.4	30.8	45.3	83.7	107.4	28.1	68.3
	66.8	32.5	92.8	106.7	41.1	78.5	0.0	23.4	112.2	63.5	22.5	76.5	38.4	56.4	80.7	35.7	129.7	105.4	18.2	149.2	72.6	87.6	70.6	114.3	112.2	82.9	67.1	105.9	109.7	94.2	78.2	15.7	107.3	45.6	118.3	78.6	138.7	114.6	127.9	115.7	54.6	59.5	73.0	60.2	113.4	85.8	110.1	46.0	76.9	73.2	26.6
	61.6	28.6	106.4	96.2	50.1	84.1	23.4	0.0	102.1	80.0	41.5	88.1	15.2	75.3	77.6	56.8	122.2	82.9	23.6	146.2	85.2	95.4	53.9	100.2	96.9	72.6	53.0	93.5	105.1	106.1	96.8	22.9	117.6	64.1	107.9	85.1	135.5	117.1	124.1	111.5	36.4	56.7	55.1	76.5	97.9	98.5	122.1	24.4	53.9	86.2	16.3
	47.1	130.5	105.7	6.0	84.6	68.1	112.2	102.1	0.0	107.3	107.1	90.9	100.0	115.1	40.4	116.9	23.6	83.3	94.3	57.0	93.8	77.6	53.3	21.1	28.3	29.6	50.1	13.6	26.8	98.1	124.2	96.8	96.0	110.2	6.2	71.6	48.2	61.8	37.9	29.7	69.3	55.9	55.5	105.7	29.3	98.4	105.8	84.6	87.0	95.8	88.0
	65.9	95.9	31.2	104.2	34.3	42.0	63.5	80.0	107.3	0.0	41.0	22.8	93.3	12.2	66.9	32.1	113.9	143.4	56.6	118.5	17.7	40.8	95.4	120.3	122.5	86.9	86.9	108.8	90.1	35.4	19.4	57.0	50.3	19.0	113.0	39.2	109.8	74.9	102.5	93.9	89.0	57.8	100.0	3.4	124.0	26.6	49.9	91.3	121.6	16.5	69.0
	60.0	54.9	70.8	102.2	25.0	61.3	22.5	41.5	107.1	41.0	0.0	55.5	56.2	34.2	70.6	15.7	121.4	117.1	21.3	136.5	51.2	68.5	75.1	113.3	112.8	79.5	69.1	103.4	99.4	72.7	56.0	20.3	86.4	23.2	113.3	60.7	126.3	98.3	116.4	105.0	62.5	51.3	78.7	37.8	114.1	64.2	88.5	58.9	90.8	51.6	35.6
	55.9	108.8	19.8	88.6	38.0	22.8	76.5	88.1	90.9	22.8	55.5	0.0	99.3	34.8	51.7	51.5	94.3	139.1	64.8	96.2	5.2	18.1	89.8	106.3	109.7	75.0	80.7	94.6	70.6	18.0	34.4	66.1	30.9	38.3	96.0	19.4	87.8	52.2	81.2	73.7	87.7	49.7	94.8	23.7	111.2	11.0	34.0	93.7	121.1	6.3	74.2
	64.8	33.6	118.3	94.0	61.6	92.5	38.4	15.2	100.0	93.3	56.2	99.3	0.0	89.4	81.3	71.7	121.6	69.6	36.8	148.2	96.8	104.7	48.2	95.1	90.7	71.5	50.0	89.9	106.9	117.1	110.8	36.7	127.7	78.4	105.5	94.0	137.7	123.1	126.0	113.3	30.9	61.9	48.1	89.9	91.6	110.0	132.9	15.7	39.9	98.1	25.1
	71.4	88.1	42.5	111.6	35.6	52.4	56.4	75.3	115.1	12.2	34.2	34.8	89.4	0.0	74.8	22.1	123.4	144.4	52.8	129.7	29.6	52.5	97.8	126.7	128.2	92.6	89.8	115.4	99.7	47.3	21.8	52.7	62.3	11.1	121.0	49.9	120.8	86.5	113.0	103.8	89.3	62.7	102.2	11.2	129.7	38.6	61.4	89.5	120.7	28.6	66.4
	16.5	105.6	68.6	37.3	46.4	29.7	80.7	77.6	40.4	66.9	70.6	51.7	81.3	74.8	0.0	78.3	50.9	95.7	62.6	68.9	54.1	41.7	48.7	54.6	58.2	25.2	40.0	42.8	29.1	62.0	84.2	65.1	64.1	70.4	46.2	33.3	58.3	43.5	47.3	35.1	56.0	21.4	53.5	65.3	59.7	60.5	73.0	68.8	85.8	56.1	61.5
	70.2	66.5	63.3	112.4	32.3	63.0	35.7	56.8	116.9	32.1	15.7	51.5	71.7	22.1	78.3	0.0	129.0	132.5	37.0	140.6	46.5	67.3	89.4	125.0	125.2	90.8	82.8	114.6	106.0	66.9	43.4	36.0	81.6	13.4	123.0	61.5	130.9	99.7	121.7	111.1	77.7	61.2	93.2	29.5	126.6	58.1	81.9	74.7	106.5	46.3	51.3
	62.9	150.8	105.6	29.3	97.2	72.1	129.7	122.2	23.6	113.9	121.4	94.3	121.6	123.4	50.9	129.0	0.0	106.1	111.4	34.5	98.2	78.2	76.1	41.5	49.3	50.1	71.9	37.0	23.8	97.2	128.7	114.0	91.6	120.4	20.7	75.2	27.3	52.9	20.2	20.9	91.4	70.7	78.7	112.9	50.0	99.7	101.5	106.6	110.6	100.0	107.2
	84.5	100.7	158.6	78.8	109.3	121.9	105.4	82.9	83.3	143.4	117.1	139.1	69.6	144.4	95.7	132.5	106.1	0.0	95.9	140.2	139.0	135.3	49.3	65.2	57.4	71.4	58.5	69.8	105.4	154.0	162.7	97.2	158.9	134.4	85.5	125.0	131.5	136.4	120.7	110.6	55.2	89.4	44.4	140.3	57.1	149.8	167.2	59.4	29.9	140.8	81.7
	48.6	45.9	82.9	88.9	27.0	62.9	18.2	23.6	94.3	56.6	21.3	64.8	36.8	52.8	62.6	37.0	111.4	95.9	0.0	131.3	61.6	73.3	55.7	97.3	95.8	65.1	50.9	88.4	91.5	82.7	74.0	2.6	94.7	41.8	100.4	63.5	120.7	98.0	109.8	97.6	41.7	41.3	58.8	53.1	97.0	75.0	98.8	37.7	69.5	62.6	14.3
	84.6	174.4	101.3	61.9	111.5	77.9	149.2	146.2	57.0	118.5	136.5	96.2	148.2	129.7	68.9	140.6	34.5	140.2	131.3	0.0	101.0	78.1	106.3	75.9	83.8	78.4	100.5	70.6	41.4	92.6	129.2	133.7	82.3	129.7	55.0	80.0	10.6	44.5	22.3	34.9	119.6	90.3	109.6	118.6	84.5	97.9	91.3	134.1	142.5	102.5	130.2
	56.9	105.0	21.4	91.3	35.3	26.2	72.6	85.2	93.8	17.7	51.2	5.2	96.8	29.6	54.1	46.5	98.2	139.0	61.6	101.0	0.0	23.1	89.9	108.6	111.7	76.6	80.8	96.9	74.5	21.6	30.6	62.8	35.4	33.3	99.1	23.0	92.5	57.2	85.6	77.8	86.8	50.1	94.8	18.5	113.2	13.4	37.5	92.0	120.1	2.0	71.8
	50.9	118.9	28.1	76.3	46.7	13.5	87.6	95.4	77.6	40.8	68.5	18.1	104.7	52.5	41.7	67.3	78.2	135.3	73.3	78.1	23.1	0.0	86.4	95.0	99.4	66.8	77.1	83.3	55.0	20.6	51.6	75.1	24.1	54.7	82.3	11.0	69.9	34.1	63.8	57.3	87.9	47.3	91.4	41.3	100.8	21.5	31.9	96.6	120.8	24.4	80.1
	35.6	80.8	109.3	47.3	62.2	73.0	70.6	53.9	53.3	95.4	75.1	89.8	48.2	97.8	48.7	89.4	76.1	49.3	55.7	106.3	89.9	86.4	0.0	46.9	43.0	28.3	9.3	42.0	66.2	104.7	114.8	57.8	110.3	88.7	58.3	75.9	96.1	91.7	84.4	72.3	17.7	40.1	5.0	92.5	44.0	100.5	118.2	32.5	37.6	91.7	44.0
	55.5	127.6	122.7	19.5	93.4	84.1	114.3	100.2	21.1	120.3	113.3	106.3	95.1	126.7	54.6	125.0	41.5	65.2	97.3	75.9	108.6	95.0	46.9	0.0	7.9	34.3	47.5	11.8	47.6	115.6	138.3	99.7	115.0	120.3	21.1	87.6	68.0	82.4	58.4	50.8	64.5	64.4	47.2	118.3	8.6	114.9	124.6	79.3	74.3	110.7	88.3
	56.9	123.7	126.7	25.7	94.1	87.9	112.2	96.9	28.3	122.5	112.8	109.7	90.7	128.2	58.2	125.2	49.3	57.4	95.8	83.8	111.7	99.4	43.0	7.9	0.0	35.7	45.1	16.8	54.3	119.9	140.9	98.2	120.1	121.3	28.8	91.4	75.8	88.8	66.0	57.9	60.7	65.6	42.6	120.3	1.5	118.7	129.6	75.1	67.6	113.7	85.9
	21.2	101.1	92.9	23.9	59.1	54.2	82.9	72.6	29.6	86.9	79.5	75.0	71.5	92.6	25.2	90.8	50.1	71.4	65.1	78.4	76.6	66.8	28.3	34.3	35.7	0.0	22.2	23.9	37.9	86.8	105.4	67.7	89.3	86.0	35.6	57.6	68.1	65.2	56.3	44.1	41.5	30.1	32.1	84.6	37.2	84.6	98.2	56.6	65.6	78.6	58.4
	26.3	81.0	100.1	44.1	54.2	63.7	67.1	53.0	50.1	86.9	69.1	80.7	50.0	89.8	40.0	82.8	71.9	58.5	50.9	100.5	80.8	77.1	9.3	47.5	45.1	22.2	0.0	40.5	59.6	95.4	106.2	53.2	101.0	81.2	55.6	66.6	90.1	83.4	78.3	65.9	19.4	30.9	14.3	84.1	46.3	91.3	108.9	34.7	45.8	82.7	40.8
	44.6	121.5	111.0	9.4	82.7	72.3	105.9	93.5	13.6	108.8	103.4	94.6	89.9	115.4	42.8	114.6	37.0	69.8	88.4	70.6	96.9	83.3	42.0	11.8	16.8	23.9	40.5	0.0	37.8	103.9	126.7	90.9	103.6	109.3	17.0	75.9	61.7	72.1	51.1	41.9	59.0	53.6	43.6	106.8	18.1	103.1	113.2	74.3	74.0	98.9	80.5
	43.6	133.4	82.8	28.5	74.8	48.3	109.7	105.1	26.8	90.1	99.4	70.6	106.9	99.7	29.1	106.0	23.8	105.4	91.5	41.4	74.5	55.0	66.2	47.6	54.3	37.9	59.6	37.8	0.0	74.7	105.0	94.0	70.7	96.9	29.5	51.5	30.8	35.1	19.1	6.5	78.4	50.2	69.9	89.2	55.5	76.5	80.6	92.8	103.3	76.3	89.3
	69.6	126.6	8.7	96.8	55.9	32.6	94.2	106.1	98.1	35.4	72.7	18.0	117.1	47.3	62.0	66.9	97.2	154.0	82.7	92.6	21.6	20.6	104.7	115.6	119.9	86.8	95.4	103.9	74.7	0.0	38.2	84.0	15.0	53.5	102.6	29.3	85.7	48.3	81.3	76.3	104.2	64.7	109.7	37.5	121.4	8.8	16.0	111.1	137.5	21.1	92.1
	84.7	109.8	30.5	121.5	53.5	56.8	78.2	96.8	124.2	19.4	56.0	34.4	110.8	21.8	84.2	43.4	128.7	162.7	74.0	129.2	30.6	51.6	114.8	138.3	140.9	105.4	106.2	126.7	105.0	38.2	0.0	74.1	52.3	32.8	129.6	53.5	121.4	84.7	115.3	108.1	108.2	76.8	119.4	22.4	142.4	31.5	48.2	109.9	140.5	28.7	87.2
	51.1	43.9	83.9	91.4	28.6	64.9	15.7	22.9	96.8	57.0	20.3	66.1	36.7	52.7	65.1	36.0	114.0	97.2	2.6	133.7	62.8	75.1	57.8	99.7	98.2	67.7	53.2	90.9	94.0	84.0	74.1	0.0	96.2	41.7	103.0	65.4	123.2	100.2	112.3	100.1	43.5	43.8	60.8	53.6	99.4	76.2	100.1	38.7	70.5	63.7	15.6
	74.7	139.4	21.8	95.7	67.7	37.5	107.3	117.6	96.0	50.3	86.4	30.9	127.7	62.3	64.1	81.6	91.6	158.9	94.7	82.3	35.4	24.1	110.3	115.0	120.1	89.3	101.0	103.6	70.7	15.0	52.3	96.2	0.0	68.2	99.8	35.0	76.5	39.6	73.9	71.1	111.9	71.4	115.2	52.3	121.5	23.7	9.9	120.3	144.9	35.3	102.8
	64.8	77.6	50.0	106.2	27.3	51.7	45.6	64.1	110.2	19.0	23.2	38.3	78.4	11.1	70.4	13.4	120.4	134.4	41.8	129.7	33.3	54.7	88.7	120.3	121.3	86.0	81.2	109.3	96.9	53.5	32.8	41.7	68.2	0.0	116.2	49.9	120.2	87.8	111.6	101.6	79.3	55.9	92.9	16.2	122.7	44.7	68.6	78.8	110.2	33.0	55.6
	53.3	136.3	110.4	11.7	90.7	73.2	118.3	107.9	6.2	113.0	113.3	96.0	105.5	121.0	46.2	123.0	20.7	85.5	100.4	55.0	99.1	82.3	58.3	21.1	28.8	35.6	55.6	17.0	29.5	102.6	129.6	103.0	99.8	116.2	0.0	76.7	47.0	64.4	37.6	31.3	74.7	62.1	60.2	111.4	29.7	103.3	109.7	90.0	91.0	101.1	94.0
	40.5	109.3	35.4	69.5	37.5	3.5	78.6	85.1	71.6	39.2	60.7	19.4	94.0	49.9	33.3	61.5	75.2	125.0	63.5	80.0	23.0	11.0	75.9	87.6	91.4	57.6	66.6	75.9	51.5	29.3	53.5	65.4	35.0	49.9	76.7	0.0	70.9	38.2	63.3	54.9	77.0	36.5	80.9	38.8	92.9	27.3	42.4	85.7	110.0	24.8	69.6
	73.9	163.7	94.4	52.8	101.4	68.6	138.7	135.5	48.2	109.8	126.3	87.8	137.7	120.8	58.3	130.9	27.3	131.5	120.7	10.6	92.5	69.9	96.1	68.0	75.8	68.1	90.1	61.7	30.8	85.7	121.4	123.2	76.5	120.2	47.0	70.9	0.0	37.4	11.8	24.4	109.1	79.7	99.5	109.7	76.6	90.3	85.9	123.6	132.6	94.1	119.6
	59.4	143.5	57.0	63.1	74.1	37.1	114.6	117.1	61.8	74.9	98.3	52.2	123.1	86.5	43.5	99.7	52.9	136.4	98.0	44.5	57.2	34.1	91.7	82.4	88.8	65.2	83.4	72.1	35.1	48.3	84.7	100.2	39.6	87.8	64.4	38.2	37.4	0.0	34.4	33.5	99.4	61.2	96.2	75.3	90.1	53.4	49.3	111.6	129.1	58.6	100.9
	62.5	152.4	89.9	42.0	91.5	60.6	127.9	124.1	37.9	102.5	116.4	81.2	126.0	113.0	47.3	121.7	20.2	120.7	109.8	22.3	85.6	63.8	84.4	58.4	66.0	56.3	78.3	51.1	19.1	81.3	115.3	112.3	73.9	111.6	37.6	63.3	11.8	34.4	0.0	12.6	97.3	68.6	87.9	102.0	66.9	84.9	83.6	111.9	121.0	87.3	108.2
	50.0	139.8	84.7	32.6	80.2	51.9	115.7	111.5	29.7	93.9	105.0	73.7	113.3	103.8	35.1	111.1	20.9	110.6	97.6	34.9	77.8	57.3	72.3	50.8	57.9	44.1	65.9	41.9	6.5	76.3	108.1	100.1	71.1	101.6	31.3	54.9	24.4	33.5	12.6	0.0	84.8	56.3	75.9	93.2	59.0	78.8	81.0	99.3	109.3	79.6	95.6
	40.1	63.1	107.5	63.3	54.7	74.6	54.6	36.4	69.3	89.0	62.5	87.7	30.9	89.3	56.0	77.7	91.4	55.2	41.7	119.6	86.8	87.9	17.7	64.5	60.7	41.5	19.4	59.0	78.4	104.2	108.2	43.5	111.9	79.3	74.7	77.0	109.1	99.4	97.3	84.8	0.0	40.8	18.7	85.8	61.7	98.7	118.9	15.3	33.4	88.4	28.4
	9.0	84.4	69.1	51.3	29.1	33.9	59.5	56.7	55.9	57.8	51.3	49.7	61.9	62.7	21.4	61.2	70.7	89.4	41.3	90.3	50.1	47.3	40.1	64.4	65.6	30.1	30.9	53.6	50.2	64.7	76.8	43.8	71.4	55.9	62.1	36.5	79.7	61.2	68.6	56.3	40.8	0.0	45.1	55.3	67.0	60.4	78.7	51.0	73.5	52.0	40.5
	40.5	81.2	114.2	49.6	66.6	77.9	73.0	55.1	55.5	100.0	78.7	94.8	48.1	102.2	53.5	93.2	78.7	44.4	58.8	109.6	94.8	91.4	5.0	47.2	42.6	32.1	14.3	43.6	69.9	109.7	119.4	60.8	115.2	92.9	60.2	80.9	99.5	96.2	87.9	75.9	18.7	45.1	0.0	97.1	43.5	105.4	123.2	32.5	33.5	96.6	46.4
	63.6	92.6	33.9	102.4	31.1	41.4	60.2	76.5	105.7	3.4	37.8	23.7	89.9	11.2	65.3	29.5	112.9	140.3	53.1	118.6	18.5	41.3	92.5	118.3	120.3	84.6	84.1	106.8	89.2	37.5	22.4	53.6	52.3	16.2	111.4	38.8	109.7	75.3	102.0	93.2	85.8	55.3	97.1	0.0	121.8	28.7	52.4	88.0	118.3	17.7	65.6
	58.3	124.7	128.2	27.0	95.5	89.4	113.4	97.9	29.3	124.0	114.1	111.2	91.6	129.7	59.7	126.6	50.0	57.1	97.0	84.5	113.2	100.8	44.0	8.6	1.5	37.2	46.3	18.1	55.5	121.4	142.4	99.4	121.5	122.7	29.7	92.9	76.6	90.1	66.9	59.0	61.7	67.0	43.5	121.8	0.0	120.2	131.0	76.0	67.9	115.2	87.0
	66.1	118.3	8.8	96.6	48.5	30.8	85.8	98.5	98.4	26.6	64.2	11.0	110.0	38.6	60.5	58.1	99.7	149.8	75.0	97.9	13.4	21.5	100.5	114.9	118.7	84.6	91.3	103.1	76.5	8.8	31.5	76.2	23.7	44.7	103.3	27.3	90.3	53.4	84.9	78.8	98.7	60.4	105.4	28.7	120.2	0.0	24.4	104.7	132.1	12.6	85.0
	82.7	142.6	18.9	105.4	71.9	45.3	110.1	122.1	105.8	49.9	88.5	34.0	132.9	61.4	73.0	81.9	101.5	167.2	98.8	91.3	37.5	31.9	118.2	124.6	129.6	98.2	108.9	113.2	80.6	16.0	48.2	100.1	9.9	68.6	109.7	42.4	85.9	49.3	83.6	81.0	118.9	78.7	123.2	52.4	131.0	24.4	0.0	126.4	152.1	37.0	107.9
	52.3	48.8	113.3	78.6	57.6	83.7	46.0	24.4	84.6	91.3	58.9	93.7	15.7	89.5	68.8	74.7	106.6	59.4	37.7	134.1	92.0	96.6	32.5	79.3	75.1	56.6	34.7	74.3	92.8	111.1	109.9	38.7	120.3	78.8	90.0	85.7	123.6	111.6	111.9	99.3	15.3	51.0	32.5	88.0	76.0	104.7	126.4	0.0	31.9	93.5	23.4
	71.3	70.8	140.9	81.3	87.3	107.4	76.9	53.9	87.0	121.6	90.8	121.1	39.9	120.7	85.8	106.5	110.6	29.9	69.5	142.5	120.1	120.8	37.6	74.3	67.6	65.6	45.8	74.0	103.3	137.5	140.5	70.5	144.9	110.2	91.0	110.0	132.6	129.1	121.0	109.3	33.4	73.5	33.5	118.3	67.9	132.1	152.1	31.9	0.0	121.7	55.2
	58.8	105.7	20.3	93.3	36.5	28.1	73.2	86.2	95.8	16.5	51.6	6.3	98.1	28.6	56.1	46.3	100.0	140.8	62.6	102.5	2.0	24.4	91.7	110.7	113.7	78.6	82.7	98.9	76.3	21.1	28.7	63.7	35.3	33.0	101.1	24.8	94.1	58.6	87.3	79.6	88.4	52.0	96.6	17.7	115.2	12.6	37.0	93.5	121.7	0.0	73.0
	45.7	44.2	93.2	82.3	36.6	68.3	26.6	16.3	88.0	69.0	35.6	74.2	25.1	66.4	61.5	51.3	107.2	81.7	14.3	130.2	71.8	80.1	44.0	88.3	85.9	58.4	40.8	80.5	89.3	92.1	87.2	15.6	102.8	55.6	94.0	69.6	119.6	100.9	108.2	95.6	28.4	40.5	46.4	65.6	87.0	85.0	107.9	23.4	55.2	73.0	0.0

Example of Route result for dataset 1.